Spark Streaming and GraphX

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Spark Streaming

Motivation

- Many applications must process large streams of live data and provide results in real-time.
  - Wireless sensor networks
  - Traffic management applications
  - Stock marketing
  - Environmental monitoring applications
  - Fraud detection tools
  - ...

Stream Processing Systems

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  - Store and index data before processing it.
  - Process data only when explicitly asked by the users.

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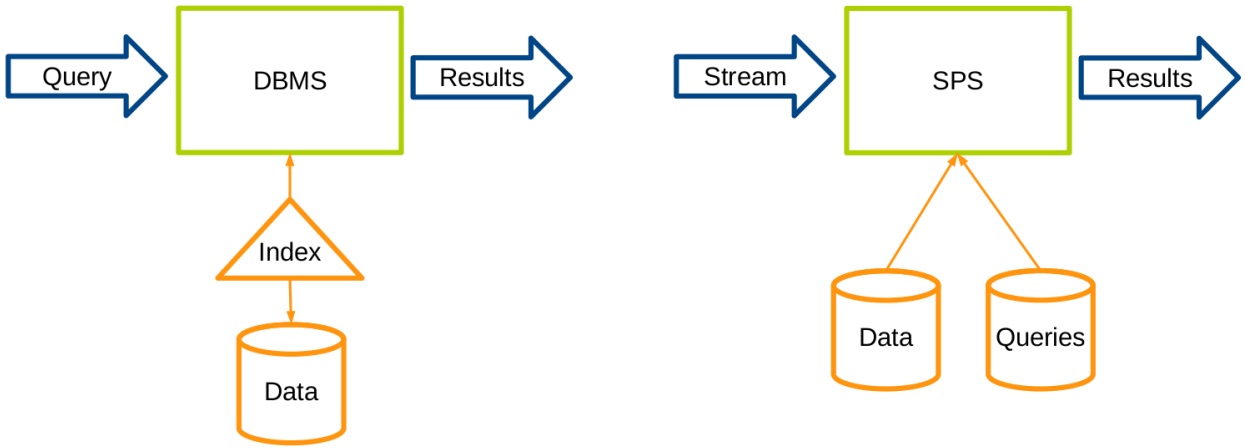
- Stream Processing Systems (SPS): data-in-motion analytics
  - Processing information as it flows, without storing them persistently.

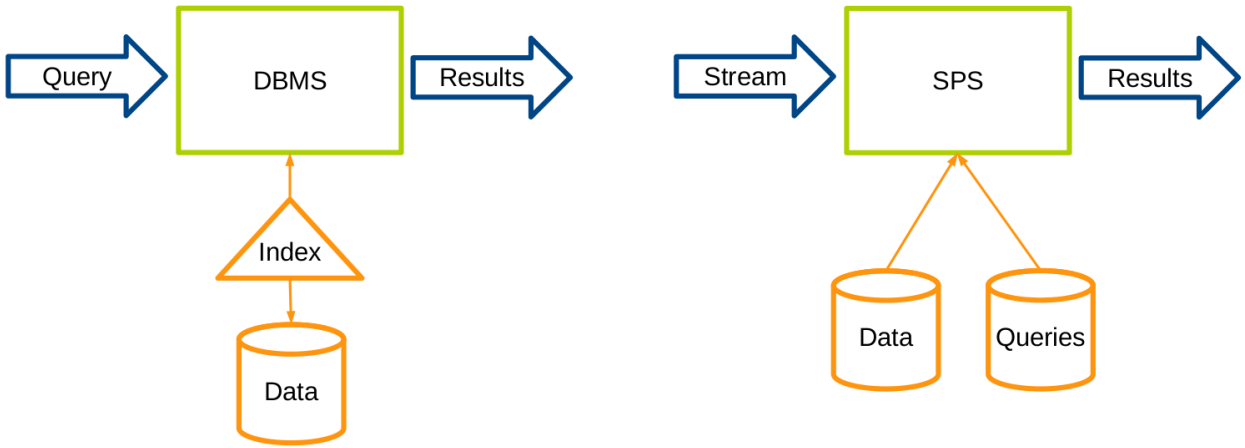
DBMS vs. SPS (1/2)

- DBMS: persistent data where updates are relatively infrequent.
- SPS: transient data that is continuously updated.



DBMS vs. SPS (2/2)

- DBMS: runs queries just once to return a complete answer.
- SPS: executes standing queries, which run continuously and provide updated answers as new data arrives.



Core Idea of Spark Streaming

- Run a streaming computation as a series of very small and deterministic batch jobs.

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  - Chop up the live stream into batches of X seconds.

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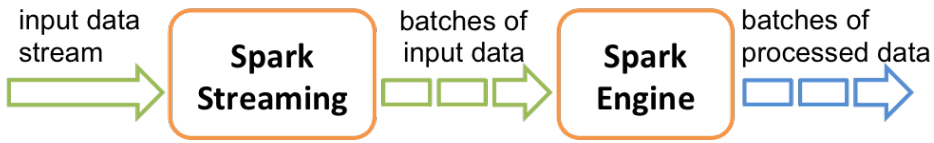
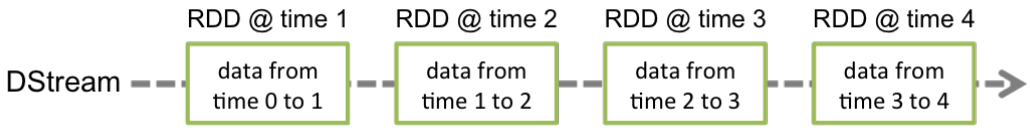
  - Discretized Stream Processing (DStream)



DStream

- DStream: sequence of RDDs representing a stream of data.
- Any operation applied on a DStream translates to operations on the underlying RDDs.



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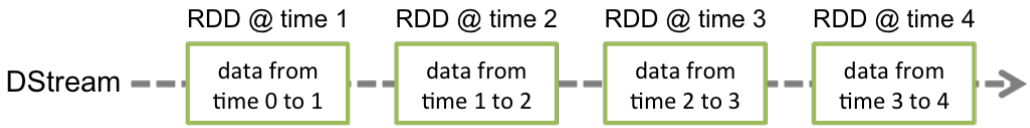
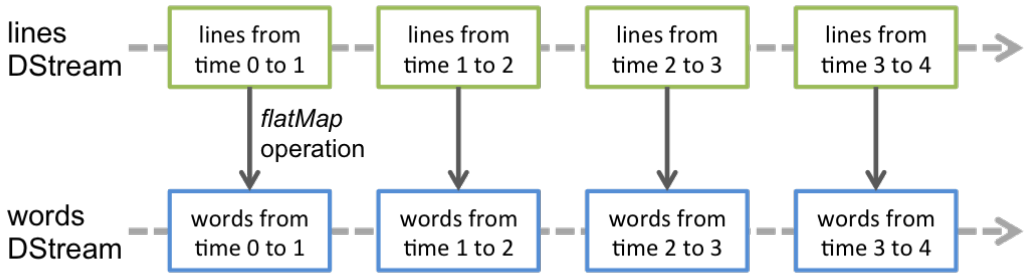




StreamingContext

- StreamingContext: the main entry point of all Spark Streaming functionality.
- To initialize a Spark Streaming program, a StreamingContext object has to be created.

```
val conf = new SparkConf().setAppName(appName).setMaster(master)
val ssc = new StreamingContext(conf, Seconds(1))
```

Source of Streaming

- Two categories of streaming sources.
- Basic sources directly available in the StreamingContext API, e.g., file systems, socket connections, ...
- Advanced sources, e.g., Kafka, Flume, Kinesis, Twitter, ...

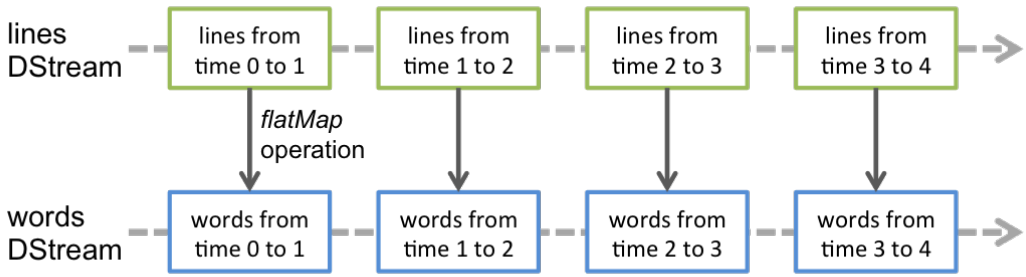
```
ssc.socketTextStream("localhost", 9999)

TwitterUtils.createStream(ssc, None)
```

DStream Transformations

- Transformations: modify data from on DStream to a new DStream.
- Standard RDD operations, e.g., map, join, ...
- DStream operations, e.g., window operations

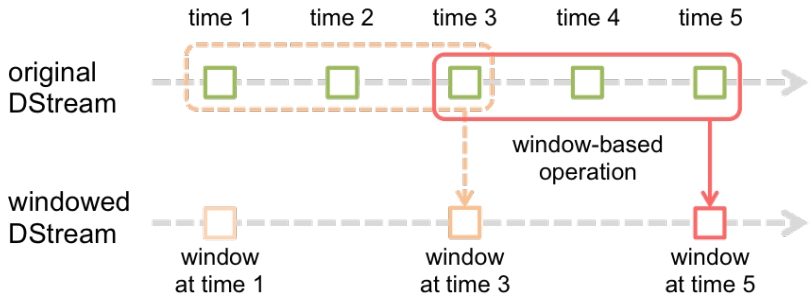
DStream Transformation Example

```
val conf = new SparkConf().setMaster("local[2]").setAppName("NetworkWordCount")
val ssc = new StreamingContext(conf, Seconds(1))

val lines = ssc.socketTextStream("localhost", 9999)

val words = lines.flatMap(_.split(" "))
val pairs = words.map(word => (word, 1))
val wordCounts = pairs.reduceByKey(_ + _)

wordCounts.print()
```



Window Operations

- Apply transformations over a sliding window of data: window length and slide interval.




```
val ssc = new StreamingContext(conf, Seconds(1))
val lines = ssc.socketTextStream(IP, Port)
val words = lines.flatMap(_.split(" "))
val pairs = words.map(word => (word, 1))

val windowedWordCounts = pairs.reduceByKeyAndWindow(_ + _,
  Seconds(30), Seconds(10))
```

MapWithState Operation

- Maintains state while continuously updating it with new information.
- It requires the checkpoint directory.
- A new operation after updateStateByKey.

```
val ssc = new StreamingContext(conf, Seconds(1))
ssc.checkpoint(".")

val lines = ssc.socketTextStream(IP, Port)
val words = lines.flatMap(_.split(" "))
val pairs = words.map(word => (word, 1))

val stateWordCount = pairs.mapWithState(
  StateSpec.function(mappingFunc))

val mappingFunc = (word: String, one: Option[Int], state: State[Int]) => {
  val sum = one.getOrElse(0) + state.getOption.getOrElse(0)
  state.update(sum)
  (word, sum)
}
```

Transform Operation

- Allows arbitrary RDD-to-RDD functions to be applied on a DStream.
- Apply any RDD operation that is not exposed in the DStream API, e.g., joining every RDD in a DStream with another RDD.

```
// RDD containing spam information
val spamInfoRDD = ssc.sparkContext.newAPIHadoopRDD(...)

val cleanedDStream = wordCounts.transform(rdd => {
 // join data stream with spam information to do data cleaning
  rdd.join(spamInfoRDD).filter(...)
  ...
})
```

Spark Streaming and DataFrame

```scala
val words: DStream[String] = ...

words.foreachRDD { rdd =>
  // Get the singleton instance of SQLContext
  val sqlContext = SQLContext.getOrCreate(rdd.sparkContext)
  import sqlContext.implicits._

  // Convert RDD[String] to DataFrame
  val wordsDataFrame = rdd.toDF("word")

  // Register as table
  wordsDataFrame.registerTempTable("words")

  // Do word count on DataFrame using SQL and print it
  val wordCountsDataFrame =
    sqlContext.sql("select word, count(*) as total from words group by word")
  wordCountsDataFrame.show()
}
```

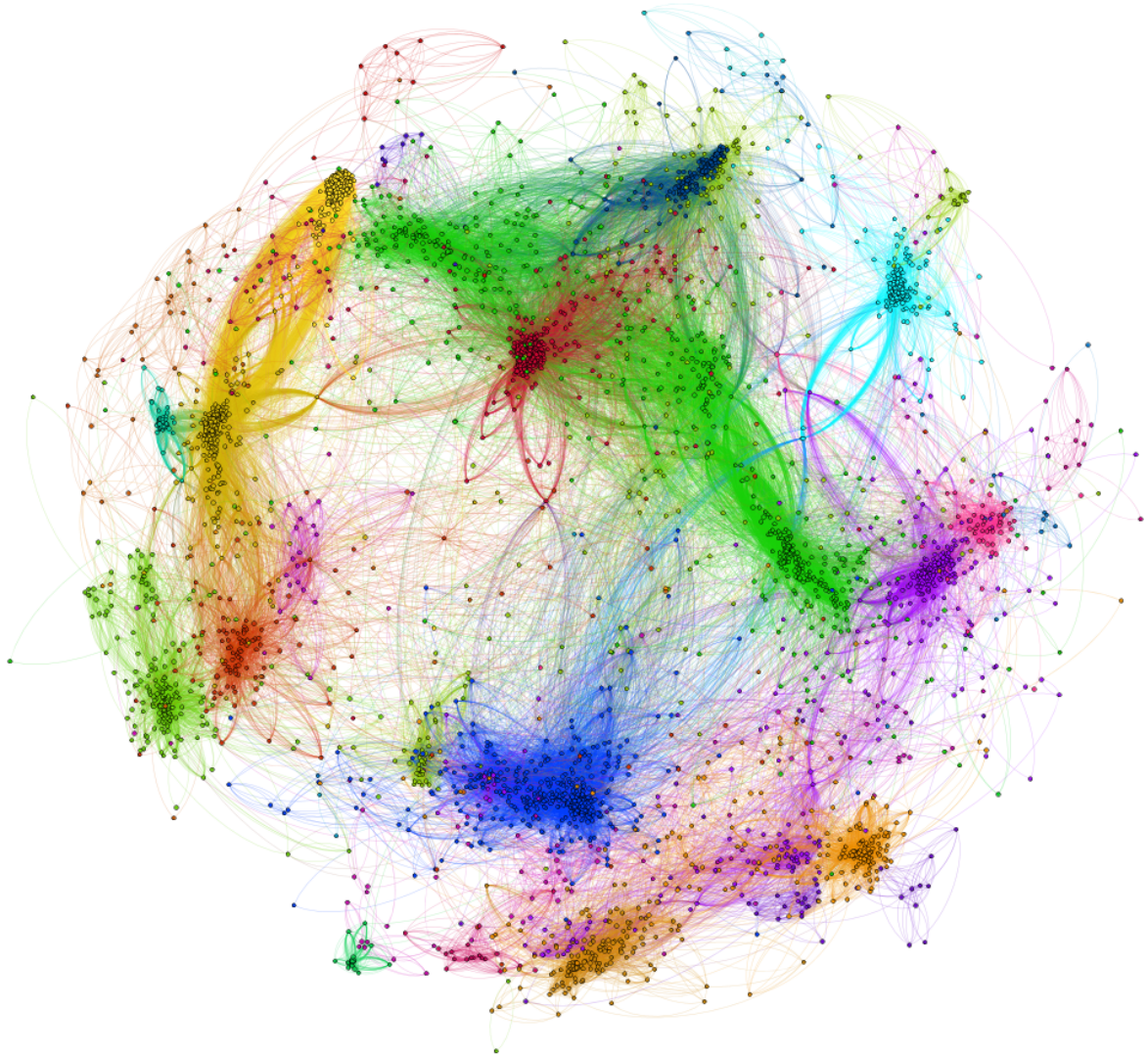
GraphX


SOUNDCLOUD

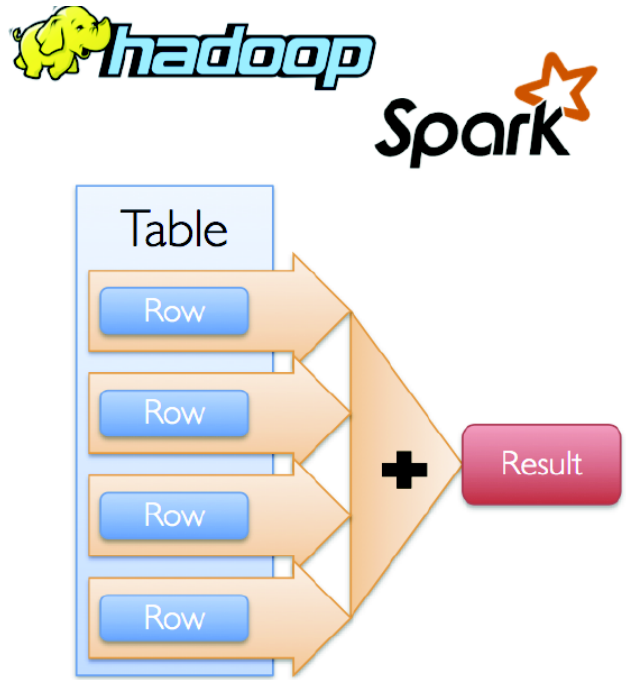
Introduction

- Graphs provide a flexible abstraction for describing relationships between discrete objects.
- Many problems can be modeled by graphs and solved with appropriate graph algorithms.

Large Graph



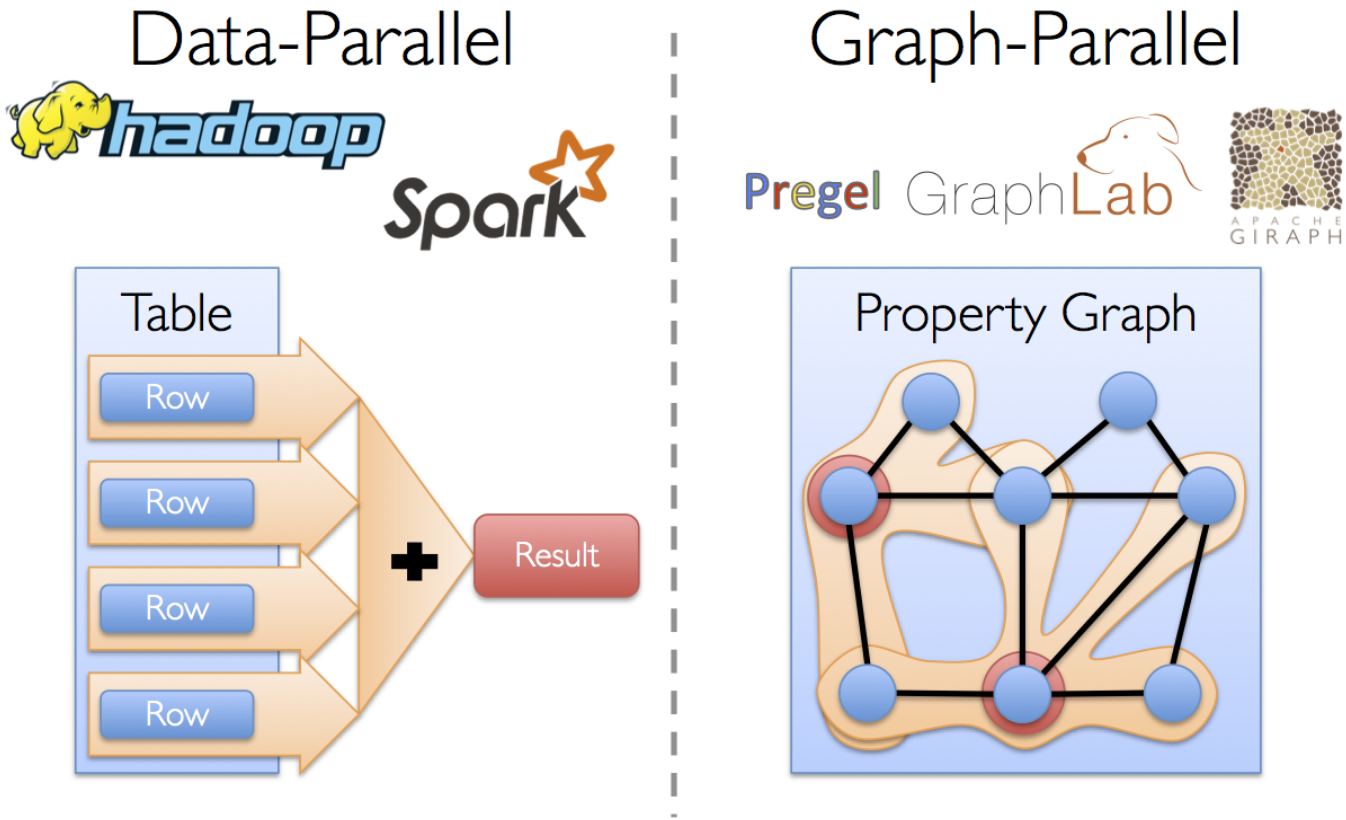
Can we use platforms like MapReduce or Spark, which are based on data-parallel model, for large-scale graph proceeding?



Graph-Parallel Processing

- Restricts the types of computation.
- New techniques to partition and distribute graphs.
- Exploit graph structure.
- Executes graph algorithms orders-of-magnitude faster than more general data-parallel systems.

Data-Parallel vs. Graph-Parallel Computation (1/3)

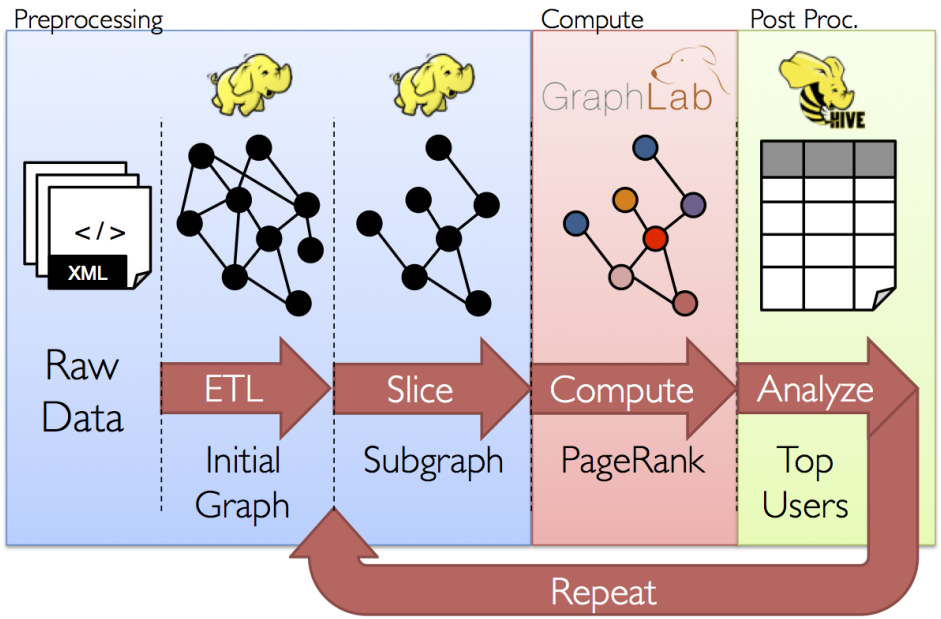


Data-Parallel vs. Graph-Parallel Computation (2/3)

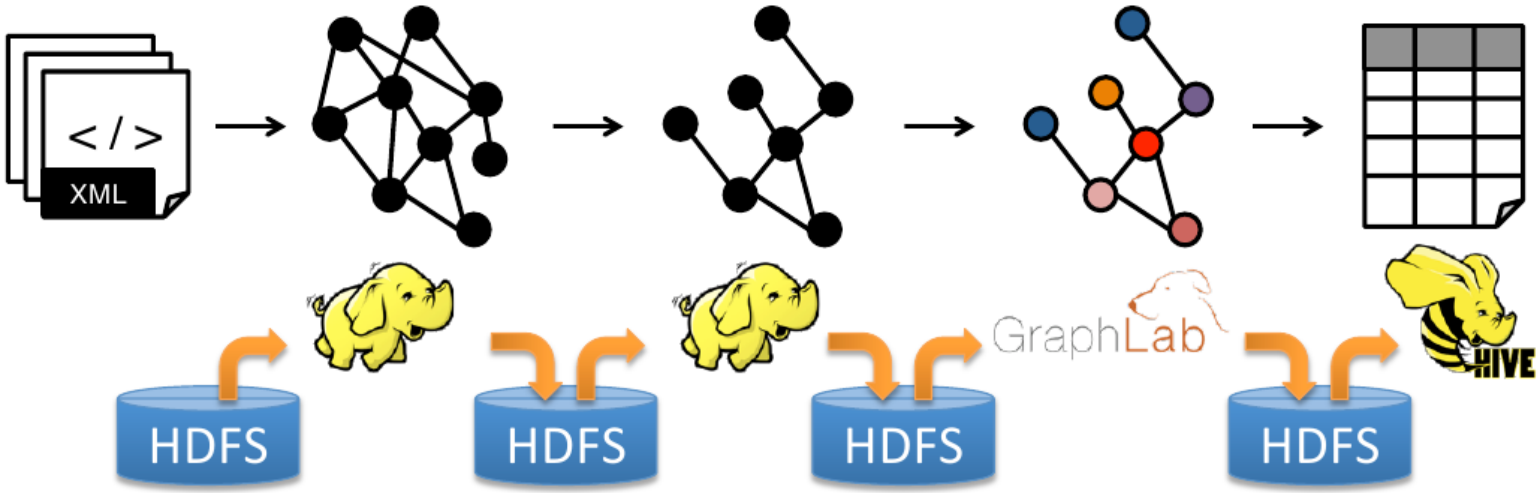
- Graph-parallel computation: restricting the types of computation to achieve performance.

Data-Parallel vs. Graph-Parallel Computation (2/3)

- Graph-parallel computation: restricting the types of computation to achieve performance.
- But, the same restrictions make it difficult and inefficient to express many stages in a typical graph-analytics pipeline.



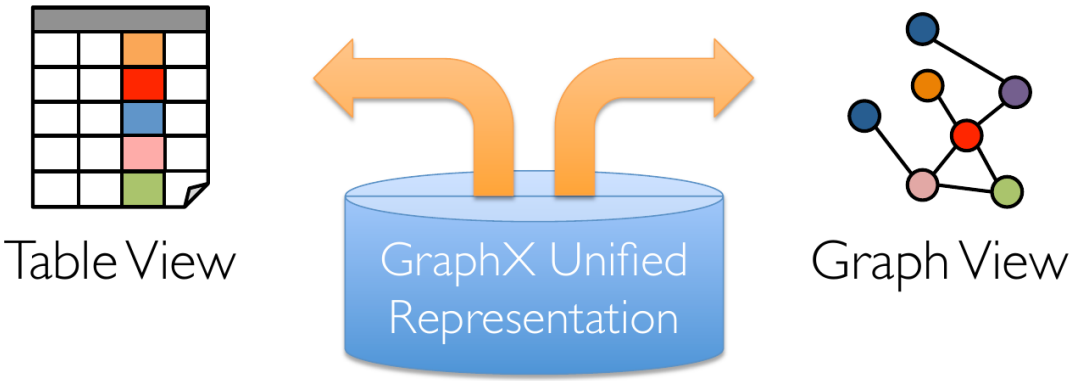
Data-Parallel vs. Graph-Parallel Computation (3/3)



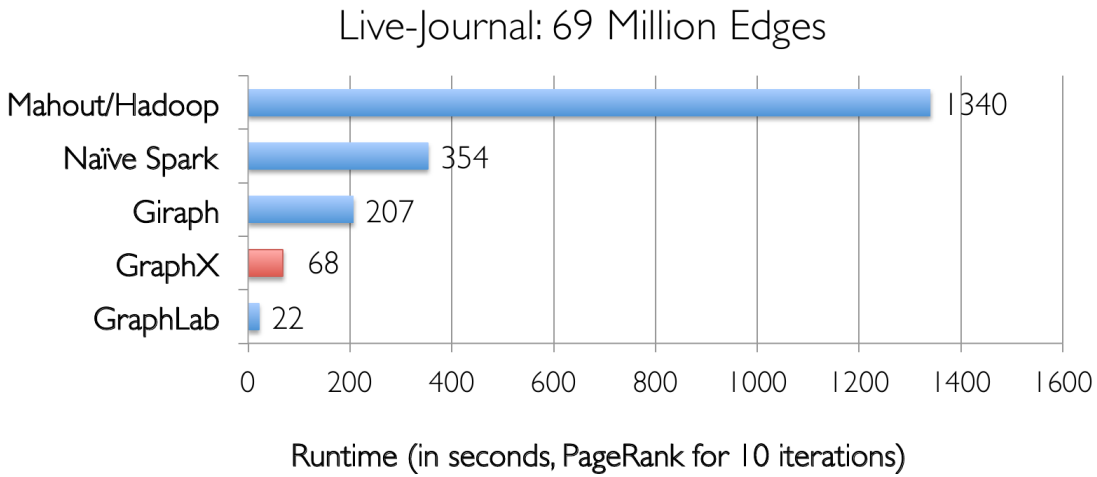
- Moving between table and graph views of the same physical data.
- Inefficient: extensive data movement and duplication across the network and file system.

GraphX

- Unifies data-parallel and graph-parallel systems.
- Tables and Graphs are composable views of the same physical data.
- Implemented on top of Spark.



GraphX vs. Data-Parallel/Graph-Parallel Systems



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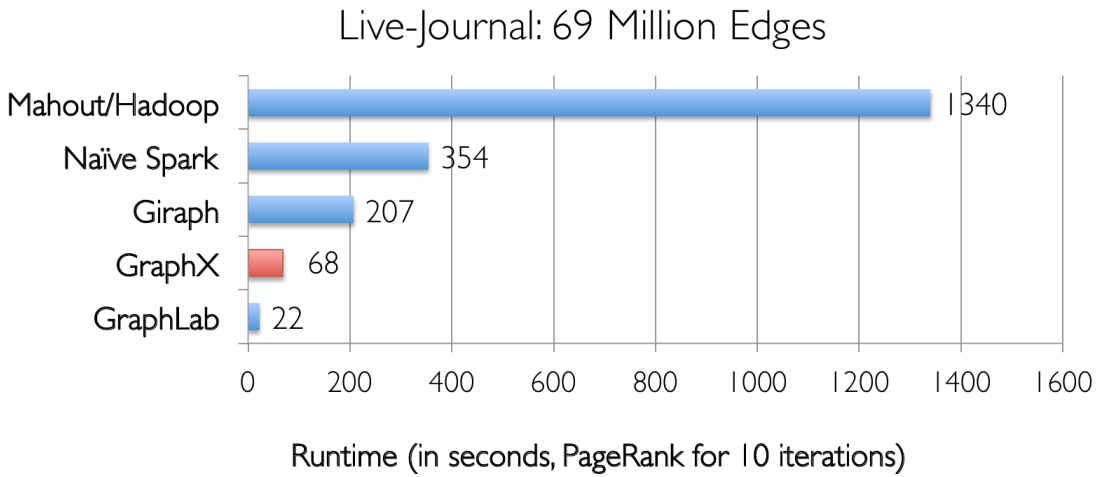
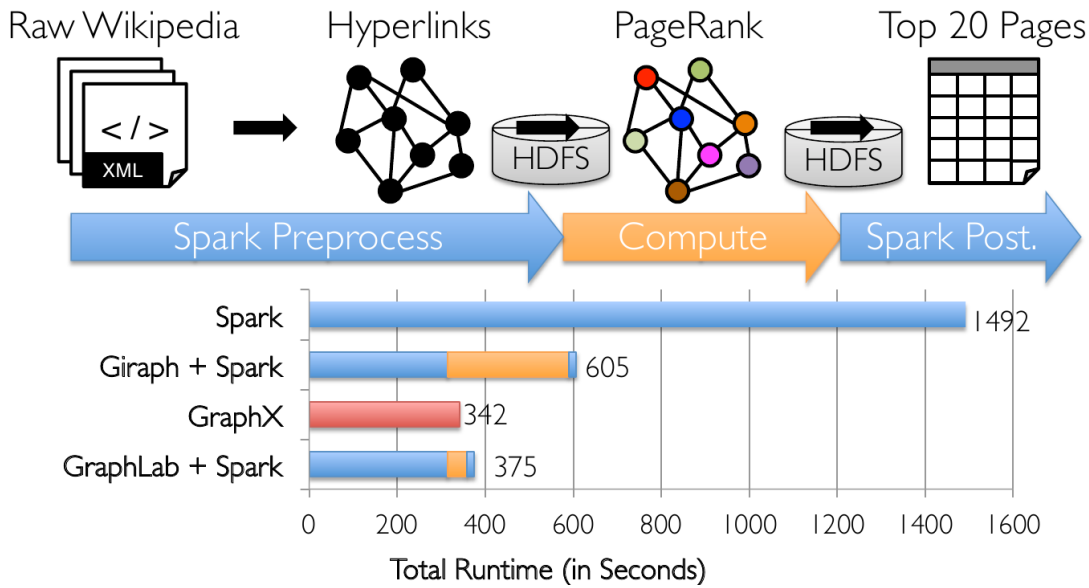
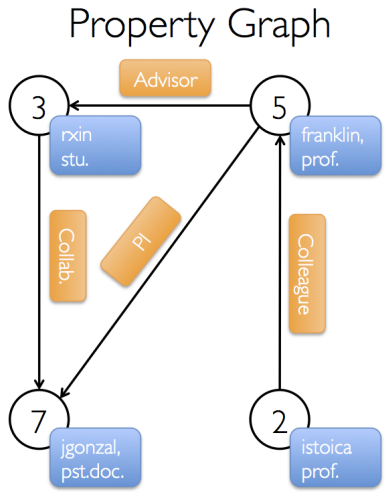




Property Graph

- Represented using two Spark RDDs:
  - Edge collection: VertexRDD
  - Vertex collection: EdgeRDD



Vertex Table

Id	Property (V)
3	(rxin, student)
7	(jgonzal, postdoc)
5	(franklin, professor)
2	(istoica, professor)

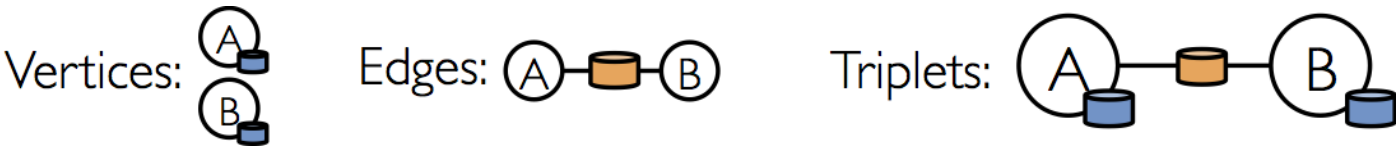
Edge Table

SrcId	DstId	Property (E)
3	7	Collaborator
5	3	Advisor
2	5	Colleague
5	7	PI

```
// VD: the type of the vertex attribute
// ED: the type of the edge attribute
class Graph[VD, ED] {
  val vertices: VertexRDD[VD]
  val edges: EdgeRDD[ED]
}
```

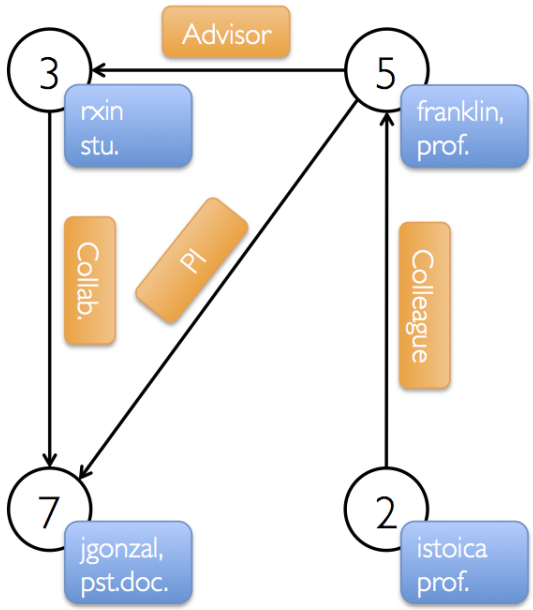
Triplets

- The triplet view logically joins the vertex and edge properties yielding an `RDD[EdgeTriplet[VD, ED]]`.



Example Property Graph (1/3)

Property Graph



Vertex Table

Id	Property (V)
3	(rxin, student)
7	(jgonzal, postdoc)
5	(franklin, professor)
2	(istoica, professor)

Edge Table

SrcId	DstId	Property (E)
3	7	Collaborator
5	3	Advisor
2	5	Colleague
5	7	PI

Example Property Graph (2/3)

```
val sc: SparkContext

// Create an RDD for the vertices
val users: VertexRDD[(String, String)] = sc.parallelize(
    Array((3L, ("rxin", "student")), (7L, ("jgonzal", "postdoc")),
          (5L, ("franklin", "prof")), (2L, ("istoica", "prof"))))

// Create an RDD for edges
val relationships: EdgeRDD[String] = sc.parallelize(
    Array(Edge(3L, 7L, "collab"),    Edge(5L, 3L, "advisor"),
          Edge(2L, 5L, "colleague"), Edge(5L, 7L, "pi")))

// Define a default user in case there are relationship with missing user
val defaultUser = ("John Doe", "Missing")

// Build the initial Graph
val userGraph: Graph[(String, String), String] =
    Graph(users, relationships, defaultUser)
```

Example Property Graph (3/3)

```
// Constructed from above
val userGraph: Graph[(String, String), String]

// Count all users which are postdocs
userGraph.vertices.filter((id, (name, pos)) => pos == "postdoc").count

// Count all the edges where src > dst
userGraph.edges.filter(e => e.srcId > e.dstId).count

// Use the triplets view to create an RDD of facts
val facts: RDD[String] = graph.triplets.map(triplet =>
    triplet.srcAttr._1 + " is the " +
    triplet.attr + " of " + triplet.dstAttr._1)
```

Property Operators

```
def mapVertices[VD2](map: (VertexId, VD) => VD2): Graph[VD2, ED]
def mapEdges[ED2](map: Edge[ED] => ED2): Graph[VD, ED2]
def mapTriplets[ED2](map: EdgeTriplet[VD, ED] => ED2): Graph[VD, ED2]
```

```
val newGraph = graph.mapVertices((id, attr) => mapUdf(id, attr))
```

Structural Operators

```
def reverse: Graph[VD, ED]
def subgraph(epred: EdgeTriplet[VD, ED] => Boolean,
  vpred: (VertexId, VD) => Boolean): Graph[VD, ED]
def mask[VD2, ED2](other: Graph[VD2, ED2]): Graph[VD, ED]
```

```
// Run Connected Components
val ccGraph = graph.connectedComponents() // No longer contains missing field

// Remove missing vertices as well as the edges to connected to them
val validGraph = graph.subgraph(vpred = (id, attr) => attr._2 != "Missing")

// Restrict the answer to the valid subgraph
val validCCGraph = ccGraph.mask(validGraph)
```

Join Operators

```
def joinVertices[U](table: RDD[(VertexId, U)])(map: (VertexId, VD, U) => VD):
  Graph[VD, ED]
def outerJoinVertices[U, VD2](table: RDD[(VertexId, U)])
  (map: (VertexId, VD, Option[U]) => VD2):
  Graph[VD2, ED]
```

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

val degreeGraph = graph.outerJoinVertices(outDegrees) {
  (id, oldAttr, outDegOpt) =>
    outDegOpt match {
      case Some(outDeg) => outDeg
      case None => 0 // No outDegree means zero outDegree
    }
}
```

Neighborhood Aggregation

```
def aggregateMessages[Msg: ClassTag](
  sendMsg: EdgeContext[VD, ED, Msg] => Unit, // map
  mergeMsg: (Msg, Msg) => Msg, // reduce
  tripletFields: TripletFields = TripletFields.All):
  VertexRDD[Msg]
```

```
val graph: Graph[Double, Int] = ...

val olderFollowers: VertexRDD[(Int, Double)] =
  graph.aggregateMessages[(Int, Double)](triplet =>
  { // Map Function
    if (triplet.srcAttr > triplet.dstAttr) {
      // Send message to destination vertex containing counter and age
      triplet.sendToDst(1, triplet.srcAttr)
    }
  },
  // Reduce Function
  (a, b) => (a._1 + b._1, a._2 + b._2)
)

val avgAgeOfOlderFollowers: VertexRDD[Double] = olderFollowers.mapValues(
  (id, value) => value match {case (count, totalAge) => totalAge / count})
```

Summary

Summary

- Spark streaming
  - Mini-batch processing
  - DStream (sequence of RDDs)
  - Transformations, e.g., stateful, window, join, transform, ...
- GraphX
  - Unifies graph-parallel and data-prallel models
  - Property graph (VertexRDD and EdgeRDD)

Questions?