





AML 2021

ANTI-MONEY LAUNDERING & FINANCIAL CRIMES VIRTUAL CONFERENCE



Improving AML Detection and Investigation using Machine Learning and Graph Databases



Today's Speakers



David Ronald
Product Marketing Director
TigerGraph



Steven Fuller
Senior Solutions Engineer
TigerGraph



UNODC

United Nations Office on Drugs and Crime

The United Nations Vienna 1988 Convention Article 3.1 defines **money laundering** as “the conversion or transfer of property, knowing that such property is derived from any offense(s), for the purpose of concealing or disguising the illicit origin of the property or of assisting any person who is involved in such offense(s) to evade the legal consequences of his actions”.

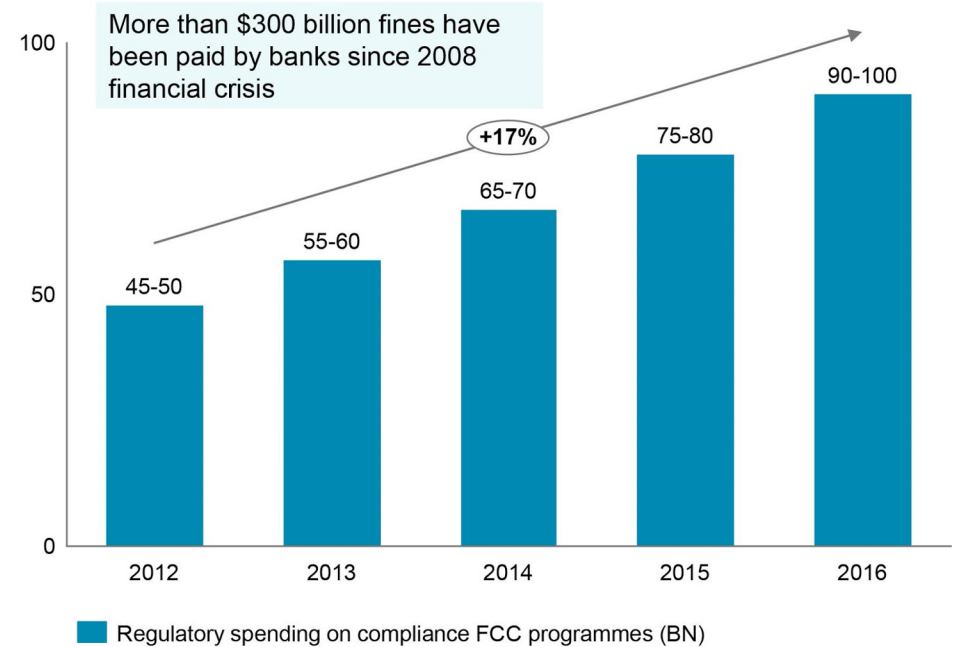
Three stages of Money Laundering:

- **Placement:** Moving funds from direct association with crimes
- **Layering:** Disguising the trail to foil pursuit
- **Integration:** Making money available to criminals from what seem to be legitimate sources

<https://www.unodc.org/unodc/en/money-laundering/overview.html>

Total aggregated US bank fines in 2020	\$14.21B
Most common violation	AML breaches

<https://finbold.com/bank-fines-2020/>



AML Considerations

Not Small

UNODC: Money laundering is now estimated to be "2–5% of global GDP, or \$800B to \$2T in current USD" (>AAPL market cap)

Not Just Banks

Entirely new counterparties now: Retail, casinos, real estate, human and drug trafficking, terrorists, cryptocurrencies, and other **networks**

Not Just Risk Scoring

Investigations need deep and wide and fast network forensics: **financial crime networks are evolving into advanced persistent threat systems**

Not Just KYC

Effective investigations also now need to avoid false positives:
KNOW YOUR CUSTOMER'S CUSTOMER: KYC(C)

Not Just Humans

Graph analytics, together with ML/AI and data science - **with humans in the loop** - together help investigators do even better

Technology Use Cases



Business Cases

- Anti Money Laundering
- Internal Fraud - Entitlements
- Credit Card & Transaction Fraud
- Identity Theft & Falsification
- Cyber - Malware
- IoT & Asset Fraud
- Audit & Compliance
- Claim, Dispute Charges
- Law Enforcement - Prosecution



Investigation - Visualization

- Advanced Visualization
- Dependency | Network Pathing | Routing | Complex Visualization
- Clustering & Community Detection
- Geospatial 'Network Mapping'
- Real Time Data - IoT Systems
- Team-based Workbench & Investigation



ML and Analytics

- Patterns - Recommendations
- What If - Planning & Visibility
- Predictive & Analytics
- Scoring and Risk
- Audit & Compliance - Historical
- Targeting Similarities
- Decision Tree Analytics

Limited Legacy Systems



NICE - ACTIMIZE

About | Help | Personalization | Regins

Dashboards Cases Work Items Research Settings Policy Manager

Blotters

CH-2012-**- Trades Details

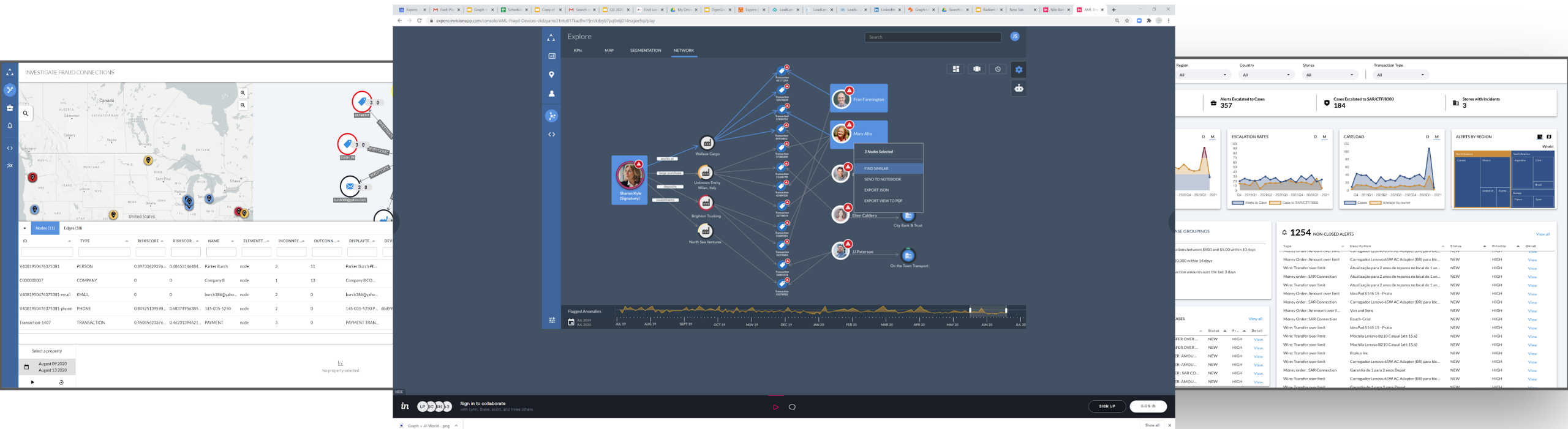
New Filter: Public
Clients Age 65 and Over
Silo 1: Equities: Value >20k & Price > \$5
Silo 2: Equities: Value >5k & Price < \$5
Silo 3: Equities: Qty > 20k
Solicited Penny Stock Purchases
Trades With Alerts
Un-Reviewed Trades
Private
Unreviewed without Alerts

Account	Rep Code	Symbol	Product Name	B/S	Qty	Price	Net Amount	Comm...	S/U	Discr...		
2	03032060	N. Bilis	A345	IBM	IBM CORP	B	50,000	\$100.00	\$5,000,000.00	\$5,000.00	S	N/A
5	04780C37	J. Kanorski	A345	FFRFX	FIDELITY ADVISOR FLOATING RATE	B	10,000	\$9.00	\$90,000.00	\$0.00	S	N/A
	07495C37	C. Benigno	A001	KDHEX	SCUDDER DREMAN HIGH RETURN	B	25	\$41.00	\$1,054.00	\$0.00	S	N/A
	08037C37	M. Tanaka	A177	YHOO	YAHOO INC	B	1,000	\$36.00	\$36,064.00	\$40.00	S	DE
Trade ID	206009	Trade Date	10/10/2012	Acct Type	Margin	Acct Details	08037C37	Acct Profile	08037C37			
Age	26	Inv. Obj.	Growth	Occupation	Financial A...	Sec. Type	Equity	Interactions	View CTFs			
Income	67,000	Net Worth		Tax Status		Rep Name	Perkins, Joe					
	08037C37	A. Castilla	A345	KGRAX	SCUDDER GROWTH FUND	S	335	\$8.00	\$3,000.00	\$0.00	S	DE
	09400C37	H. Marcus	8778	PAL	NORTH AMERICAN PALLADIUM LTD	B	1,000	\$7.00	\$7,774.00	\$24.00	S	N/A
	11315C37	R. Sanchez	A222	KDHAX	SCUDDER DREMAN HIGH RETURN	B	1	\$44.00	\$50.00	\$0.00	S	N/A
	14581C37	J. Chung	A222	LTXK	LTX CORP	B	800	\$6.00	\$4,968.00	\$24.00	S	N/A
	17835C37	H. Markman	8778	BLI	BIG LOTS INC	S	6,000	\$11.00	\$68,912.00	\$0.00	S	N/A
	18918C37	J. Peck	A177	SBUX	STARBUCKS CORP	S	100	\$55.00	\$5,501.00	\$24.00	S	N/A
	18990C37	L. Stock	A177	MMAM	MEDICAL MAKEOVER CORP OF AMERICA	B	1,000	\$10.00	\$424.00	\$24.00	S	N/A
	19110C37	J. Pearl	A222	PDYN	PARADYNE NETWORKS INC	B	1,500	\$3.45	\$5,175.00	\$24.00	S	N/A

- No depth of context: Mules? Sometimes. Fraud rings? No.
- Heavy overhead in terms of integration, operations, human-in-the-loop investigations.
- Lack of speed, scale, insight into connected data.



Better Investigative Insights

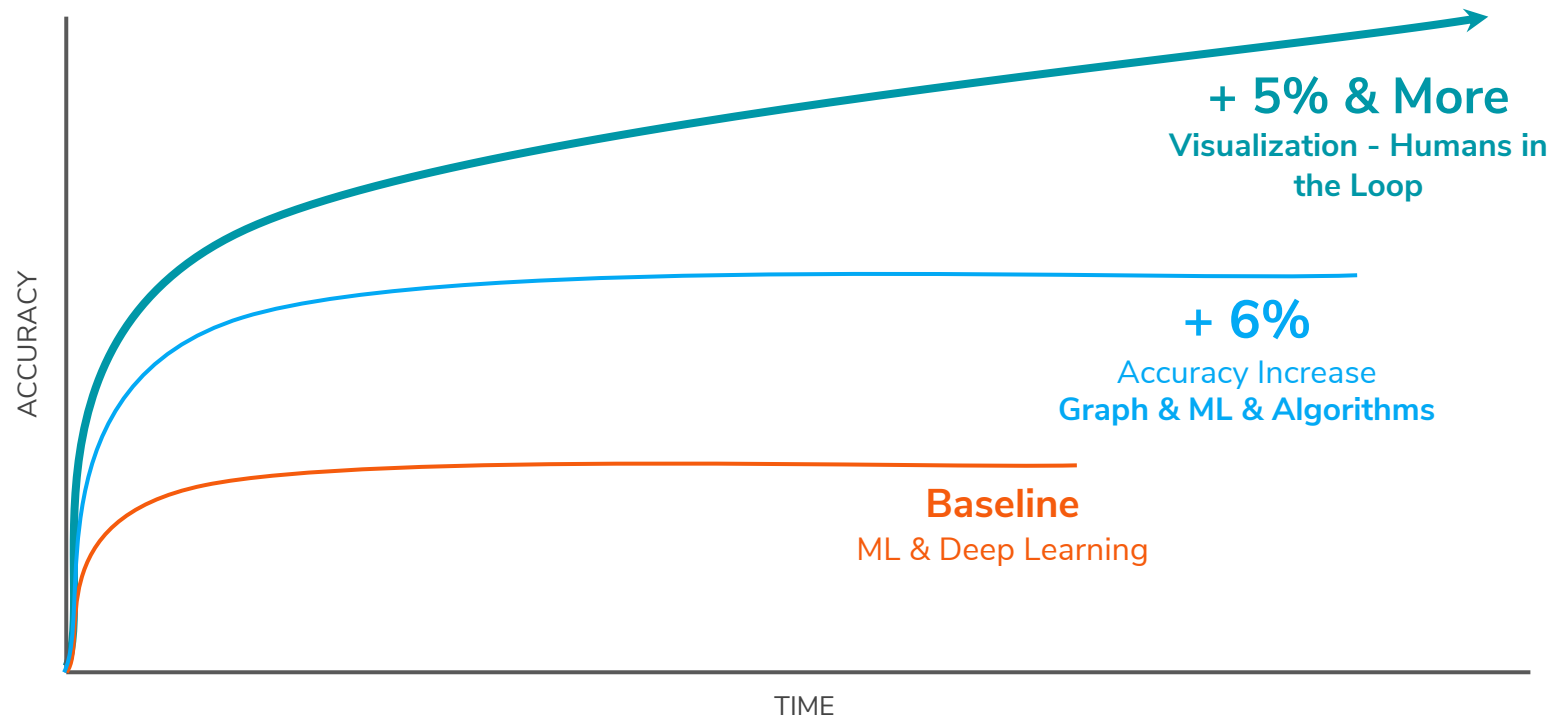


- Actionable investigative insights obtained using machine learning and graph databases

Better Analytics Accuracy

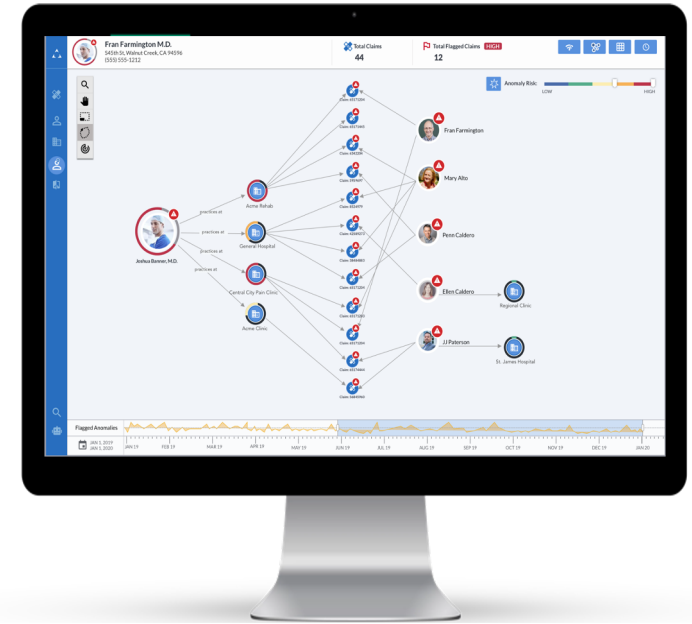


Graph + machine learning + humans = improved accuracy of AML investigations




Benefits of AML Workbench

- **Increase accuracy of alerts** - human and algorithms (eg, false positives)
- **Decrease false positives** - capture and incorporate human instincts and expertise (especially for expert users)
- **Increase speed & efficiency** - more accurate and trusted outcomes (both automated & human)
- **Improve operational efficiency** - reduce the level of effort needed to investigate alerts and create cases
- **Adapt to changes** - add new alerts and rules to address new patterns
- **Continuous improvement** - system can learn, adapt & get better over time





Introduction to Graph Databases

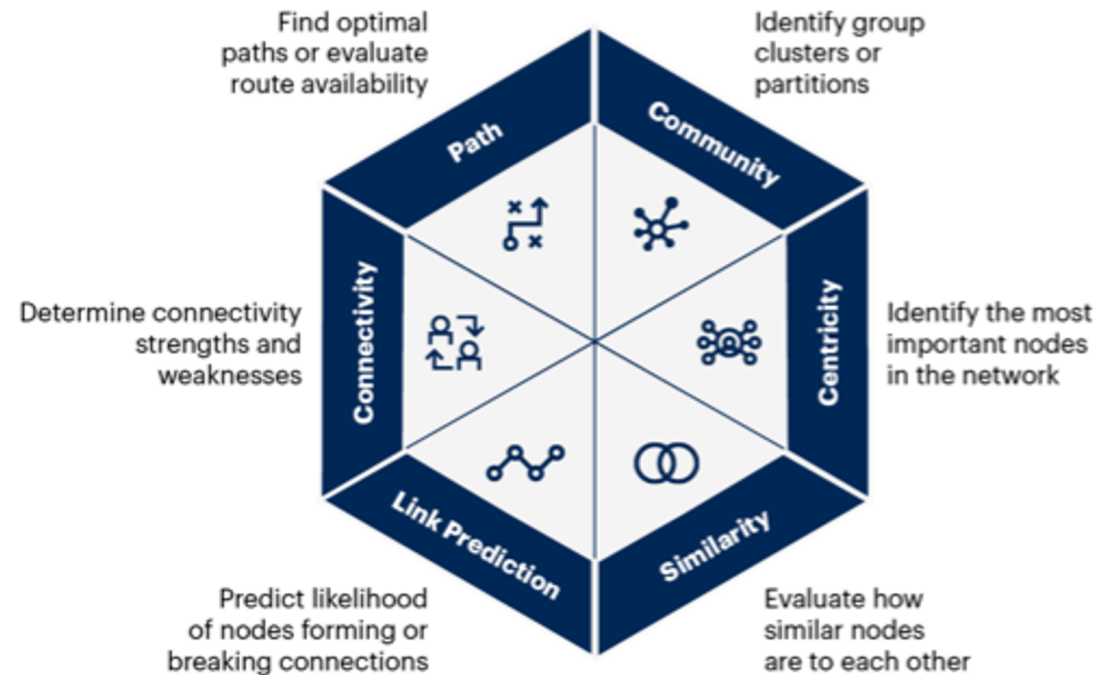


*“Graph analysis is possibly the single most effective competitive differentiator for organizations pursuing data-driven operations **and decisions after the design of data capture.**”*

Gartner[®]

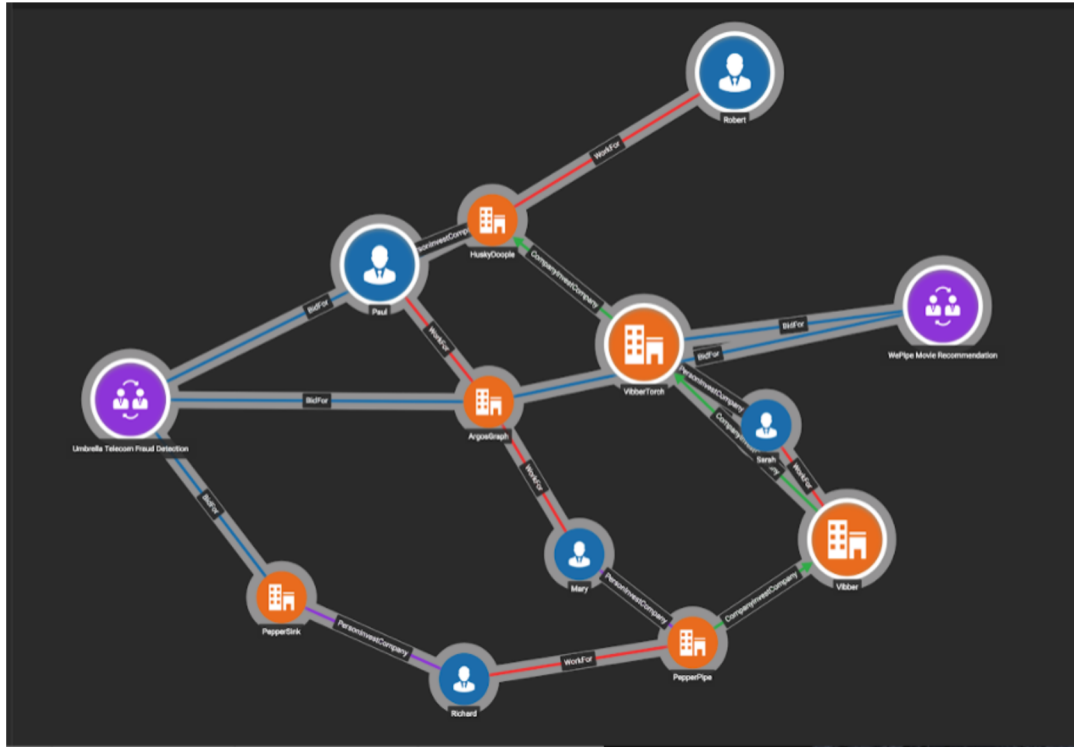
Six Types of Graph Analytics

Graph can be used to analyze all sorts of relationships across all kinds of systems even beyond process or beyond the confines of individual operational models.



Source: "Understanding When Graph Technologies Are Best for Your Business Use Case", Jim Hare et al, 2020

A Sample Graph



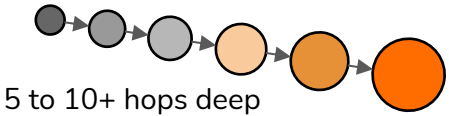

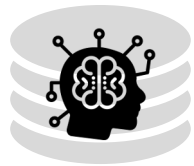
Graph databases consist of **vertices** and **edges**

- **Vertices** - data entities
 - for example - person, account, transaction
- **Edges** - the relationships between those entities
 - for example - person opens account, money moves from one account to another account

A graph stores the relationships between data entities - or can be used to uncover relationships between data entities

Why Graph Databases?



Feature	Design Difference	Benefit
Deep-Link Pattern Discovery  <p>5 to 10+ hops deep</p>	<ul style="list-style-type: none">• Native graph, for speed and efficiency	<ul style="list-style-type: none">• Uncovers hard-to-find patterns• Operational, real-time analytics
Handling Massive Scale 	<ul style="list-style-type: none">• Distributed database architecture• Massively parallel processing• Compressed storage reduces footprint and messaging	<ul style="list-style-type: none">• Integrates all your data• Automatic partitioning• Complete data → better detection
In-Database Analytics 	<ul style="list-style-type: none">• GSQL: High-level yet Turing-complete language• User-extensible graph algorithm library, runs in-database• ACID (OLTP) & accumulators (OLAP)	<ul style="list-style-type: none">• Avoids transferring data• Richer graph context• In-place machine learning



Better AML with Graph

Richer, smarter connected data

- Uncover connections, break down silos

Deeper, more far-reaching questions

- Search far and wide faster and more easily

Enhance investigations with non-obvious information

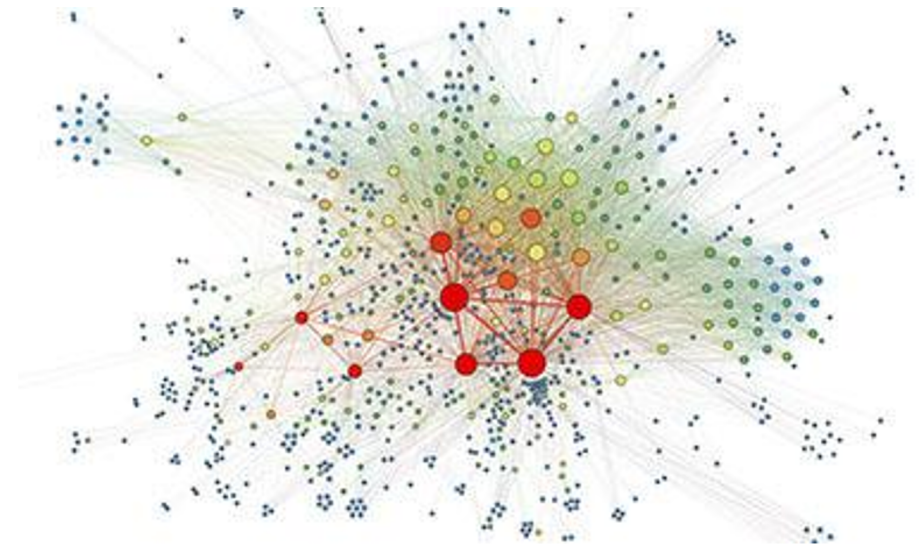
- Connect SARs from prior investigations

Discover hidden behaviors and compare patterns

- Decide which investigations have a high probability of a successful outcome

Explainable results

- AI/ML-based results are credible and understood by humans
- Visual exploration



About TigerGraph

Connect Datasets & Pipelines

Friction-free scale out from GB to TB to PB with lowest cost of ownership

UNITEDHEALTH GROUP®

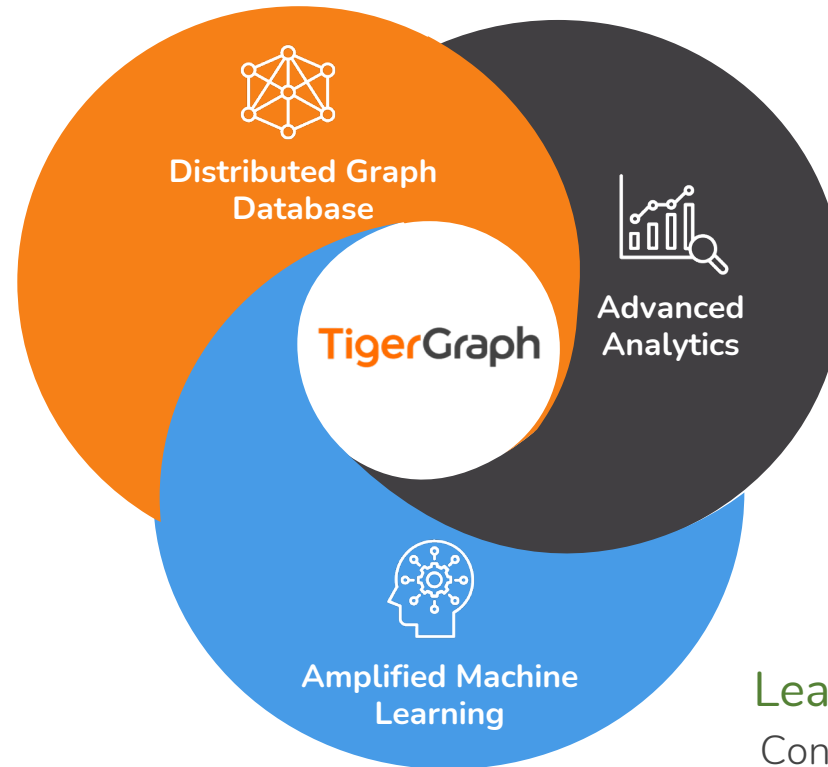
Customer 360 connecting 200+ datasets and pipelines

Fortune 50 Retailer

Item 360 for ecommerce across 100+ datasets



Identity graph connecting 50+ data pipelines



Analyze Connected Data

10-100x faster than current solutions



Supply chain planning: 3 weeks to 45 minutes



Fraud Detection: batch to real-time for 300M calls/day

Learn from Connected Data

Continuous graph-based feature generation & training

intuit.

AI-based Customer 360 for entity resolution, recommendation engine, fraud detection

Mapping a Road to Success



Data sources:

- Product Catalog
- Transactions
- Operations
- Customers
- Social Networks
- Sales CRM

1 AML Graph



2 Link & Merge Entities

- Rule-based
- ML-based

3 Build Initial Visualization System

Human Exploratory Learning

- Get to know your business/data better
- Define useful measures and displays, particularly for fraud investigation and confirmation

Unsupervised Learning

- Run graph algorithms to characterize your data: connections, groupings, frequent patterns, outliers
- What is typical/frequent vs. atypical?

4 Use Graph+ML to Detect & Investigate Money Laundering

Extract Graph Features

- Measure closeness and paths to entities of interest
- Detect communities and clusters (Louvain)
- Measure similarity between entities (Cosine, Jaccard)
- Rank the influence of entities (PageRank)
- Graph Embedding (Node2Vec)

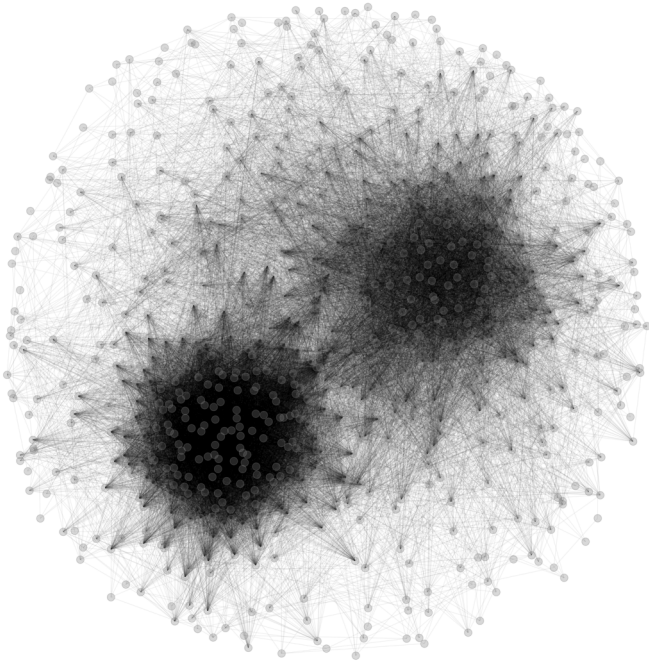
Gather Training Data

Train Your ML Model with Graph Data

- Export graph data to external ML platform
- In-database ML

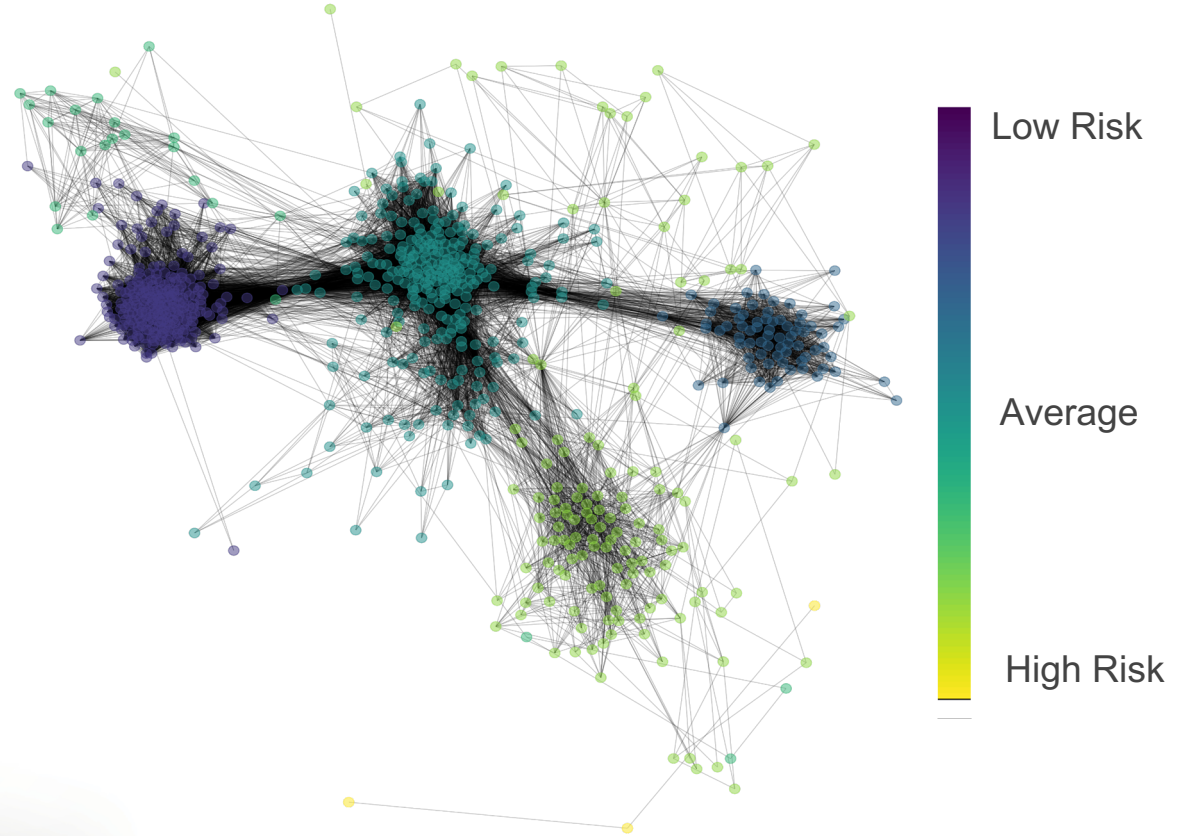
Viewing Risk in a Graph

An unstructured graph of unrelated bank transactions



vs.

Same graph, automatically clustered by their history
Louvain Communities with graph + ML algorithms





Demonstration

Thank You



David Ronald
Product Marketing Director
TigerGraph
david.ronald@tigergraph.com



Steven Fuller
Senior Solutions Engineer
TigerGraph
steven.fuller@tigergraph.com



Thank You

