Hands-on 5:
Graph processing

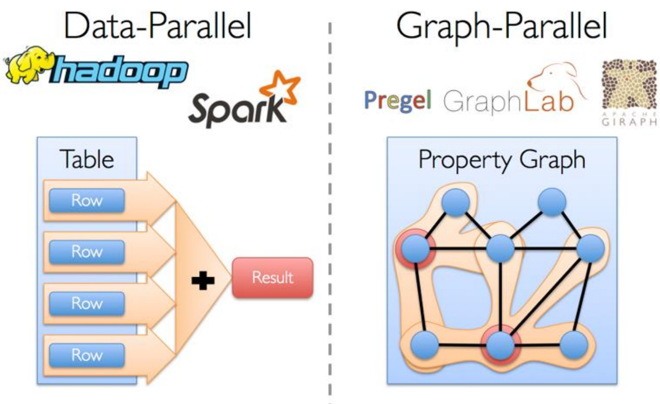
1. Objective

The objective of this hands on is to let you "touch" the challenges implied in dealing with graphs definition and processing.

- In class we will use the Spark tool GraphX for implementing several mini-tasks.
- At **HOME** you will
    - Design and implement an intelligent Page Rank solution.
    - Implement a simple Page Rank algorithm with the map – reduce model and implement it in Hadoop.

1. Background on graph parallel computation[1]

From social networks to language modelling, the growing scale and importance of graph data has driven the development of numerous new graph-parallel systems (e.g., Giraph and GraphLab). By restricting the types of computation that can be expressed and introducing new techniques to partition and distribute graphs, these systems can efficiently execute sophisticated graph algorithms orders of magnitude faster than more general data-parallel systems.

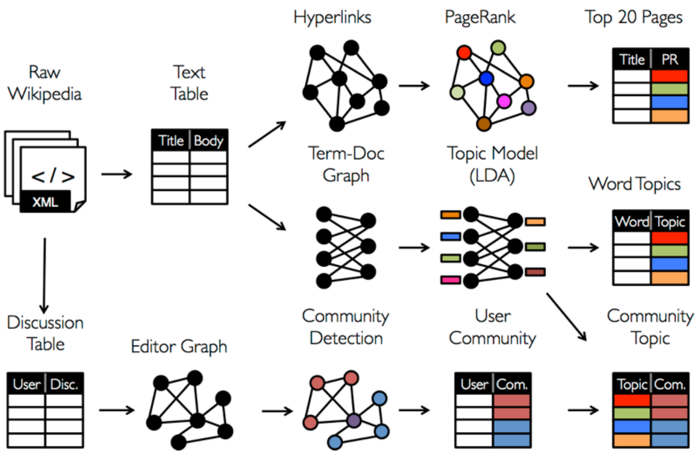


While graph-parallel systems are optimized for iterative diffusion algorithms like PageRank they are not well suited to more basic tasks like constructing the graph, modifying its structure, or expressing computation that spans multiple graphs. These tasks typically require data-movement outside of the graph topology and are often more naturally expressed as operations on tables in more traditional data-parallel systems like Map-Reduce.

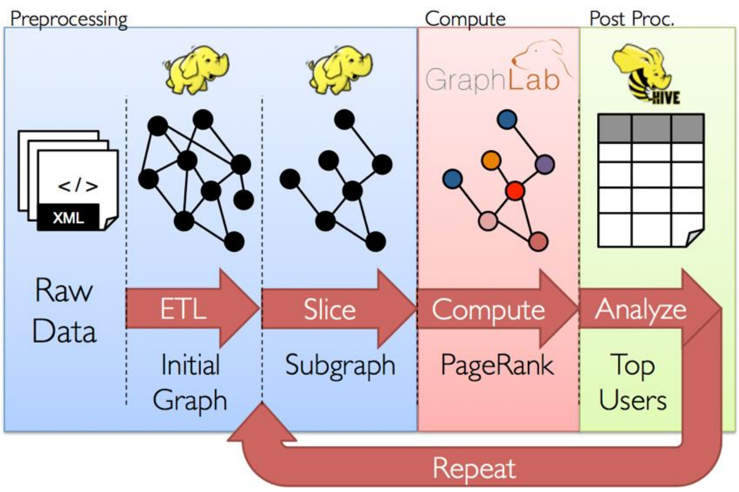
Furthermore, the way we look at data depends on our objectives. Thus, the same raw data may require many different table and graph views throughout the analysis process (see Figure below). Moreover, it is often desirable to be able to move between table and graph views of the same physical data and to leverage the properties of each view to easily and efficiently express computation. However,

[1] https://databricks-training.s3.amazonaws.com/graph-analytics-with-graphx.html

existing graph analytics pipelines compose graph-parallel and data-parallel systems, leading to extensive data movement and duplication and a complicated programming model.



It is often desirable to be able to move between table and graph views of the same physical data and to leverage the properties of each view to easily and efficiently express computation. However, existing graph analytics pipelines compose graph-parallel and data-parallel systems, leading to extensive data movement and duplication and a complicated programming model.



The goal of the GraphX project is to unify graph-parallel and data-parallel computation in one system with a single composable API. The GraphX API enables users to view data both as graphs and as collections (i.e., RDDs) without data movement or duplication. By incorporating recent advances in graph-parallel systems, GraphX is able to optimize the execution of graph operations.

2. Getting started with Spark graph processing

GraphX is the new (alpha) Spark API for graphs (e.g., Web-Graphs and Social Networks) and graph-parallel computation (e.g., PageRank and Collaborative Filtering). GraphX extends the Spark RDD abstraction by introducing the Resilient Distributed Property Graph: a directed multigraph with properties attached to each vertex and edge.

To support graph computation, GraphX exposes a set of fundamental operators (e.g., subgraph, `joinVertices`, and `mapReduceTriplets`) as well as an optimized variant of the Pregel[2] API. In addition, GraphX includes a growing collection of graph algorithms and builders to simplify graph analytics tasks.

In this hads-on we use GraphX to analyze Wikipedia data and implement graph algorithms in Spark. We will work with a subset of the Wikipedia traffic statistics data from May 5-7, 2009. In particular, this dataset only includes a subset of all Wikipedia articles. The GraphX API is currently only available in Scala.

2.1.1 Importing GraphX

Start the Spark-Shell by running the following in the terminal.

```
$ spark-shell
```

Import GraphX by pasting the following lines in your Spark shell.

```
import org.apache.spark.graphx._
import org.apache.spark.graphx.lib._
import org.apache.spark.rdd.RDD
```

Note that the `'._'` at the end of the import statement is a wildcard that tells Scala to import everything in that package, similar to `` `.*` `` in Java.

2.1.2 Property graph

The Property graph[3] is a directed multigraph with properties attached to each vertex and edge. A directed multigraph is a directed graph with potentially multiple parallel edges sharing the same source and destination vertex.

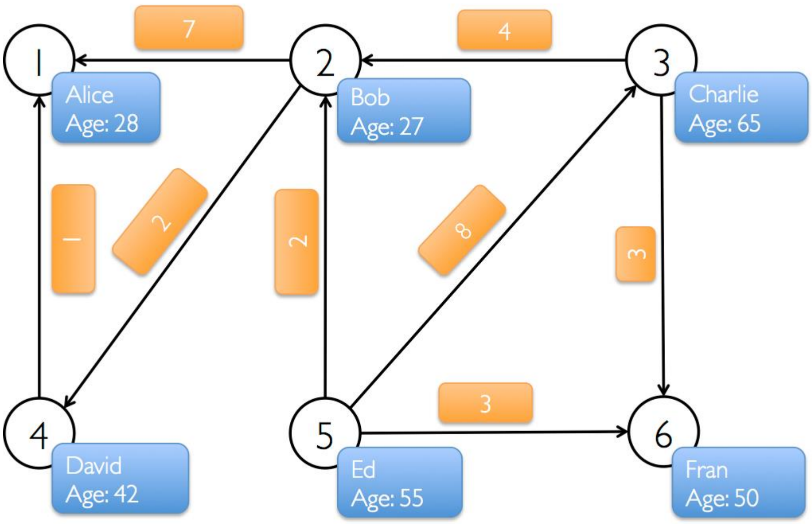
The ability to support parallel edges simplifies modelling scenarios where multiple relationships (e.g., co-worker and friend) can appear between the same vertices.

Each vertex is keyed by a *unique* 64-bit long identifier (`VertexID`). Similarly, edges have corresponding source and destination vertex identifiers. The properties are stored as Scala/Java objects with each edge and vertex in the graph.

Throughout the first half of this hands-on we will use the following toy property graph to have the opportunity to learn about the graph data model and the GraphX API. In this example we have a small social network with users and their ages modeled as vertices and likes modeled as directed edges. In this fictional scenario users can like other users multiple times.

[2] http://spark.apache.org/docs/latest/graphx-programming-guide.html#pregel

[3] https://spark.apache.org/docs/1.1.0/graphx-programming-guide.html#the-property-graph



We begin by creating the property graph from arrays of vertices and edges. Later we will demonstrate how to load real data. Paste the following code into the spark shell.

```
val vertexArray = Array(
  (1L, ("Alice", 28)),
  (2L, ("Bob", 27)),
  (3L, ("Charlie", 65)),
  (4L, ("David", 42)),
  (5L, ("Ed", 55)),
  (6L, ("Fran", 50))
  )
val edgeArray = Array(
  Edge(2L, 1L, 7),
  Edge(2L, 4L, 2),
  Edge(3L, 2L, 4),
  Edge(3L, 6L, 3),
  Edge(4L, 1L, 1),
  Edge(5L, 2L, 2),
  Edge(5L, 3L, 8),
  Edge(5L, 6L, 3)
  )
```

Here we use the `Edge` class. Edges have a `srcId` and a `dstId` corresponding to the source and destination vertex identifiers. In addition, the `Edge` class has an `attr` member which stores the edge property (in this case the number of likes).

Using `sc.parallelize` construct the following RDDs from the `vertexArray` and `edgeArray` variables.

```
val vertexRDD: RDD[(Long, (String, Int))] = // Implement
val edgeRDD: RDD[Edge[Int]] = // Implement
```

```
1. View solution
val vertexRDD: RDD[(Long, (String, Int))] = sc.parallelize(vertexArray)
val edgeRDD: RDD[Edge[Int]] = sc.parallelize(edgeArray)
```

Now we are ready to build a property graph. The basic property graph constructor takes an RDD of vertices (with type RDD[(VertexId, V)]) and an RDD of edges (with type `RDD[Edge[E]]`) and builds a graph (with type `Graph[V, E]`). Try the following:

```
val graph: Graph[(String, Int), Int] = Graph(vertexRDD, edgeRDD)
```

The vertex property for this graph is a tuple `(String, Int)` corresponding to the `User Name` and `Age` and the edge property is just an `Int` corresponding to the number of `Likes` in our hypothetical social network.

Like RDDs, property graphs are immutable, distributed, and fault-tolerant. Changes to the values or structure of the graph are accomplished by producing a new graph with the desired changes. Note that substantial parts of the original graph (i.e. unaffected structure, attributes, and indices) are reused in the new graph.

2.1.2 Graph views

In many cases we will want to extract the vertex and edge RDD views of a graph (e.g., when aggregating or saving the result of calculation). As a consequence, the `graph` class contains members (`graph.vertices` and `graph.edges`) to access the vertices and edges of the graph. While these members extend `RDD[(VertexId, V)]` and `RDD[Edge[E]]` they are actually backed by optimized representations that leverage the internal GraphX representation of graph data.

Use `graph.vertices` to display the `names` of the `users` that are at least `30` years old. The output should contain (in addition to lots of log messages):

```
David is 42
Fran is 50
Ed is 55
Charlie is 65
```

Here is a hint:

```
graph.vertices.filter {
  case (id, (name, age)) => /* implement */
}.collect.foreach {
  case (id, (name, age)) => /* implement */
}
```

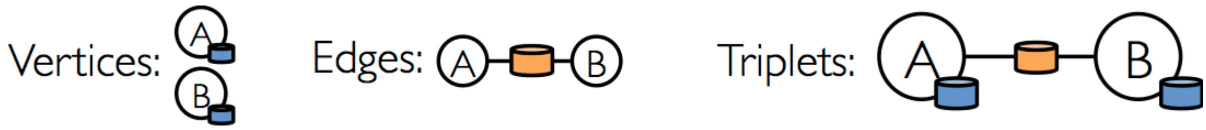
2. View solution

```
// Solution 1
graph.vertices.filter {
   case (id, (name, age)) => age > 30
}.collect.foreach {
   case (id, (name, age)) => println(s"$name is $age")
}

// Solution 2
graph.vertices.filter(
   v => v._2._2 > 30
).collect.foreach(
   v => println(s"${v._2._1} is ${v._2._2}")
)

// Solution 3
for ((id,(name,age)) <- graph.vertices.filter {
   case (id,(name,age)) => age > 30
}.collect) { println(s"$name is $age")}
```

In addition to the vertex and edge views of the property graph, GraphX also exposes a triplet view. The triplet view logically joins the vertex and edge properties yielding an `RDD[EdgeTriplet[VD, ED]]` containing instances of the [`EdgeTriplet`]() class. This *join* can be expressed graphically as:



The `EdgeTriplet` class extends the `Edge` class by adding the `srcAttr` and `dstAttr` members which contain the source and destination properties respectively.

Use the `graph.triplets` view to display who likes who. The output should look like:

```
Bob likes Alice
Bob likes David
Charlie likes Bob
Charlie likes Fran
David likes Alice
Ed likes Bob
Ed likes Charlie
Ed likes Fran
```

Here is a partial solution:

```
for (triplet <- graph.triplets.collect) {
 /**
   * Triplet has the following Fields:
   *   triplet.srcAttr: (String, Int) // triplet.srcAttr._1 is the name
   *   triplet.dstAttr: (String, Int)
   *   triplet.attr: Int
   *   triplet.srcId: VertexId
   *   triplet.dstId: VertexId
   */
}
```

```
3. View solution
```

```
for (triplet <- graph.triplets.collect) {
  println(s"${triplet.srcAttr._1} likes ${triplet.dstAttr._1}")
}
```

If someone likes someone else more than 5 times than that relationship is getting pretty serious. For extra credit, find the lovers.

```
4. View solution
```

```
for (triplet <- graph.triplets.filter(t => t.attr > 5).collect) {
  println(s"${triplet.srcAttr._1} loves ${triplet.dstAttr._1}")
}
```

2.1.3 Graph operators

Just as RDDs have basic operations like `count, map, filter, and reduceByKey`, property graphs also have a collection of basic operations. The following is a list of some of the many functions exposed by the Graph API.

```scala
/** Summary of the functionality in the property graph */
class Graph[VD, ED] {
  // Information about the Graph
  val numEdges: Long
  val numVertices: Long
  val inDegrees: VertexRDD[Int]
  val outDegrees: VertexRDD[Int]
  val degrees: VertexRDD[Int]

  // Views of the graph as collections
  val vertices: VertexRDD[VD]
  val edges: EdgeRDD[ED]
  val triplets: RDD[EdgeTriplet[VD, ED]]

  // Change the partitioning heuristic
  def partitionBy(partitionStrategy: PartitionStrategy): Graph[VD, ED]

  // Transform vertex and edge attributes
  def mapVertices[VD2](map: (VertexID, VD) => VD2): Graph[VD2, ED]
  def mapEdges[ED2](map: Edge[ED] => ED2): Graph[VD, ED2]
  def mapEdges[ED2](map: (PartitionID, Iterator[Edge[ED]]) =>
Iterator[ED2]): Graph[VD, ED2]
  def mapTriplets[ED2](map: EdgeTriplet[VD, ED] => ED2): Graph[VD, ED2]

  // Modify the graph structure
  def reverse: Graph[VD, ED]
  def subgraph(
      epred: EdgeTriplet[VD,ED] => Boolean = (x => true),
      vpred: (VertexID, VD) => Boolean = ((v, d) => true))
    : Graph[VD, ED]
  def groupEdges(merge: (ED, ED) => ED): Graph[VD, ED]

  // Join RDDs with the graph
  def joinVertices[U](table: RDD[(VertexID, U)])(mapFunc: (VertexID, VD, U)
=> VD): Graph[VD, ED]
  def outerJoinVertices[U, VD2](other: RDD[(VertexID, U)])
      (mapFunc: (VertexID, VD, Option[U]) => VD2)
    : Graph[VD2, ED]

  // Aggregate information about adjacent triplets
  def collectNeighbors(edgeDirection: EdgeDirection):
VertexRDD[Array[(VertexID, VD)]]
  def mapReduceTriplets[A: ClassTag](
      mapFunc: EdgeTriplet[VD, ED] => Iterator[(VertexID, A)],
      reduceFunc: (A, A) => A)
    : VertexRDD[A]

  // Iterative graph-parallel computation
  def pregel[A](initialMsg: A, maxIterations: Int, activeDirection:
EdgeDirection)(
      vprog: (VertexID, VD, A) => VD,
      sendMsg: EdgeTriplet[VD, ED] => Iterator[(VertexID,A)],
      mergeMsg: (A, A) => A)
    : Graph[VD, ED]

  // Basic graph algorithms
  def pageRank(tol: Double, resetProb: Double = 0.15): Graph[Double,
Double]
  def connectedComponents(): Graph[VertexID, ED]
  def triangleCount(): Graph[Int, ED]
```

```
  def stronglyConnectedComponents(numIter: Int): Graph[VertexID, ED]
}
```

These functions are split between Graph and GraphOps. However, thanks to the "magic" of Scala implicits the operators in GraphOps are automatically available as members of Graph.

Computing the in-degree of each vertex

We can compute the in-degree of each vertex (defined in GraphOps) by the following:

```
val inDegrees: VertexRDD[Int] = graph.inDegrees
```

The graph.inDegrees operators returned a VertexRDD[Int] (recall that this behaves like RDD[(VertexId, Int)]).

Computing the in/out-degree of each vertex

We use a set of common graph operators. First we define a User class to better organize the vertex property and build a new graph with the user property.

```
// Define a class to more clearly model the user property
case class User(name: String, age: Int, inDeg: Int, outDeg: Int)
// Create a user Graph
val initialUserGraph: Graph[User, Int] = graph.mapVertices{
   case (id, (name, age)) => User(name, age, 0, 0)
}
```

Notice that we initialized each vertex with 0 in and out degree. Now we join the in and out degree information with each vertex building the new vertex property:

```
// Fill in the degree information
val userGraph =
initialUserGraph.outerJoinVertices(initialUserGraph.inDegrees) {
  case (id, u, inDegOpt) => User(u.name, u.age, inDegOpt.getOrElse(0),
u.outDeg)
}.outerJoinVertices(initialUserGraph.outDegrees) {
  case (id, u, outDegOpt) => User(u.name, u.age, u.inDeg,
outDegOpt.getOrElse(0))
}
```

Here we use the outerJoinVertices method of Graph which has the following (confusing) type signature:

```
def outerJoinVertices[U, VD2](other: RDD[(VertexID, U)])
      (mapFunc: (VertexID, VD, Option[U]) => VD2)
    : Graph[VD2, ED]
```

Notice that outerJoinVertices takes *two* argument lists. The first contains an RDD of vertex values and the second argument list takes a function from the id, attribute, and Optional matching value in the RDD to a new vertex value. Note that it is possible that the input RDD may not contain values for some of the vertices in the graph. In these cases the Option argument is empty and optOutDeg.getOrElse(0) returns 0.

Using the degreeGraph print the number of people who like each user:

```
User 1 is called Alice and is liked by 2 people.
User 2 is called Bob and is liked by 2 people.
User 3 is called Charlie and is liked by 1 people.
User 4 is called David and is liked by 1 people.
User 5 is called Ed and is liked by 0 people.
User 6 is called Fran and is liked by 2 people.
```

5. View solution

```
for ((id, property) <- userGraph.vertices.collect) {
  println(s"User $id is called ${property.name} and is liked by
${property.inDeg} people.")
}
```

Print the names of the users who are liked by the same number of people they like.

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```
userGraph.vertices.filter {
  case (id, u) => u.inDeg == u.outDeg
}.collect.foreach {
  case (id, property) => println(property.name)
}
```

2.1.4 MapReduce Triplets Operator

Using the property graph from Section 2.1, suppose we want to find the oldest follower of each user. The `mapReduceTriplets` operator allows us to do this. It enables **neighborhood aggregation**, and its simplified signature is as follows:

```
class Graph[VD, ED] {
  def mapReduceTriplets[MsgType](
      // Function from an edge triplet to a collection of messages (i.e.,
Map)
      map: EdgeTriplet[VD, ED] => Iterator[(VertexId, MsgType)],
      // Function that combines messages to the same vertex (i.e., Reduce)
      reduce: (MsgType, MsgType) => MsgType)
    : VertexRDD[MsgType]
}
```

The map function is applied to each edge triplet in the graph, yielding messages destined to the adjacent vertices. The reduce function aggregates messages destined to the same vertex. The operation results in a `VertexRDD` containing the aggregate message for each vertex.

We can find the oldest follower for each user by sending a message containing the name and age of each follower and aggregating the messages by taking the message from the older follower:

```
// Find the oldest follower for each user
val          oldestFollower:          VertexRDD[(String,          Int)]          =
userGraph.mapReduceTriplets[(String, Int)](
  // For each edge send a message to the destination vertex with the attribute
of the source vertex
  edge => Iterator((edge.dstId, (edge.srcAttr.name, edge.srcAttr.age))),
  // To combine messages take the message for the older follower
  (a, b) => if (a._2 > b._2) a else b
  )
```

Display the oldest follower for each user:

```
David is the oldest follower of Alice.
Charlie is the oldest follower of Bob.
Ed is the oldest follower of Charlie.
Bob is the oldest follower of David.
Ed does not have any followers.
Charlie is the oldest follower of Fran.
```

```
userGraph.vertices.leftJoin(oldestFollower)      {       (id,       user,
optOldestFollower) =>
  /**
   * Implement: Generate a string naming the oldest follower of each user
   * Note: Some users may have no messages optOldestFollower.isEmpty if
they have no followers
   *
   * Try using the match syntax:
   *
   *  optOldestFollower match {
   *    case None => "No followers! implement me!"
   *    case Some((name, age)) => "implement me!"
   *  }
   *
   */
}.collect.foreach {
  case (id, str) => println(str)
}
```

```
7. View solution
```

```
userGraph.vertices.leftJoin(oldestFollower) { (id, user, optOldestFollower)
=>
  optOldestFollower match {
    case None => s"${user.name} does not have any followers."
    case  Some((name,  age))  =>  s"${name}  is  the  oldest  follower  of
${user.name}."
  }
}.collect.foreach { case (id, str) => println(str) }
```

As an exercise, try finding the average follower age of the followers of each user.

```
8. View solution
```

```
val   averageAge:   VertexRDD[Double]   =   userGraph.mapReduceTriplets[(Int,
Double)](
  // map function returns a tuple of (1, Age)
  edge => Iterator((edge.dstId, (1, edge.srcAttr.age.toDouble))),
  // reduce function combines (sumOfFollowers, sumOfAge)
  (a, b) => ((a._1 + b._1), (a._2 + b._2))
  ).mapValues((id, p) => p._2 / p._1)

// Display the results
userGraph.vertices.leftJoin(averageAge) { (id, user, optAverageAge) =>
  optAverageAge match {
    case None => s"${user.name} does not have any followers."
    case Some(avgAge) => s"The average age of ${user.name}\'s followers is
$avgAge."
```

```
  }
}.collect.foreach { case (id, str) => println(str) }
```

2.1.5 Subgraph

Suppose we want to study the community structure of users that are 30 or older. To support this type of analysis GraphX includes the subgraph operator that takes vertex and edge predicates and returns the graph containing only the vertices that satisfy the vertex predicate (evaluate to true) and edges that satisfy the edge predicate *and connect vertices that satisfy the vertex predicate*.

In the following we restrict our graph to the users that are 30 or older.

```
val olderGraph = userGraph.subgraph(vpred = (id, user) => user.age >=
30)
```

Lets examine the communities in this restricted graph:

```
// compute the connected components
val cc = olderGraph.connectedComponents

// display the component id of each user:
olderGraph.vertices.leftJoin(cc.vertices) {
  case (id, user, comp) => s"${user.name} is in component ${comp.get}"
}.collect.foreach{ case (id, str) => println(str) }
```

Connected components are labeled (numbered) by the lowest vertex Id in that component. Notice that by examining the subgraph we have disconnected `David` from the rest of his community. Moreover his connections to the rest of the graph are through younger users.

2.2 Analysing graphs

Now that we have learned about the individual components of the GraphX API, we are ready to put them together to build a real analytics pipeline. In this section, we will start with Wikipedia link data, use GraphX operators to analyze the structure, and then use Spark operators to examine the output of the graph analysis, all from the Spark shell.

2.2.1 Load Wikipedia articles

Wikipedia provides `XML dumps` of all articles in the encyclopaedia. The latest dump is 44 GB, so it has been preprocessed and filtered it (using Spark and GraphX, of course!) to fit on your machines. We extracted all articles with “`Berkeley`” in the title, as well as all articles linked from and linking to those articles. The resulting dataset is stored in two files:

- `"data/graphx-wiki-vertices.txt"`
- `"data/graphx-wiki-edges.txt"`.

The graphx-wiki-vertices.txt file contains articles by `ID` and `title`, and the `graphx-wiki-edges.txt` file contains the link structure in the form of source-destination ID pairs.

Load these two files into RDDs:

```
val articles: RDD[String] = sc.textFile("data/graphx-wiki-
vertices.txt")
val links: RDD[String] = sc.textFile("data/graphx-wiki-edges.txt")
```

2.2.3 Look at the first article

Display the title of the first article:

```
articles.first
// res0: String = 6598434222544540151   Adelaide Hanscom Leeson
```

2.2.4 Construct the graph

Now let's use the articles and links to construct a graph of Berkeley-related articles. First, we parse the article rows into pairs of vertex ID and title:

```
val vertices = articles.map { line =>
  val fields = line.split('\t')
  (fields(0).toLong, fields(1))
}
```

Next, we parse the link rows into `Edge` objects with the placeholder `0` attribute:

```
val edges = links.map { line =>
  val fields = line.split('\t')
  Edge(fields(0).toLong, fields(1).toLong, 0)
}
```

Finally, we can create the graph by calling the `Graph` constructor with our vertex RDD, our edge RDD, and a default vertex attribute. The default vertex attribute is used to initialize vertices that are not present in the vertex RDD, but are mentioned by an edge (that is, pointed to by a link). This data set has been pre-cleaned to remove such inconsistencies, but many real datasets are "dirty." We will use an empty title string as the default vertex attribute to represent the target of a broken link.

We also cache the resulting graph in memory to avoid reloading it from disk each time we use it.

```
val graph = Graph(vertices, edges, "").cache()
```

Let us force the graph to be computed by counting how many articles it has:

```
graph.vertices.count
```

The first time the graph is created, GraphX constructs index data structures for all the vertices in the graph and detects and allocates missing vertices. Computing the triplets will require an additional join but this should run quickly now that the indexes have been created.

```
graph.triplets.count
```

Let's look at the first few triplets:

```
graph.triplets.take(5).foreach(println(_))
// ((146271392968588,Computer Consoles Inc.),(7097126743572404313,Berkeley
Software Distribution),0)
// ((146271392968588,Computer Consoles
Inc.),(8830299306937918434,University of California, Berkeley),0)
// ((1889887370673623,Anthony Pawson),(8830299306937918434,University of
California, Berkeley),0)
// ((1889887578123422,Anthony Wilden),(6990487747244935452,Busby
Berkeley),0)
```

```
// ((3044656966074398,Pacific Boychoir),(8262690695090170653,Uc
berkeley),0)
```

As mentioned earlier, every triplet in this dataset mentions Berkeley either in the source or the destination article title.

2.2.5 Running PageRank on Wikipedia

We can now do some actual graph analytics. For this example, we are going to run PageRank to evaluate what the most important pages in the Wikipedia graph are. PageRank is part of a small but growing library of common graph algorithms already implemented in GraphX. However, the implementation is simple and straightforward, and just consists of some initialization code, a vertex program and message combiner to pass to Pregel.

```
val prGraph = graph.pageRank(0.001).cache()
```

`Graph.pageRank` returns a graph whose vertex attributes are the `PageRank` values of each page. The `0.001` parameter is the error tolerance that tells `PageRank` when the ranks have converged.

However, this means that while the resulting graph `prGraph` only contains the `PageRank` of the vertices and no longer contains the original vertex properties including the title.

Luckily, we still have our graph that contains that information. Here, we can perform a join of the vertices in the `prGraph` that have the information about relative ranks of the vertices with the vertices in the `graph` that have the information about the mapping from vertex to article title. This yields a new `graph` that has combined both pieces of information, storing them both in a tuple as the new vertex attribute. We can then perform further table-based operators on this new list of vertices, such as finding the ten most important vertices (those with the highest pageranks) and printing out their corresponding article titles. Putting this all together, and we get the following set of operations to find the titles of the ten most important articles in the Berkeley subgraph of Wikipedia.

```
val titleAndPrGraph = graph.outerJoinVertices(prGraph.vertices) {
  (v, title, rank) => (rank.getOrElse(0.0), title)
}

titleAndPrGraph.vertices.top(10) {
  Ordering.by((entry: (VertexId, (Double, String))) => entry._2._1)
}.foreach(t => println(t._2._2 + ": " + t._2._1))
```

2.3 Further reading

- More about Spark Graphix http://spark.apache.org/docs/latest/graphx-programming-guide.html

3. Homework

- Implement a simple Page Rank using Hadoop (see challenge statement)
- You can propose and develop a project around graph analytics. You can combine the problem with streaming graphs as asked in the streaming challenge in hands on 3.