# Using Deep Learning and Graph Analysis against Cyberattacks

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@SpatialHannes

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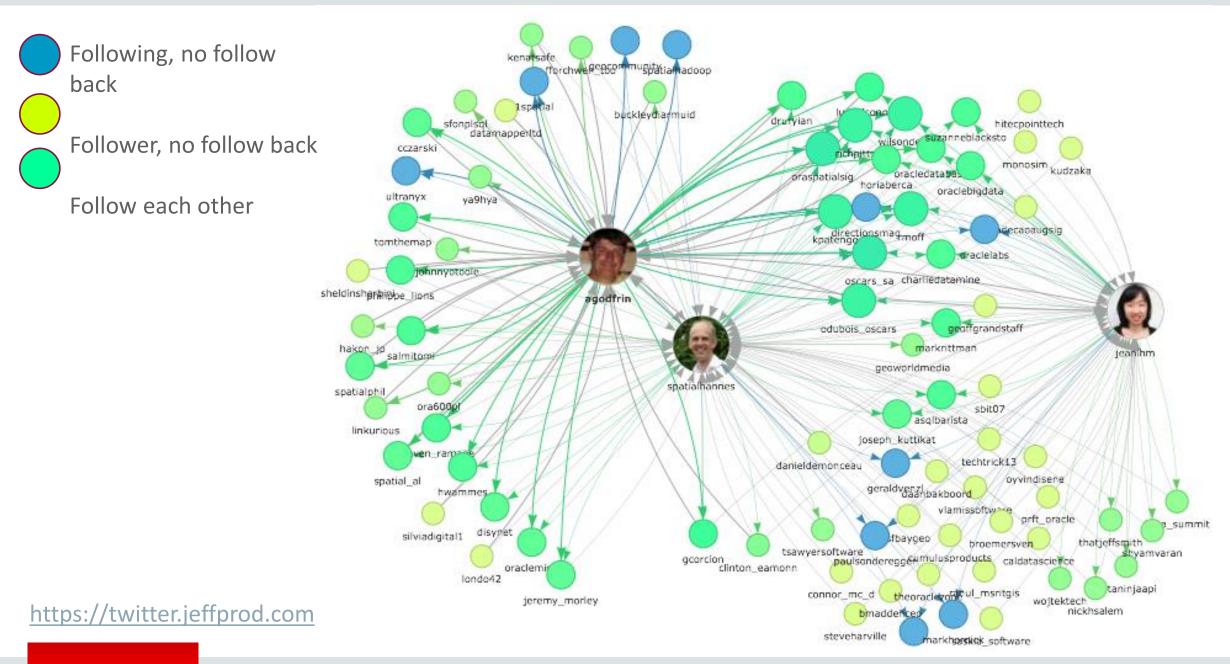


### Agenda

- **1** Introduction to graph analysis
- <sup>2</sup> Using Oracle's graph technologies to work with graphs
- Combining graph analysis and machine learning
- Using machine learning for network intrusion detection

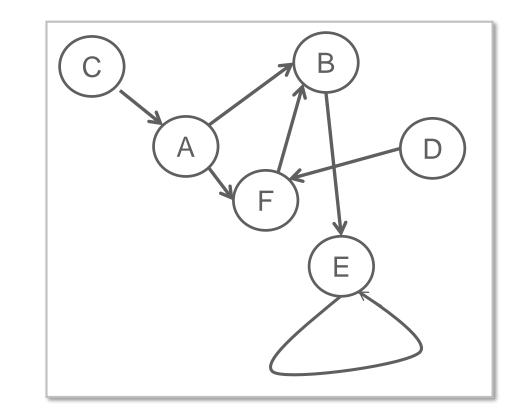
#### 5 Wrap-up





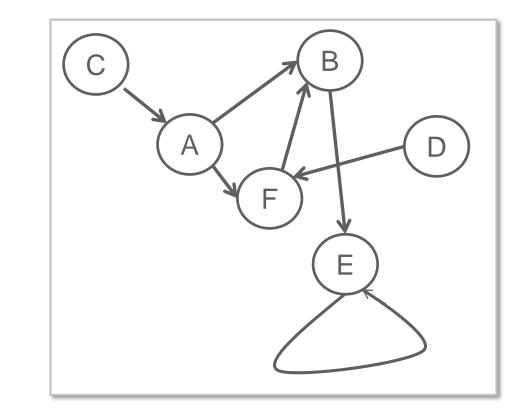
# Graph Data Model

- What is a graph?
  - Data model representing entities as vertices and relationships as edges
  - Optionally including attributes
  - Also known as "linked data"
- What are typical graphs?
  - Social Networks
    - LinkedIn, facebook, Google+, ...
  - IP Networks, physical networks, ...
  - Knowledge Graphs
    - Apple SIRI, Google Knowledge Graph, ...



# Graph Data Model

- Why are graphs popular?
  - Easy data modeling
    - "whiteboard friendly"
  - Flexible data model
    - No predefined schema, easily extensible
    - Particularly useful for sparse data
  - Insight from graphical representation
    - Intuitive visualization
  - Enabling new kinds of analysis
    - Overcoming some limitations in relational technology
    - Basis for Machine Learning (Neural Networks)



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# **Categories of Graph Analysis**

#### **Computational Graph Analytics**

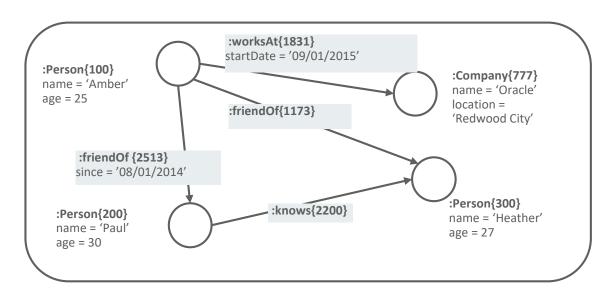
- Compute values on vertices and edges
- Traversing graph or iterating over graph (usually repeatedly)
- Procedural logic
- Examples:

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Shortest Path, PageRank, Weakly
 Connected Components, Centrality, ...

#### **Graph Pattern Matching**

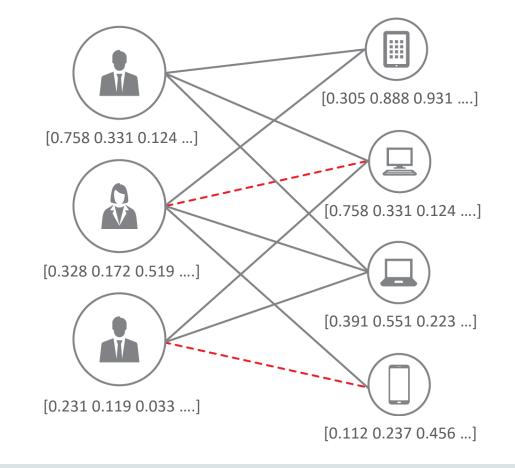
- Based on description of pattern
- Find all matching sub-graphs



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# **Detecting similarities – Recommentation Engines**

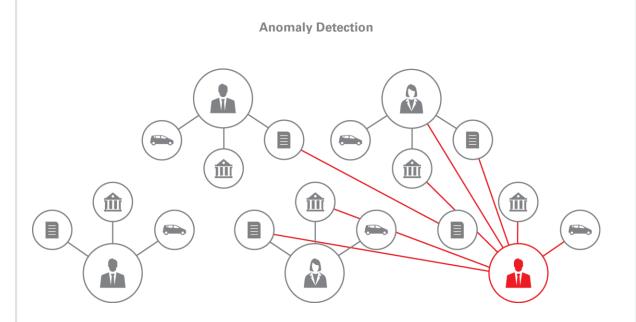
- Identifying users with similar behaviour or buying pattern
- Viewing customer-item relations as large (sparse) matrix
  - Customers as one dimension, items as other
- Matrix cells filled with rating/rank
  - Represent as graph, not as matrix
- Collaborative Filtering [1] algorithm solves taste signature of customers, items
  - Resulting vectors are like DNA
- Inner product of vectors reflects quality of match
   [1] https://en.wikipedia.org/wiki/Collaborative\_filtering



## Detecting Outliers – Graph Analysis and Anomaly Detection

• Requirement:

- Identify entities from a large dataset that look different than others, especially in their relationships
- Approaches:
  - Define an anomaly pattern, find all instances of the pattern in the graph
  - Given nodes in the same category, find nodes that stand out (eg. low Pagerank value)



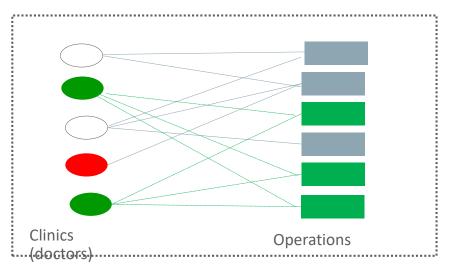
### Use case: Fraud Detection in Healthcare

- Example for potential fraud detection
  - Public domain dataset
  - Medical providers and their operations
- Question
  - Are there any medical providers that are suspicious
  - medical providers that perform different operations than their fellows

(e.g. eye doctors doing plastic surgery)

#### Approach

- Create graph between doctors and operations
- Apply personalized pagerank (a.k.a equivalent to random walking)
- Identify doctors that are *far* from their fellows



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### Introducing: Oracle Big Data Spatial and Graph

Spatial Analysis:

- Location Data Enrichment
- Proximity and containment analysis, Clustering
- Spatial data preparation (Vector, Raster)
- Interactive visualization



#### Property Graph Analysis:

- Graph Database
- In-memory Analysis Engine
- Scalable Network Analysis Algorithms
- Developer APIs



### In-memory Analytics Engine – Product Packaging

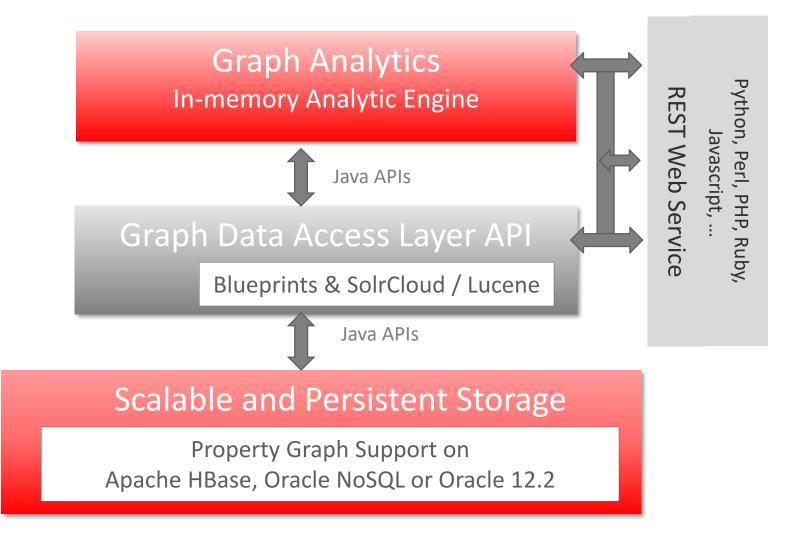
#### **Oracle Big Data Spatial and Graph**

- Available for Big Data platform — Hadoop, HBase, Oracle NoSQL
- Supported both on BDA and commodity hardware
  - CDH and Hortonworks
- Database connectivity through Big Data Connectors or Big Data SQL
- Included in Big Data Cloud Service

#### **Oracle Spatial and Graph (DB option)**

- Available with Oracle 12.2 (EE)
- Using tables for graph persistence
- In-database graph analytics
  - Sparsification, shortest path, page rank, triangle counting, WCC, sub graph generation...
- SQL queries possible
  - Integration with Spatial, Text, Label Security, RDF Views, etc.

### Oracle Big Data Graph Architecture





# Creating a Graph

- From a relational model
  - Rows in tables usually become vertices
  - Columns become properties on vertices
  - Relationships become edges

VIDEO_SALES_ORDERS		SALES_C	SALES_ORDER_LINE_ITEMS			VIDEO_PRODUCTS	
SALES_ID	CUST_NAME	SALES_ID	LINE_ID	PROD_ID		PROD_ID	PROD_DESC
10	SMITH	10	1	1000		1000	TOY STORY
20	JONES	10	2	3000		2000	TRUE LIES
30	TURNER	20	1	4000		3000	POPCORN
40	ADAMS	20	2	3000		4000	STARGATE
		20	3	2000			
		30	1	1000			
		30	2	1000		L	
		40	1	4000			

- Join tables in n:m relations are transformed into relationships, columns become properties on edges
- Interactively through API or graphical tool
  - Adding vertices, edges, properties to a given graph
- From graph exchange formats
  - GraphML, GraphSON, GML (Graph Modeling Language)

### Creating a Graph from Network Traffic

- Capture network traffic (source/target IP address and port, protocol, state, duration, ...)
- Model each IP address as vertex
- Model each record (from source IP to destination IP) as an edge
- Attributes can become properties on the edge
- Utilities available to convert CSV to graph
  - OraclePropertyGraphUtilsBase.convertCSV2OPV
  - OraclePropertyGraphUtilsBase.convertCSV2OPE

[59.166.0.1,62377,149.171.126.4,53,udp,CON,0.001044,130,162,31,29,0,0,dns,498084.2813,620689.625,2,
192.168.241.243,259,192.168.241.243,49320,icmp,URH,0,1780,0,64,0,0,0,-,196.4095,0,5,0,0,0,0,356,
192.168.241.243,49320,192.168.241.243,0xc0a8,icmp,URH,0,1780,0,64,0,0,0,-,196.4095,0,5,0,0,0,0,0,3
59.166.0.6,38993,149.171.126.0,53,udp,CON,0.00106,132,164,31,29,0,0,dns,498113.1875,618867.875,2,2
59.166.0.9,59720,149.171.126.8,53,udp,CON,0.00107,132,164,31,29,0,0,dns,493457.9375,613084.125,2,2
59.166.0.4,21489,149.171.126.7,53,udp,CON,0.001144,130,162,31,29,0,0,dns,454545454688,566433.5625,2



### Agenda

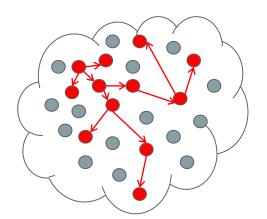
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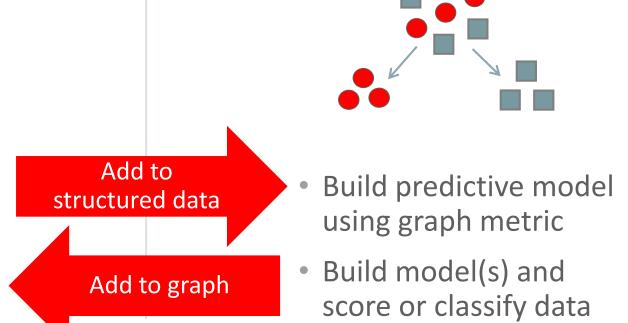
### **Combining Graph Analytics and Machine Learning**

#### **Graph Analytics**



- Compute graph metric(s)
- Explore graph or compute new metrics using ML result

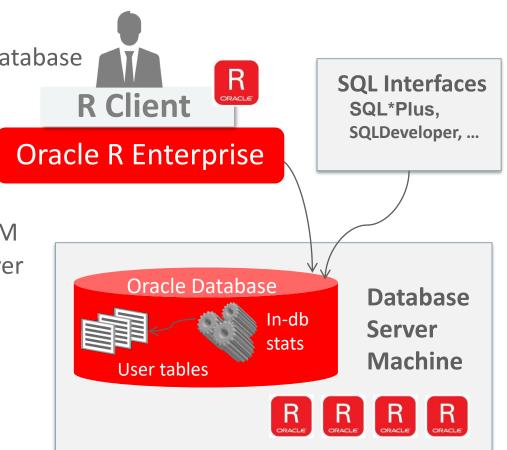
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### Machine Learning

# Using Oracle R Enterprise for Machine Learning Use Oracle Database as a high performance compute environment

- Transparency layer
  - Leverage proxy objects (ore.frames) data remains in the database
  - Overload R functions that translate functionality to SQL
  - Use standard R syntax to manipulate database data
- Parallel, distributed ML algorithms
  - Scalability and performance
  - Exposes in-database machine learning algorithms from ODM
  - Additional R-based algorithms executing and database server
- Embedded R execution
  - Store and invoke R scripts in Oracle Database
  - Data-parallel, task-parallel, and non-parallel execution
  - Invoke R scripts at Oracle Database server from R or SQL
  - Use open source CRAN packages



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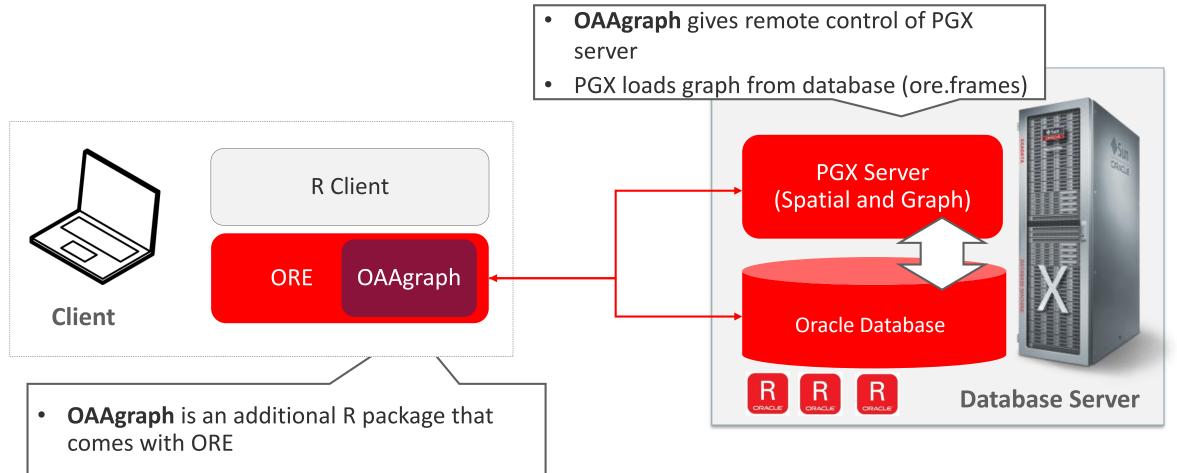
# One option: OAAgraph integration with R



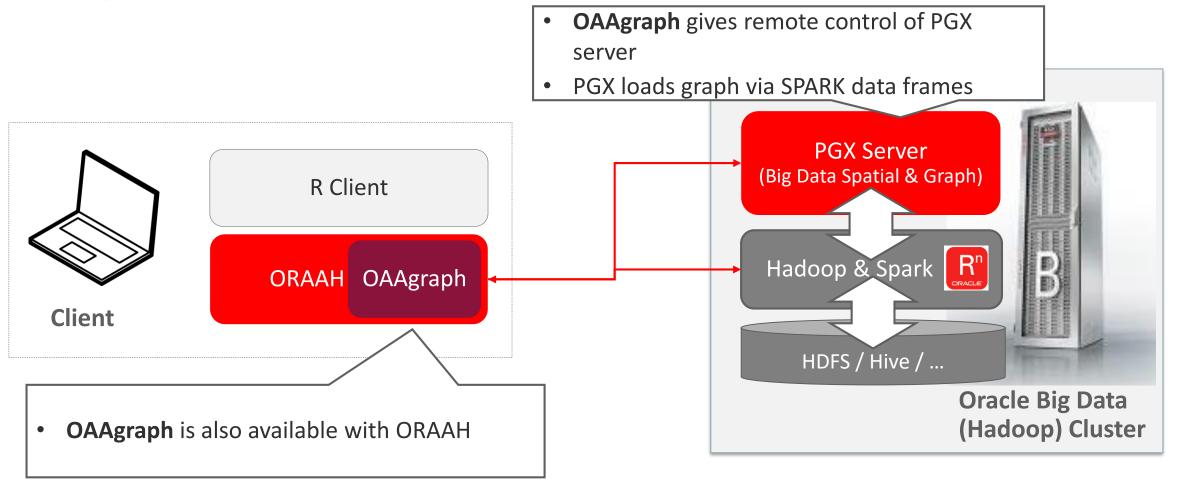
- OAAgraph integrates in-memory engine into ORE and ORAAH
- Adds powerful graph analytics and querying capabilities to existing analytical and machine learning portfolio of ORE and ORAAH
- Built-in algorithms of PGX available as R functions
- PGQL pattern matching
- Concept of "cursor" allows browsing of in-memory analytical results using R data structures (R data frame), allows further client-side processing in R
- Exporting data back to Database / Spark allows persistence of results and further processing using existing ORE and ORAAH analytical functions



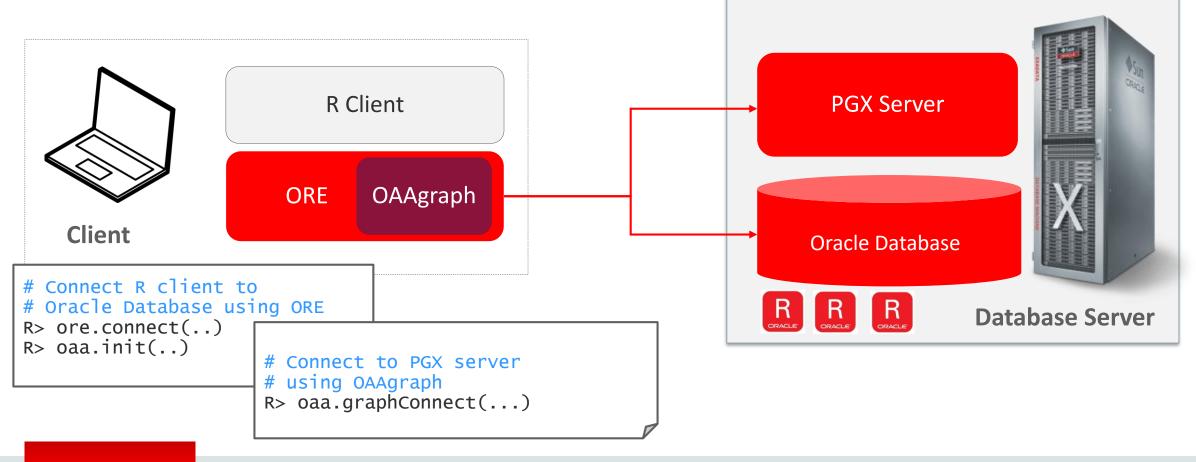
### OAAgraph Architecture



### OAAgraph Architecture



Initialization and Connection



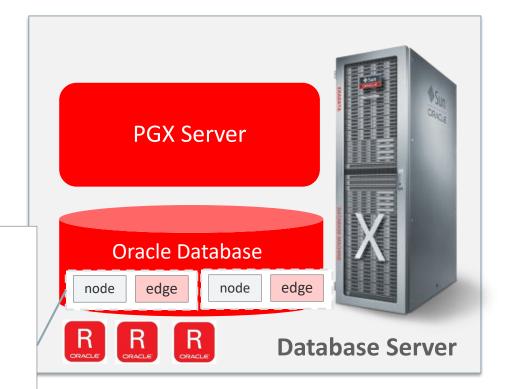
- Data Source
  - Graph data is represented as two tables
    - Nodes and Edges
  - Multiple graphs can be stored in database
    - Using user-specified, unique table names

Node ID	Node Prop 1 (name)	Node Prop 2 (age)	•••						
1238	John	39							
1299	Paul	41							
4818	•••	•••							

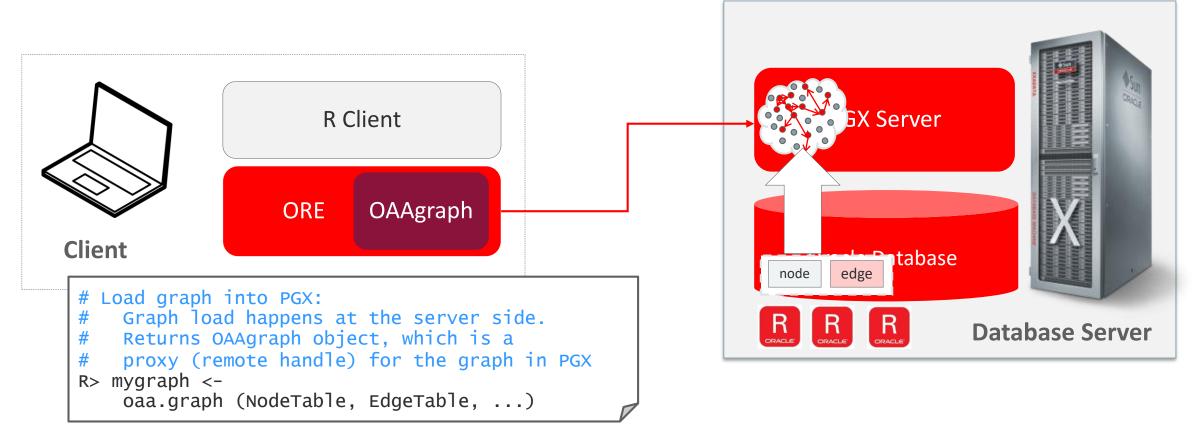
Nodo Tablo

Edge Table

From Node	To Node	Edge Prop 1 (relation)	
1238	1299	Likes	
1299	4818	FriendOf	•••
1299 6637		FriendOf	

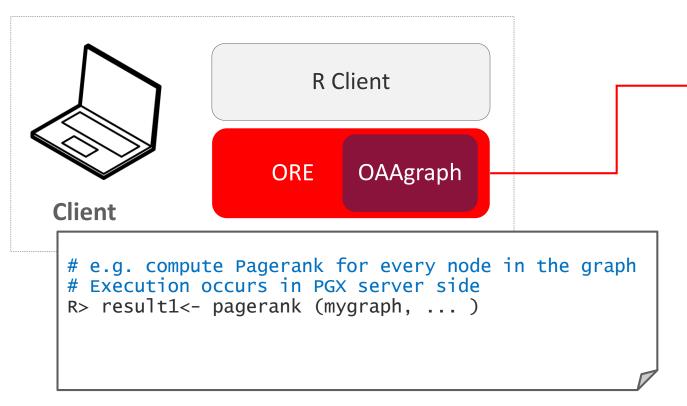


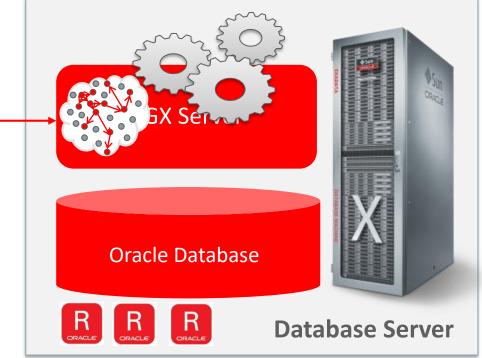
Loading Graph



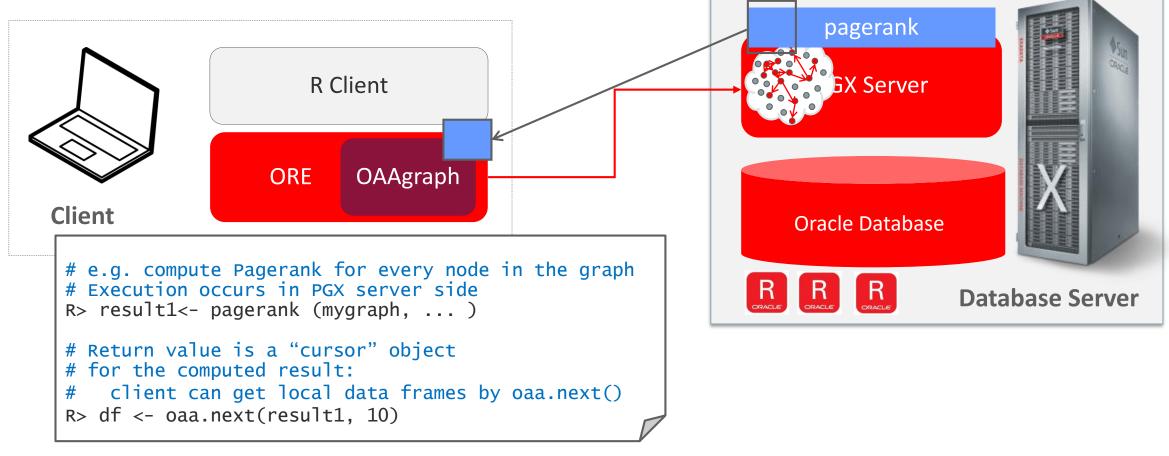


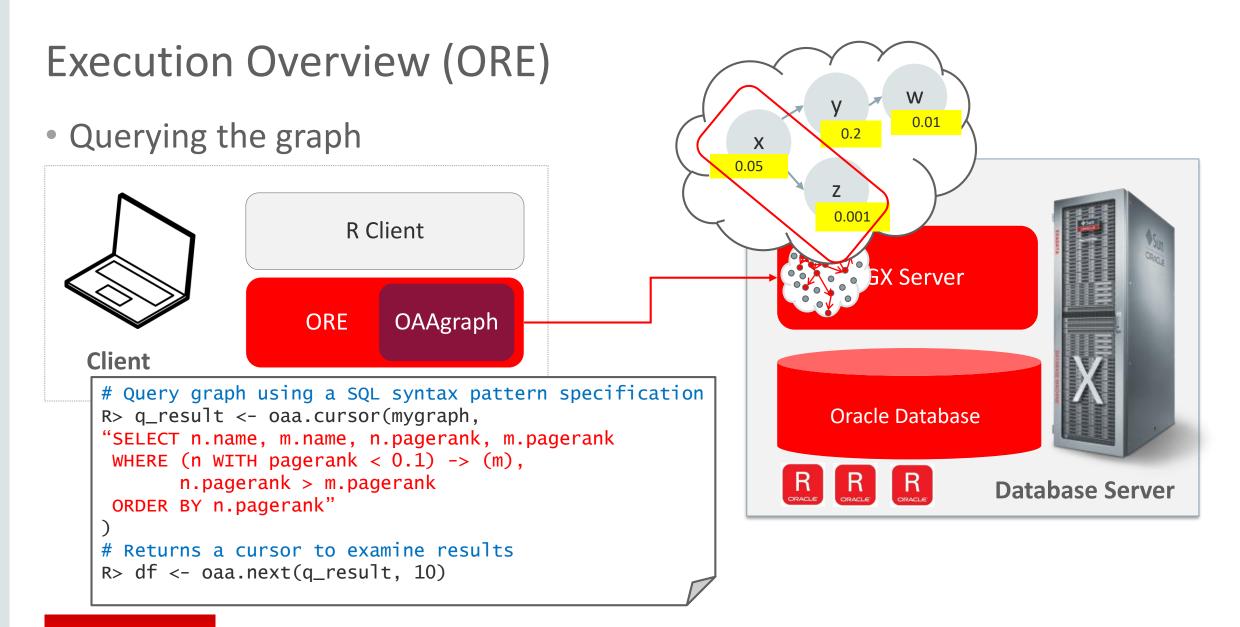
• Running Graph Algorithm



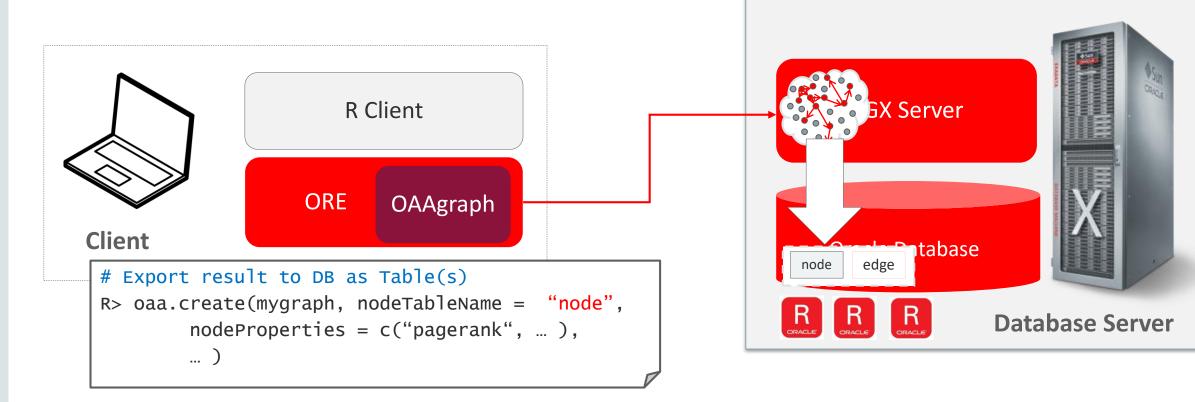






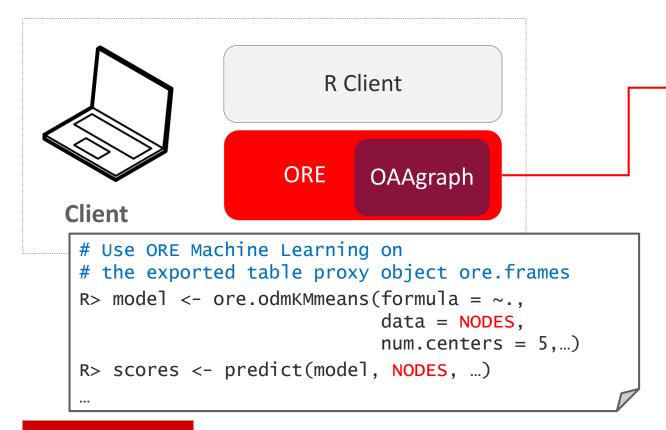


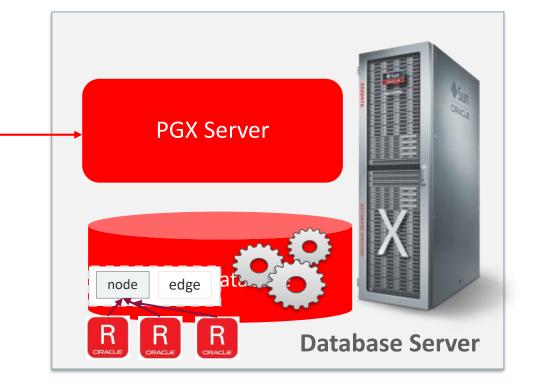
• Exporting the result to DB





• Continuing analysis with ORE





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### Use case: Network Intrusion Detection Using deep learning and graph analysis

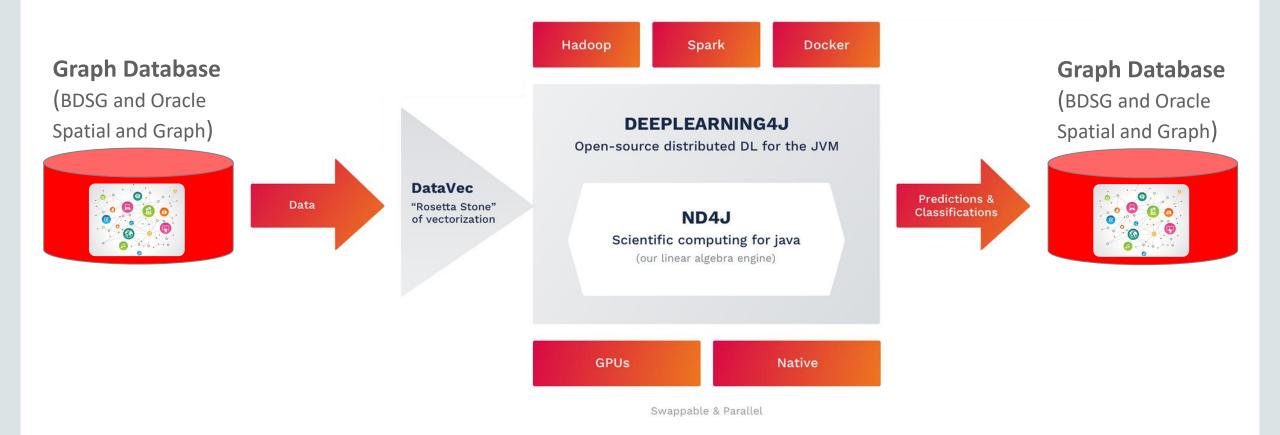
- Determining if network activity is legitimate or fraudulent
  - Based on sequence of network activity (as above)
  - Complementary to firewalls, network intrusion prevention system, ...
- Possible approaches
  - "Signature-based", using labeled dataset of known attacks (supervised learning)
  - Anomaly-based, trying to detect previously unseen attacks
- Most effective systems make use of both
  - Combined with rules engine
- Tested supervised learning in project using DL4J

### Supervised learning Training dataset

- Labeled Network data set from Univ. of South Wales
  - UNSW-NB15 data set specifically created for **Network Intrusion Detection** systems
  - Generated by IXIA PerfectStorm tool in Cyber Range Lab of Australian Centre for Cyber Security
  - Real modern normal activities plus synthetic contemporary attack behaviours
  - Partitioned into training set (175K records) and testing set (82K records)
  - nine types of attacks Fuzzers, Analysis, Backdoors, DoS, Exploits, Generic, Reconnaissance, Shellcode and Worms
- Moustafa, Nour, and Jill Slay. "UNSW-NB15: a comprehensive data set for network intrusion detection systems (UNSW-NB15 network data set)."*Military Communications and Information Systems Conference (MilCIS)*, 2015. IEEE, 2015.
- Moustafa, Nour, and Jill Slay. "The evaluation of Network Anomaly Detection Systems: Statistical analysis of the UNSW-NB15 data set and the comparison with the KDD99 data set." Information Security Journal: A Global Perspective (2016): 1-14.



### Prototype with Skymind and DeepLearning4J





### **Processing Workflow**

- Understanding the dataset
  - 49 features in each record IP addresses, integer, float, timestamp, ...
- Data cleansing
  - Converting Hex to number
- Creating vector as input to DL4J deep learning engine
  - Categorical to One Hot transformation of status strings
- Build Neural Network
  - Train and subsequently test quality using testing set
- Transfer result to graph database
  - Further analysis

selection	a Cleansing & paration	1 No 2 3 4 5 Networl 7 8 9 10	Name Type Description Image: Source IP address Image: Source
• Understand the data			10       source to destination time to live value       Integer       Source to destination time to live value       Integer       Destination to source time to live value       Integer       Integer       Destination to source time to live value       Integer       Integer       Source packets retransmitted or dropped       Integer       Integer       Destination packets retransmitted or dropped       Integer       Integer       Destination packets retransmitted or dropped       Integer
<ul> <li>Features of</li> </ul>	2 1 srcip r 3 2 sport i	C [19 20 20 20 20 20 21 20 21 20 21 20 21 20 21 20 21 20 21 20 21 20 20 21 20 20 20 20 20 20 20 20 20 20	18 Dpkts integer Destination to source packet count Image: Source TCP window advertisement value Image: Source TCP base sequence number Image: Sourc
	6         5 proto         r           7         6 state         r           8         7 dur         F	nteger Desti <sup>26</sup> nominal Trans <sup>28</sup> nominal Indic <sup>29</sup> Float Reco <sup>31</sup> nteger Sour <sup>32</sup>	25       trans_depinteger       Represents the pipelined depth into the connection of http request/response transaction       Image: Connection of http reparts/response transaction       Image: Connection of http reparts/response
	10         9 dbytes         1           11         10 sttl         1           12         11 dttl         1           13         12 sloss         1	nteger Desti 34 nteger Sour 35 nteger Desti 37 nteger Sour 38 nteger Sour 39	32 Dintpkt       Float       Destination interpacket arrival time (mSec)       Image: Construction of the sec of the s
	15         14 service         r           16         15 Sload         F           17         16 Dload         F	nteger Desti 40 nominal http, 41 Float Soun 43 Float Desti 45 ntegor Soun 46	39       is_ftp_log Binary       If the ftp session is accessed by user and password then 1 else 0.       If the ftp session is accessed by user and password then 1 else 0.         40       ct_ftp_cm integer       No of flows that has a command in ftp session.       Image: Common second in the se
		nteger Soun 46 nteger Desti 47 48 49 50	45       ct_src_dp(integer       No of connections of the same source address (1) and the destination port (4) in 100 connections according to the last time (26).         46       (t_dst_sp(integer       No of connections of the same destination address (3) and the source port (2) in 100 connections according to the last time (26).         47       (t_dst_src_integer       No of connections of the same source (1) and the destination (3) address in in 100 connections according to the last time (26).         48       attack_cat nominal       The name of each attack category. In this data set , nine categories e.g. Fuzzers, Analysis, Backdoors, DoS Exploits, Generic, Reconnaissance, Shellcode and Worms         49       Label       binary       O for normal and 1 for attack records



- One round of clean up.
  - Ports should be all integer based, however, there are Hex values
  - Action: convert them back to decimal

59.166.0.1,62377,149.171.126.4,53,udp,CON,0.001044,130,162,31,29,0,0,dns,498084.2813,620689.625,2,192.168.241.243,259,192.168.241.243,49320.icmp,URH,0,1780,0,64,0,0,0,-,196.4095,0,5,0,0,0,0,0,356,192.168.241.243,49320,192.168.241.243,**0**xc0a8, cmp,URH,0,1780,0,64,0,0,0,-,196.4095,0,5,0,0,0,0,0,0,359,166.0.6,38993,149.171.126.0,53,udp,CON,0.00106,132,164,31,29,0,0,dns,498113,1875,618867.875,2,259.166.0.4,21489,149.171.126.7,53,udp,CON,0.00107,132,164,31,29,0,0,dns,493457.9375,613084.125,2,259.166.0.8,45682,149.171.126.7,53,udp,CON,0.001257,130,162,31,29,0,0,dns,413683.375,515513.125,2,259.166.0.8,45682,149.171.126.8,53,udp,CON,0.001124,132,164,31,29,0,0,dns,413683.375,515513.125,2,259.166.0.8,32958,149.171.126.8,53,udp,CON,0.001075,146,178,31,29,0,0,dns,409750.9063,583629.9375,259.166.0.8,55879,149.171.126.3,53,udp,CON,0.001075,146,178,31,29,0,0,dns,469750.9063,583629.9375,259.166.0.8,55879,149.171.126.3,53,udp,CON,0.001075,146,178,31,29,0,0,dns,473967.6875,588868.9375,259.166.0.2,31439,149.171.126.3,53,udp,CON,0.001075,146,178,31,29,0,0,dns,473967.6875,588868.9375,259.166.0.2,31439,149.171.126.3,53,udp,CON,0.001075,146,178,31,29,0,0,dns,543255.8125,662325.5625,259.166.0.2,31439,149.171.126.3,53,udp,CON,0.001075,146,178,31,29,0,0,dns,543255.8125,662325.5625,259.166.0.2,31439,149.171.126.3,53,udp,CON,0.001088,146,178,31,29,0,0,dns,543255.8125,662325.5625,259.166.0.2,31439,149.171.126.3,53,udp,CON,0.001088,146,178,31,29,0,0,dns,543255.8125,6524411.75,2,259.166.0.3,45426,149.171.126.3,53,udp,CON,0.001053,132,164,31,29,0,0,dns,501424.5,622981.9375,2,2,59.166.0.3,45426,149.171.126.3,53,udp,CON,0.001075,132,164,31,29,0,0,dns,501424.5,622981.9375,2,2,59.166.0.3,45426,149.171.126.3,53,udp,CON,0.001053,132,164,31,29,0,0,dns,450127.875,559249.8125,2,59.166.0.9,28993,149.171.126.3,53,udp,CON,0.001173,132,164,31,29,0,0,dns,450127.875,559249.8125,2,59.166.0.9,28993,149.171.126.3,53,udp,CON,0.001173,132,164,31,29,0,0,dns,450127.875,559249.8125,2,59.166.0.9,28993,149.171.126.9,53,udp,CON,0.001173,132,164,31,29,0,0,dns,450127.8





### Understand the data & define transformations

.remokeColumns("timestamp start", "timestamp end", "source ip", "destination ip", /
 "source TCP base sequence num", "dest TCP base sequence num","attack categor
.filter(new FilterInvalidValues("source port", "destination port")) //Remove example
.transform(new ReplaceEmptyIntegerWithValueTransform("count flow http methods", 0))
.transform(new ConditionalTransform("is ftp login", 1, 0, "service", Arrays,asList("
.transform(new StringToCategoricalTransform("service", "-", "dns", "http", "smtp", '
.transform(new StringToCategoricalTransform("transaction protocol", "other", Arr
.transform(new MapAllStringsExceptListTransform("state", "other", Arrays,asList("FIN
NT=490469, RST=528, TST=8, ACC=43, REQ=9043, no=7, URH=54})
.transform(new IntegerToCategoricalTransform("equal ips and ports", Arrays,asList("r
.transform(new IntegerToCategoricalTransform("is ftp login", Arrays,asList("r
.transform(new IntegerToCategoricalTransform("state", "FIN", "CON", "INT", "RST", "RE
.transform(new IntegerToCategoricalTransform("state", "FIN", "CON", "INT", "RST", "RE
.transform(new IntegerToCategoricalTransform("is ftp login", Arrays,asList("rot ftp', categoricalToOneHot("is ftp login", "equal ips and ports", "state", "transaction protocol")

Categorical to One Hot transformation

Service "dns" becomes



 Executed transformations with Scala & Apache Spark using Oracle's Big Data stack

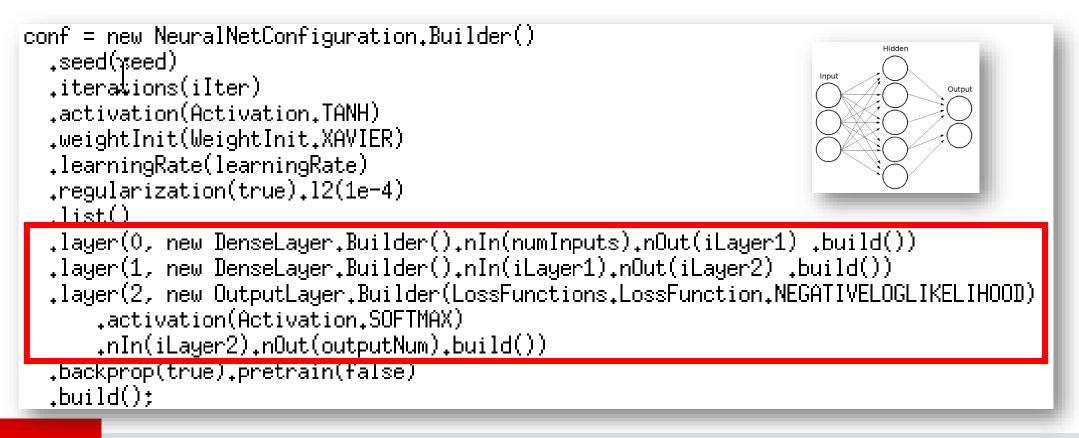
```
val stringData = jsc.textFile("/user/oracle/UNSW-complete-all-removedhex.csv");
import org.datavec.spark.transform.AnalyzeSpark;
import org.datavec.spark.transform.SparkTransformExecutor;
import org.datavec.spark.transform.misc.StringToWritablesFunction;
val swf = new StringToWritablesFunction(recordReader);
val parsedInputData = stringData.map(swf)
val processedData = SparkTransformExecutor.execute(parsedInputData, tp);
```

Save the RDD back to CSV format

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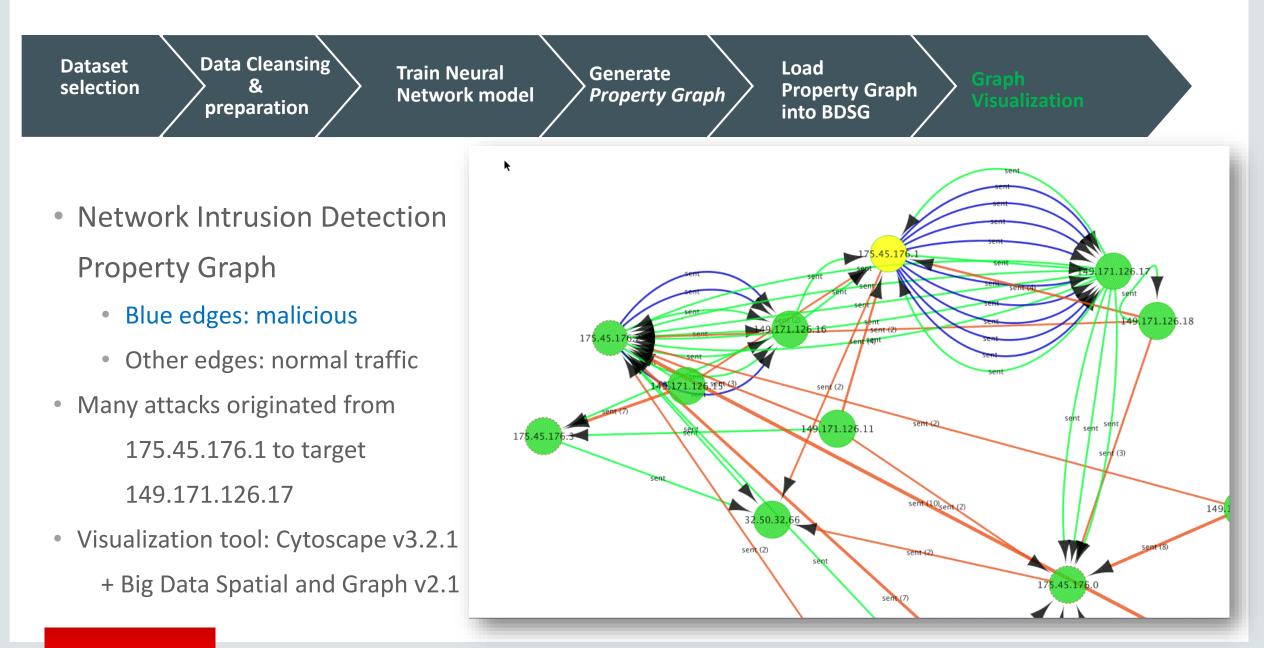
• Built a Multi-Layer Perceptron (MLP) Neural Network





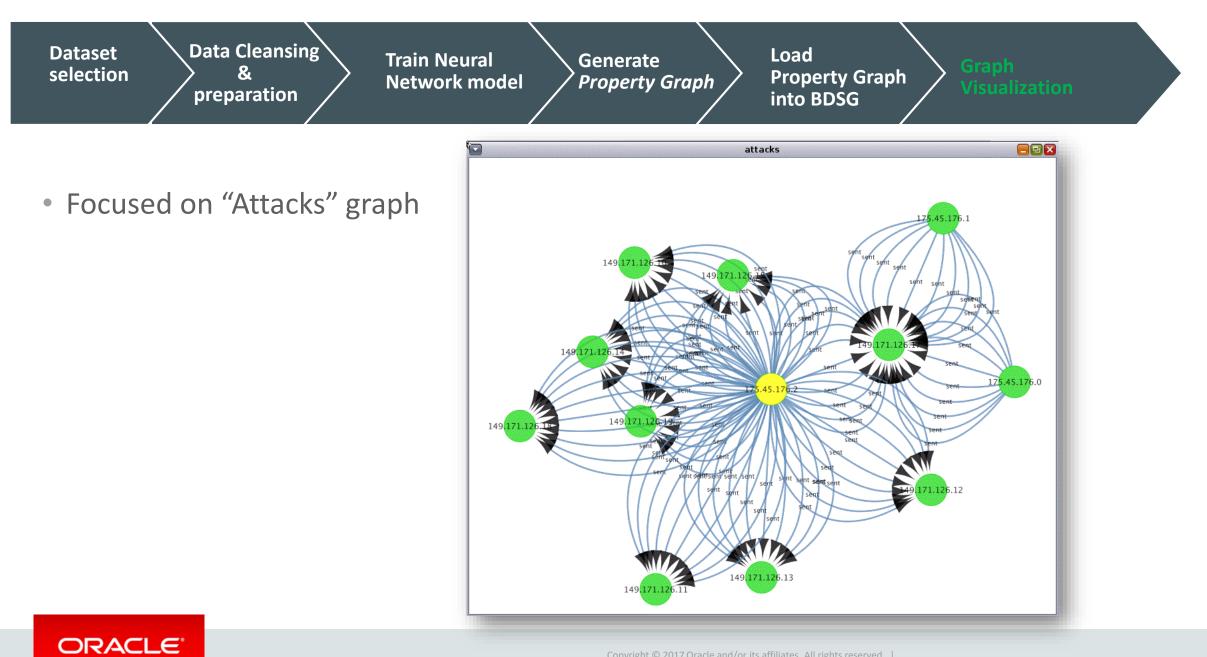
- Tested the quality of MLP NN
  - After 800 iterations of training
    - Accuracy: 0.9811
    - Precision: 0.9894
    - Recall: 0.9286
    - F1 Score: 0.958

- Hidden Input Output
- Labeled as "non-intrusion" classified as "non-intrusion": 46 times
- Labeled as "intrusion" classified as "non-intrusion": 1 time
- Labeled as "intrusion" classified as "intrusion": 6 times ((46+6)/(46+6+1) = 0.9811)
- Long Short-Term Memory (LSTM) NN gave similar F1 result



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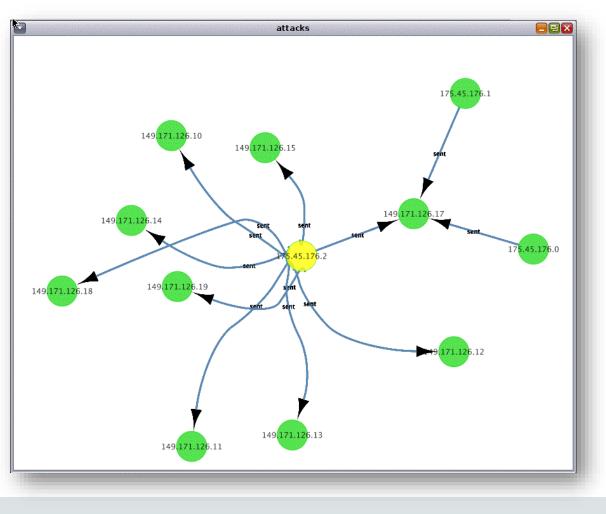
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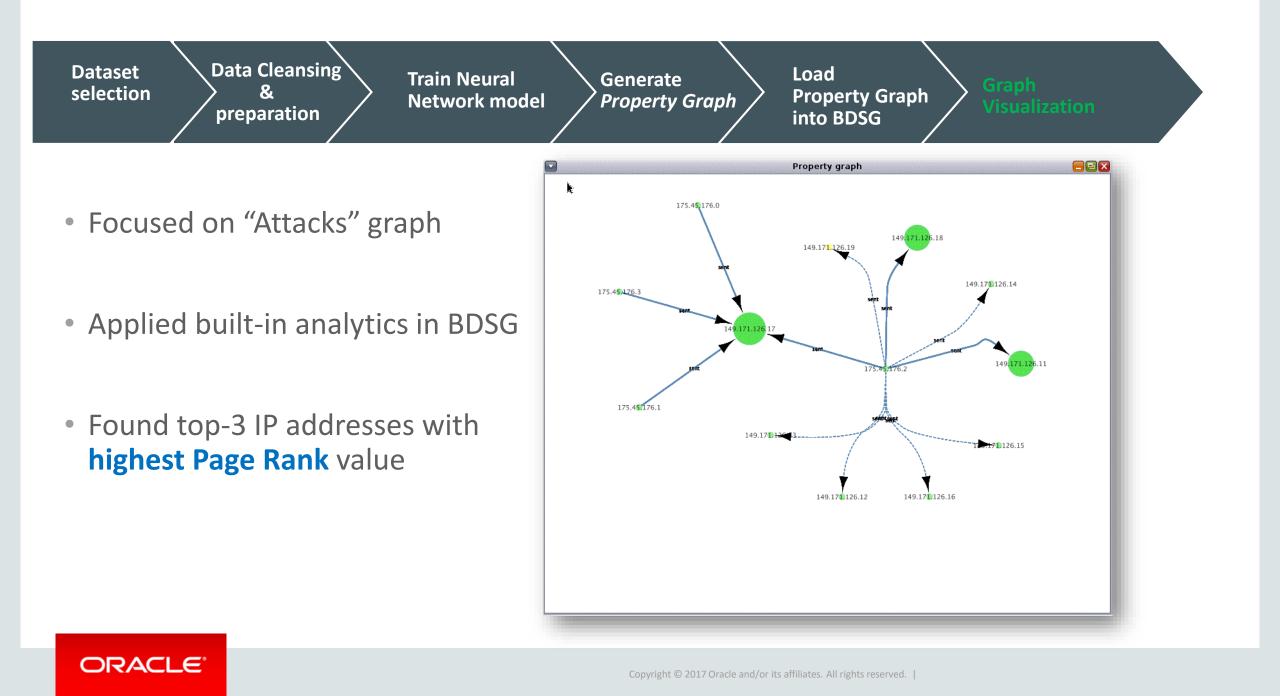


• Focused on "Attacks" graph



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## Summary Graph analytics and machine learning



- Graph databases are powerful tools, complementing machine learning technologies
  - Especially strong for analysis of graph topology and multi-hop relationships
- Graph analytics offer new insight which can be used as input to machine learning

   Especially relationships, dependencies and behavioural patterns
- Oracle Big Data Spatial and Graph and Oracle 12.2 Spatial and Graph offer
  - Comprehensive analytics through various APIs
  - Scaleable, parallel in-memory processing with 40+ graph algorithms pre-built
  - Integration with R, integration with SPARK, integration with relational database
  - Secure and scaleable graph storage on Hadoop using Oracle NoSQL or HBase or Oracle database
- Running both on-premise or in the Cloud

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## Resources



- Oracle Big Data Spatial and Graph OTN product page: <u>www.oracle.com/technetwork/database/database-technologies/bigdata-spatialandgraph</u>
  - White papers, software downloads, documentation and videos
- Oracle Big Data Lite Virtual Machine a free sandbox to get started: www.oracle.com/technetwork/database/bigdata-appliance/oracle-bigdatalite-2104726.html
- Hands On Lab included in /opt/oracle/oracle-spatial-graph/
  - Content also available on GITHub under http://github.com/oracle/BigDataLite/
- Blog examples, tips & tricks: <a href="https://www.blogs.oracle.com/bigdataspatialgraph">blogs.oracle.com/bigdataspatialgraph</a>
- У @OracleBigData, @SpatialHannes, @agodfrin, @JeanIhm
- in Oracle Spatial and Graph Group

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## Interested in project experience, best practices, networking? Spatial and Graph Summit

- IOUG Business Intelligence, Warehousing and Analytics SIG have established annual BIWA Summit
  - Rebranded as Analytics and Data Summit
  - Planned for March 20 22, 2018 at OracleHQ
- Spatial and Graph Summit is separate track
  - Lots of interesting material from previous years available on OTN
- Opportunity for interaction with Spatial PM and Dev't team







# Integrated Cloud Applications & Platform Services

