

[DEV5420] When Graphs Meet Machine Learning

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**Live for
the Code**

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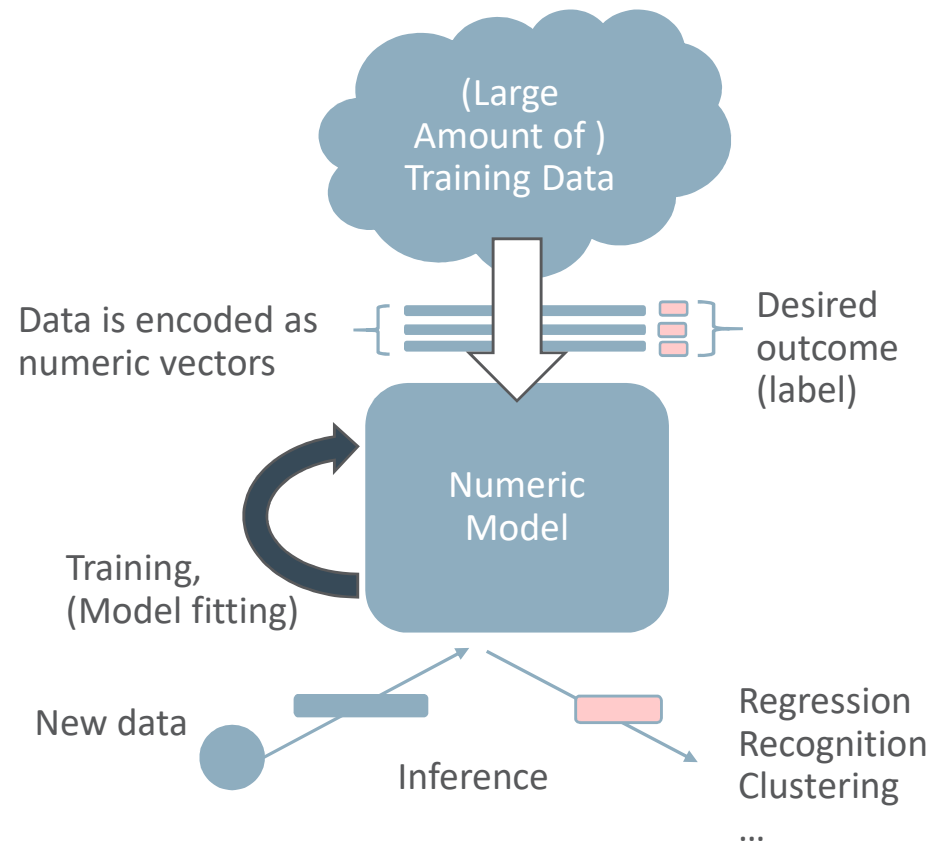
The following is intended to outline our general product direction. It is intended for information purposes only, and may not be incorporated into any contract. It is not a commitment to deliver any material, code, or functionality, and should not be relied upon in making purchasing decisions. The development, release, timing, and pricing of any features or functionality described for Oracle's products may change and remains at the sole discretion of Oracle Corporation.

Agenda

- 1 Machine Learning and Graph Analysis
- 2 Encoding Relationship Distance
- 3 Encoding Irregular Structure
- 4 Current Works and Directions

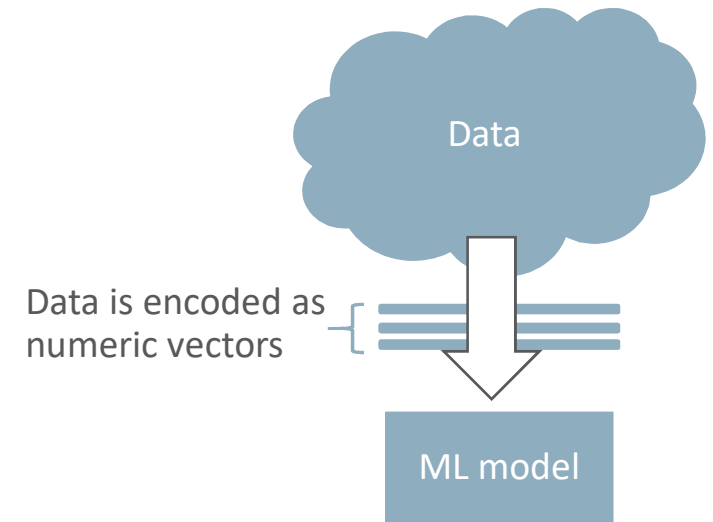
Machine Learning

- A very popular concept these days.
 - A system that progressively improves its performance from data
- How it's done: Supervised Learning*
 - Training Data, encoded as numeric vectors
 - Feed into numeric model
 - Train or fit the model to produce desired outcome for given data
 - Given new data, the model can infer its outcome
 - (for tasks like regression, recognition, clustering ...)



What's the problem, then?

- What is your data?
 - More precisely, what is the information that you want to exploit from your data?
 - How that information can be encoded (as numeric vectors) to feed into ML model?



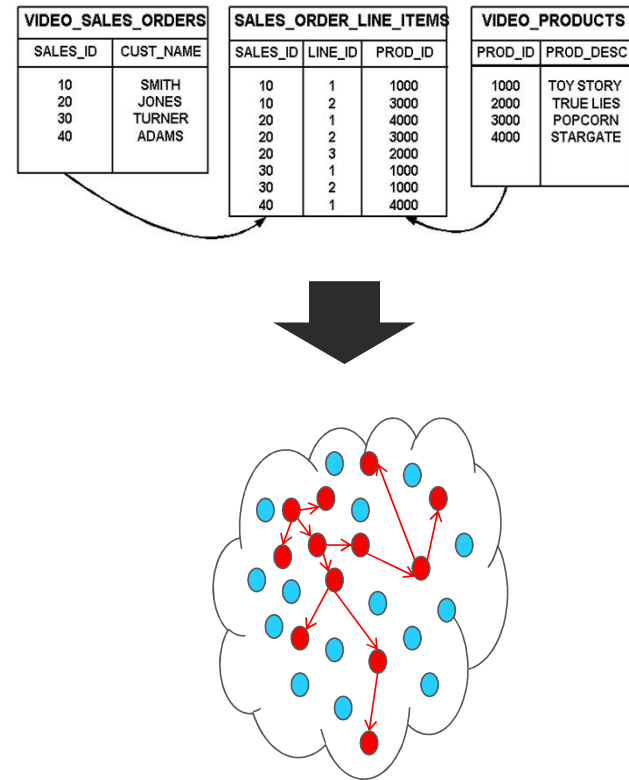
Example) Personalized Product Recommendation

Would like to recommend items that are purchased a lot by *similar* people who had purchased a lot of *similar* items that are purchased by the target customer (i.e. popular to people-like-me)

How to extract this information?
How to encode this information and feed into ML pipeline?

Graph Modeling and Analysis

- Graph Modeling
 - Represent your (relational) dataset as a graph
 - Entities become vertices
 - Relationships become edges
- ➔ Fined-grained relationships are captured in graph
- Graph Benefits
 - Quickly query multi-hop relationships
 - Visualize your data and explore it interactively
 - Analyze your data using graph signals ✓

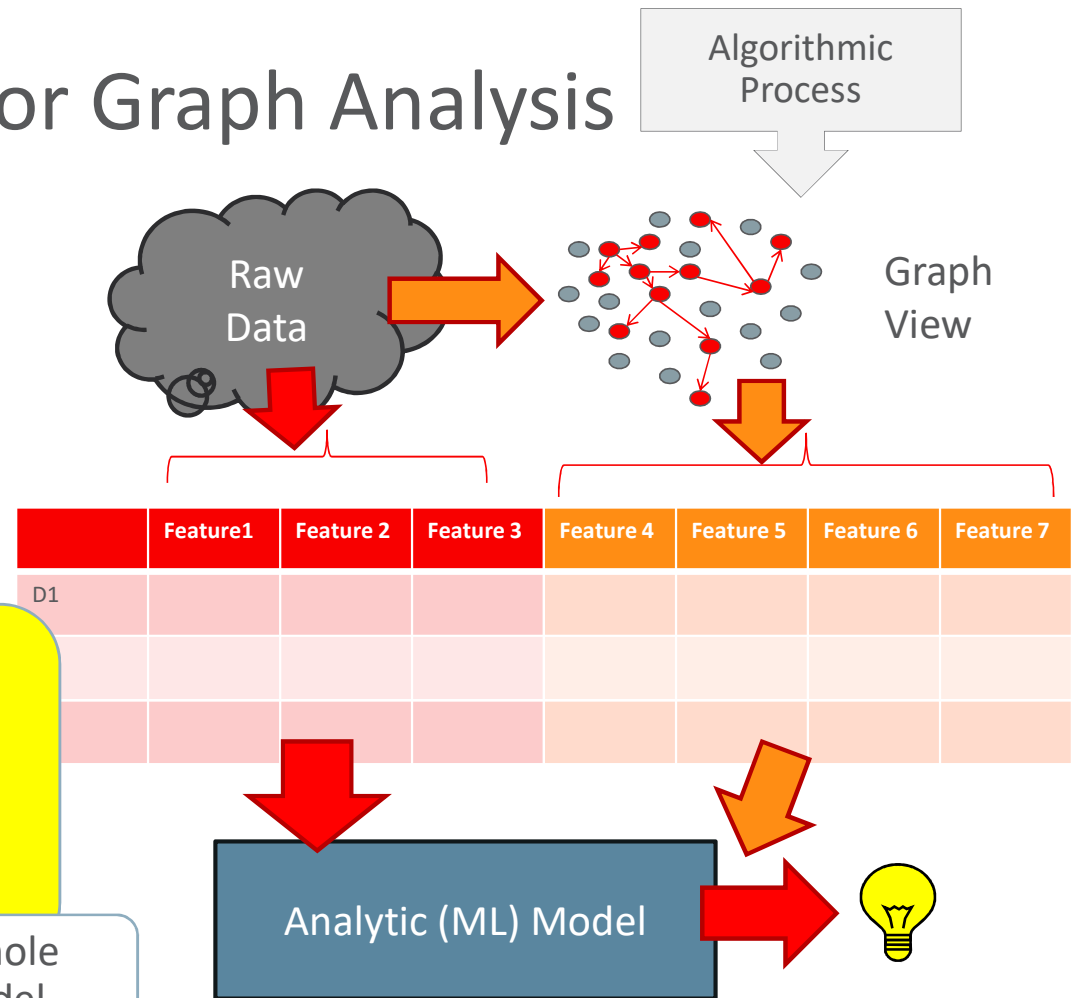


Conventional Approach for Graph Analysis

- Graph representation captures fine-grained relationship between data entities
- By applying *graph algorithms*, one can get useful information from the graph
- Or produce additional features that can be added into analytic (ML) model

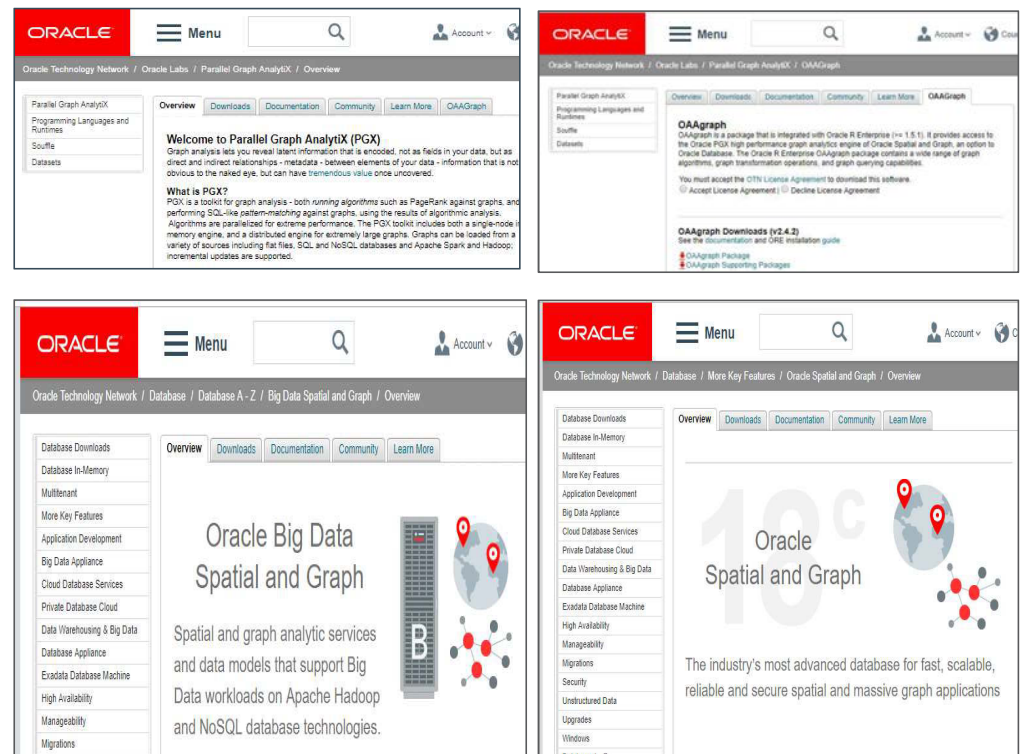
- More conventional , algorithmic approach
- Still **very** effective. Requires no training data (free from cold starting problem)
- Will cover more in another session: [DEV5397] *Automate Anomaly Detection with Graph Analytics*

→ This talk tries to feed the whole graph information into ML model



Graph Tooling in Oracle

- (Not going too deep here)
- Oracle provides graph technology with several different flavors
 - Oracle Spatial and Graph:Database
 - BDSG: Big Data Appliance
 - OAA.Graph (R): Advanced Analytics
 - Graph Cloud Service
- Key components are shared between these projects



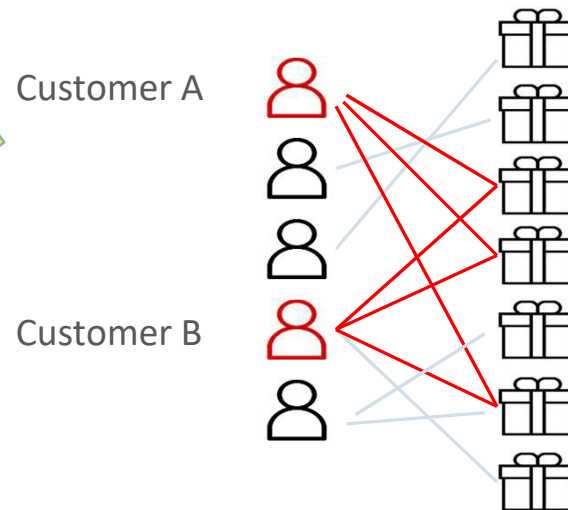
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Data Entity Distance in Graph

- Graph captures fine-grained relationship between data entities
 - ➔ Closeness by such relationship can be defined and measured on the graph

Customer A and B are *close* to each other (because they purchased the same items a lot)



Graph gives you several ways to define and measure distance between vertices:

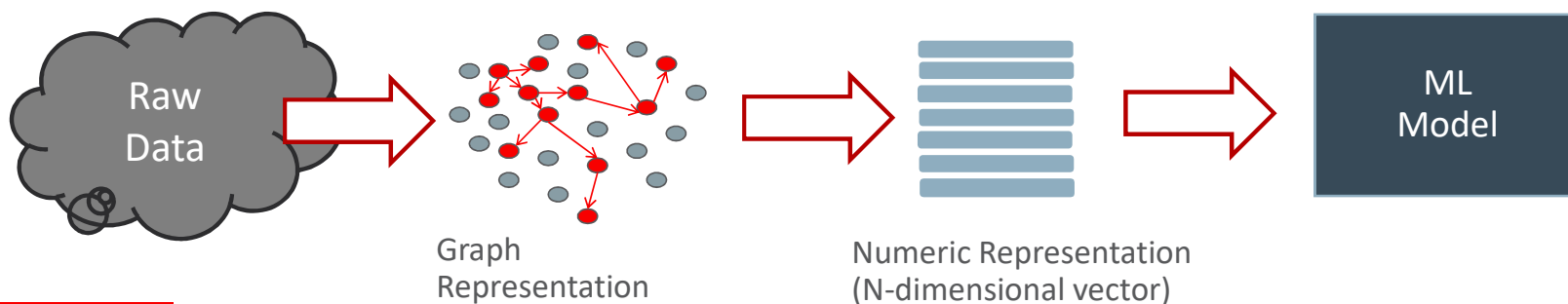
- Shortest path
- Hop distance
- Maximum flow
- Common neighbor count
- **Random walk distance**
- ...

Going Back to the Problem

- Graph captures distance between data entities.
- You want feed this distance information into your ML pipeline
- You need numeric representation of your data that retains the distance information

x, y : data entity (represented as vertex in graph)
 $v(x), v(y)$: n-dimensionsal vector representation of x and y

x, y close in graph $\rightarrow \|v(x) - v(y)\|$ small in n-dimensional vector space



How to achieve this?

- There are several approaches now
 - (Academia and Industry)
 - An early approach that exploits techniques from modern NLP (natural language processing)
 - Word2Vec : a ML technique that learns closeness between words from large number of sentences
 - Perform many random walks on the graph
 - Apply W2V technique on random walk traces, treating vertices as words.

KDD'14

DeepWalk: Online Learning of Social Representations

Bryan Perozzi
Stony Brook University
Department of Computer
Science

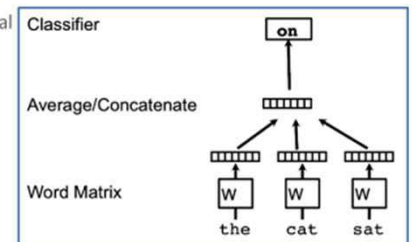
Rami Al-Rfou
Stony Brook University
Department of Computer
Science

Steven Skiena
Stony Brook University
Department of Computer
Science

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Word2vec: Word-to-vector model

- Represent each word as a low-dimensional word
- Word similarity = vector similarity
- Key idea: *Predict surrounding words of every word in the context*
- Models:
 - Continuous Bag of Words (CBOW)
 - Skip-gram



Paper: *Distributed Representations of Words and Phrases and their Compositionality*, NIPS'13

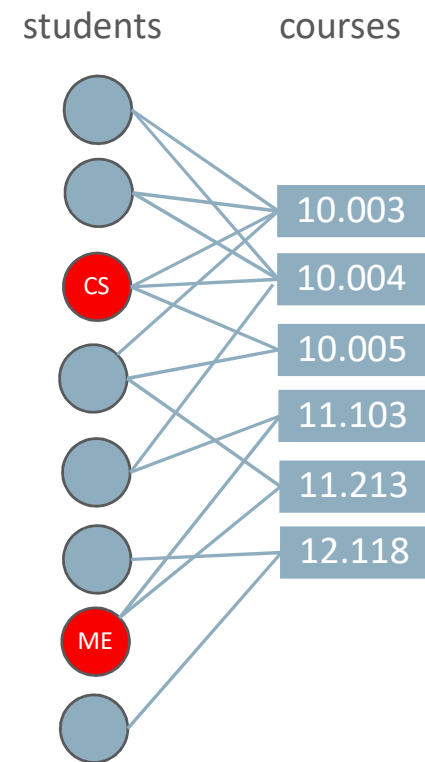
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12

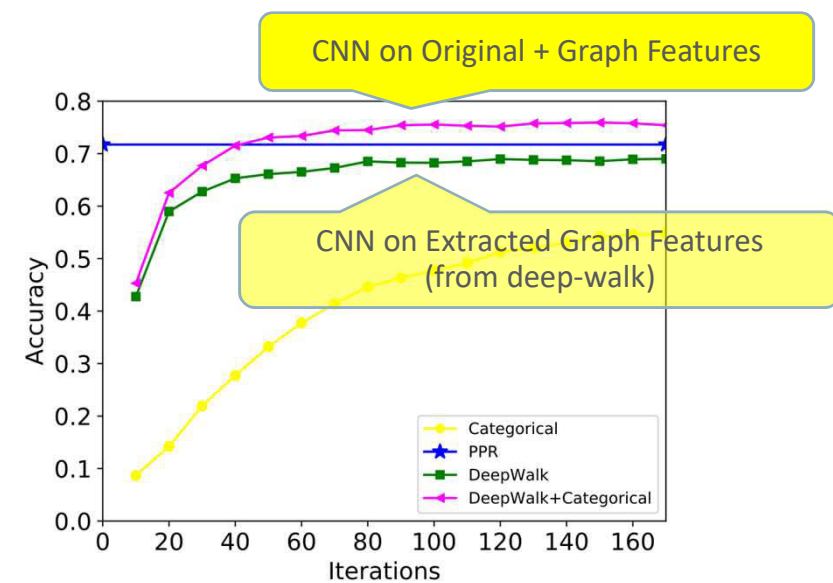
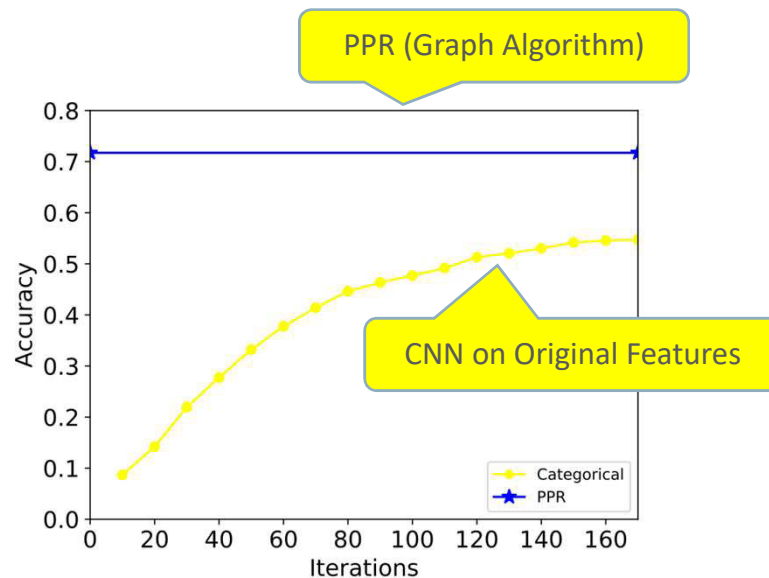
Example

- Student classification
 - A dataset from university
 - Can you predict a student's major or department just by looking at the classmates in the course that (s)he is taking?
- Note: you can consider this as an emulation of customer segmentation problem
 - Student => Customer
 - Course taking => Item or service purchase
 - Department => Segment label



Results

- (Result #1) Graph-based prediction gives better result than naïve application of ML (e.g. CNN) on basic student features (e.g. age, gender, background, ...)
- (Result #2) Deep-Walk preserves information from graph representation
- (Result #3) Deep-Walk allows to combined graph data with other features



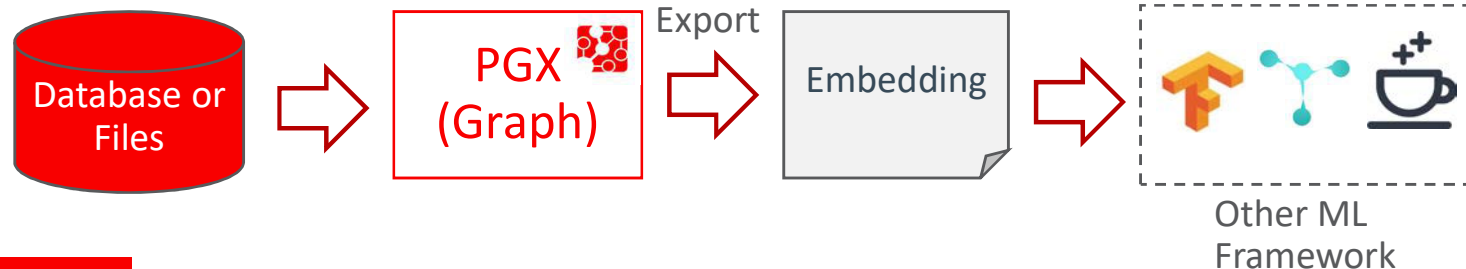
Sounds complicated, how can I use this technique easily?

- We have an implementation in our graph package (PGX)
 - Load graph model
 - Compute graph embedding
 - Query embedding directly on graph
 - Export graph embedding

```
Shell  Java
pgx> model = analyst.deepWalkModelBuilder().
    setMinWordFrequency(1).
    setBatchSize(512).
    setNumEpochs(1).
    setLayerSize(100).
    setLearningRate(0.05).
    setMinLearningRate(0.0001).
    setWindowSize(3).
    setWalksPerVertex(6).
    setWalkLength(4).
    setSampleRate(0.00001).
    setNegativeSample(2).
    setValidationFraction(0.01).
    build()

Training the DeepWalk model
We can train a DeepWalk model with the specified (default) parameters.

Shell  Java
pgx> model.fit(graph)
```

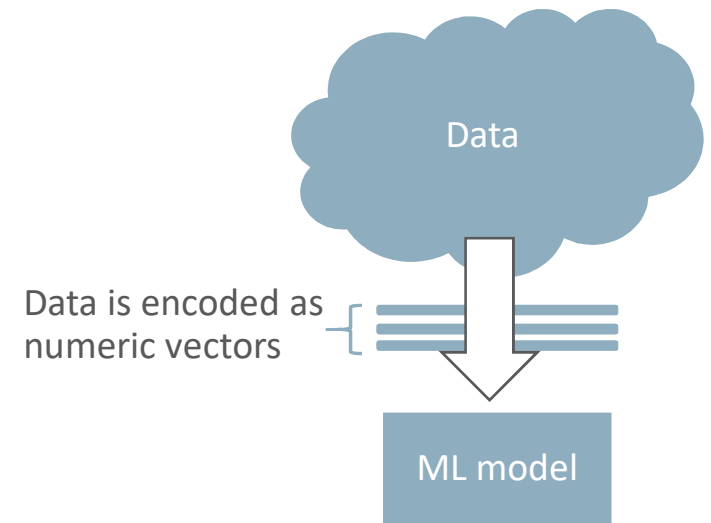


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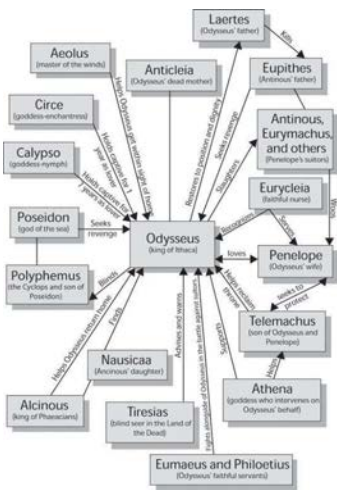
Yet Another Encoding Problem

- Again you want to
 - Capture relationships between entities and
 - Feed it into ML model
- But this time
 - Your focus is not an individual entity
 - Rather, you want to characterize *group of entities* that are related one another
 - Where these relationship structures are irregular and arbitrary
 - Still you want analyze these groups with ML
 - Challenge: how ‘irregular structures in entity relationships’ can be encoded for ML tasks?

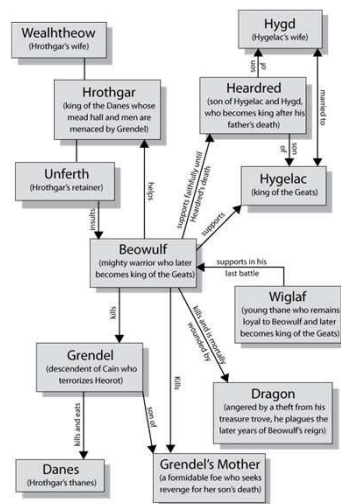


Classic Literature Example

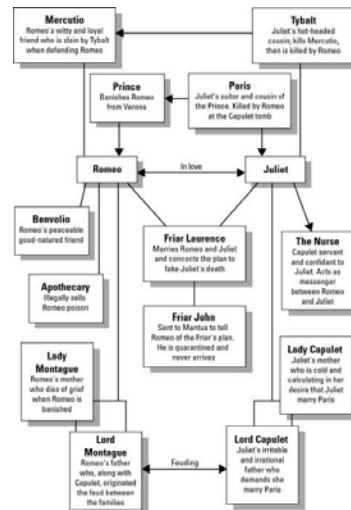
- Main character relationships in classic literature
 - Can we use ML to tell which pieces have similar character relationships? Cluster pieces by their similarity?
 - Given a modern piece, identify what classic piece has the most similar structure?



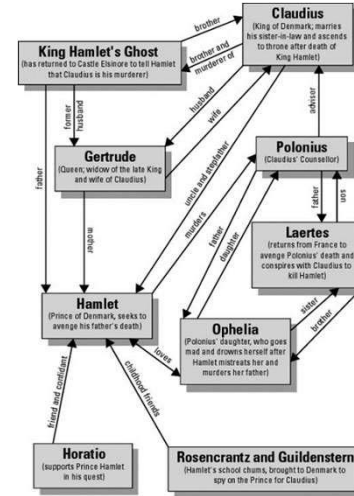
Odyssey



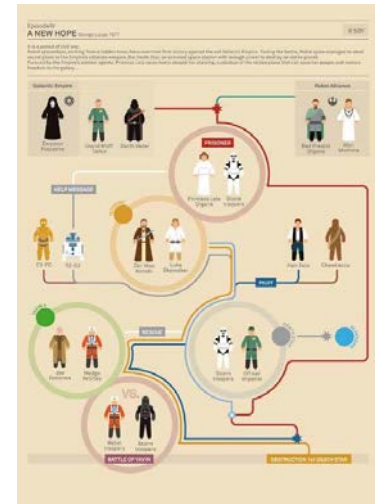
Beowulf



Romeo & Juliet



Hamlet



Star Wars: Episode IV

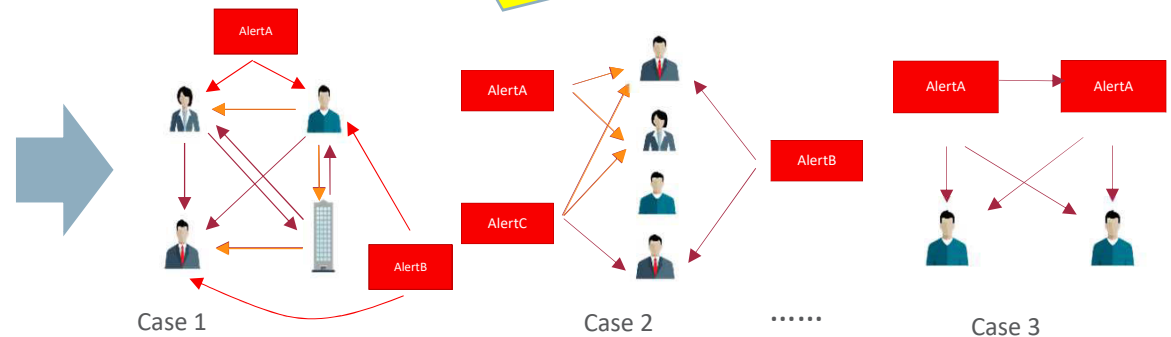
More Serious Example – Anti-Money Laundering

- An application from financial domain
 - Real-time monitoring of financial transactions
 - ➔ Any suspicious transactions are *tagged* as an event (but with a lot of false-positives)
 - Correlated events are gathered up to form a case
 - ➔ Each case is put under investigation (by experts)
 - ➔ A case can end up with either real or false positive

Can we train a ML model to distinguish real money laundering from false positives?
How to encode these structures?

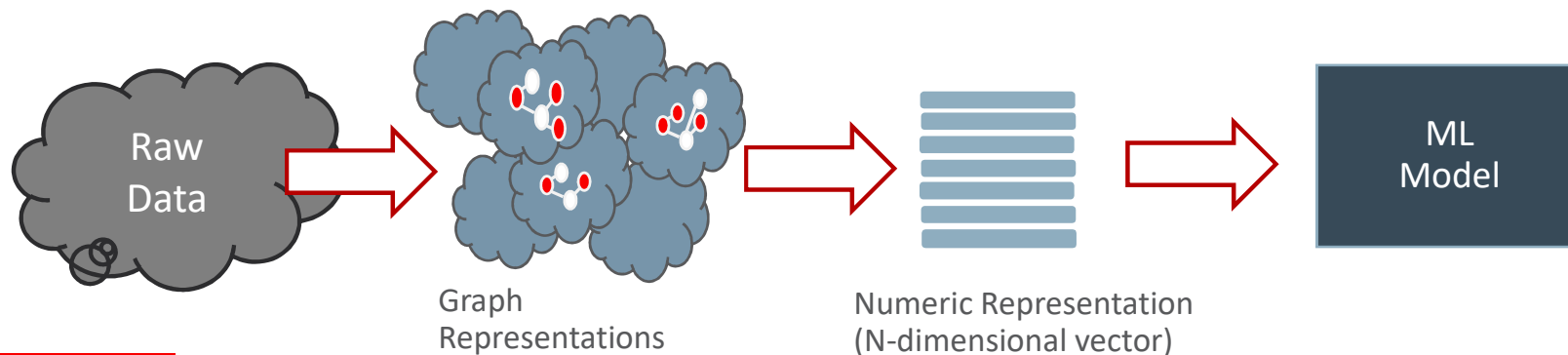
Originator	Beneficiary	Time Stamp	Amount	...
Paul	Zion Bank	6/19 5:59:59.336 UTC+8	\$ 30,000	... ✓
Jack	E-Weddingbands LLC	6/19 5:59:59.516 UTC+8	\$ 112,000	... ⚠
James	Provo Bank	6/19 6:01:20.222 UTC+8	\$ 150.00	... ✓
Steve	Linda	6/19 6:02:55.222 UTC+8	\$ 999.30	... ✓
...

Real-Time Transaction Monitoring



Problem Definition Again

- Now the dataset is a set of (relatively small) graphs
- We would like to find N-dimensional vector representation of each graph such that
- If two graph $G1$, $G2$ are *similar in shape*, $\|v(G1) - v(G2)\|$ small in the N-dimensional vector space

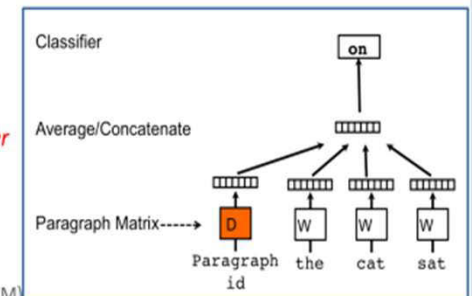


Approach

- Again, adopt a technique from NLP, or sequence-based learning
 - i.e: Paragraph2Vec → learn from large text corpus. Paragraphs composed of *similar* words are close in embedding space
 - Consider each graph as paragraph
 - Generate random-walk on each graphs
 - Apply Paragraph2Vec model (each graph become a paragraph)

Paragraph2vec: Paragraph-to-vector model

- Represent each paragraph as a low-dimensional word
- Paragraph similarity = vector similarity
- Key idea: *Paragraph acts as a memory over the context words*
- Models:
 - Distributed Bag of Words (PV-DBOW)
 - Distributed Memory Paragraph Vector (PV-DM)



Paper: *Distributed Representations of Sentences and Documents, ICML'14*

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20

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Adding Secret Sauces

- We applied some of our own techniques
 - better quality of answer than naïve application of paragraph2vec
 - (1) Consider multiple properties (rather than single label)
 - (2) When generating traces, consider edges (instead of vertices) as words.
 - (3) Attach global properties of the each graph -- e.g. size of graph

Sounds complicated, how can I use this technique easily? (2)

- We have an implementation in our graph package (PGX)
 - Load data – unconnected graphs
 - Compute graph embedding
 - Query embedding directly or
 - Export graph embedding

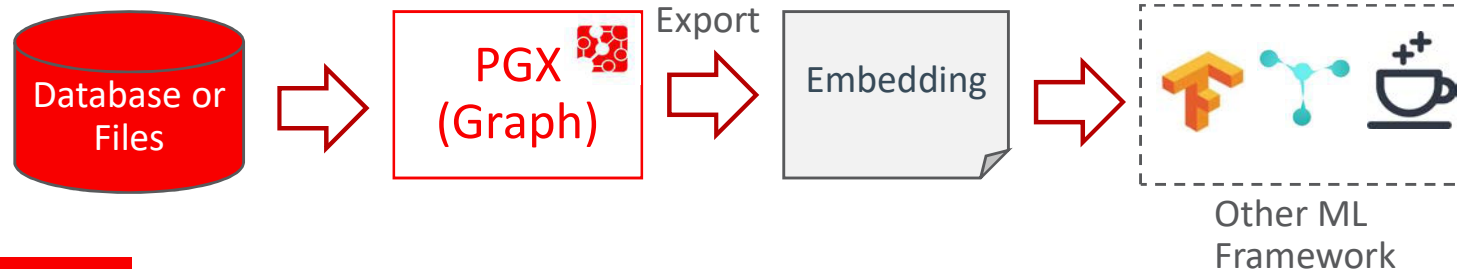
```
Shell  Java

pgx> model = analyst.pg2vecModelBuilder().
    setGraphLetIdPropertyName("graph_id").
    setVertexPropertyNames(Arrays.asList("category")).
    setMinWordFrequency(1).
    setBatchSize(128).
    setNumEpochs(5).
    setLayerSize(200).
    setLearningRate(0.04).
    setMinLearningRate(0.0001).
    setWindowSize(4).
    setWalksPerVertex(5).
    setWalkLength(8).
    setUseGraphletSize(true).
    setValidationFraction(0.05).
    build();

Training the Pg2vec model

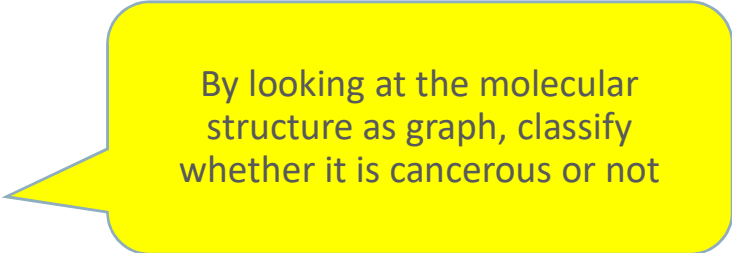
We can train a Pg2vec model with the specified (default or customized) settings and

pgx> model.fit(graph)
```



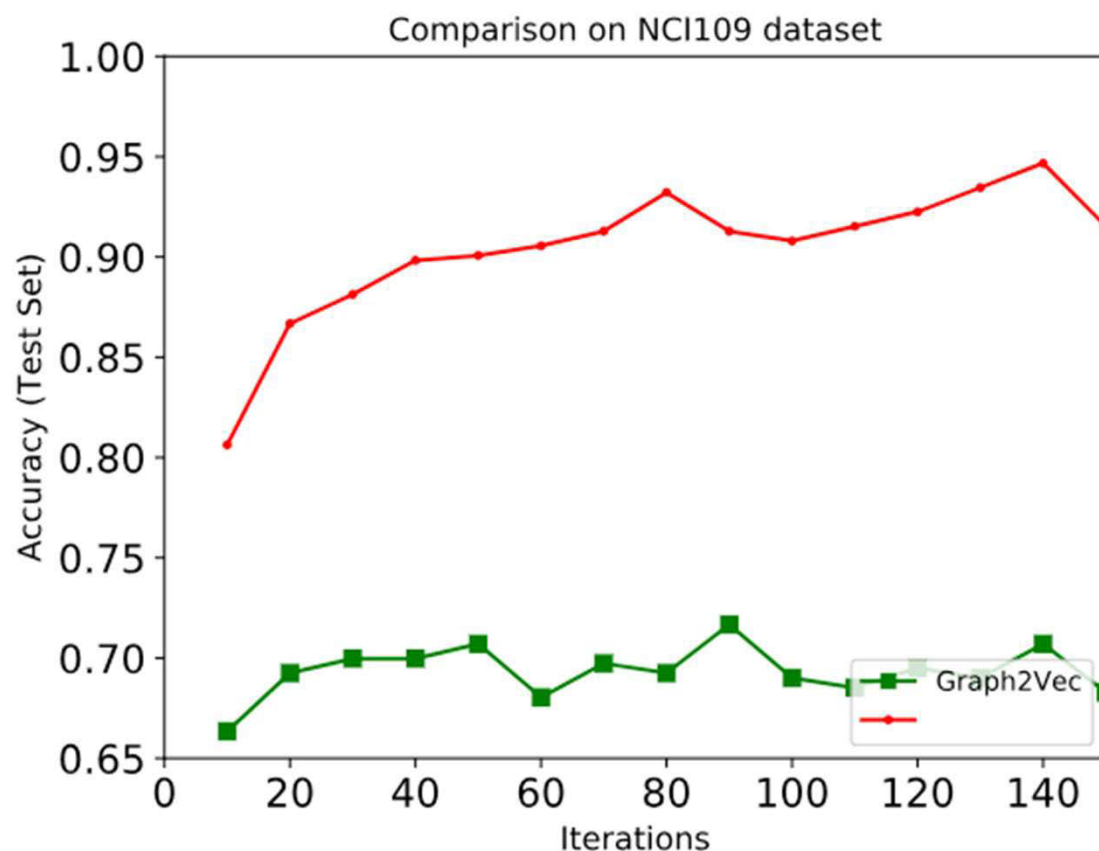
Evaluation

- **Datasets: cheminformatics**
 - **National Cancer Institute (NCI109)**
 - #Graphs: 4127
 - #Vertices: ranges from 35 to 111
 - #Edges: ranges from 152 to 476
 - *Cancer types (binary classification)*
 - **Proteins**
 - #Graphs: 1113
 - #Vertices: ranges from 9 to 620
 - #Edges: ranges from 64 to 4048
 - *Protein types (binary classification)*



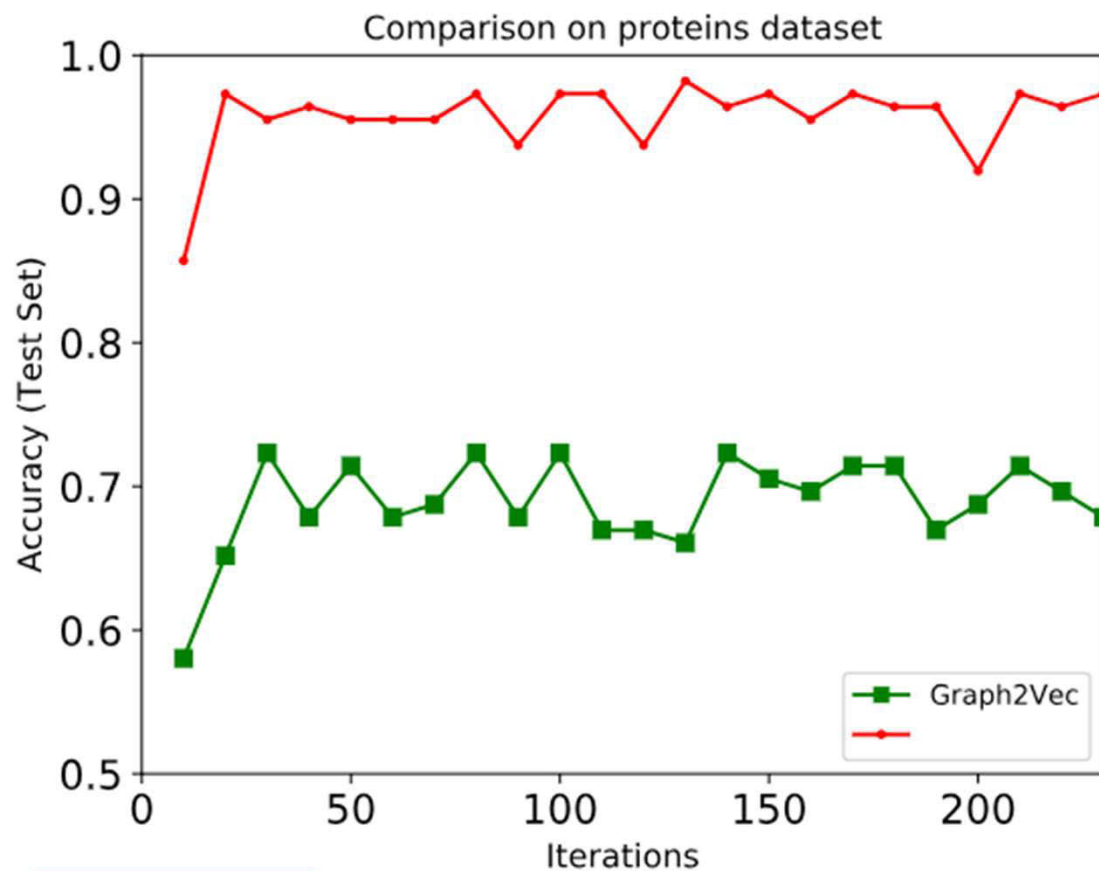
By looking at the molecular structure as graph, classify whether it is cancerous or not

Classification task: NCI109 dataset



- Train:test = 9:1
- Quality improvement
 - ~**22%** in classification acc.
- Comparison:
 - Graph2vec (MLG'17)
 - Similar approach to ours without the secret sauce

Classification task: Proteins dataset



- Train:test = 9:1
- Quality improvement
 - ~25% in classification acc.

GraphLet similarity: Anti-Money Laundering dataset

Graph Statistics

Graph Visualization

Get Similar graphs (based on cosine similarity): Input -> Threshold, graphId

Similarity Threshold	GraphId
0.2	189

Similar	Score
189	1
73	0.994
212	0.991
164	0.985
135	0.898
109	0.659
75	0.65

Graph Statistics

GraphId: 189

labels(x)	COUNT(*)
[ALERT, 114000124]	1
[ADDRESS]	1
[116000050, ALERT]	14
[CUSTOMER]	1

Page 1 of 1 (1-4 of 4 items)

Graph Statistics

GraphId: 73

labels(x)	COUNT(*)
[ADDRESS]	2
[116000063, ALERT]	1
[116000050, ALERT]	13
[CUSTOMER]	1

Page 1 of 1 (1-4 of 4 items)

Graph Statistics

GraphId: 212

labels(x)	COUNT(*)
[ADDRESS]	1
[ALERT, 114000124]	1
[116000050, ALERT]	14
[CUSTOMER]	1

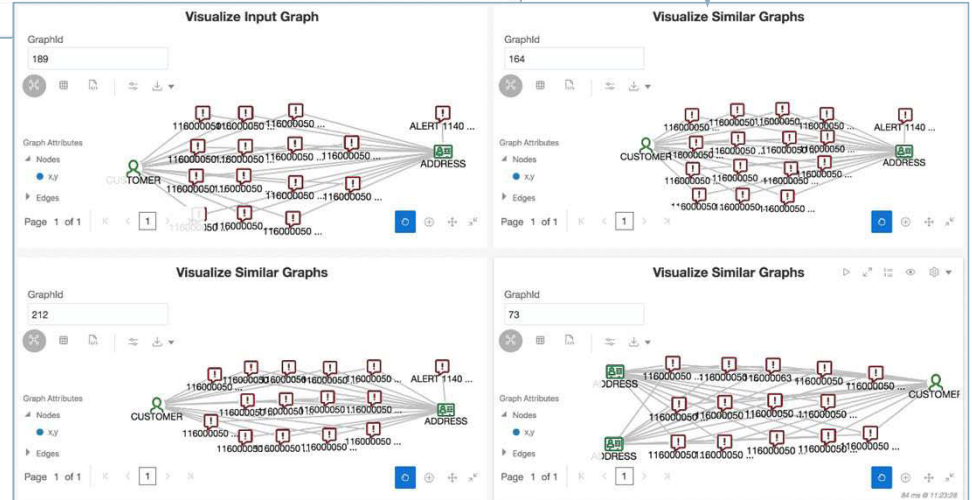
Page 1 of 1 (1-4 of 4 items)

Graph Statistics

GraphId: 164

labels(x)	COUNT(*)
[ALERT, 114000124]	1
[ADDRESS]	1
[116000050, ALERT]	15
[CUSTOMER]	1

Page 1 of 1 (1-4 of 4 items)



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Demo

Demo (Recording)


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Graphs and Machine Learning

- By the way, combining graph and machine learning is a trend
 - Many in industry and academia are looking at this problem
 - And applying it to solving real problems

Pintrest

 Pinterest Engineering [Follow](https://careers.pinterest.com/)
Inventive engineers building the first visual discovery engine, 175 billion ideas and counting.
<https://careers.pinterest.com/>
Aug 15 · 8 min read

PinSage: A new graph convolutional neural network for web-scale recommender systems


Ruining He | Pinterest engineer, Pinterest Labs

Deep learning methods have achieved unprecedented performance on a broad range of machine learning and artificial intelligence tasks like visual recognition, speech recognition and machine translation. However, despite amazing progress, deep learning research has mainly focused on data defined on Euclidean domains, such as grids (e.g., images) and sequences (e.g., speech, text). Nonetheless, most interesting data, and challenges, are defined on non-Euclidean domains such as graphs, manifolds and recommender systems. The main question is, how to define basic deep learning operations for such complex data types. With a growing and global service, we don't have the option of a system that won't scale for everyday use. Our answer came in the form of PinSage, a random-walk Graph Convolutional Network capable of learning embeddings for nodes in web-scale graphs containing billions of objects.

Alibaba

This article is part of the Academic Alibaba series and is taken from the paper entitled "Billion-scale Commodity Embedding for E-commerce Recommendation in Alibaba" by Jizhe Wang, Pipei Huang, Huan Zhao, Zhibo Zhang, Binqiang Zhao, and Dik Lun Lee, accepted by KDD. The full paper can be read [here](#).

Recommendation, which aims at providing users with attention-grabbing items based on their preferences, is a key technology in Alibaba's e-commerce site Taobao. The homepage of the Mobile Taobao app, shown below, is generated based on users' past behaviors with recommendation techniques.



Google

Relational inductive biases, deep learning, and graph networks

SEPTEMBER 19, 2018

tags: Machine Learning

[Battaglia et al., arXiv'18](#)

Earlier this week we saw the argument that causal reasoning (where most of the interesting questions lie!) requires more than just associational machine learning. Structural causal models have at their core a graph of entities and relationships between them. Today we'll be looking at a position paper with a wide team of authors from DeepMind, Google Brain, MIT, and the University of Edinburgh, which also makes the case for *graph networks* as a foundational building block of the next generation of AI. In other words, bringing back and re-integrating some of the techniques from the AI toolbox that were prevalent when resources were more limited.

“ We argue that combinatorial generalization must be a top priority for AI to achieve human-like abilities, and that structured representation and computations are key to realizing this objective... We explore how using relational inductive biases within deep learning architectures can facilitate learning about entities, relations, and the rules for composing them.

Other use cases

- In general, graph analysis can be combined with ML for various applications
- Where analyzing entity-entity relationships is required
 - Personalized Recommendation, Customer segmentation, ...
 - Fraud Detection – Health care, Insurance, ...
 - Cyber Security – Network Intrusion
 - SNS analysis
 - Fake new detections
 - ...

Directions

- Improving Scalability
 - Increasing the size of graph (e.g. tens of billions of vertices)
- Combining structure (relationship) and other raw observation
 - E.g. Item attributes + Co-purchase Information
 - Finding more elegant solution than simple ensemble techniques

Summary

- Modern techniques for combining Graph Analysis and Machine Learning
- Graph captures fine-grained relationships between data entities
- Adopt techniques from NLP to encode relationship information
 - Vertex2Vector (capture relationship-induced distance between entities)
 - Graph2Vector (capture similarities between graph instances)
- Applicable to many real-world applications
- Implementation (soon) available in Oracle's graph package

Related Talks

Date and Time	Location	Title
Monday, 9:00 a.m. - 9:45 a.m.	Moscone West - Room 2016	Graph Query Language For Navigating Complex Data [DEV5447]
Monday, 10:30 a.m. - 11:15 a.m.	Moscone West - Room 2022	When Graphs Meet Machine Learning [DEV5420]
Monday, 11:30 a.m. - 12:15 p.m.	Moscone West - Room 2022	Automate Anomaly Detection with Graph Analytics [DEV5397]
Monday, 12:30 p.m. - 1:15 p.m.	Moscone West - Room 2022	Oracle Database MLE: JavaScript, Python, and More <i>in</i> the Database [DEV5082]
Monday, 1:30 p.m. - 2:15 p.m..	Moscone West - Room 2003	How to Build Geospatial Analytics with Python and Oracle Database [DEV5185]
Monday, 4:45 p.m. - 5:30 p.m.	Moscone West - Room 3004	Introduction to Graph Analytics and Oracle Graph Cloud Service [TRN4098]
Monday, 5:45 p.m. - 6:30 p.m.	Moscone West - Room 3004	How to Analyze Data Warehouse Data as a Graph [TRN4099]
Thursday, 2:00 p.m. - 2:45 p.m.	Moscone West - Room 2018	Analyzing Blockchain and Bitcoin Transaction Data as Graphs [DEV4835]

Date and Time	Location	Title (Meet The Experts)
Tuesday, noon - 1:00 p.m.	Moscone West – Lounge B	Graph Analysis and Database Technologies
Tuesday, 3:00 p.m. – 4:00 p.m	Moscone West – Lounge B	Graph Analysis and Machine Learning (Graph Queries and Analysis)
Wednesday, 10:00 a.m. - 11:00 a.m.	Moscone West - Lounge B	Graph Analysis and Database Technologies
Wednesday, 11:00 a.m. - noon	Moscone West - Lounge A	Graph Analysis and Machine Learning (Graph Queries and Analysis)

Spatial and Graph at OOW 2018

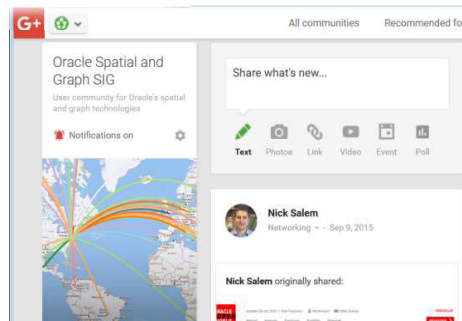
View this list at tinyurl.com/SpatialGraphOOW18

Demos

Date/Time	Title	Location
<ul style="list-style-type: none">Monday 9:45 am – 5:45 pmTuesday 10:30 am – 5:45 pmWednesday 10:30 am– 4:45 pm	<p>Oracle Spatial and Graph Database, Analytics, and Cloud Services</p> 	<p>Moscone South Exhibit Hall ('The Exchange')</p> <ul style="list-style-type: none">Oracle Demogrounds: Cloud Platform > Application Development areaKiosk # APD-WU3

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