neo4j

# Graph Machine Learning for 2024

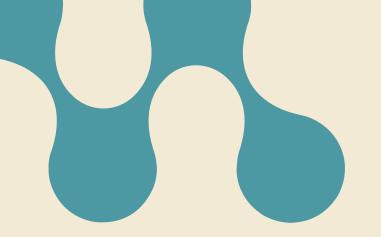
### Agenda

- **GML** Overview
- Looking Forward: Where is this Going? (Hint: GenAI)
- 3. Using GML to Enrich a Grounding Knowledge Graph
- Demo-Semantic Search with Recommendations



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## **GML** Overview

### What is a Graph?

Simply put, a graph consists of nodes connected by relationships

Graph databases, like Neo4j, structure and store data as graphs

### **Property Graph Components**

**Nodes** represent entities in the graph



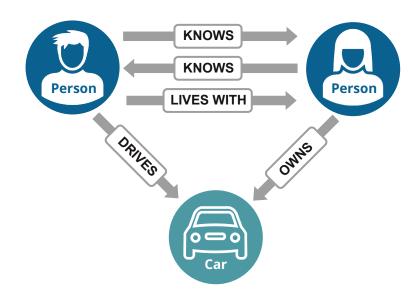




### **Property Graph Components**

**Nodes** represent entities in the graph

**Relationships** represent associations or interactions between nodes

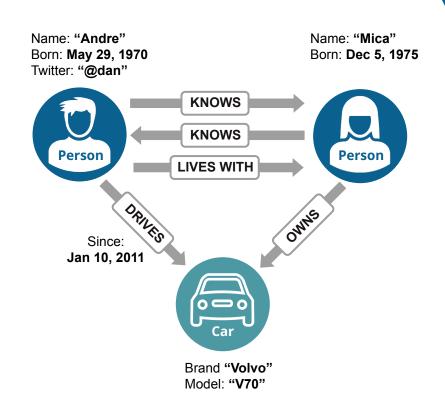


### **Property Graph Components**

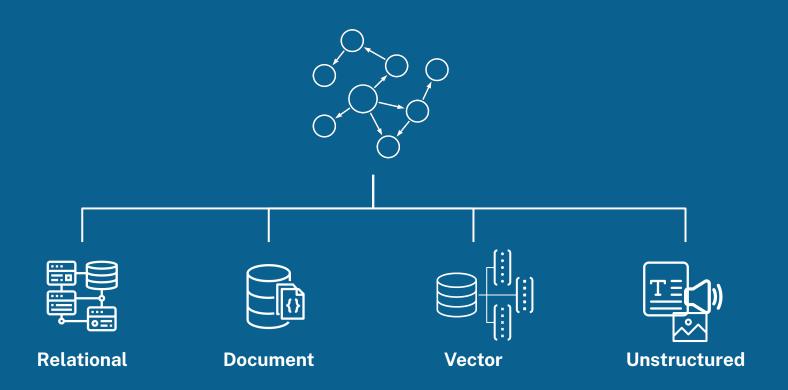
**Nodes** represent entities in the graph

**Relationships** represent associations or interactions between nodes

**Properties** represent attributes of nodes or relationships



### Graph is the Superset of All Data Structures for Al



### What is Graph Machine Learning (GML)?

The application of machine learning to graphs, specifically for predictive and prescriptive tasks

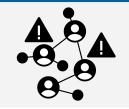
#### **Many Applications**

#### Recommendation



What should I recommend to a customer next?

#### **Fraud Detection**



How do I identify fraud rings and suspect activity?

#### **Customer 360**



Can I resolve information and relationships across fragmented customer records?

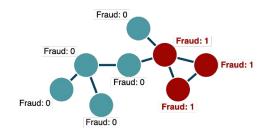
#### **Supply Chain**



What is the most optimal route through a supply chain network?

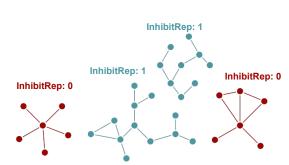
### **Supervised GML Tasks**

#### Train on labeled graphs to make predictions



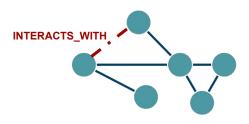
#### **Node Property Prediction**

Predict a discrete or continuous node property, called **node classification** and **node regression** respectively.



#### **Graph Property Prediction**

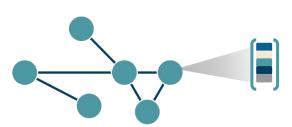
Predict a discrete or continuous property of a graph or subgraph.



#### **Link Prediction**

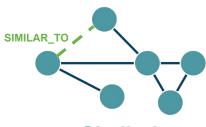
Predict if a relationship should exist between two nodes. Often a binary classification task, but can sometimes include more link types or continuous properties.

### **Unsupervised GML Tasks**



#### **Representation Learning**

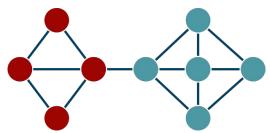
Automatically generate features based on graph structure for downstream ML and EDA.



#### **Similarity**

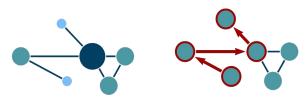
Find and measure similar pairs of nodes in the graph. Use for recommendation, entity resolution, and more.

#### Training on unlabeled graphs to learn patterns



#### **Clustering / Community Detection**

Identify groups of nodes that have higher connectivity between each other than the rest of the graph.



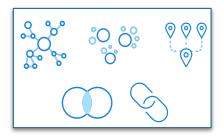
#### **Centrality & Pathfinding**

Find important and influential entities in the graph. Identify and evaluate more efficient paths and trees.

### How to Accomplish Graph Machine Learning?

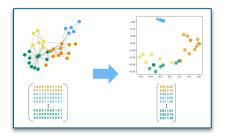
#### Classic Graph Algorithms

Results from algorithms like pagerank for centrality, Louvain for community detection, or node similarity.



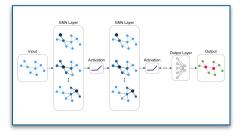
#### Non-GNN Graph Embeddings

Low-dim vector representations of nodes s.t. similarity between vectors approximates similarity between nodes (can also be for triples, paths, or sub-graphs)



### Graph Neural Networks (GNNs)

End-to-end solution for the ML task. Compression happens in hidden layers and is learned during model training



### **Graph Algorithms**

- Use independently for unsupervised community detection, similarity, centrality, or pathfinding.
- Use as features for conventional downstream models, such as linear and logistic regressions, random forests, or neural networks to perform GML tasks.



#### **Pathfinding & Search**

- A\* Shortest Path
- All Pairs Shortest Path
- Breadth & Depth First Search
- Delta-Stepping Single-Source
- Dijkstra Single-Source
- Dijkstra Source-Target
- Minimum Spanning Tree & K-Spanning Tree
- Random Walk
- Yen's K Shortest Path
- Minimum Directed Steiner Tree
- Topological Sort
- Longest Path



#### **Community Detection**

- · Conductance Metric
- K-1 Colorina
- K-Means Clustering
- Label Propagation
- Leiden Algorithm
- Local Clustering Coefficient
- Louvain Algorithm
- Max K-Cut
- Modularity Optimization
- Speaker Listener Label Propagation
- Strongly Connected Components
- Triangle Count
- Weakly Connected Components



#### Centrality

- ArticleRank
- Betweenness Centrality & Approx.
- Closeness Centrality
- Degree Centrality
- Eigenvector Centrality
- Harmonic Centrality
- Hyperlink Induced Topic Search (HITS)
- Influence Maximization (CELF)
- PageRank
- Personalized PageRank



#### **Topological Link Prediction**

- Adamic Adar
- Common Neighbors
- Preferential Attachment
- Resource Allocations
- Same Community
- Total Neighbors



#### **Similarity**

- K-Nearest Neighbors (KNN)
- Node Similarity
- Filtered KNN & Node Similarity
- Cosine & Pearson Similarity Functions
- Euclidean Distance Similarity Function
- **Euclidean Similarity Function**
- · Jaccard & Overlap Similarity Functions



### **Node Embeddings**

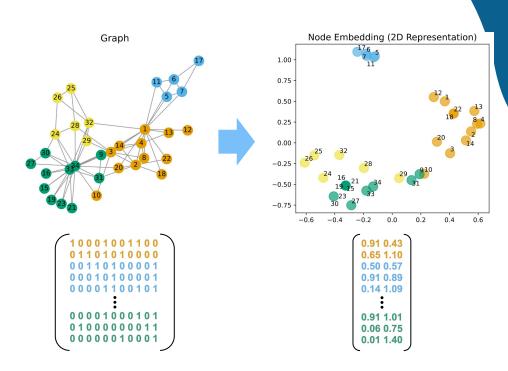
#### Most Common Type of Graph Embedding

#### What?

- Low-dimensional representations of nodes
- Similarity between vectors approximate similarity between nodes in the graph

#### Why?

- Save time & reduce work for generating ML features - Generating custom features manually can be time consume and imprecise, embeddings help automate and scale the process.
- Increase downstream ML performance



### **Graph Neural Networks (GNN)**

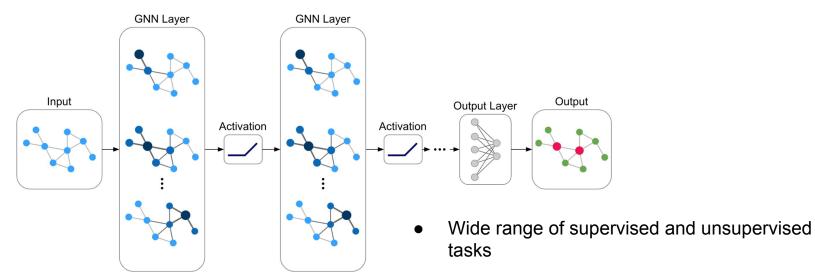
Take Graph as Input



**Transform Into** Intermediate **Embeddings** 



**Feed into Final** Layer for a **Prediction Task** 



Common examples: GCN, GraphSAGE, GAT

### **GNNs Have Their Pros and Cons**

#### Pros

- Can automatically learns important signals in the graph
- Most recent GNNs are inductive (train a model and predict on new graph data)
- Potential to handle deep complex graph structure
- End-to-end solution for supervised learning

#### Cons

- Relatively complicated. Can still be difficult to construct, tune, and avoid overfitting. Requires high degree of technical expertise.
- Can be difficult to scale. High time & space complexity. Usually requires accelerated hardware-like GPU.
- Limited depth. Usually "shallow" to prevent over-smoothing and/or reaching the diameter of the graph
- Low interpretability/explainability

## **Looking Forward -**Where is this Going?

### **Generative AI is Taking Storm!**

Automate data retrieval tasks

Improve customer service experiences

Expedite reading, 3 understanding, & summarizing Generate content & code

#### **POWERING GENERATIVE AI APPS**

#### What GenAl Can't Do!



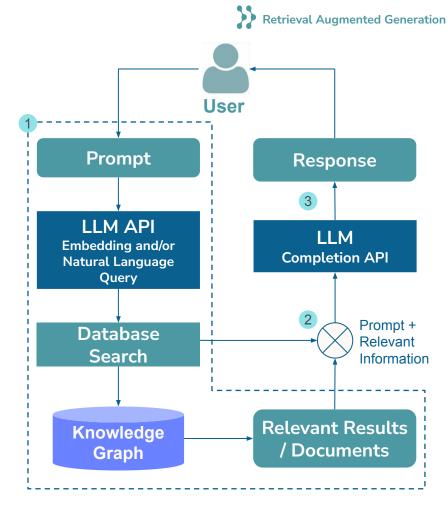
Lack of enterprise domain knowledge Limited input sizes for fine tuning Inability to verify answers Sensitive to prompt phrasing & injection **Hallucinates** Ethical & data bias concerns

### Generative AI, LLMs and Knowledge Graphs





RAG enables... **Natural language** search on factual information retrieved from a database





### Where is GML Valuable?

### In Model **Enhancement**

Use GML in Language Models & Foundation Modeling

### **Knowledge Graph Enrichment**

Use GML to Enrich Knowledge Graphs for Improved RAG

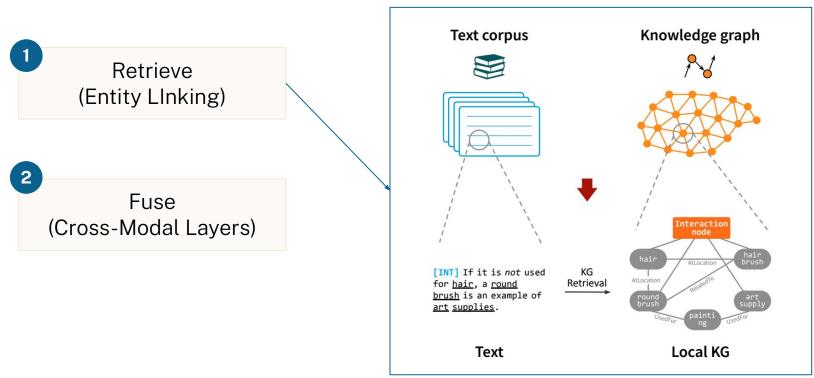
Large graph model research underway in academia

#### **GreaseLM** & **DRAGON**

High-Level Methodology:

- 1. **Retrieve:** Retrieve entities from KG based on prompt using Entity Linking
- Fuse: Leverage model that fuses LM and GNN together to generate a response based on prompt and subgraph

**GreaseLM** (**G**raph **Reas**oning **E**nhanced **L**anguage **M**odels For Question Answering)

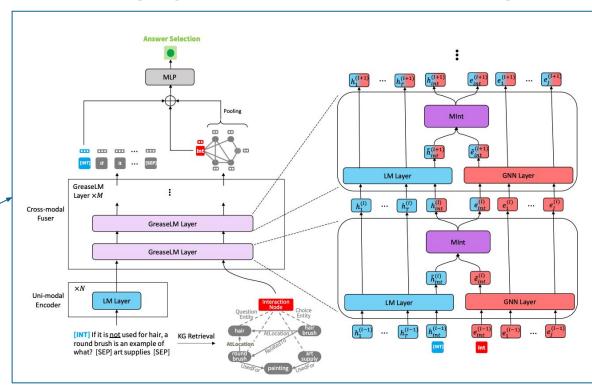


**GreaseLM** (**G**raph **Reas**oning **E**nhanced **L**anguage **M**odels For Question Answering)

Retrieve (Entity LInking)

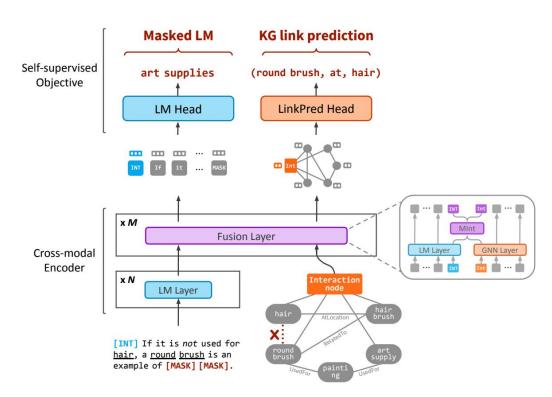
Fuse (Cross-Modal Layers)

\*Use Pre-Trained LM and GNN



**DRAGON** (**D**eep Bidi**r**ectional L**a**n**g**uage-Kn**o**wledge Graph Pretrai**n**ing)

Similar to GreaseLM but as its own foundation model with pre-training / self-supervised objective function



Quick Note on Upcoming Work: Integrating Semi-Structured Knowledge into Language Models

- Splitting prompts into sub-portions for different structured and unstructured tasks
- Use different retrieval mechanisms (graph, text, etc.) for each subportion as appropriate

#### Still In Development. Research Ongoing

### Overall:

- **Future potential** -Research indicates Graph Models in RAG paradigm can improve performance in some instances
- Still very new Nascent academic research at this point
- Not the most accessible for application at the moment

### Where is GML Valuable?

# In Model Enhancement

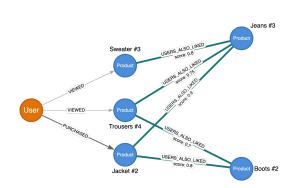
Use GML in Language Models & Foundation Modeling

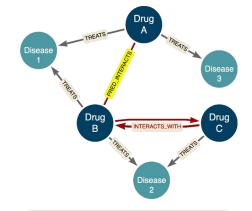
# Knowledge Graph Enrichment

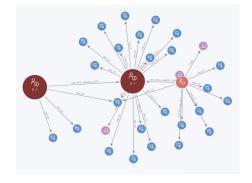
Use GML to Enrich Knowledge Graphs for improved RAG

### **GML** in Knowledge Graph Enrichment

Enhance the Graph to enable LLMs to not only use facts, but also make intelligence inferences on your enterprise data

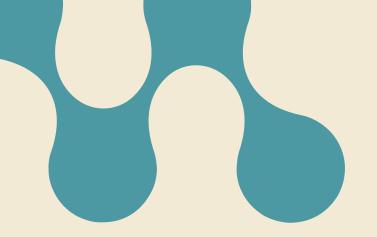






Similarity for Recommendation and Entity Resolution

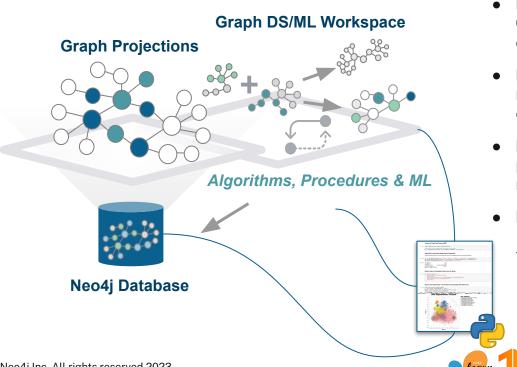
Link Prediction to Discover Missing Relationships Node Prediction,
Community Detection
& Centrality Scoring
For Tagging and
Identifying Entities



## Demo with Neo4j

### Neo4j Graph Data Science

#### highly optimized, massively parallel, scalable



- Run graph algorithms to generate insights: 65+ algorithms across centrality, path finding, community detection, similarity, and more
- **Engineer graph features for ML:** Leverage relationship information with algorithms & node embeddings
- **Build graph native ML pipelines:** Link prediction, node classification & property regression
- **Integrate with external ML frameworks:** Python client, blazing fast import & export, formatting for dataframes and tensors

### Demo

#### **H&M Personalized Fashion Recommendations**

Provide product recommendations based on previous purchases





neo4j-product-examples/ml-genai/tree/main/retail-hm

## Thank you!