



# Graph Databases and Machine Learning: Finding a Happy Marriage

Victor Lee, November 12, 2018

# Know Your Speaker

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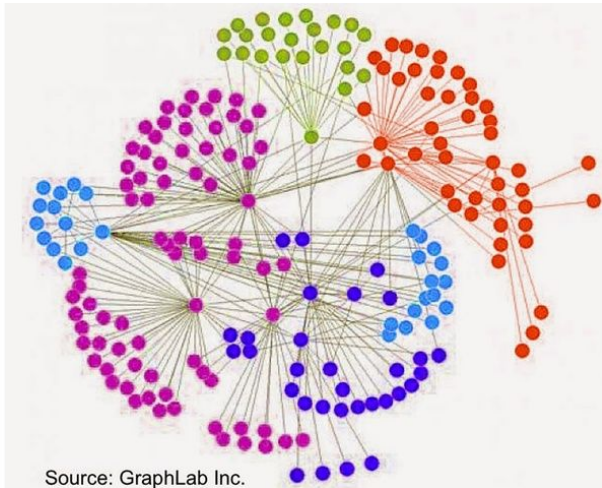


- **Mission:** Unleash the power of interconnected data for deeper insights and better outcomes
- **Technology:** Industry's First and Only Native Massively Parallel Processing(MPP) Graph Technology
- **Product:** The world's fastest graph database used by organizations including AliPay, Intuit, Uber, Visa, Zillow



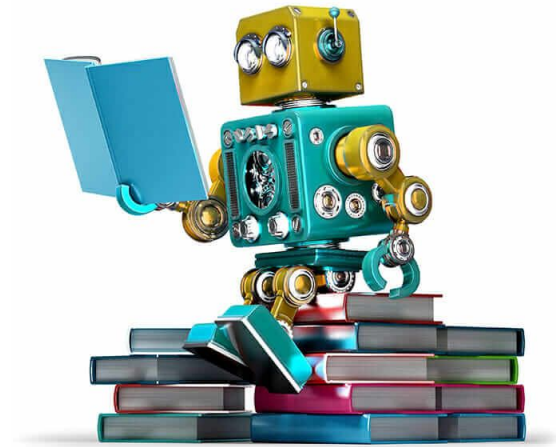
# Two Hot Items: A Good Match?

## Graph Database



New, exciting way to represent information and to query it.

## Machine Learning



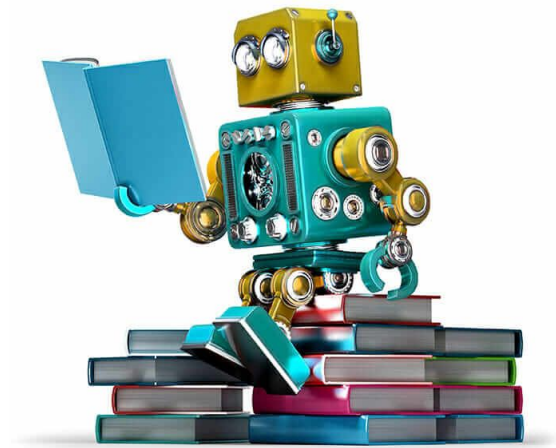
Established powerhouse for predictions and "smart" systems, but still tricky to use.

*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®**

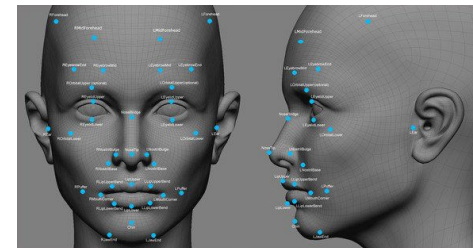
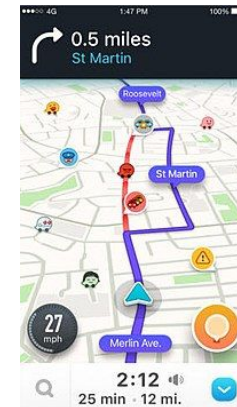
# What is Machine Learning?

- Branch of AI
- Making predictions, models, or optimizations using incomplete or inexact data
  - Model? Weather
  - Optimization? Best driving route, best investment portfolio



# Uses of Machine Learning

- Virtual Personal Assistants
  - Voice-to-text
  - Semantic analysis
  - Formulate a response
- Real-time route optimization
  - Waze, Google Maps
- Image Recognition
  - Facial recognition
  - X-ray / CT scan reading
- Effective spam filters



# Machine Learning Techniques

- **Supervised Learning**

Humans provide "training data" with known correct answers

- Decision Trees
- Nearest Neighbor
- Hidden Markov Model, Naïve Bayesian
- Linear Regression
- Support Vector Machines (SVM)
- Neural Networks

- **Unsupervised Learning**

No "correct" answer; detect patterns or summarize

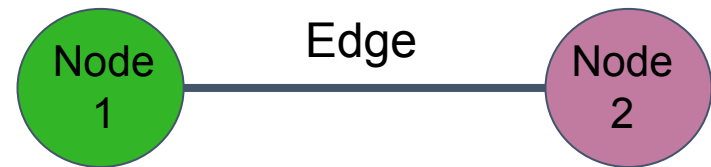
- Clustering, Partitioning, Outlier detection
- Neural Networks
- Dimensionality reduction



# Graphs (Networks) are all around us



**Graph:** collection of **nodes** and links ("**edges**") between nodes

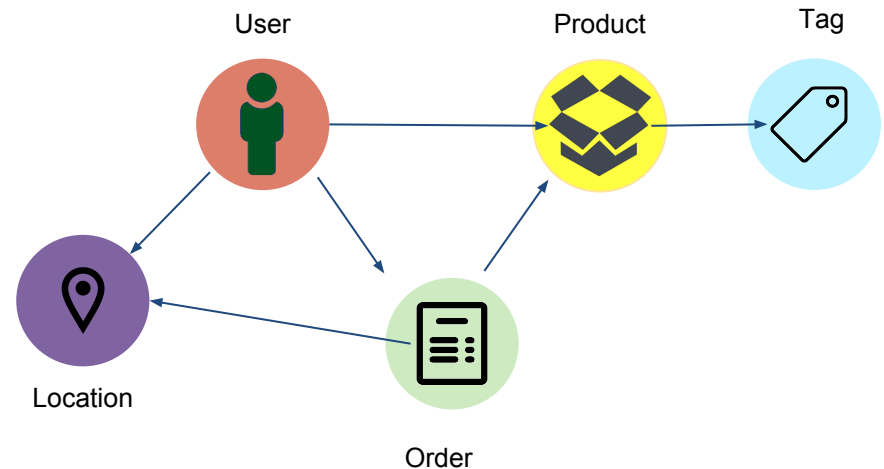


- Data Never Sleeps
- Internet of Things
- BIG Data
- Social Networks



# Graph Database - The Natural Choice for Interconnected Data

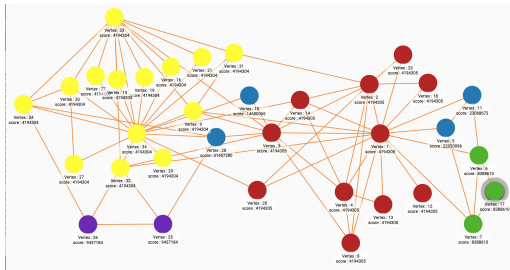
- **Natural storage model** for interconnected data
- **Natural for transactions:** transaction = edge
- **Natural for computational knowledge/inference/learning** – "connect the dots"



# Matchmaking: Consider Each Party

## Graph Databases

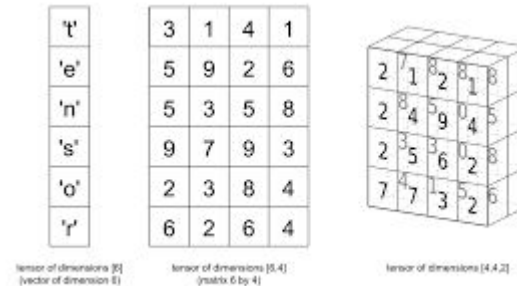
- Stores data as nodes & edges.
- An edge (link) IS a data object.



- Capabilities of platforms and query languages vary:
  - All are good at storing data
  - Wide range of analytical abilities

## Machine Learning (ML)

- Wants data as vector, array, or tensor



- Computationally intensive, long and time-consuming
- Requires good quality input data:  
Garbage in, garbage out
- Many methods to choose from

# ML Features and Modeling

- Most/All ML methods try to correlate *features* (properties/attributes) with the target result.

	Feat 1	Feat 2	Feat 3	Result
Item 1	X	0	0	X
Item 2	X	X	0	0
Item 3	X	0	X	?

- Quality of modeling depends on quality of features
  - Having the right features
  - Having the right distribution of values & results
- Don't know which features are needed!

# ML Features and Modeling

- If you don't know the right features yet, then just try to have LOTS of features.
- Big Data 3 V's:
  - **Volume**
  - **Variety**
  - Velocity
- Example:
  - Suppose family medical history is the best predictor of an ailment.
  - If you don't know family medical history, you won't be able to make good predictions

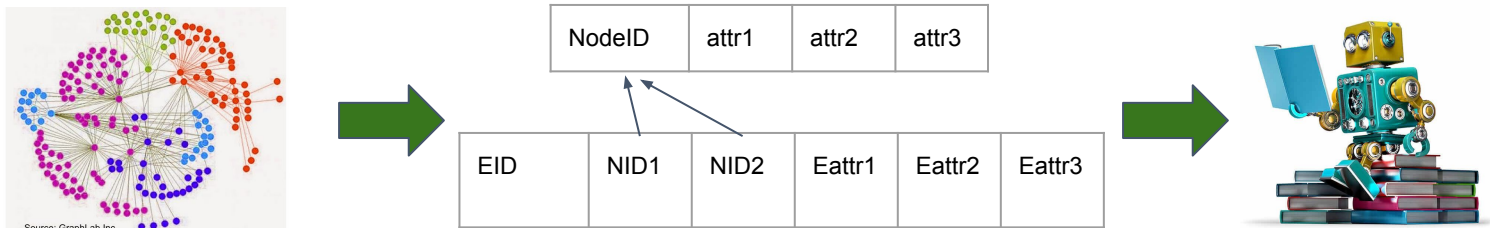
# 3 Possible Arrangements for Graph DB + ML

1. Graph Data leaves home and moves to ML.
2. ML moves into the Graph Database.
3. A Graph Database and ML partnership.



# #1 - Graph Data leaves home and moves to ML

- Export relevant graph data
- Simple analogy to Relational Database:
  - Table(s) of node data
  - Table(s) of edge data



- Traditional approach
  - ML is fed data from DBs or just data files
- Business Value
  - Easy to deploy
  - Graph DB still valuable for non-ML queries and analytics

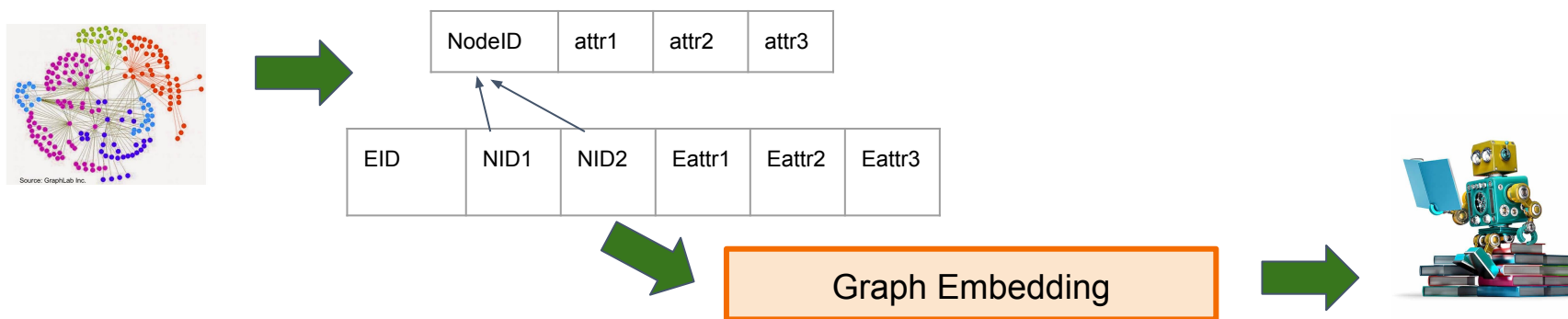


# Exporting Graph Data to ML: Concerns

- Is exported data really "flat" enough?
  - Edge records refers to Node records
  - ML algorithms usually want records to be independent
  - One answer is **graph embedding**
- Graph Embedding

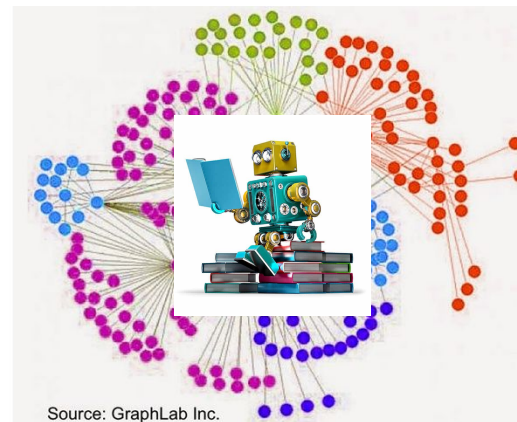
"Mapping a graph's nodes and edges to points in space."

  - Example: drawing a graph on paper is mapping to 2D space.
  - General graphs can be drawn in 3D space → tensor



## #2 - ML moves into the Graph Database

- Implement ML algorithm as an advanced query
- Novel Approach:  
in-graph analytics
- Business Value
  - Integration
  - Eliminate need for separate systems





















# ML in Graph Database: Concerns

1. Computational power of Graph DB
2. Graph query language's algorithmic expressiveness
3. Expressing ML algorithms in Graph terms

Only 3rd Gen. Native Parallel Graphs satisfy 1 and 2.

# Evolution of Graph Databases

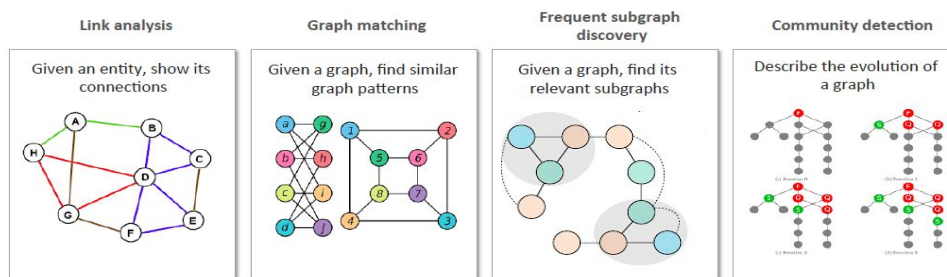
	Graph 1.0 single server, non-parallel	Graph 2.0 NoSQL base for storage	Graph 3.0 Native, Parallel
Native Graph Storage			
Parallel Loading	 Days to load terabytes	 Days to load terabytes	 Hours to load terabytes
Parallel Multi-Hop Analytics	 Times out after 2 hops	 Runs out of time/memory after 2 hops	 Sub-second across 10+ hops
Parallel Updates (in real-time)			 Mutable/ Transactional
Scale up to Support Query Volume		 Scales for simple queries (1-2 hops)	 2 billion+/day in production
Privacy for Sensitive Data			 MultiGraph service

# Graph Query Languages

- **SparQL (RDF):** Designed for semantic reasoning, but not computationally intensive work
- **Gremlin (Apache):** Older scheme. Declarative. Very awkward to write complex tasks.
- **Cypher (Neo4j):** Known by many. Okay for analytics if you couple it with Java.
- **GSQL (TigerGraph):** Designed for big data analytics.
  - Built-in parallelism and accumulation.
  - Syntax is natural and familiar for algorithms.

# Example: Graph Algorithm Libraries

- Some Graph Databases provide libraries of standard graph algorithms
  - Measure/discover characteristics of a graph
  - PageRank, Community Detection, Shortest Path, etc.

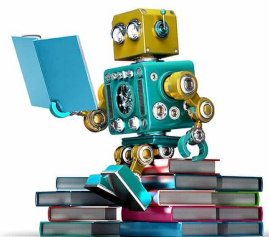
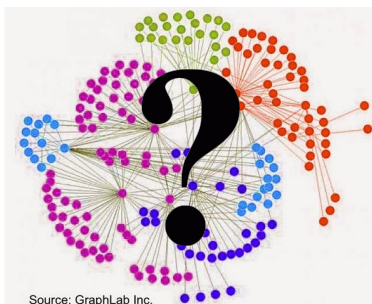


- **GSQL** is well-suited for algorithms
  - Library is written in GSQL
  - Users can see the code and modify as desired
- **Cypher** is less well-suited
  - Library is pre-compiled function calls
  - User can't see how the algorithms are written or modify them



# Expressing ML Algorithms in Graph Terms

- Not widely known how to execute most ML algorithms on a graph.

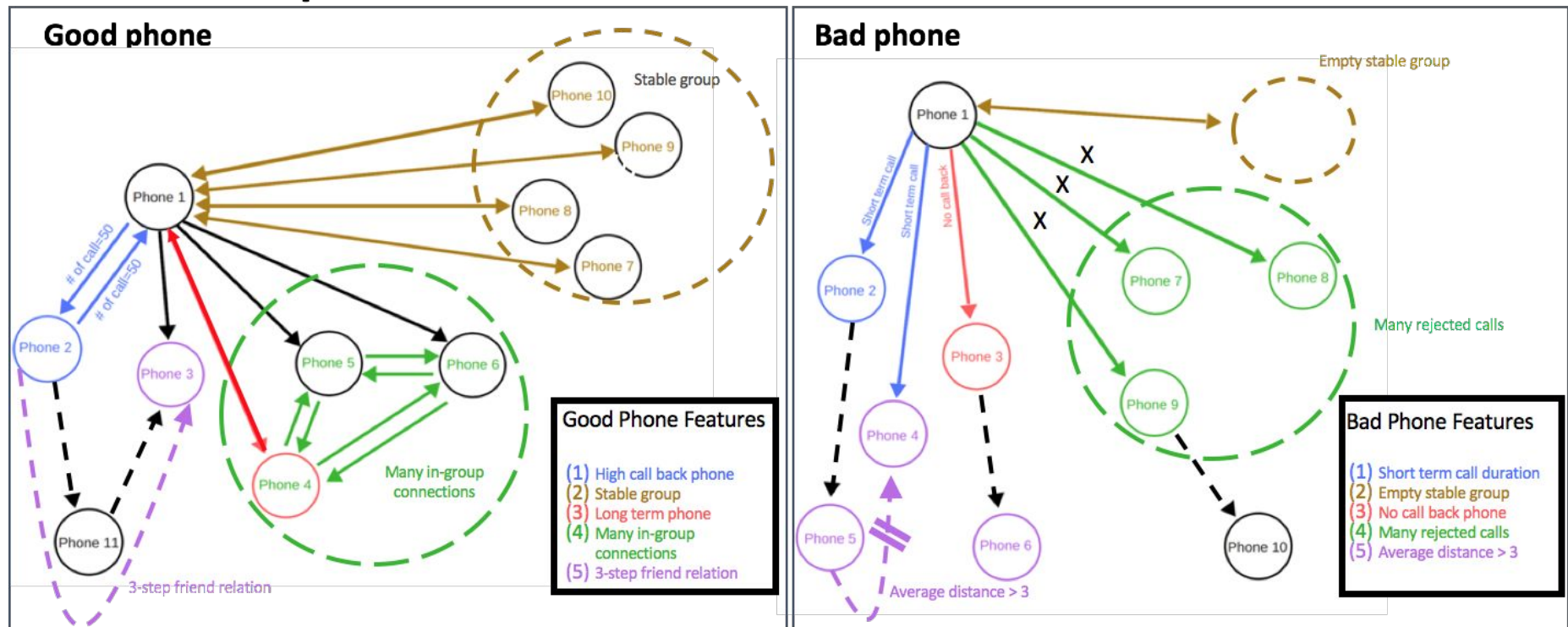


- Same problem as with exporting the Graph data:
  - ML is used to flat data
  - How to make edges a benefit instead of a hinderance?
- This marriage proposal needs further work.

# #3 - A Graph Database and ML partnership

- Multi-Step process:
  - a. First, Graph DB runs queries to extract graph-based features
  - b. Send graph features to ML system.
  - c. ML system, enriched by new graph features, learns a predictive model.
  - d. Model can be applied back to graph for real-time prediction.
- Seems more like a transactional partnership than a marriage.

# Example: China Mobile Fraud Detection using Graph Features for ML

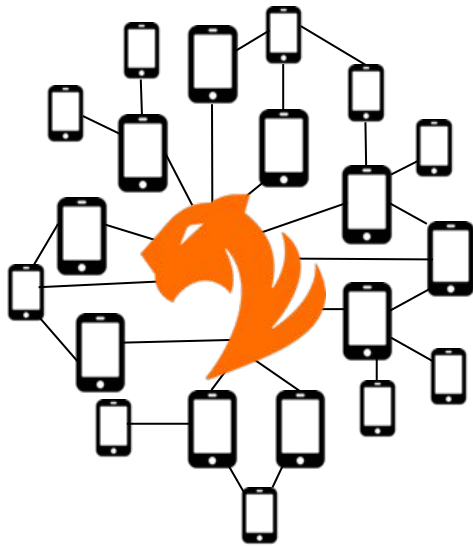


Download the solution brief at - <https://info.tigergraph.com/MachineLearning>

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# Generating New Training Data for ML to Detect Phone-Based Scam

Graph with 600M phones and 15B call edges, 1000s of calls/second.  
Feed ML with new training data with 118 features per phone.



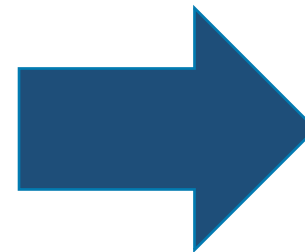
Tens – Hundreds  
of Billions of calls

## Phone 1 Features

- (1) High call back phone
- (2) Stable group
- (3) Long term phone
- (4) Many in-group connections
- (5) 3-step friend relation

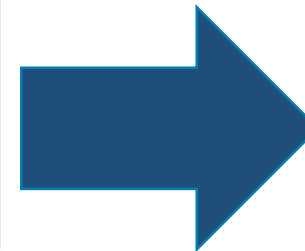
## Phone 2 Features

- (1) Short term call duration
- (2) Empty stable group
- (3) No call back phone
- (4) Many rejected calls
- (5) Avg. distance > 3



## Training Data

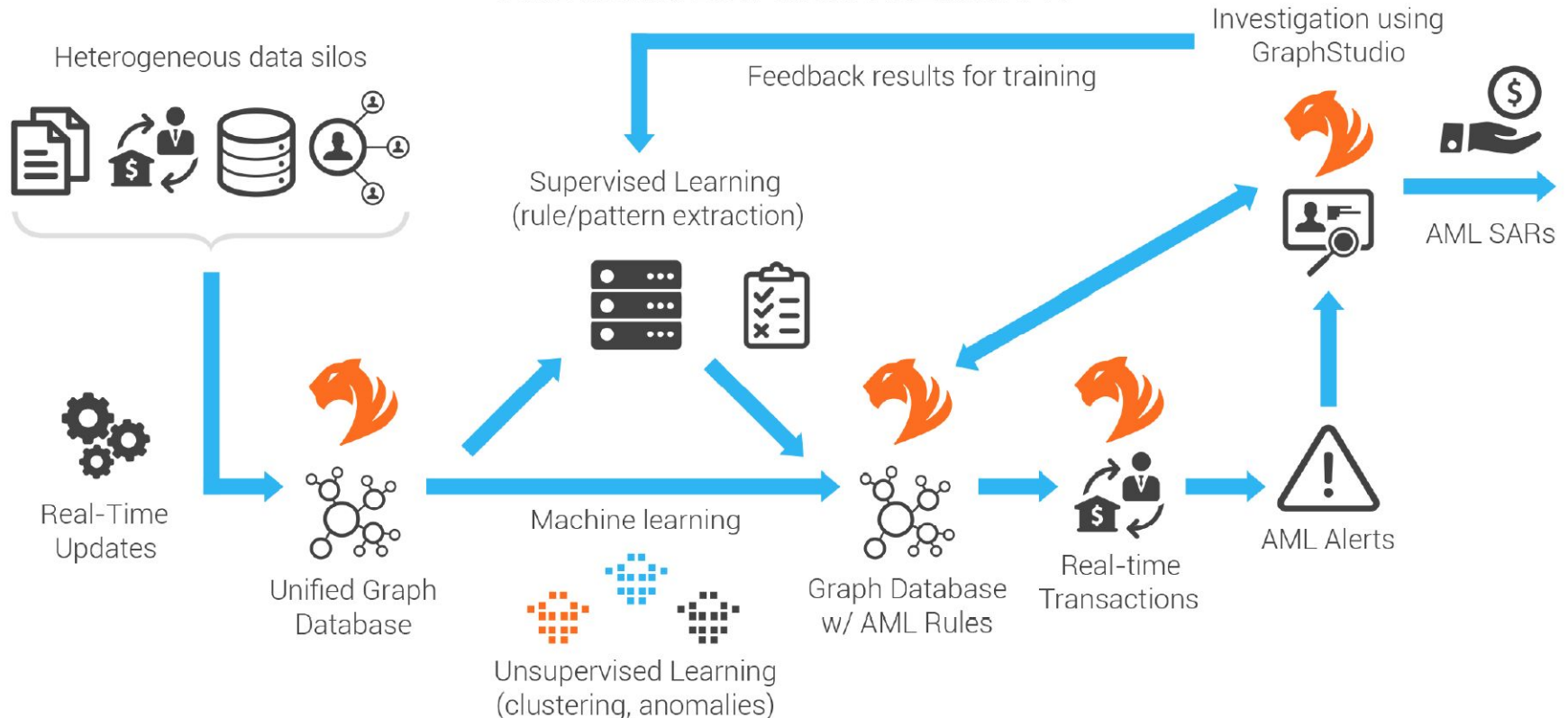
118 per phone x 600  
Million phones =  
70 Billion new features



Machine  
Learning  
Solution

# Graph-enhanced workflow for Anti-Money Laundering

## AML WORKFLOW WITH TIGERGRAPH



# Summary

Graph Databases and Machine Learning both represent powerful tools for getting more value from data.



## 3 Proposals for Marrying Graph DBs + ML:

- Export Graph Data to ML system
  - Conventional, but not clear how to treat the data.
- Perform ML within Graph Database
  - Need fast, scalable analytical Graph DB. ML methods not yet ported to Graph DB.
- Export Graph Features to ML system
  - Improves ML results; in practice now.



# Final Thoughts

- Room for diversity.
- Healthy marriages evolve over time.

**THANK YOU**