

Strata+ Hadoop WORLD

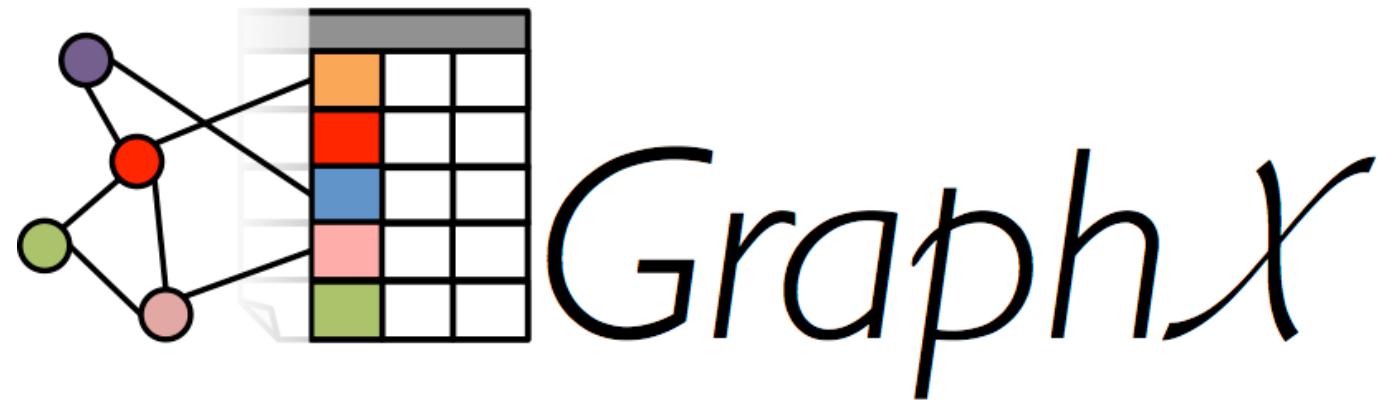
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#StrataHadoop



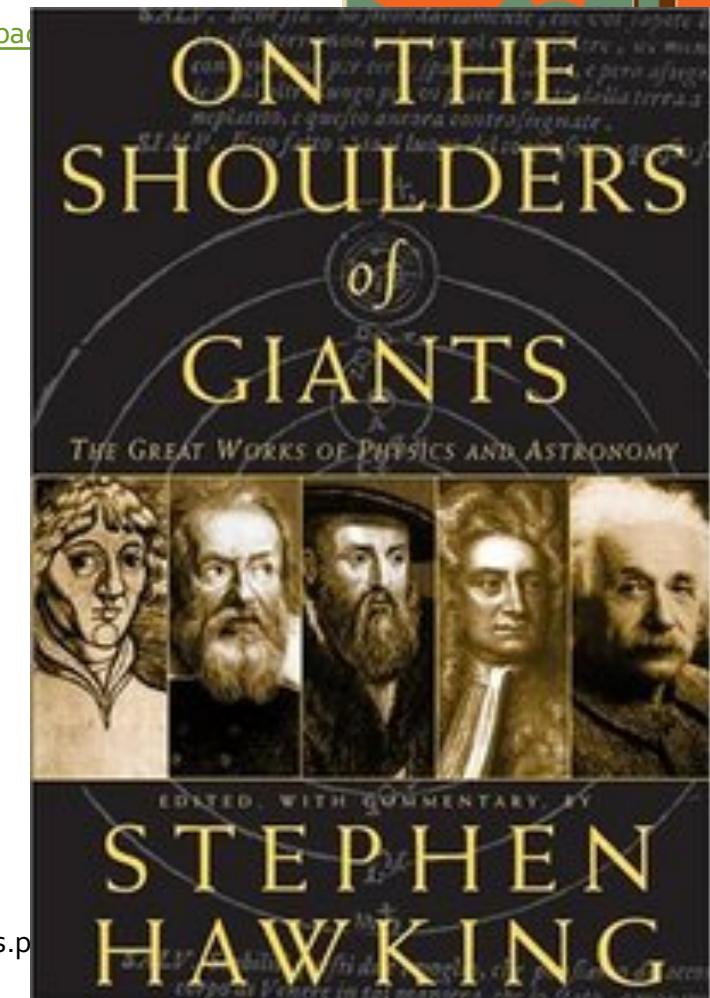
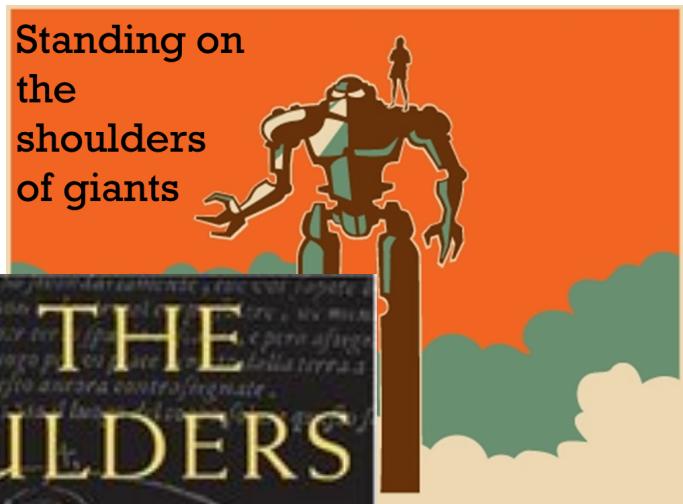
AGENDA-TOPIC	TIME	DATA	DESCRIPTION	ASIMOV THE ROBOT SERIES THE NAKED SUN
1. Graph Processing Is Introduced	10 Min		Graph Processing vs GraphDB; Introduction to Spark GraphX	
2. Basics are Discussed & A Graph Is Built	10 Min	Simple Graph	Edge, Vertex, Graph	
3. GraphX API Landscape Is discussed	5 Min		Explain APIs	
4. Graph Structures Are Examined	5 Min		Indegree, outdegree et al	
5. Community, Affiliation & Strengths Are Explored	5 Min		Connected components, Triangle et al	
6. Algorithms Are Developed	10 Min		PartitionStrategy (is what makes GraphParallel work), PageRank, Connected Components; APIs to implement Algorithms viz. aggregateMessages, Pregel Type Signature – aggregateMessages Algorithms with aggregateMessages	CONTENTS INTRODUCTION 1. A ROBOT IS CREATED 1 2. A ROBOT IS ENCOUNTERED 18 3. A ROBOT IS VIEWED 50 4. A ROBOT IS REVERED 59 5. A ROBOT IS DEFENDED 74 6. A ROBOT IS REVITED 105 7. A ROBOT IS DESTROYED 110 8. A ROBOT IS DEFENDED 115 9. A ROBOT IS DEFENDED 147 10. A CELLS ARE TRACKED 155 11. A ROBOT IS DEFENDED 155 12. A TARGET IS MISSED 161 13. A ROBOT IS CONFONDED 175
7. Case Study (AlphaGo Tweets) Is Conducted	10 Min	AlphaGo Retweet Data	Pipeline, Map attributes to Properties, Vertices & edges, create Graph and run algorithms	
8. Questions Are Asked & Answered	10 Min			

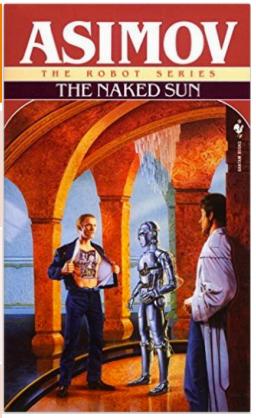
AGENDA THIS STYLED AFTER ASIMOV'S ROBOT SERIES !!!

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JUNE 1, 2016

THANKS TO THE GIANTS WHOSE WORK HELPED TO PREPARE THIS TUTORIAL

1. [Paco Nathan, Scala Days 2015, https://www.youtube.com/watch?v=P_V71n-gtDs](https://www.youtube.com/watch?v=P_V71n-gtDs)
2. Big Data Analytics with Spark-Apress <http://www.amazon.com/Big-Data-Analytics-Spark-Practitioners/dp/1484209656>
3. Apache Spark Graph Processing-Packt <https://www.packtpub.com/big-data-and-business-intelligence/apache-spark-graph-processing>
4. Spark GarphX in Action - Manning
5. <http://hortonworks.com/blog/introduction-to-data-science-with-apache-spark/>
6. <http://stanford.edu/~rezab/nips2014workshop/slides/ankur.pdf>
7. Mining Massive Datasets book v2 <http://infolab.stanford.edu/~ullman/mmds/ch10.pdf>
- <http://web.stanford.edu/class/cs246/handouts.html>
8. <http://www.cs.princeton.edu/~chazelle/courses/BIB/pagerank.htm>
9. <http://kukuruku.co/hub/algorithms/social-network-analysis-spark-graphx>
10. Zeppelin Setup
 - <http://sparktutorials.net/setup-your-zeppelin-notebook-for-data-science-in-apache-spark>
11. Data
 - http://www.transtats.bts.gov/DL_SelectFields.asp?Table_ID=236&DB_Short_Name=On-Time
 - <http://openflights.org/data.html>
12. <https://adventuresincareerdevelopment.files.wordpress.com/2015/04/standing-on-the-shoulders-of-giants.pdf>



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7. Case Study (AlphaGo Tweets) Is Conducted	10 Min	AlphaGo Retweet Data	E2E Pipeline w/real data, Map attributes to Properties, vertices & edges, create graph and run algorithms	
8. Questions Are Asked & Answered	10 Min			

AGENDA TITLES STYLED AFTER ASIMOV'S ROBOT SERIES !!!

Graph Applications

- Many applications from social network to understanding collaboration, diseases, routing logistics and others
- Came across 3 interesting applications, as I was preparing the materials !!

1) Project effectiveness by social network analysis on the projects' collaboration structures :

"EC is interested in the impact generated by those projects ... analyzing this latent impact of TEL projects by applying social network analysis on the projects' collaboration structures ... TEL projects funded under FP6, FP7 and eContentplus, and identifies central projects and strong, sustained organizational collaboration ties."

2) Weak ties in pathogen transmission : "structural motif... Giraffe social networks are characterized by social cliques in which individuals associate more with members of their own social clique than with those outside their clique ... Individuals involved in weak, between-clique social interactions are hypothesized to serve as bridges by which an infection may enter a clique and, hence, may experience higher infection risk ... individuals who engaged in more between-clique associations, that is, those with multiple weak ties, were more likely to be infected with gastrointestinal helminth parasites ... "

3) Panama papers : The leak presented them with a wealth of information, millions of documents, but no guide to structure ... (ie community detection)

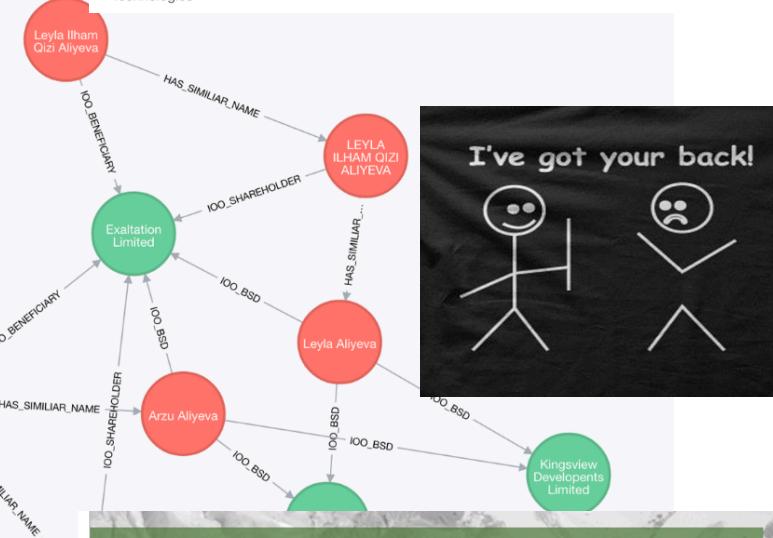
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Access full-text

Social Network Analysis of European Project Consortia to Reveal Impact of Technology-Enhanced Learning Projects

CONFERENCE PAPER · JULY 2012 with 168 READS

DOI: 10.1109/ICALT.2012.41
Conference: Proceedings of the 2012 IEEE 12th International Conference on Advanced Learning Technologies



Oxford Journals > Science & Mathematics > Behavioral Ecology > Advance Access > 10.1093/beheco/arw035

The “strength of weak ties” and helminth parasitism in giraffe social networks

Kimberly L. VanderWaal^a, Vincent Obanda^b, George P. Omondi^c, Brenda McCowan^{d,e}, Hui Wang^f, Hsieh Fushing^g and Lynne A. Isbell^h

^a Department of Veterinary Population Medicine, University of Minnesota, 1365 Gortner Avenue, St. Paul, MN 55108, USA.

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Why Panama Papers Journalists Use Graph Databases

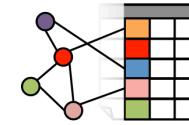
Graph based systems

- Graphs are everywhere – web pages, social networks, people's web browsing behavior, logistics etc.
 - Working w/ graphs has become more important. And harder due to the scale and complexity of algorithms
- Two kinds – processing and querying
- Processing – GraphX, Pregel BSP, GraphLab
- Querying – AllegroGraph, Titan, Neo4j, RDF stores.
 - SPARQL query language
- Graph DBs have queries, can process large dataset
- Graph processing can run complex algorithms
- For Graph Analytics systems both are required
 - Process on graphx, store in neo4j is a good alternative.
 - E.g. Panama papers analytics

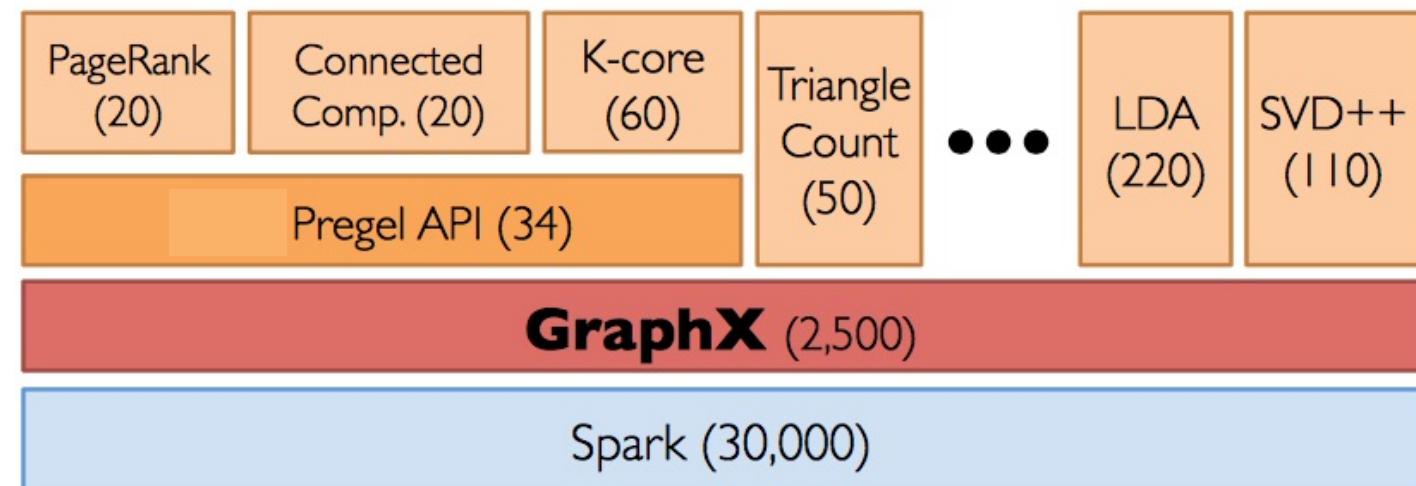
Graph Processing Frameworks

- History – Graph based systems were specialized in nature
 - Graph partitioning is hard ✓ *We will see, later, GraphX's PartitionStrategy*
 - Primitives of record based systems were different than what graph based systems needed
- Rapid innovation in distributed data processing frameworks – MapReduce etc
 - Disk based, with limited partitioning abilities
 - Still an impedance mismatch
- Graph-parallel over Data Parallel RDD ! – Best of both worlds ?

Enter Spark

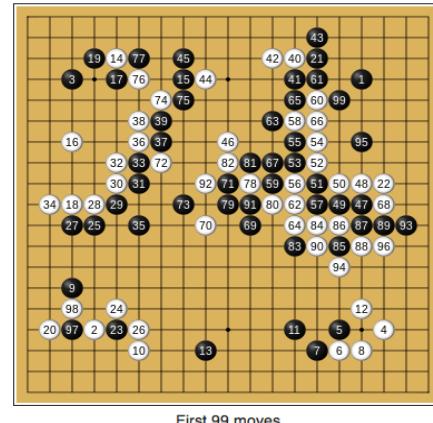


- More powerful partitioning mechanism
- In-memory system makes iterative processing easier
- GraphX – Graph processing built on top of Spark
- Graph **processing** at scale (distributed system)
- Fast evolving project
- *Line Count from the Spark Source Code (v1.6.0)*
- *PageRank*
 - 60 lines w/aggregateMessages
 - runUntilConvergence – 60 lines w/Pregel
- *Trianglecount* – 50 Lines; *SVD++* (150 Lines)
- *Pregel* – lots of comments (> 100 lines/159 -44 lines so 34 is right – example of PageRank w/Pregel API – uses old mapReduceTriplets
- *LDA* in MLLIB/Clustering (~400), - Document, Term = vertices, edges = document -> Term



GraphX ...

- Graph processing at Scale - “Graph Parallel System”
- Has a rich
 - Computational Model
 - Edges, Vertices, Property Graph
 - Bipartite & tripartite graphs (Users-Tags-Web pages)
 - Algorithms (PageRank,...)
- Current focus on computation than query
- APIs include :
 - Attribute Transformers,
 - Structure transformers,
 - Connection Mining & Algorithms
- GraphFrames – interesting development
- Exercises (lots of interesting graph data)
 - Airline data, co-occurrence & co-citation from papers
 - The AlphaGo Community – ReTweet network
 - Wikipedia Page Rank Analysis using GraphX



Graphx Paper : <https://www.usenix.org/system/files/conference/osdi14/osdi14-paper-gonzalez.pdf>

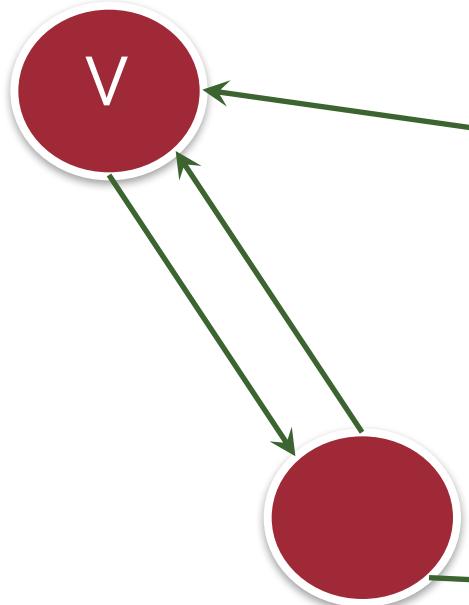
Pragel paper : http://kowshik.github.io/JPregel/pregeg_paper.pdf

Scala, python support <https://issues.apache.org/jira/browse/SPARK-3789>

Java API for Graphx <https://issues.apache.org/jira/browse/SPARK-3665>

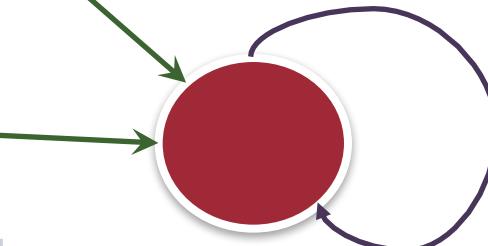
LDA <https://issues.apache.org/jira/browse/SPARK-1405>

GraphX-Basics



Vertex	Vertex(VertexId,VD)	VD can be any object
Edges	Edge(ED)	ED can be any object
Graph	Graph(VD,ED)	

Structural Queries	Indegrees, vertices,...
Attribute Transformers	mapVertices, ...
Structure Transformers, Join	Reverse, subgraph
Connection Mining	connectedComponents, triangles
Algorithms	Aggregate messages, PageRank

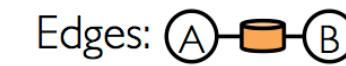


Interesting Objects

- *EdgeTriplet*
- *EdgeContext*



Vertices:



Edges:

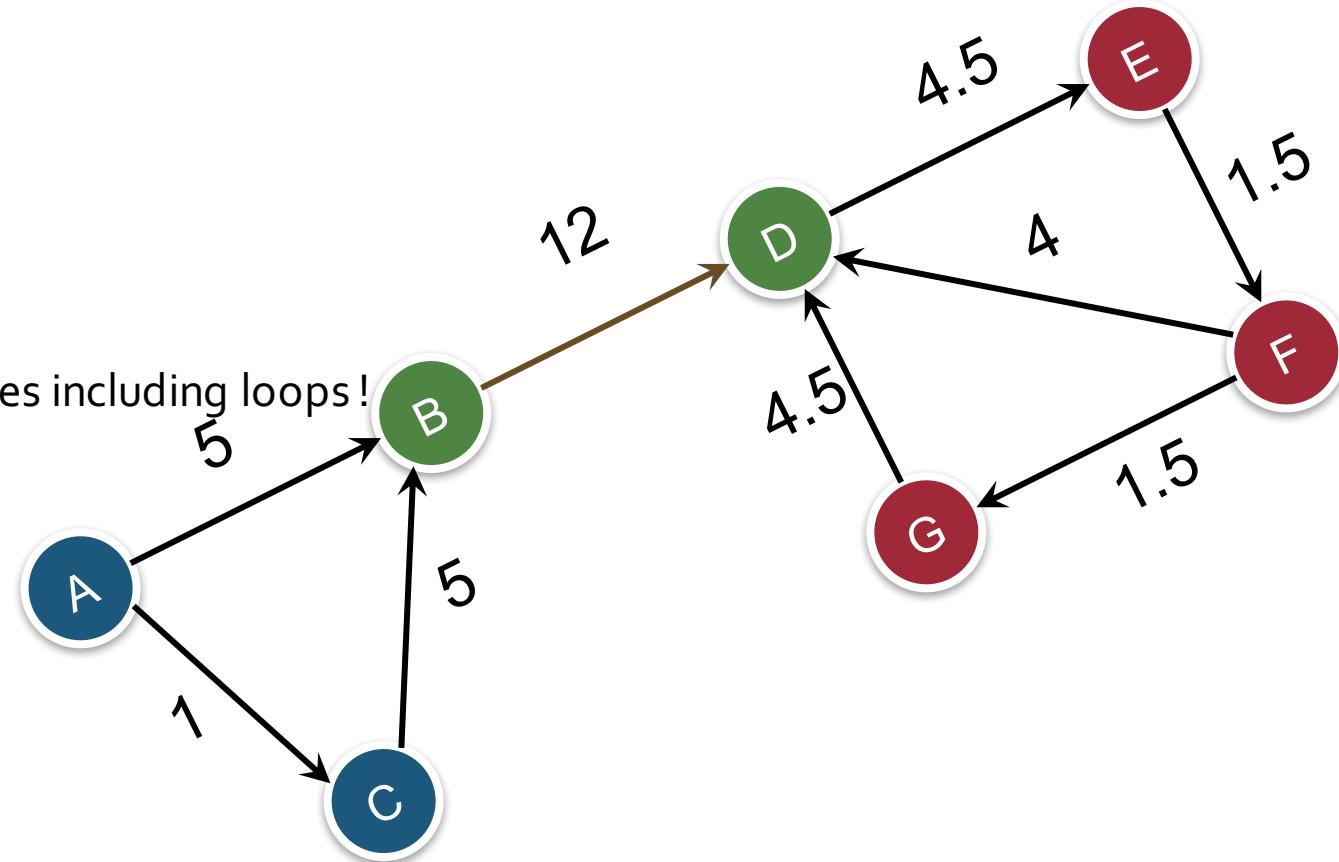


Triplets:

<http://ampcamp.berkeley.edu/big-data-mini-course/graph-analytics-with-graphx.html>

GraphX-Basics

- Computational Model
 - Directed MultiGraph
 - Directed - so in-degree & out-degree
 - MultiGraph – so multiple parallel edges between nodes including loops!
 - Algorithms beware – can cyclic, loops
 - Property Graph
 - vertexID(64bit long) int
 - Need property, cannot ignore it
 - Vertex, Edge Parameterized over object types
 - Vertex[(VertexId, VD)], Edge[ED]
 - Attach user-defined objects to edges and vertices (ED/VD)



Good exercises <https://www.sics.se/~amir/files/download/dic/answers6.pdf>

Graphs and Social Networks-Prof. Jeffrey D. Ullman Stanford University
<http://web.stanford.edu/class/cs246/handouts.html>
G-N Algorithm for inbetweeness

GraphX-Basics



- For our hands-on we will run thru 2 Zeppelin notebooks (<https://goo.gl/qCwZiq> & <https://goo.gl/EKHCFq>):

a. First we will work with the following Giraffe graph

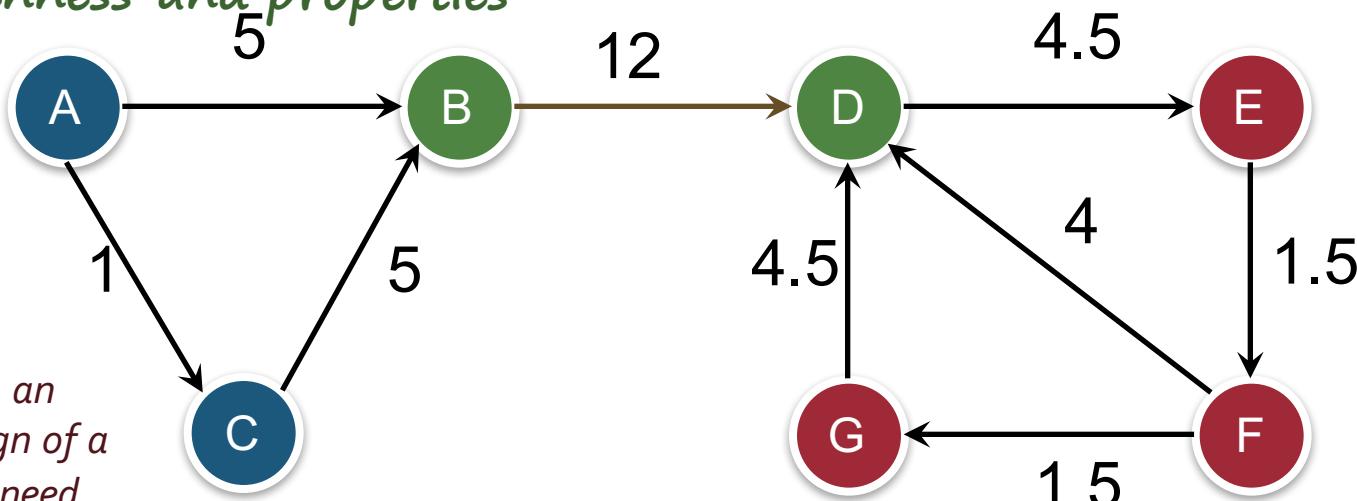
- ... carefully chosen with interesting betweenness and properties
- ... for understanding the APIs

b. Second, we will develop a retweet pipeline

- With the AlphaGo twitter topic
- 2 GB/330K tweets, 200K edges,...

Fun facts about centrality betweenness : It shows how many paths an edge is part of, i.e. relevancy. High centrality betweenness is the sign of a bottleneck, point of single failure – these edges need HA, probably need alternate paths for re routing, are susceptible to parasite infections and good candidates for a cut !

Good exercises <https://www.sics.se/~amir/files/download/dic/answers6.pdf>



Graphs and Social Networks-Prof. Jeffrey D. Ullman Stanford University
<http://web.stanford.edu/class/cs246/handouts.html>
G-N Algorithm for inbetweenness

```
val vertexList = List(  
  (1L, Person("Alice", 18)),  
  (2L, Person("Bernie", 17)),  
  (3L, Person("Cruz", 15)),  
  (4L, Person("Donald", 12)),  
  (5L, Person("Ed", 15)),  
  (6L, Person("Fran", 10)),  
  (7L, Person("Genghis", 854)))
```

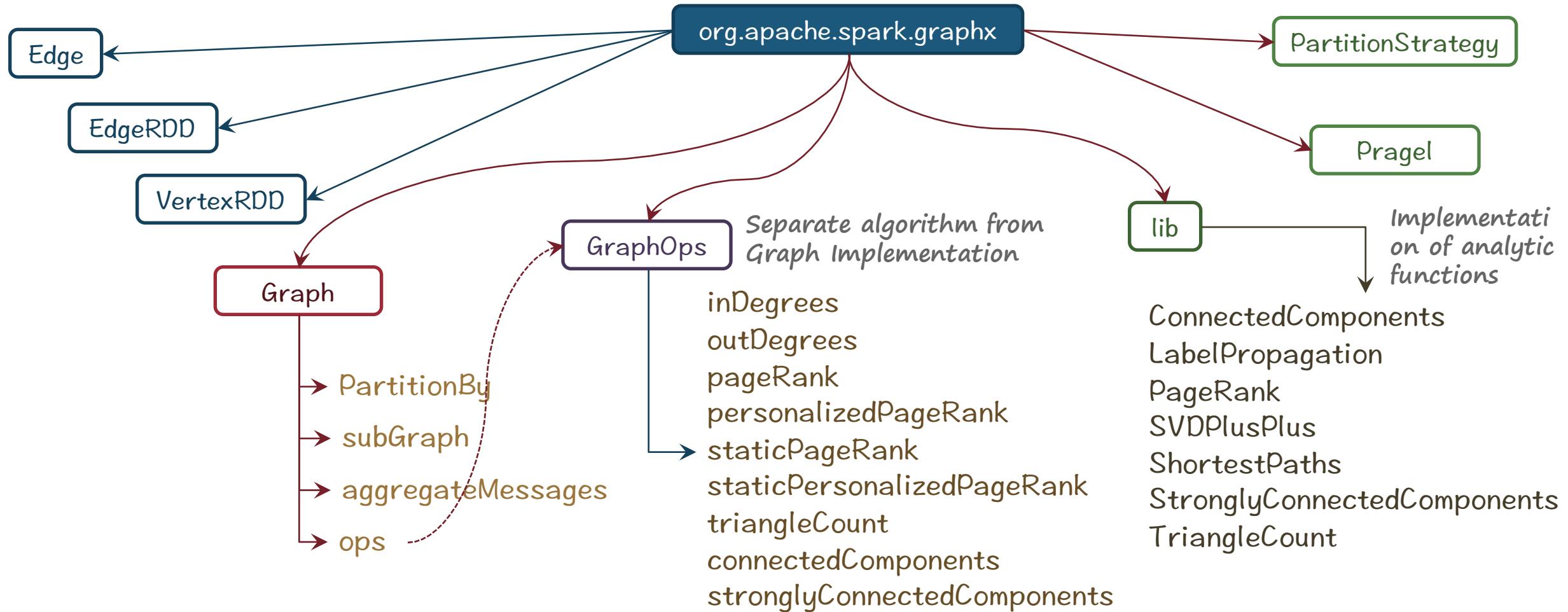
Build A Graph

```
case class Person(name:String,age:Int)  
  
val defaultPerson = Person("NA",0)  
  
val vertexList = List(  
    (1L, Person("Alice", 18)),  
    (2L, Person("Bernie", 17)),  
    (3L, Person("Cruz", 15)),  
    (4L, Person("Donald", 12)),  
    (5L, Person("Ed", 15)),  
    (6L, Person("Fran", 10)),  
    (7L, Person("Genghis",854))  
)  
  
val edgeList = List(  
    Edge(1L, 2L, 5),  
    Edge(1L, 3L, 1),  
    Edge(3L, 2L, 5),  
    Edge(2L, 4L, 12),  
    Edge(4L, 5L, 4),  
    Edge(5L, 6L, 2),  
    Edge(6L, 7L, 2),  
    Edge(7L, 4L, 5),  
    Edge(6L, 4L, 4)  
)  
  
val vertexRDD = sc.parallelize(vertexList)  
val edgeRDD = sc.parallelize(edgeList)  
val graph = Graph(vertexRDD, edgeRDD,defaultPerson)  
//  
println("Edges = " + graph.numEdges)  
println("Vertices = " + graph.numVertices)  
//  
val vertices = graph.vertices  
vertices.collect.foreach(println)  
val edges = graph.edges  
edges.collect.foreach(println)  
val triplets = graph.triplets  
triplets.take(3)  
triplets.map(t=>t.toString).collect().foreach(println)  
//
```

- There are 4 ways
 - GraphLoader.edgeListFile(...)
 - From RDDs (shown above)
 - fromEdgeTuples <- Id tuples
 - fromEdges <- edgeList

```
# Comment Line  
# Source Id <\t> Target Id  
1 -5  
1 2  
2 7  
1 8
```

Graph API Landscape



 org.apache.spark.graphx
PartitionStrategy

```
trait PartitionStrategy extends Serializable
```

Represents the way edges are assigned to edge partitions based on their source and destination vertex IDs.

- ▶ Linear Supertypes
- ▶ Known Subclasses

Ordering: Alphabetic By Inheritance

Inherited: [PartitionStrategy](#) [Serializable](#) [Serializable](#) AnyRef Any
 Hide All Show All

Visibility: [Public](#) [All](#)

Abstract Value Members

```
abstract def getPartition(src: VertexId, dst: VertexId, numParts: PartitionID): PartitionID
```

Returns the partition number for a given edge.

Hint:

Many details are documented in the object not in the class e.g. [PartitionStrategy](#), [Graph](#),...

 org.apache.spark.graphx
PartitionStrategy

```
object PartitionStrategy extends Serializable
```

Collection of built-in [PartitionStrategy](#) implementations.

- ▶ Linear Supertypes

Ordering: Alphabetic By Inheritance

Inherited: [PartitionStrategy](#) [Serializable](#) [Serializable](#) AnyRef Any
 Hide All Show All

Visibility: [Public](#) [All](#)

Value Members

- object [CanonicalRandomVertexCut](#) extends [PartitionStrategy](#) with Product with Serializable
Assigns edges to partitions by hashing the source and destination vertex IDs in a canonical direction, resulting in a random vertex cut that collocates all edges between two vertices, regardless of direction.
- object [EdgePartition1D](#) extends [PartitionStrategy](#) with Product with Serializable
Assigns edges to partitions using only the source vertex ID, colocating edges with the same source.
- object [EdgePartition2D](#) extends [PartitionStrategy](#) with Product with Serializable
Assigns edges to partitions using a 2D partitioning of the sparse edge adjacency matrix, guaranteeing a $2 * \sqrt{\text{numParts}}$ bound on vertex replication.
- object [RandomVertexCut](#) extends [PartitionStrategy](#) with Product with Serializable
Assigns edges to partitions by hashing the source and destination vertex IDs, resulting in a random vertex cut that collocates all same-direction edges between two vertices.
- def [fromString](#)(s: String): [PartitionStrategy](#)
Returns the PartitionStrategy with the specified name.

Graphx Structure API

```
graph.numEdges  
graph.numVertices
```

```
res14: Long = 9  
res15: Long = 7  
Took 1 seconds
```

```
val vertices = graph.vertices  
vertices.collect.foreach(println)
```

```
vertices: org.apache.spark.graphx.VertexRDD[Person] = VertexRDDImpl[26] at RDD at VertexRDD.scala:57  
(4, Person(Donald, 12))  
(1, Person(Alice, 18))  
(5, Person(Ed, 15))  
(6, Person(Fran, 10))  
(2, Person(Bernie, 17))  
(3, Person(Cruz, 15))  
(7, Person(Genghis, 854))
```

```
val inDeg = graph.inDegrees // Followers  
inDeg.collect()  
val outDeg = graph.outDegrees // Follows  
outDeg.collect()  
val allDeg = graph.degrees  
allDeg.collect()
```

```
inDeg: org.apache.spark.graphx.VertexRDD[Int] = VertexRDDImpl[26] at RDD at VertexRDD.scala:57  
res24: Array[(org.apache.spark.graphx.VertexId, Int)] = Array((4,3), (5,1), (6,1), (2,2), (3,1), (7,1))  
outDeg: org.apache.spark.graphx.VertexRDD[Int] = VertexRDDImpl[30] at RDD at VertexRDD.scala:57  
res25: Array[(org.apache.spark.graphx.VertexId, Int)] = Array((4,1), (1,2), (5,1), (6,2), (2,1), (3,1), (7,1))  
allDeg: org.apache.spark.graphx.VertexRDD[Int] = VertexRDDImpl[34] at RDD at VertexRDD.scala:57  
res26: Array[(org.apache.spark.graphx.VertexId, Int)] = Array((4,4), (1,2), (5,2), (6,3), (2,3), (3,2), (7,2))
```

```
Took 2 seconds
```

```
val edges = graph.edges  
edges.collect.foreach(println)
```

```
edges: org.apache.spark.graphx.EdgeRDD[Edge] = EdgeRDDImpl[12] at RDD at EdgeRDD.scala:57  
Edge(1,2,5)  
Edge(1,3,1)  
Edge(2,4,12)  
Edge(3,2,5)  
Edge(4,5,4)  
Edge(5,6,2)  
Edge(6,4,4)  
Edge(6,7,2)  
Edge(7,4,5)
```

```
val triplets = graph.triplets  
triplets.take(3)  
triplets.map(t=>t.toString).collect().foreach(println)
```

```
triplets: org.apache.spark.rdd.RDD[org.apache.spark.graphx.EdgeTriplet[Person, Int]] = EdgeTripletRDDImpl[12] at RDD at EdgeTripletRDD.scala:57  
res21: Array[org.apache.spark.graphx.EdgeTriplet[Person, Int]] = Array((2,Person(Bernie,17)),(4,Person(Donald,12)),12)  
((1,Person(Alice,18)),(2,Person(Bernie,17)),5)  
((1,Person(Alice,18)),(3,Person(Cruz,15)),1)  
((2,Person(Bernie,17)),(4,Person(Donald,12)),12)  
((3,Person(Cruz,15)),(2,Person(Bernie,17)),5)  
((4,Person(Donald,12)),(5,Person(Ed,15)),4)  
((5,Person(Ed,15)),(6,Person(Fran,10)),2)  
((6,Person(Fran,10)),(4,Person(Donald,12)),4)  
((6,Person(Fran,10)),(7,Person(Genghis,854)),2)  
((7,Person(Genghis,854)),(4,Person(Donald,12)),5)
```

Community-Affiliation-Strengths

- Applied in many ways
- For example in Fraud & Security Applications
- Triangle detection – for spam servers
- The age of a community is related to the density of triangles
 - New community will have few triangles, then triangles start to form
- Strong affiliation ie Heavy hitter = $\text{sqrt}(m)$ degrees!
 - Heavy hitter triangle !
- Connected Communities – structure

What's the most interesting application of Machine Learning that LinkedIn has in place?



Deepak Agarwal, Head of relevance and Machine Learning at LinkedIn
3k Views • Upvoted by William Chen, Data Scientist at Quora

Almost every product at LinkedIn is powered by Machine Learning. Choosing one would be like selecting a favorite kid out of many. I will list some of the most significant ones, but this is my no means an exhaustive list.

1. Feed Relevance
2. People you may know
3. Jobs recommendations
4. Search (people, recruiter, others)
5. Email and notification relevance
6. Advertising
7. Course recommendation

What kind of tools/languages do Machine Learning engineers at LinkedIn use?



Deepak Agarwal, Head of relevance and Machine Learning at LinkedIn
2.7k Views • Upvoted by Nikhil Garg, I lead a team of Quora engineers working on ML/NLP problems

For offline: Pig, scalding, Spark, good old Hadoop, GraphX

Algorithms

- Graph-Parallel Computation
 - aggregateMessages() Function
 - Pregel() (<https://issues.apache.org/jira/browse/SPARK-5062>)
- pageRank()
 - Influential papers in a citation network
 - Influencer in retweet
- staticPageRank()
 - Static no of iterations, dynamic tolerance – see the parameters (tol vs. numIter)
- personalizedPageRank()
 - Personalized PageRank is a variation on PageRank that gives a rank relative to a specified “source” vertex in the graph – “People You May Know”
- shortestPaths, SVD++
 - LabelPropagation (LPA) as described by Raghavan et al in their 2007 paper “Near linear time algorithm to detect community structures in large-scale networks”
 - Computationally inexpensive way to Identify communities
 - Convergence not guaranteed
 - Might end up with trivial solution i.e. single community
 - SDVPlusPlus takes an RDD of Edges
 - The Global Clustering Coefficient, is better in that it always returns a number between 0 and 1
 - For comparing connectnedness between different sized communities

<http://graphframes.github.io/user-guide.html>

```
def aggregateMessages[A](sendMsg: (EdgeContext[VD, ED, A]) => Unit, mergeMsg: (A, A) => A,  
  tripletFields: TripletFields = TripletFields.All)(implicit arg0: ClassTag[A]): VertexRDD[A]
```

Aggregates values from the neighboring edges and vertices of each vertex. The user-supplied sendMsg function is invoked on each edge of the graph, generating 0 or more messages to be sent to either vertex in the edge. The mergeMsg function is then used to combine all messages destined to the same vertex.

A the type of message to be sent to each vertex

sendMsg runs on each edge, sending messages to neighboring vertices using the [EdgeContext](#).

mergeMsg used to combine messages from sendMsg destined to the same vertex. This combiner should be commutative and associative.

tripletFields which fields should be included in the [EdgeContext](#) passed to the sendMsg function. If not all fields are needed, specifying this can improve performance.

▪ Versatile Function useful for implementing PageRank et al

- Can be difficult at first, but easier to comprehend if treated as a combined map-reduce function (it was called **MapReduceTriplets !! With a slightly different signature**)

- aggregateMessage[Msg] (

- map(edgeContext=> mapFun, <- this can be up or down ie sendToDst or Src!)
 - reduce(Msg,Msg) => reduceFun)

attr: ED

The attribute associated with the edge.

dstAttr: VD

The vertex attribute of the edge's destination vertex.

dstId: [VertexId](#)

The vertex id of the edge's destination vertex.

sendToDst(msg: A): Unit

Sends a message to the destination vertex.

sendToSrc(msg: A): Unit

Sends a message to the source vertex.

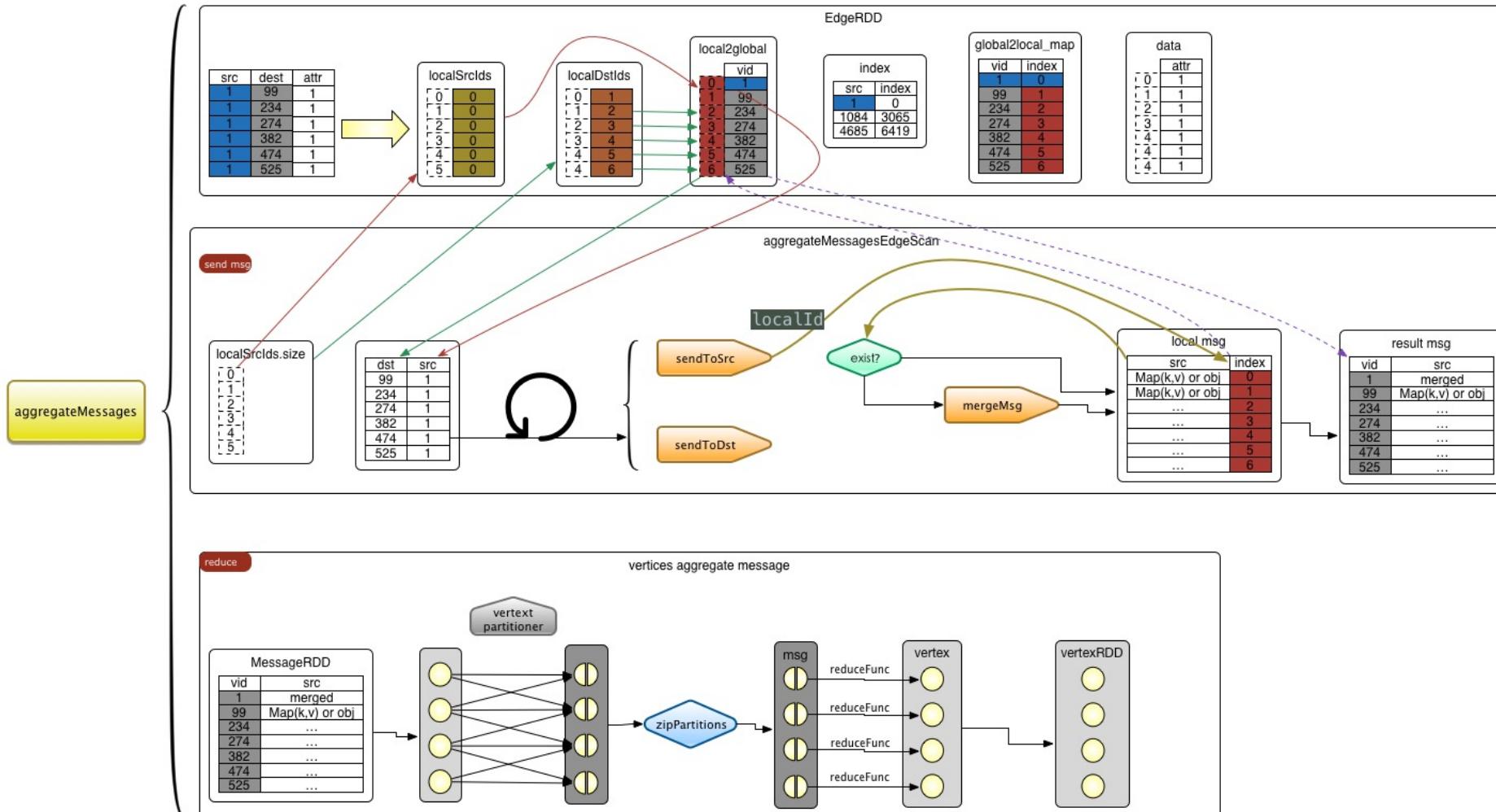
srcAttr: VD

The vertex attribute of the edge's source vertex.

srcId: [VertexId](#)

The vertex id of the edge's source vertex.

If you really want to know what is underneath the aggregateMessages()...



```
val oldestFollower = graph.aggregateMessages[Int]{
  edgeContext => edgeContext.sendToDst(edgeContext.srcAttr.age), //sendMsg
  (x,y) => math.max(x,y) //mergeMsg
}
oldestFollower.collect()
```

→ sendToDst vs sendToSrc

```
oldestFollower: org.apache.spark.graphx.VertexRDD[Int] = VertexRDDImpl[2056] at RDD at VertexRDD.scala:57
res79: Array[(org.apache.spark.graphx.VertexId, Int)] = Array((4,854), (5,12), (6,15), (2,18), (3,18), (7,10))
```

```
val oldestFollowee = graph.aggregateMessages[Int]{
  edgeContext => edgeContext.sendToSrc(edgeContext.srcAttr.age), //sendMsg
  (x,y) => math.max(x,y) //mergeMsg
}
oldestFollowee.collect()
```

```
oldestFollowee: org.apache.spark.graphx.VertexRDD[Int] = VertexRDDImpl[2092] at RDD at VertexRDD.scala:57
res99: Array[(org.apache.spark.graphx.VertexId, Int)] = Array((4,12), (1,18), (5,15), (6,10), (2,17), (3,15), (7,854))
```

```
val oDegree = graph.aggregateMessages[Int]{
  edgeContext => edgeContext.sendToSrc(1), //sendMsg
  (x,y) => x+y //mergeMsg
}
oDegree.collect()
graph.outDegrees.collect()
```

```
oDegree: org.apache.spark.graphx.VertexRDD[Int] = VertexRDDImpl[2100] at RDD at VertexRDD.scala:57
res104: Array[(org.apache.spark.graphx.VertexId, Int)] = Array((4,1), (1,2), (5,1), (6,2), (2,1), (3,1), (7,1))
res105: Array[(org.apache.spark.graphx.VertexId, Int)] = Array((4,1), (1,2), (5,1), (6,2), (2,1), (3,1), (7,1))
```

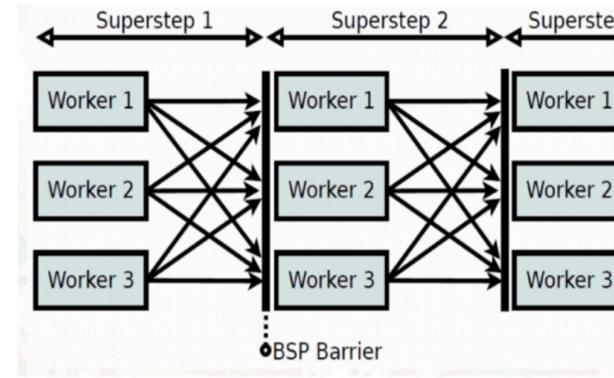
```
val iDegree = graph.aggregateMessages[Int]{
  edgeContext => edgeContext.sendToDst(1), //sendMsg
  (x,y) => x+y //mergeMsg
}
iDegree.collect()
graph.inDegrees.collect()
```

```
iDegree: org.apache.spark.graphx.VertexRDD[Int] = VertexRDDImpl[2096] at RDD at VertexRDD.scala:57
res101: Array[(org.apache.spark.graphx.VertexId, Int)] = Array((4,3), (5,1), (6,1), (2,2), (3,1), (7,1))
res102: Array[(org.apache.spark.graphx.VertexId, Int)] = Array((4,3), (5,1), (6,1), (2,2), (3,1), (7,1))
```

A Bridging Model for Parallel Computation

The success of the von Neumann model of sequential computation motivates the fact that it is an efficient bridge between software and hardware: high-level languages can be efficiently compiled on to this model; yet it can be efficiently implemented in hardware. The author argues that an analogous bridge between software and hardware is required for parallel computation if that is to become as widely used. This article introduces the bulk-synchronous parallel (BSP) model as a candidate for this role, and gives results quantifying its efficiency both in implementing high-level language features and algorithms, as well as in being implemented in hardware.

Leslie K. Valiant



Source: <https://cs.uwaterloo.ca/~kdaudjee/courses/cs848/slides/jenny.pdf>

Pregel BSP API

- Bulk Synchronous Parallel Message Passing API
 - Developed by Leslie Valiant¹
 - Synchronized distributed super steps
 - Super Step – local, in-memory computations
- Computations on the vertex – “Think like a Vertex”
- graphx.lib.LabelPropagationAlgorithm uses Pregel internally
- graphx.lib.PageRank uses Pragel (for the runUntilConvergenceWithOptions version, while it uses the aggregateMessages for the runWithOptions(staticPageRank) version)
- Pregel is implemented succinctly with the old mapReduceTriplets API

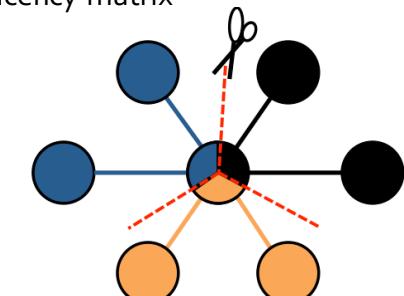
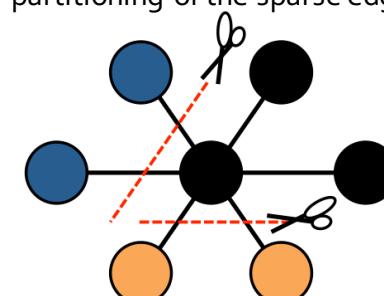
Graphx Partitioning & Processing

- Unlike a relational table, graph processing is contextual w.r.t a neighborhood
 - Maintain locality, equal size partitioning
- Edge-cut : The communication & storage overhead of an edge-cut is directly proportional to the number of edges that are cut
- Vertex-cut : The communication and storage overhead of a vertex-cut is directly proportional to the sum of the number of machines spanned by each vertex
- Vertex-cut strategy by default (balance hot-spot issue due to power law/Zipf's Law) w/ min replication of edges
- Batch processing/not streaming

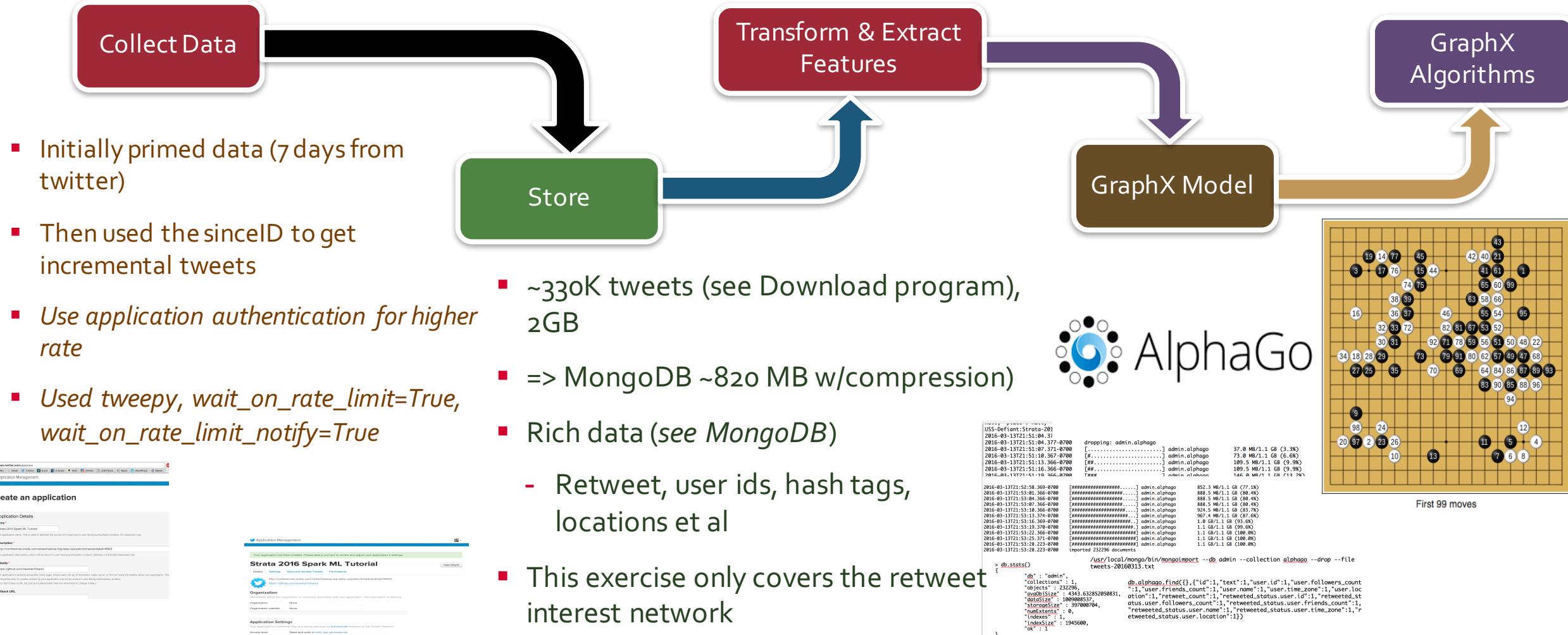
`groupEdges(merge: (ED, ED) ⇒ ED): Graph[VD, ED]`

Merges multiple edges between two vertices into a single edge. For correct results, the graph must have been partitioned using [partitionBy](#).

- `Org.apache.spark.graphx.Graph.`
 - `partitionBy(partitionStrategy: PartitionStrategy, numPartitions: Int)`
 - `partitionBy(partitionStrategy: PartitionStrategy)`
 - 4 PartitionStrategies
 - 1) `RandomVertexCut`(usually the best) : random vertex cut that collocates all same-direction edges between two vertices (hashing the source and destination vertex IDs)
 - 2) `CanonicalRandomVertexCut` - a random vertex cut that collocates all edges between two vertices, regardless of direction (hashing the source and destination vertex IDs in a canonical direction) ... remember *GraphX is multi graph*
 - 3) `EdgePartition1D` - Assigns edges to partitions using only the source vertex ID, colocating edges with the same source
 - 4) `EdgePartition2D` : 2D partitioning of the sparse edge adjacency matrix



AlphaGo Tweets Analytics Pipeline



#StrataHadoop

Strata + Hadoop WORLD

1-Extract Tweets

```
%pyspark
import tweepy

apiKey = [REDACTED]
apiSecret = [REDACTED]
accessToken = [REDACTED]
accessTokenSecret = [REDACTED]

auth = tweepy.AppAuthHandler(apiKey, apiSecret) # OAuthHandler(apiKey, apiSecret)
# auth.set_access_token(accessToken, accessTokenSecret)
api = tweepy.API(auth, wait_on_rate_limit=True, wait_on_rate_limit_notify=True)

if (not api):
    print ("Can't Authenticate")
    sys.exit(-1)

# http://www.karabbelkar.info/2015/01/how-to-use-twitters-search-rest-api-most-effectively./
```

```
Downloading max 10000000 tweets
Downloaded 100 tweets
Downloaded 200 tweets
Downloaded 300 tweets
Downloaded 400 tweets
Downloaded 500 tweets
Downloaded 600 tweets
Downloaded 700 tweets
Downloaded 800 tweets
Downloaded 900 tweets
Downloaded 1000 tweets
Downloaded 1100 tweets
Downloaded 1200 tweets
Downloaded 1300 tweets
Downloaded 1400 tweets
Downloaded 1500 tweets
Downloaded 1600 tweets
Downloaded 1700 tweets
Downloaded 1800 tweets
Downloaded 1900 tweets
Downloaded 2000 tweets
Downloaded 2100 tweets
Downloaded 2200 tweets
Downloaded 2300 tweets
Downloaded 2400 tweets
Downloaded 2500 tweets
Downloaded 2600 tweets
Downloaded 2700 tweets
Downloaded 2800 tweets
Downloaded 2900 tweets
Downloaded 3000 tweets
Downloaded 3100 tweets
Downloaded 3200 tweets
Downloaded 3300 tweets
Downloaded 3400 tweets
Downloaded 3500 tweets
Downloaded 3600 tweets
Downloaded 3700 tweets
Downloaded 3800 tweets
Downloaded 3900 tweets
Downloaded 4000 tweets
Downloaded 4100 tweets
Downloaded 4200 tweets
Downloaded 4300 tweets
Downloaded 4400 tweets
Downloaded 4500 tweets
Downloaded 4600 tweets
Downloaded 4700 tweets
Downloaded 4800 tweets
Downloaded 4900 tweets
Downloaded 5000 tweets
Downloaded 5100 tweets
No more tweets found
Downloaded 5166 tweets, Saved to tweets.txt
```

```
%pyspark
import sys
import jsonpickle
import os

searchQuery = 'AlphaGo' # this is what we're searching for
maxTweets = 10000000 # Some arbitrary large number
tweetsPerQry = 100 # this is the max the API permits
fName = 'tweets.txt' # We'll store the tweets in a text file.

# If results from a specific ID onwards are reqd, set since_id to that ID.
# else default to no lower limit, go as far back as API allows
sinceId = 712410062820511744 # 711720090954108928 # 710883718903140353 # 710312094227300352 # 709817136437403649# 709550216467185664 # 70921104719872000L# None

# If results only below a specific ID are, set max_id to that ID.
# else default to no upper limit, start from the most recent tweet matching the search query.
max_id = -1L

tweetCount = 0
print("Downloading max {0} tweets".format(maxTweets))
with open(fName, 'w') as f:
    while tweetCount < maxTweets:
        try:
            if (max_id <= 0):
                if (not sinceId):
                    new_tweets = api.search(q=searchQuery, count=tweetsPerQry)
                else:
                    new_tweets = api.search(q=searchQuery, count=tweetsPerQry, since_id=sinceId)
            else:
                if (not sinceId):
                    new_tweets = api.search(q=searchQuery, count=tweetsPerQry, max_id=str(max_id - 1))

            if len(new_tweets) == 0:
                break
```

2-Pipeline screen shots

- Get max tweet id
 - db.alphago.find().sort({id:-1}).limit(1).pretty()
 - "id" : NumberLong("709550216467185664"),
 - db.alphago.find().sort({id:+1}).limit(1).pretty()
 - "id" : NumberLong("709211132498714627")
 - /usr/local/mongo/bin/mongoimport --db admin
 - 232296
 - Min : "id" : NumberLong("7058455675372210")
 - Max : "id" : NumberLong("7092111047198720")
 - /usr/local/mongo/bin/mongoimport --db admin
 - +21368
 - Min : "id" : NumberLong("7058455675372210")
 - Max : "id" : NumberLong("709550216467185664")
 - Count : 253664
 - /usr/local/mongo/bin/mongoimport --db admin
 - +38452
 - Min: "id_str" : "705845567537221632",
 - Max: "id" : NumberLong("709817136437403664")
 - Count : 292116

screen shots

```
USS-Defiant:Strata-2016 ksankar$ /usr/local/mongo/bin/mongoexport --db admin --collection alphago --fieldFile export_fields.txt -o data-01.json
2016-03-13T23:07:30.219+0700 connected to: localhost
2016-03-13T23:07:31.219+0700 [....] admin.alphago 0/232296 (0.0%)
2016-03-13T23:07:31.219+0700 [....] admin.alphago 0/232296 (0.0%)
2016-03-13T23:07:33.221+0700 [....] admin.alphago 0/232296 (0.0%)
2016-03-13T23:07:34.221+0700 [....] admin.alphago 0/232296 (0.0%)
2016-03-13T23:07:35.220+0700 [....] admin.alphago 0/232296 (0.0%)
2016-03-13T23:07:36.219+0700 [....] admin.alphago 8000/232296 (3.4%)
2016-03-13T23:07:37.221+0700 [....] admin.alphago 8000/232296 (3.4%)
2016-03-13T23:07:38.220+0700 [....] admin.alphago 8000/232296 (3.4%)
2016-03-13T23:07:39.221+0700 [#....] admin.alphago 16000/232296 (6.9%)
2016-03-13T23:07:40.221+0700 [#....] admin.alphago 16000/232296 (6.9%)
2016-03-13T23:07:41.222+0700 [#....] admin.alphago 16000/232296 (6.9%)
2016-03-13T23:07:42.221+0700 [#....] admin.alphago 16000/232296 (6.9%)
2016-03-13T23:07:43.224+0700 [##....] admin.alphago 24000/232296 (10.3%)
2016-03-13T23:07:44.222+0700 [##....] admin.alphago 24000/232296 (10.3%)
2016-03-13T23:07:45.219+0700 [##....] admin.alphago 24000/232296 (10.3%)
2016-03-13T23:07:46.221+0700 [##....] admin.alphago 32000/232296 (13.8%)
2016-03-13T23:07:47.219+0700 [##....] admin.alphago 32000/232296 (13.8%)
2016-03-13T23:09:04.219+0700 [#####] admin.alphago 184000/232296 (79.2%)
2016-03-13T23:09:05.221+0700 [#####] admin.alphago 192000/232296 (82.7%)
2016-03-13T23:09:06.222+0700 [#####] admin.alphago 192000/232296 (82.7%)
2016-03-13T23:09:08.220+0700 [#####] admin.alphago 192000/232296 (82.7%)
2016-03-13T23:09:09.222+0700 [#####] admin.alphago 200000/232296 (86.1%)
2016-03-13T23:09:10.224+0700 [#####] admin.alphago 200000/232296 (86.1%)
2016-03-13T23:09:11.222+0700 [#####] admin.alphago 200000/232296 (86.1%)
2016-03-13T23:09:12.221+0700 [#####] admin.alphago 208000/232296 (89.5%)
2016-03-13T23:09:13.223+0700 [#####] admin.alphago 208000/232296 (89.5%)
2016-03-13T23:09:14.221+0700 [#####] admin.alphago 208000/232296 (89.5%)
2016-03-13T23:09:15.220+0700 [#####] admin.alphago 208000/232296 (89.5%)
2016-03-13T23:09:16.219+0700 [#####] admin.alphago 208000/232296 (89.5%)
2016-03-13T23:09:17.221+0700 [#####] admin.alphago 216000/232296 (93.0%)
2016-03-13T23:09:18.219+0700 [#####] admin.alphago 216000/232296 (93.0%)
2016-03-13T23:09:19.221+0700 [#####] admin.alphago 216000/232296 (93.0%)
2016-03-13T23:09:20.219+0700 [#####] admin.alphago 224000/232296 (96.4%)
2016-03-13T23:09:21.229+0700 [#####] admin.alphago 224000/232296 (96.4%)
2016-03-13T23:09:22.221+0700 [#####] admin.alphago 224000/232296 (96.4%)
2016-03-13T23:09:23.221+0700 [#####] admin.alphago 224000/232296 (96.4%)
2016-03-13T23:09:23.446+0700 [#####] admin.alphago 232296/232296 (100.0%)
2016-03-13T23:09:23.446+0700 exported 232296 records
■ /usr/local/mongo/bin/mongoimport --db admin --collection alphago --file tweets-20160316.txt
+17331
Min: "id" : NumberLong("705845567537221632"),
Max: "id" : NumberLong("7103120942273000352"),
Count : 309447
■ /usr/local/mongo/bin/mongoimport --db admin --collection alphago --file tweets-20160318.txt
+10797
Min: "id" : NumberLong("705845567537221632"),
Max: "id" : NumberLong("710883718903140353"),
Count : 320244
■ /usr/local/mongo/bin/mongoimport --db admin --collection alphago --file tweets-20160320.txt
+11511
```

- /usr/local/mongo/bin/mongoimport --db admin --collection alphago --file tweets-20160322.txt
 - +5166
 - Min: "id" : NumberLong("705845567537221632"),
 - Max: "id" : NumberLong("712410062820511744"),
 - Count : 336921

3-Twitter gives lots of fields in Mongo

```
|> db.alphago.find().sort({_id:-1}).limit(1).pretty()
{
  "_id" : ObjectId("56f1cc2a6e19ba0bcd5f9ddc"),
  "contributors" : null,
  "truncated" : false,
  "text" : "RT @cdixon: \"The human mind is still 50,000 times more energy efficient than machine intelligence.\" https://t.co/bChxqspT3M https://t
.co/pp...",
  "is_quote_status" : false,
  "in_reply_to_status_id" : null,
  "in_reply_to_user_id" : null,
  "id" : NumberLong("712410062820511744"),
  "favorite_count" : 0,
  "source" : "<a href=\"http://twitter.com/download/android\" rel=\"nofollow\">Twitte
  "retweeted" : false,
  "coordinates" : null,
  "entities" : {
    "symbols" : [ ],
    "media" : [
      {
        "source_user_id" : 2529971,
        "source_status_id_str" : "711298715646955520",
        "expanded_url" : "http://twitter.com/cdixon/status/71129871
        "display_url" : "pic.twitter.com/pp5ZtNQMOU",
        "source_status_id" : NumberLong("711298715646955520"),
        "media_url_https" : "https://pbs.twimg.com/media/Cd8KaKEVIAw6mg.jpg"
        "source_user_id_str" : "2529971",
        "url" : "https://t.co/pp5ZtNQMOU",
        "id_str" : "711298710643220480",
        "sizes" : [
          {
            "large" : {
              "h" : 669,
              "w" : 1024,
              "resize" : "fit"
            },
            "small" : {
              "h" : 222,
              "w" : 340,
              "resize" : "fit"
            }
          }
        ],
        "media" : [
          {
            "resizes" : {
              "large" : {
                "h" : 669,
                "w" : 1024,
                "resize" : "fit"
              },
              "medium" : {
                "h" : 392,
                "w" : 600,
                "resize" : "fit"
              },
              "thumb" : {
                "h" : 150,
                "w" : 150,
                "resize" : "crop"
              }
            },
            "indices" : [
              124,
              140
            ],
            "type" : "photo",
            "id" : NumberLong("711298710643220480"),
            "media_url" : "http://pbs.twimg.com/media/Cd8KaKEVIAw6mg.jpg"
          }
        ],
        "hashtags" : [ ],
        "user_mentions" : [
          {
            "indices" : [
              3,
              10
            ],
            "screen_name" : "cdixon",
            "id" : 2529971,
            "name" : "Chris Dixon",
            "id_str" : "2529971"
          }
        ],
        "urls" : [
          {
            "indices" : [
              100,
              123
            ],
            "url" : "https://t.co/bChxqspT3M",
            "expanded_url" : "http://jacquesmattheij.com/another-way-of-lc
          }
        ]
      }
    ],
    "favorited" : false,
    "user" : {
      "follow_request_sent" : null,
      "has_extended_profile" : false,
      "profile_use_background_image" : true,
      "id" : 2529971,
      "verified" : true,
      "profile_text_color" : "333333",
      "profile_image_url_https" : "https://pbs.twimg.com/profile_images/68346924104658944/80a5XAs0_normal.png",
      "profile_sidebar_fill_color" : "DDEEF6",
      "entities" : {
        "url" : {
          "urls" : [
            {
              "indices" : [
                0,
                22
              ],
              "url" : "http://t.co/VviCcFN0iV",
              "expanded_url" : "http://cdixon.org/aboutme/",
              "display_url" : "cdixon.org/aboutme/"
            }
          ]
        },
        "description" : {
          "urls" : [ ]
        }
      },
      "followers_count" : 218312,
      "protected" : false,
      "location" : "CA & NYC",
      "default_profile_image" : false,
      "id_str" : "2529971",
      "lang" : "en",
      "utc_offset" : -14400,
      "statuses_count" : 9225,
      "description" : "programming, philosophy, history, internet, startups, investing",
      "friends_count" : 3376,
      "profile_background_image_url_https" : "https://pbs.twimg.com/profile_background_images/543964120664403968/0IKm7siW.png",
      "profile_link_color" : "89C9FA",
      "profile_sidebar_fill_color" : "DDEEF6"
    }
  }
}
```

4-Extract Retweet Fields

&

5-Store in CSV

```
%pyspark
import pymongo
from pymongo import MongoClient

print "      pymongo : %s" % (pymongo.version)
client=MongoClient('localhost', 27017)
db = client["admin"] #db name
alphago=db["alphago"]

cursor = alphago.find({},{"id":1,"text":1,"user.id":1,"user.followers_count":1,"user.friends_count":1,"user.name":1,"user.time_zone":1,"user.location":1,
"retweet_count":1,"retweeted_status.user.id":1,"retweeted_status.user.followers_count":1,"retweeted_status.user.friends_count":1,"retweeted_status.user.name":1,
"retweeted_status.user.time_zone":1,"retweeted_status.user.location":1})
print cursor.count()
```

```
%pyspark
# write csv file
count = 0
#with open('reTweetNetwork-small.psv', 'w') as f:
with open('reTweetNetwork-large.psv', 'w') as f:
    for doc in cursor:
        tweetId = doc["id"]
        tweetCount = doc["retweet_count"]
        tweetText = "NA" #doc["text"].encode('ascii', 'ignore').replace('\n', ' ').replace('\r', '')
        srcUserId = doc["user"]["id"]
        srcUserName = doc["user"]["name"].encode('ascii', 'ignore')
        if (srcUserName is not None):
            srcUserName = srcUserName.rstrip().lstrip()
        if (srcUserName is None):
            srcUserName="NA"
        srcUserLocation = doc["user"]["location"].encode('ascii', 'ignore')
        if (srcUserLocation is not None):
            srcUserLocation = srcUserLocation.rstrip().lstrip()
        if (srcUserLocation is None):
            srcUserLocation="NA"
        srcUserTz = doc["user"]["time_zone"]
        if (srcUserTz is not None):
            srcUserTz = srcUserTz.rstrip().lstrip()
        if (srcUserTz is None):
            srcUserTz="NA"
        srcUserFr = doc["user"]["friends_count"]
        if (not (type( srcUserFr) is int)):
            srcUserFr = 0
        srcUserFol = doc["user"]["followers_count"]
        if (not (type( srcUserFol) is int)):
            srcUserFol = 0
        if ( "retweeted_status" in doc):
            destUserId = doc["retweeted_status"]["user"]["id"]
            destUserName = doc["retweeted_status"]["user"]["name"].encode('ascii', 'ignore')
            if (destUserName is not None):
```

```
                .....
                destUserTz = doc["retweeted_status"]["user"]["time_zone"]
                if (destUserTz is not None):
                    destUserTz = destUserTz.rstrip().lstrip()
                if (destUserTz is None):
                    destUserTz = "NA"
                destUserFr = doc["retweeted_status"]["user"]["friends_count"]
                destUserFol = doc["retweeted_status"]["user"]["followers_count"]
            else:
                destUserId = "NA"
                destUserName = "NA"
                destUserLocation = "NA"
                destUserTz = "NA"
                destUserFr = "NA"
                destUserFol = "NA"
            if ("retweeted_status" in doc): # write only retweets, as we want to create the retweet network
                f.write('{0}|{1}|{2}|{3}|{4}|{5}|{6}|{7}|{8}|{9}|{10}|{11}|{12}|{13}|{14}\n'.format(tweetId, tweetCount, tweetText, srcUserId, srcUserName,
                srcUserLocation, srcUserTz, srcUserFr, srcUserFol, destUserId, destUserName, destUserTz, destUserFr, destUserFol))
                # count += 1
                #if (count > 10000):
                #    break
            print "*** Done ***"
```

```

val sqlContext = new org.apache.spark.sql.SQLContext(sc)
val df = sqlContext.read
  .format("com.databricks.spark.csv")
  .option("header", "false") // Use first line of all files as header
  .option("inferSchema", "true") // Automatically infer data types
  .option("delimiter", ",")
  .load("reTweetNetwork-small.psv")

df.show(5)
df.count()

sqlContext: org.apache.spark.sql.SQLContext = org.apache.spark.sql.SQLContext@29b11
df: org.apache.spark.sql.DataFrame = [C0: bigint, C1: int, C2: string, C4: string, C5: string, C6: string, C7: int, C8: int, C9: bigint, C10: string, C11: string, C12: string, C13: int, C14: int]
+-----+-----+-----+-----+-----+-----+-----+-----+-----+
| C0 | C1 | C2 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 | C14 |
+-----+-----+-----+-----+-----+-----+-----+-----+-----+
| 1709210987015114752 | 2 | NAI | 589277295 | Unsigned Heroes! | Seattle | WA | Arizona | 91912703 | 12798452 | Erick Schonfeld! | New York | Central Time |
| 1709210994875039744 | 25 | NAI | 271007340 | Johnny Apuan! | None | 1252 | 99 | 1344951 | WIRED | San Francisco/New... | Pacific Time |
| 1709210924771467264 | 39 | NAI | 166001040 | Nedpool Canterbury New Ze... | Wellington | 1033 | 572 | 8917142 | Dan Kaminsky | Chief Scientist, ... | Pacific Time |
| 1709210923928559616 | 25 | NAI | 3244208187 | Deen over Duniyal | Mars | None | 93 | 223 | 1344951 | WIRED | San Francisco/New... | Pacific Time |
| 1709210919729963008 | 25 | NAI | 274975425 | Farzan Sabet! | Eastern Time | CUS ... | 373 | 862 | 1344951 | WIRED | San Francisco/New... | Pacific Time |
+-----+-----+-----+-----+-----+-----+-----+-----+-----+
only showing top 5 rows

```

```

// Create vertices & edges
case class User(name:String, location:String, tz : String, fr:Int, fol:Int)
case class Tweet(id:String, count:Int)

val graphData = df.rdd
graphData.take(2)

val vert1 = graphData.map(row => (row(3).toString.toLong,User(row(4).toString, row(5).toString, row(6).toString, row(7).toString.toInt, row(8).toString.toInt)))
vert1.count()
vert1.take(3)

val vert2 = graphData.map(row => (row(9).toString.toLong,User(row(10).toString, row(11).toString, row(12).toString, row(13).toString.toInt, row(14).toString.toInt)))
vert2.count()
vert2.take(3)

val vertX = vert1.++(vert2)
vertX.count()

val edgX = graphData.map(row => (Edge(row(3).toString.toLong, row(9).toString.toLong,(row(0),row(1)))))
edgX.take(3)

val rtGraph = Graph(vertX,edgX)

```

6-Read as dataframe

7-Create Vertices, Edges & Objects

8-Finally the graph

& run algorithms

```

val ranks = rtGraph.pageRank(0.1).vertices
ranks.take(2)
val topUsers = ranks.sortBy(_._2, false).take(3).foreach(println)
val topUsersWNames = ranks.join(rtGraph.vertices).sortBy(_._2._1, false).take(3).foreach(println)

ranks: org.apache.spark.graphx.VertexRDD[Double] = VertexRDDImpl[627] at RDD at VertexRDD.scala:57
res92: Array[(org.apache.spark.graphx.VertexId, Double)] = Array((144366820,0.15), (9734132,0.15))
(11821362,322.9447926136434)
(1482581556,84.10384874154467)
(14497118,43.956874999999826)
topUsers: Unit = ()
(11821362,(322.9447926136434,User(Statsman Bruno,Stockholm,Stockholm,53,79094)))
(1482581556,(84.10384874154467,User(Demis Hassabis,,None,11,22637)))
(14497118,(43.956874999999826,User(Ken Kawamoto,Kokubunji, Tokyo,Tokyo,549,5675)))
topUsersWNames: Unit = ()
Took 3 seconds

```

How many retweets ?

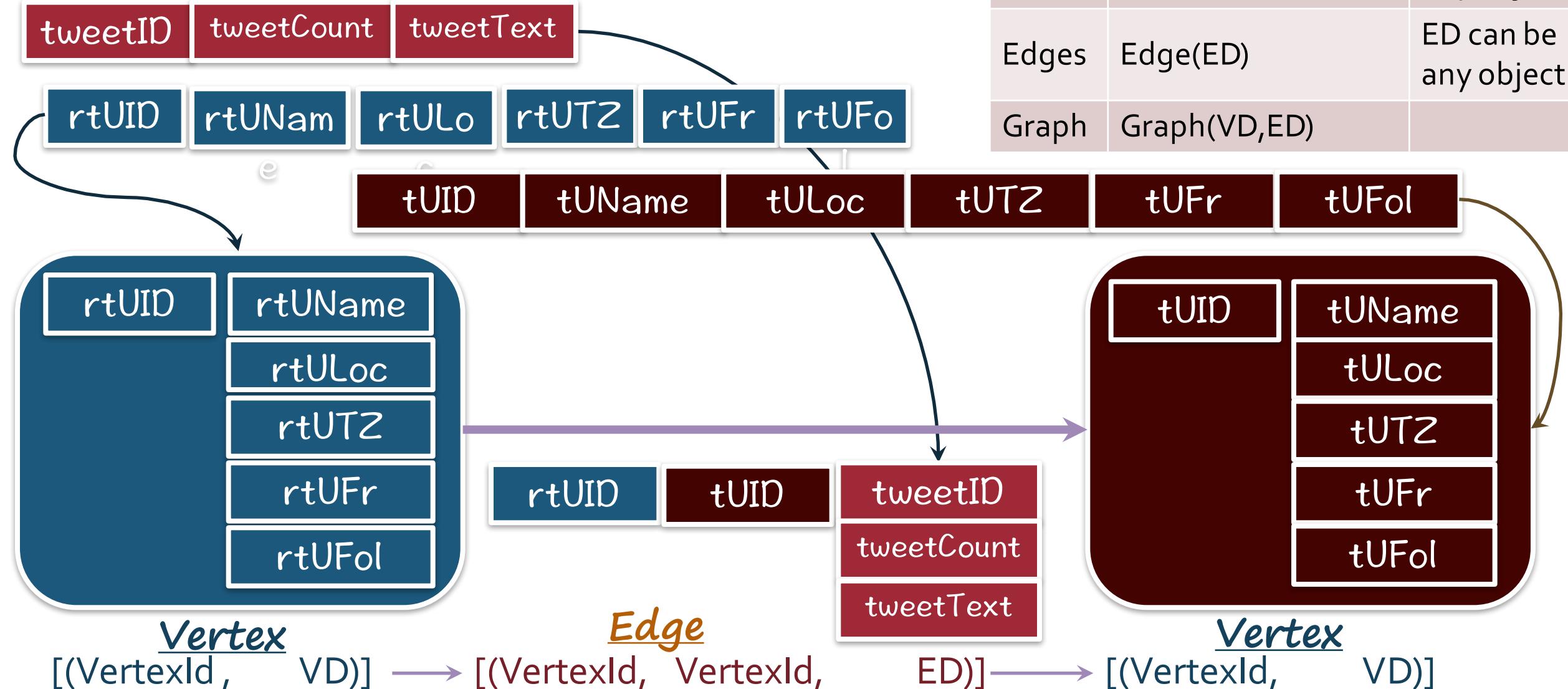
```

Took 0 seconds
val iDeg = rtGraph.inDegrees
val oDeg = rtGraph.outDegrees
iDeg: org.apache.spark.graphx.VertexRDD[Int] = VertexRDDImpl[648] at RDD at VertexRDD.scala:57
oDeg: org.apache.spark.graphx.VertexRDD[Int] = VertexRDDImpl[475] at RDD at VertexRDD.scala:57
Took 1 seconds

iDeg.take(3)
iDeg.sortBy(_._2, false).take(3).foreach(println)
iDeg
res36: Array[(org.apache.spark.graphx.VertexId, Int)] = Array((630222308,1), (149925820,11), (169630984,2))
res37: Array[(org.apache.spark.graphx.VertexId, Int)] = Array((11821362,2574), (1482581556,860), (14497118,360))
Took 1 seconds (outdated)

```

The Art of an AlphaGo GraphX



```

val sqlContext = new org.apache.spark.sql.SQLContext(sc)
val df = sqlContext.read
  .format("com.databricks.spark.csv")
  .option("header", "false") // Use first line of all files as header
  .option("inferSchema", "true") // Automatically infer data types
  .option("delimiter", "|")
  .load("reTweetNetwork-small.psv") 1
df.show(5)
df.count()

```

```

// Create vertices & edges
case class User(name:String, location:String, tz : String, fr:Int, fol:Int)
case class Tweet(id:String, count:Int)

```

```

val graphData = df.rdd
//graphData.take(2).foreach(println)

```

```

val vert1 = graphData.map(row => (row(3).toString.toLong, User(row(4).toString, row(5).toString, row(6).toString, row(7).toString.toInt, row(8).toString.toInt)))
vert1.count()
//vert1.take(3).foreach(println)

```

```

val vert2 = graphData.map(row => (row(9).toString.toLong, User(row(10).toString, row(11).toString, row(12).toString, row(13).toString.toInt, row(14).toString.toInt)))
vert2.count()
//vert2.take(3).foreach(println)

```

```

val vertX = vert1.++(vert2)
vertX.count()
vertX.take(3).foreach(println) 2

```

```

defined class User
defined class Tweet
graphData: org.apache.spark.rdd.RDD[org.apache.spark.sql.Row] = MapPartitionsRDD[962] at rdd at <console>:38
vert1: org.apache.spark.rdd.RDD[(Long, User)] = MapPartitionsRDD[963] at map at <console>:43
res85: Long = 10001
vert2: org.apache.spark.rdd.RDD[(Long, User)] = MapPartitionsRDD[964] at map at <console>:43
res88: Long = 10001
vertX: org.apache.spark.rdd.RDD[(Long, User)] = UnionRDD[965] at $plus$plus at <console>:47
res91: Long = 20002
(589277295,User(Unsigned Heroes,Seattle WA,Arizona,919,2703))
(271007340,User(Johnny Apuan,NA,NA,1252,99))
(166001040,User(Nedpool,Canterbury New Zealand,Wellington,1033,572))

```

4

```

val rtGraph = Graph(vertX,edgX)
//How big ?
rtGraph.vertices.count
rtGraph.edges.count
rtGraph: org.apache.spark.graphx.Graph[User,Tweet] = org.apache.spark.graphx.impl.GraphImpl@244747b4
res98: Long = 9743
res99: Long = 10001
Took 9 seconds

val edgX = graphData.map(row => (Edge(row(3).toString.toLong, row(9).toString.toLong, Tweet(row(0).toString, row(1).toString.toInt))))
edgX.take(3).foreach(println)
edgX.count()
edgX: org.apache.spark.rdd.RDD[org.apache.spark.graphx.Edge[Tweet]] = MapPartitionsRDD[966] at map at <console>:41
Edge(589277295,12798452,Tweet(709210987015114752,2))
Edge(271007340,1344951,Tweet(709210994875039744,25))
Edge(166001040,8917142,Tweet(709210924771467264,39))
res95: Long = 10001

```

3

```

val ranks = rtGraph.pageRank(0.1).vertices
ranks.take(2)
val topUsers = ranks.sortBy(_._2,false).take(3).foreach(println)
val topUsersWNAMES = ranks.join(rtGraph.vertices).sortBy(_._2._1,false).take(3).foreach(println)

```

```

ranks: org.apache.spark.graphx.VertexRDD[Double] = VertexRDDImpl[1136] at RDD at VertexRDD.scala:57
res101: Array[(org.apache.spark.graphx.VertexId, Double)] = Array((144366820,0.15), (9734132,0.15))
(11821362,322.9447926136434)
(1482581556,84.29509874154466)
(14497118,43.95687499999826)
topUsers: Unit = ()

```

5

```

(11821362,(322.9447926136434,User(Statsman Bruno,Stockholm,Stockholm,53,79094)))
(1482581556,(84.29509874154466,User(Demis Hassabis,NA,NA,11,22637)))
(14497118,(43.95687499999826,User(Ken Kawamoto,Kokubunji, Tokyo,Tokyo,549,5675)))
topUsersWNAMES: Unit = ()
Took 3 seconds

```

I
enjoyed a lot
preparing
the materials...
Hope
you enjoyed more
attending...
@ksankar

THANK
YOU



Grazie
ଧ୍ୟବାଦ

