

Data Intensive Computing Platforms

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Big Data

... everyone talks about it, nobody really knows how to do it, everyone thinks everyone else is doing it, so everyone claims they are doing it.

- Dan Ariely



Big data is data that exceeds the processing capacity of conventional database systems. The data is too big, moves too fast, or doesn't fit the strictures of your database architectures. To gain value from this data, you must choose an alternative way to process it.

- O'Reilly



O'REILLY[®]

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- O'Reilly

Too Many Words



O'REILLY®

Big data is the data characterized by 3 attributes: volume, variety and velocity.

- IBM



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- IBM

Random Words



Big data is the data characterized by 4 key attributes: volume, variety, velocity and value.

- Oracle

The Oracle logo, consisting of the word "ORACLE" in a bold, red, sans-serif font with a registered trademark symbol (®) at the end.

Big data is the data characterized by 4 key attributes: volume, variety, velocity and value.

Buzzwords

- Oracle

ORACLE®

Let's Define Big Data In Simple Words



DevOps Borat

@DEVOPS_BORAT

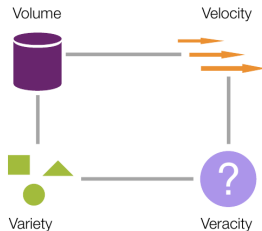
Small Data is when is fit in RAM.
Big Data is when is crash because
is not fit in RAM.

2/6/13, 8:22 AM



The Four Dimensions of Big Data

- ▶ **Volume**: data size
- ▶ **Velocity**: data generation rate
- ▶ **Variety**: data heterogeneity
- ▶ This 4th V is for **V**acillation:
Veracity/Variability/Value



Big Data Sources



How Much Data?

- ▶ **Google:** 100 PB/day process, 15000 PB storage
- ▶ **EBay:** 100 PB/day, 90 PB storage
- ▶ **Baidu:** 10-100 PB/day, 2000 PB storage
- ▶ **Facebook:** 600 TB/day, 300 PB storage
- ▶ **Spotify:** 2.2 TB/day, 100 PB storage



[<https://followthedata.wordpress.com/2014/06/24/data-size-estimates>]

Two Driving Factors

- ▶ Cloud computing
- ▶ Open source communities



Who Uses Big Data?

- ▶ Banking
- ▶ Government
- ▶ Manufacturing
- ▶ Education
- ▶ Health care
- ▶ ...



How To Store and Process Big Data?

Scale Up vs. Scale Out (1/2)

- ▶ Scale **up** or scale **vertically**: adding **resources** to a **single** node in a system.
- ▶ Scale **out** or scale **horizontally**: adding **more nodes** to a system.

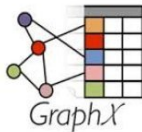


Scale Up vs. Scale Out (2/2)

- ▶ Scale **up**: more **expensive** than scaling out.
- ▶ Scale **out**: more challenging for **fault tolerance** and **software development**.



APACHE
HBASE



Storm

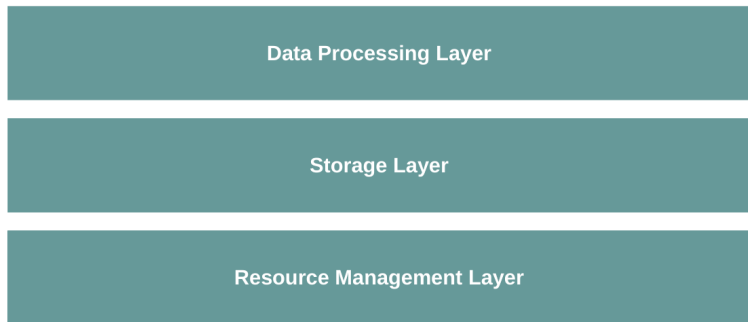


S4 distributed stream
computing platform

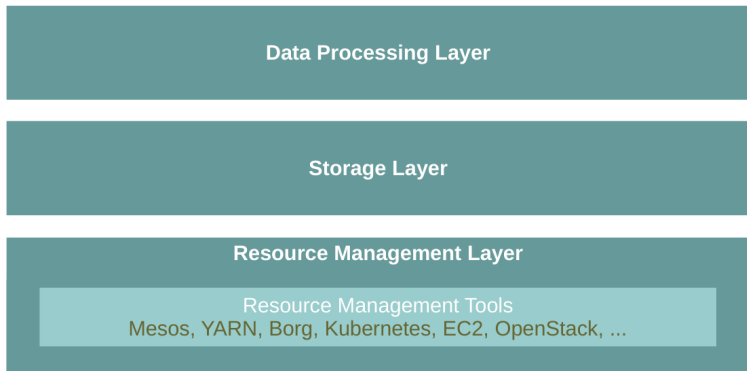


Google Cloud Platform

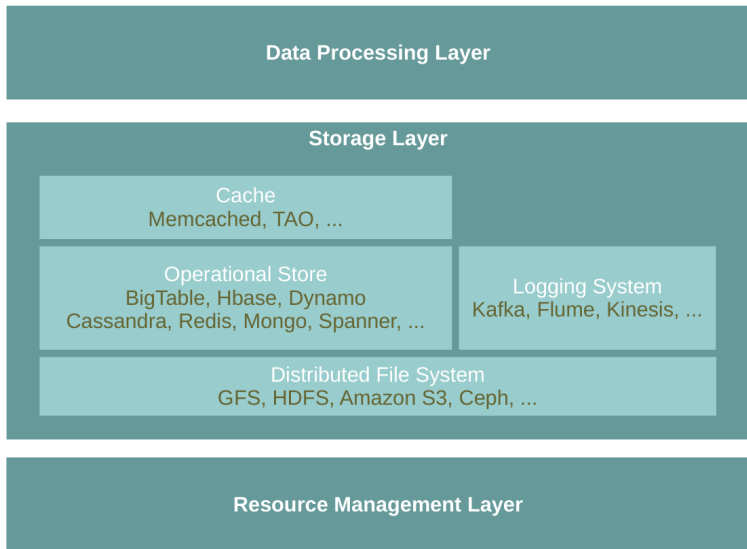
Three Main Layers: Big Data Stack



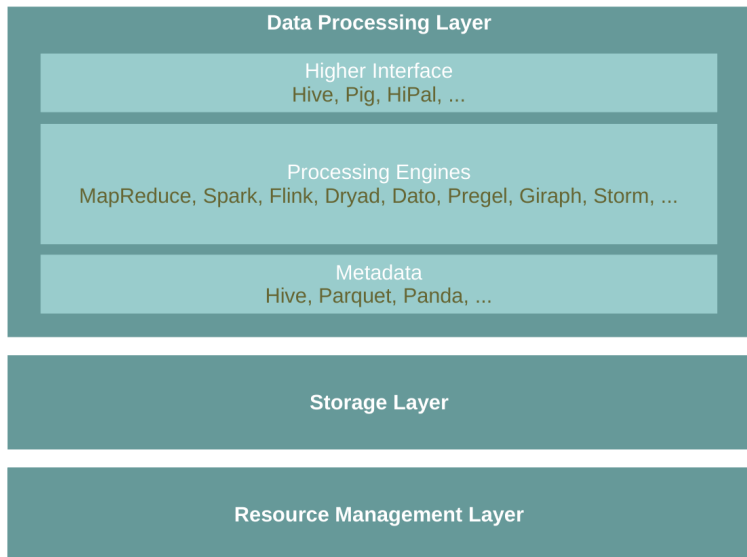
Resource Management Layer



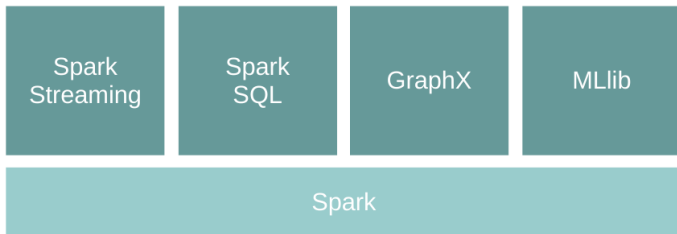
Storage Layer



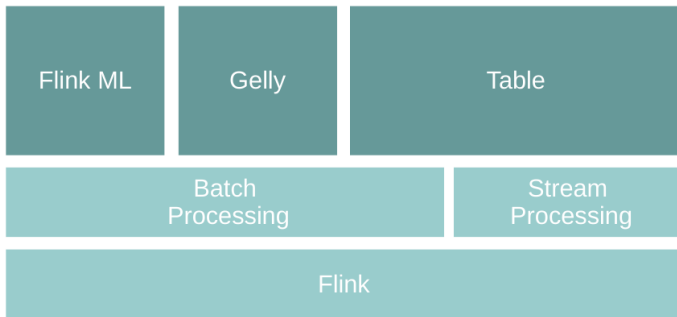
Processing Layer



Spark Processing Engine



Flink Processing Engine



Scala

- ▶ **Scala**: scalable language
- ▶ A blend of **object-oriented** and **functional programming**
- ▶ Runs on the **Java Virtual Machine**
- ▶ Designed by Martin Odersky at **EPFL**



- ▶ **Functions** are **first-class** citizens:
 - Defined **anywhere** (including inside other functions).
 - Passed as **parameters** to functions and **returned as results**.
 - **Operators** to compose functions.

Scala Variables

- ▶ **Values**: immutable
- ▶ **Variables**: mutable

```
var myVar: Int = 0  
val myVal: Int = 1
```

- ▶ Scala data types:
 - Boolean, Byte, Short, Char, Int, Long, Float, Double, String

If ... Else

```
var x = 30;

if (x == 10) {
  println("Value of X is 10");
} else if (x == 20) {
  println("Value of X is 20");
} else {
  println("This is else statement");
}
```

Loop

```
var a = 0
var b = 0
for (a <- 1 to 3; b <- 1 until 3) {
  println("Value of a: " + a + ", b: " + b )
}
```

```
// loop with collections
val numList = List(1, 2, 3, 4, 5, 6)
for (a <- numList) {
  println("Value of a: " + a)
}
```

Functions

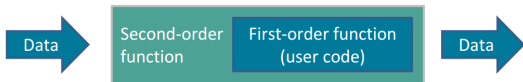
```
def functionName([list of parameters]): [return type] = {  
    function body  
    return [expr]  
}  
  
def addInt(a: Int, b: Int): Int = {  
    var sum: Int = 0  
    sum = a + b  
    sum  
}  
  
println("Returned Value: " + addInt(5, 7))
```

Anonymous Functions

- ▶ Lightweight syntax for defining functions.

```
var mul = (x: Int, y: Int) => x * y
println(mul(3, 4))
```

Higher-Order Functions



```
def apply(f: Int => String, v: Int) = f(v)

def layout(x: Int) = "[" + x.toString() + "]"

println(apply(layout, 10))
```

Collections (1/2)

- ▶ **Array**: **fixed-size** sequential collection of elements of the **same type**

```
val t = Array("zero", "one", "two")
val b = t(0) // b = zero
```


Collections (1/2)

- ▶ **Array**: **fixed-size** sequential collection of elements of the **same type**

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val t = Array("zero", "one", "two")
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- ▶ **List**: sequential collection of elements of the **same type**

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```

Collections (1/2)

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val t = Array("zero", "one", "two")
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```

- ▶ **List**: sequential collection of elements of the same type

```
val t = List("zero", "one", "two")
val b = t(0) // b = zero
```

- ▶ **Set**: sequential collection of elements of the same type without duplicates

```
val t = Set("zero", "one", "two")
val t.contains("zero")
```

Collections (2/2)

- ▶ **Map**: collection of **key/value pairs**

```
val m = Map(1 -> "sics", 2 -> "kth")  
val b = m(1) // b = sics
```

Collections (2/2)

- ▶ **Map**: collection of **key/value pairs**

```
val m = Map(1 -> "sics", 2 -> "kth")
val b = m(1) // b = sics
```

- ▶ **Tuple**: A **fixed** number of items of **different types** together

```
val t = (1, "hello")
val b = t._1 // b = 1
val c = t._2 // c = hello
```

Functional Combinators

- ▶ **map**: applies a function over each element in the list

```
val numbers = List(1, 2, 3, 4)
numbers.map(i => i * 2) // List(2, 4, 6, 8)
```

- ▶ **flatten**: it collapses one level of nested structure

```
List(List(1, 2), List(3, 4)).flatten // List(1, 2, 3, 4)
```

- ▶ **flatMap**: map + flatten
- ▶ **foreach**: it is like map but returns nothing

Classes and Objects

```
class Calculator {  
  val brand: String = "HP"  
  def add(m: Int, n: Int): Int = m + n  
}  
  
val calc = new Calculator  
calc.add(1, 2)  
println(calc.brand)
```

Classes and Objects

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```

- ▶ A singleton is a class that can have only **one instance**.

```
object Test {  
  def main(args: Array[String]) { ... }  
}  
  
Test.main(null)
```

Case Classes and Pattern Matching

- ▶ **Case classes** are used to store and match on the contents of a class.
- ▶ They are designed to be used with **pattern matching**.
- ▶ You can construct them **without using new**.

```
case class Calc(brand: String, model: String)

def calcType(calc: Calc) = calc match {
  case Calc("hp", "20B") => "financial"
  case Calc("hp", "48G") => "scientific"
  case Calc("hp", "30B") => "business"
  case _ => "Calculator of unknown type"
}

calcType(Calc("hp", "20B"))
```


Data Intensive Computing

Motivation

- ▶ We have a **huge text document**.
- ▶ **Count** the number of times each **distinct word** appears in the file



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- ▶ If the file **fits in memory**: `words(doc.txt) | sort | uniq -c`



Motivation

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- ▶ Count the number of times each distinct word appears in the file
- ▶ If the file fits in memory: `words(doc.txt) | sort | uniq -c`
- ▶ If not?

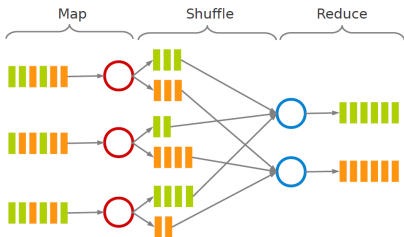


MapReduce Programming Model

▶ `words(doc.txt) | sort | uniq -c`

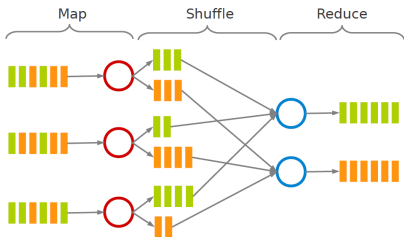
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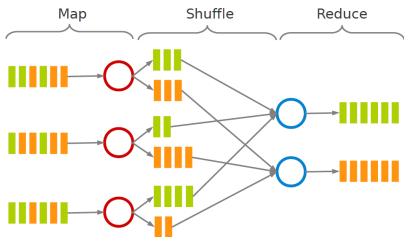
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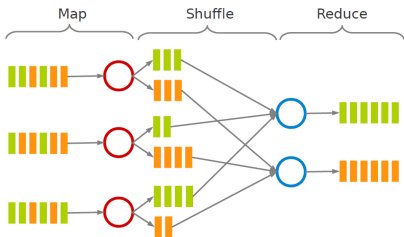
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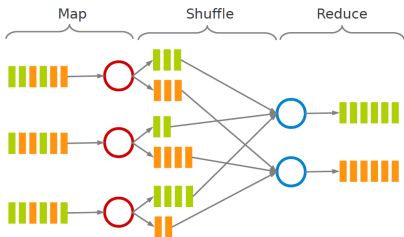
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- ▶ **Reduce**: **aggregate**, summarize, filter or transform.



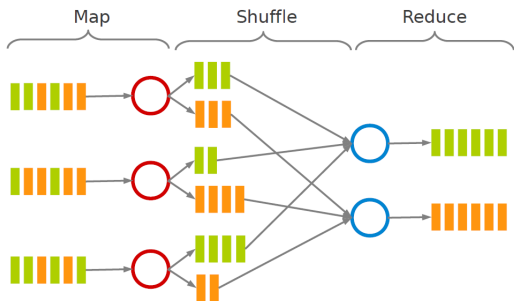
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- ▶ **Reduce**: **aggregate**, summarize, filter or transform.
- ▶ **Write** the result.



MapReduce Dataflow

- ▶ **map** function: processes data and generates a set of intermediate key/value pairs.
- ▶ **reduce** function: merges all intermediate values associated with the same intermediate key.



Word Count in MapReduce

- ▶ Consider doing a word count of the following file using MapReduce:

```
Hello World Bye World  
Hello Hadoop Goodbye Hadoop
```

Word Count in MapReduce - `map`

- ▶ The `map` function reads in words one a time and outputs `(word, 1)` for each parsed input word.
- ▶ The `map` function `output` is:

```
(Hello, 1)
(World, 1)
(Bye, 1)
(World, 1)
(Hello, 1)
(Hadoop, 1)
(Goodbye, 1)
(Hadoop, 1)
```

Word Count in MapReduce - shuffle

- ▶ The **shuffle** phase between **map** and **reduce** phase creates a list of values associated with each key.
- ▶ The **reduce** function **input** is:

```
(Bye, (1))  
(Goodbye, (1))  
(Hadoop, (1, 1))  
(Hello, (1, 1))  
(World, (1, 1))
```

Word Count in MapReduce - reduce

- ▶ The **reduce** function sums the numbers in the list for each key and outputs **(word, count)** pairs.
- ▶ The output of the reduce function is the output of the MapReduce job:

```
(Bye, 1)
(Goodbye, 1)
(Hadoop, 2)
>Hello, 2)
(World, 2)
```

The Word Count Mapper

```
public static class MyMap extends Mapper<...> {
    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();

    public void map(LongWritable key, Text value, Context context)
        throws IOException, InterruptedException {
        String line = value.toString();
        StringTokenizer tokenizer = new StringTokenizer(line);

        while (tokenizer.hasMoreTokens()) {
            word.set(tokenizer.nextToken());
            context.write(word, one);
        }
    }
}
```


The Word Count Reducer

```
public static class MyReduce extends Reducer<...> {
    public void reduce(Text key, Iterator<...> values, Context context)
        throws IOException, InterruptedException {
        int sum = 0;

        while (values.hasNext())
            sum += values.next().get();

        context.write(key, new IntWritable(sum));
    }
}
```

The Word Count Driver

```
public static void main(String[] args) throws Exception {
    Configuration conf = new Configuration();
    Job job = new Job(conf, "wordcount");

    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);

    job.setMapperClass(MyMap.class);
    job.setCombinerClass(MyReduce.class);
    job.setReducerClass(MyReduce.class);

    job.setInputFormatClass(TextInputFormat.class);
    job.setOutputFormatClass(TextOutputFormat.class);

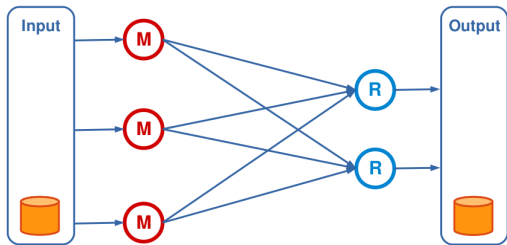
    FileInputFormat.addInputPath(job, new Path(args[0]));
    FileOutputFormat.setOutputPath(job, new Path(args[1]));

    job.waitForCompletion(true);
}
```

Spark

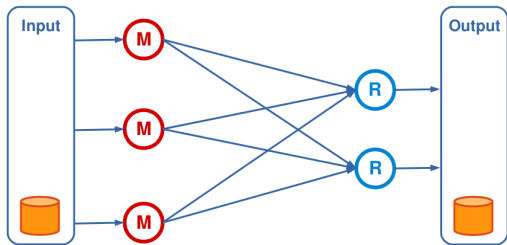
Motivation (1/4)

- ▶ Most current **cluster programming models** are based on **acyclic data flow** from stable storage to stable storage.



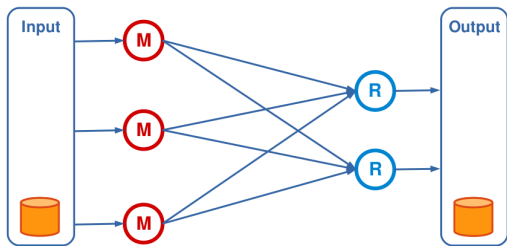
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- ▶ Most current **cluster programming models** are based on **acyclic data flow** from stable storage to stable storage.
- ▶ **Benefits** of data flow: runtime can decide **where** to run **tasks** and can **automatically recover** from **failures**.



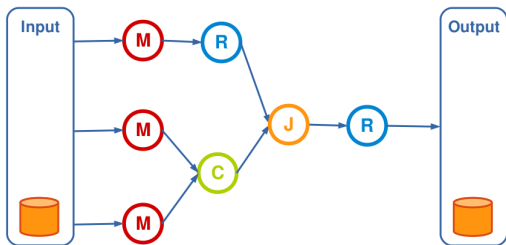
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- ▶ **Benefits** of data flow: runtime can decide **where** to run **tasks** and can **automatically recover** from **failures**.
- ▶ E.g., **MapReduce**



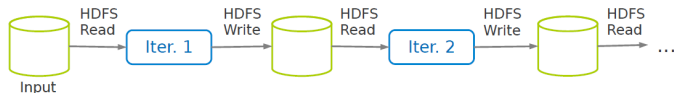
Motivation (2/4)

- ▶ MapReduce programming model has not been designed for **complex** operations, e.g., **data mining**.



Motivation (3/4)

- ▶ Very expensive (slow), i.e., always goes to disk and HDFS.

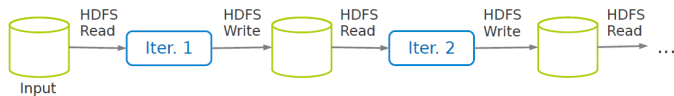


Motivation (4/4)

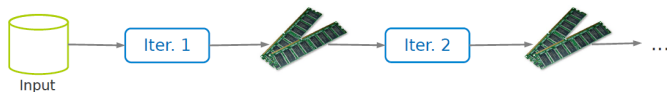
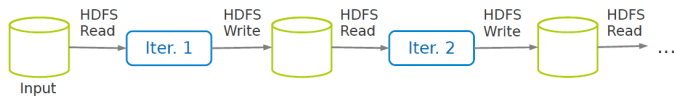
- ▶ Extends MapReduce with **more** operators.
- ▶ Support for advanced **data flow** graphs.
- ▶ **In-memory** and **out-of-core** processing.



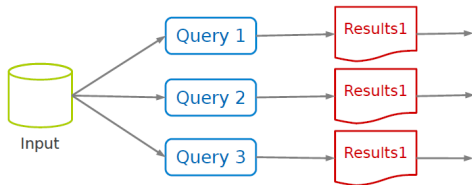
Spark vs. MapReduce (1/2)



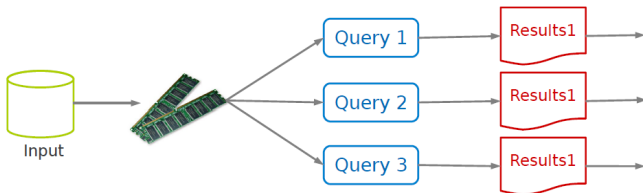
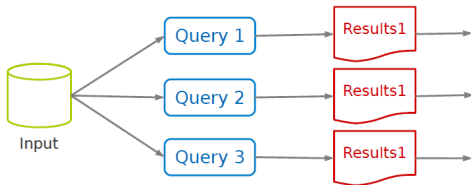
Spark vs. MapReduce (1/2)



Spark vs. MapReduce (2/2)



Spark vs. MapReduce (2/2)



Challenge

How to design a distributed memory abstraction that is both **fault tolerant** and **efficient**?

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Solution

Resilient Distributed Datasets (RDD)

Resilient Distributed Datasets (RDD) (1/2)

- ▶ A **distributed memory** abstraction.
- ▶ **Immutable collections** of **objects** spread across a cluster.
 - Like a `LinkedList <MyObjects>`



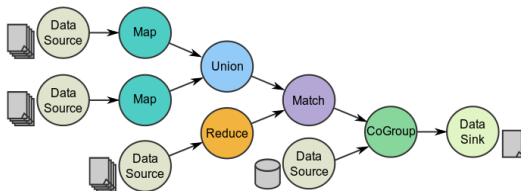
Resilient Distributed Datasets (RDD) (2/2)

- ▶ An **RDD** is divided into a number of **partitions**, which are **atomic** pieces of information.
- ▶ Partitions of an RDD can be stored on different **nodes** of a cluster.



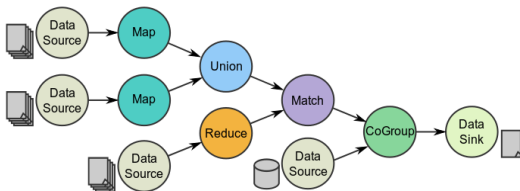
Spark Programming Model

- ▶ A **data flow** is composed of any number of **data sources**, **operators**, and **data sinks** by connecting their inputs and outputs.



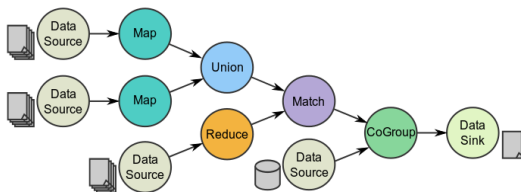
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- ▶ Operators are **higher-order functions** that execute **user-defined functions** in parallel.



Spark Programming Model

- ▶ A **data flow** is composed of any number of **data sources**, **operators**, and **data sinks** by connecting their inputs and outputs.
- ▶ Operators are **higher-order functions** that execute **user-defined functions** in parallel.
- ▶ Two types of RDD operators: **transformations** and **actions**.



RDD Operators (1/2)

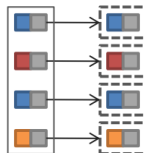
- ▶ **Transformations:** **lazy** operators that create **new** RDDs.
- ▶ **Actions:** launch a **computation** and return a **value** to the program or write data to the external storage.

RDD Operators (2/2)

Transformations	<ul style="list-style-type: none"><i>map</i>($f : T \Rightarrow U$) : $RDD[T] \Rightarrow RDD[U]$<i>filter</i>($f : T \Rightarrow \text{Bool}$) : $RDD[T] \Rightarrow RDD[T]$<i>flatMap</i>($f : T \Rightarrow \text{Seq}[U]$) : $RDD[T] \Rightarrow RDD[U]$<i>sample</i>($\text{fraction} : \text{Float}$) : $RDD[T] \Rightarrow RDD[T]$ (Deterministic sampling)<i>groupByKey</i>() : $RDD[(K, V)] \Rightarrow RDD[(K, \text{Seq}[V])]$<i>reduceByKey</i>($f : (V, V) \Rightarrow V$) : $RDD[(K, V)] \Rightarrow RDD[(K, V)]$<i>union</i>() : $(RDD[T], RDD[T]) \Rightarrow RDD[T]$<i>join</i>() : $(RDD[(K, V)], RDD[(K, W)]) \Rightarrow RDD[(K, (V, W))]$<i>cogroup</i>() : $(RDD[(K, V)], RDD[(K, W)]) \Rightarrow RDD[(K, (\text{Seq}[V], \text{Seq}[W]))]$<i>crossProduct</i>() : $(RDD[T], RDD[U]) \Rightarrow RDD[(T, U)]$<i>mapValues</i>($f : V \Rightarrow W$) : $RDD[(K, V)] \Rightarrow RDD[(K, W)]$ (Preserves partitioning)<i>sort</i>($c : \text{Comparator}[K]$) : $RDD[(K, V)] \Rightarrow RDD[(K, V)]$<i>partitionBy</i>($p : \text{Partitioner}[K]$) : $RDD[(K, V)] \Rightarrow RDD[(K, V)]$
Actions	<ul style="list-style-type: none"><i>count</i>() : $RDD[T] \Rightarrow \text{Long}$<i>collect</i>() : $RDD[T] \Rightarrow \text{Seq}[T]$<i>reduce</i>($f : (T, T) \Rightarrow T$) : $RDD[T] \Rightarrow T$<i>lookup</i>($k : K$) : $RDD[(K, V)] \Rightarrow \text{Seq}[V]$ (On hash/range partitioned RDDs)<i>save</i>($\text{path} : \text{String}$) : Outputs RDD to a storage system, e.g., HDFS

RDD Transformations - Map

- ▶ All pairs are **independently** processed.



RDD Transformations - Map

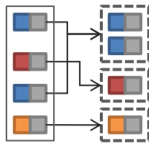
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```
// passing each element through a function.  
val nums = sc.parallelize(Array(1, 2, 3))  
val squares = nums.map(x => x * x) // {1, 4, 9}  
  
// selecting those elements that func returns true.  
val even = squares.filter(_ % 2 == 0) // {4}
```

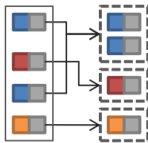

RDD Transformations - Reduce

- ▶ Pairs with **identical key** are grouped.
- ▶ Groups are independently processed.



RDD Transformations - Reduce

- ▶ Pairs with **identical key** are grouped.
- ▶ Groups are independently processed.



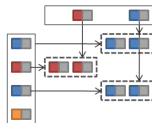
```
val pets = sc.parallelize(Seq(("cat", 1), ("dog", 1), ("cat", 2)))
```

```
pets.groupByKey()  
// {(cat, (1, 2)), (dog, (1))}
```

```
pets.reduceByKey((x, y) => x + y)  
or  
pets.reduceByKey(_ + _)  
// {(cat, 3), (dog, 1)}
```

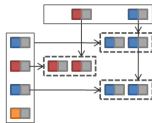
RDD Transformations - Join

- ▶ Performs an **equi-join** on the key.
- ▶ Join candidates are independently processed.



RDD Transformations - Join

- ▶ Performs an **equi-join** on the key.
- ▶ Join candidates are independently processed.



```
val visits = sc.parallelize(Seq(("h", "1.2.3.4"),
                                ("a", "3.4.5.6"),
                                ("h", "1.3.3.1")))

val pageNames = sc.parallelize(Seq(("h", "Home"),
                                    ("a", "About")))

visits.join(pageNames)
// ("h", ("1.2.3.4", "Home"))
// ("h", ("1.3.3.1", "Home"))
// ("a", ("3.4.5.6", "About"))
```

Basic RDD Actions (1/2)

- ▶ Return all the elements of the RDD as an array.

```
val nums = sc.parallelize(Array(1, 2, 3))  
nums.collect() // Array(1, 2, 3)
```

Basic RDD Actions (1/2)

- ▶ Return all the elements of the RDD as an array.

```
val nums = sc.parallelize(Array(1, 2, 3))  
nums.collect() // Array(1, 2, 3)
```

- ▶ Return an array with the first n elements of the RDD.

```
nums.take(2) // Array(1, 2)
```

Basic RDD Actions (1/2)

- ▶ Return all the elements of the RDD as an array.

```
val nums = sc.parallelize(Array(1, 2, 3))  
nums.collect() // Array(1, 2, 3)
```

- ▶ Return an array with the first n elements of the RDD.

```
nums.take(2) // Array(1, 2)
```

- ▶ Return the number of elements in the RDD.

```
nums.count() // 3
```

Basic RDD Actions (2/2)

- ▶ Aggregate the elements of the RDD using the given function.

```
nums.reduce((x, y) => x + y)  
or  
nums.reduce(_ + _) // 6
```


Basic RDD Actions (2/2)

- ▶ Aggregate the elements of the RDD using the given function.

```
nums.reduce((x, y) => x + y)  
or  
nums.reduce(_ + _) // 6
```

- ▶ Write the elements of the RDD as a text file.

```
nums.saveAsTextFile("hdfs://file.txt")
```

SparkContext

- ▶ Main entry point to Spark functionality.
- ▶ Available in `shell` as variable `sc`.
- ▶ Only one `SparkContext` may be active per JVM.

```
// master: the master URL to connect to, e.g.,  
// "local", "local[4]", "spark://master:7077"  
val conf = new SparkConf().setAppName(appName).setMaster(master)  
  
new SparkContext(conf)
```

- ▶ Turn a collection into an RDD.

```
val a = sc.parallelize(Array(1, 2, 3))
```

Creating RDDs

- ▶ Turn a collection into an RDD.

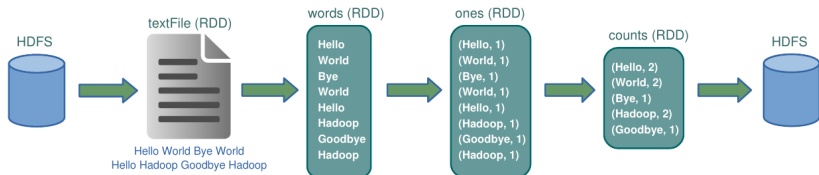
```
val a = sc.parallelize(Array(1, 2, 3))
```

- ▶ Load text file from local FS, HDFS, or S3.

```
val a = sc.textFile("file.txt")  
val b = sc.textFile("directory/*.txt")  
val c = sc.textFile("hdfs://namenode:9000/path/file")
```

Example 1

```
val textFile = sc.textFile("hdfs://...")  
  
val words = textFile.flatMap(line => line.split(" "))  
val ones = words.map(word => (word, 1))  
val counts = ones.reduceByKey(_ + _)  
  
counts.saveAsTextFile("hdfs://...")
```



Example 2

```
val textFile = sc.textFile("hdfs://...")
val sics = textFile.filter(_.contains("SICS"))
val cachedSics = sics.cache()
val ones = cachedSics.map(_ => 1)
val count = ones.reduce(_ + _)
```

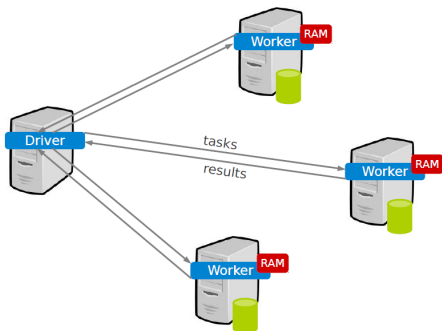
Example 2

```
val textFile = sc.textFile("hdfs://...")
val sics = textFile.filter(_.contains("SICS"))
val cachedSics = sics.cache()
val ones = cachedSics.map(_ => 1)
val count = ones.reduce(_ + _)
```

```
val textFile = sc.textFile("hdfs://...")
val count = textFile.filter(_.contains("SICS")).count()
```

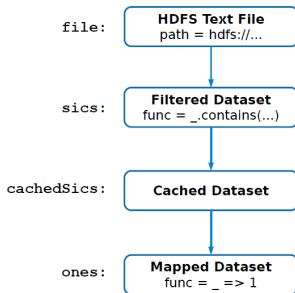
Spark Execution Model

- ▶ A Spark application consists of a **driver program** that runs the user's **main** function and executes various **parallel operations** on a cluster.



Lineage

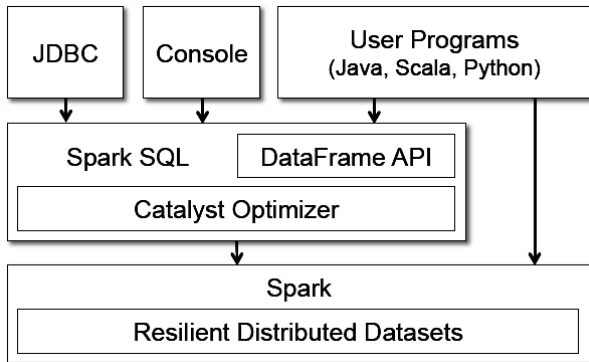
- ▶ **Lineage:** transformations used to build an RDD.
- ▶ **RDDs** are stored as a chain of objects capturing the **lineage** of each RDD.



```
val file = sc.textFile("hdfs://...")
val sics = file.filter(_.contains("SICS"))
val cachedSics = sics.cache()
val ones = cachedSics.map(_ => 1)
val count = ones.reduce(_+_)
```

Spark SQL

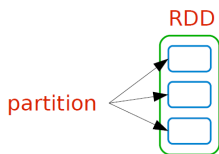
Spark and Spark SQL



- ▶ A **DataFrame** is a **distributed collection of rows**
- ▶ **Homogeneous schema.**
- ▶ Equivalent to a **table** in a relational database.

Adding Schema to RDDs

- ▶ **Spark + RDD**: **functional** transformations on partitioned collections of **opaque objects**.
- ▶ **SQL + DataFrame**: **declarative** transformations on partitioned collections of **tuples**.



Name	Age	Height
Name	Age	Height
Name	Age	Height
Name	Age	Height
Name	Age	Height
Name	Age	Height

Creating DataFrames

- ▶ The **entry point** into all functionality in **Spark SQL** is the **SQLContext**.
- ▶ With a **SQLContext**, applications can create **DataFrames** from an **existing RDD**, from a **Hive table**, or from **data sources**.

```
val sc: SparkContext // An existing SparkContext.  
val sqlContext = new org.apache.spark.sql.SQLContext(sc)  
  
val df = sqlContext.read.json(...)
```

DataFrame Operations (1/2)

- ▶ Domain-specific language for structured data manipulation.

```
// Show the content of the DataFrame
df.show()
// age name
// null Michael
// 30 Andy
// 19 Justin

// Print the schema in a tree format
df.printSchema()
// root
// |-- age: long (nullable = true)
// |-- name: string (nullable = true)

// Select only the "name" column
df.select("name").show()
// name
// Michael
// Andy
// Justin
```

DataFrame Operations (2/2)

- ▶ Domain-specific language for structured data manipulation.

```
// Select everybody, but increment the age by 1
df.select(df("name"), df("age") + 1).show()
// name      (age + 1)
// Michael null
// Andy      31
// Justin   20

// Select people older than 21
df.filter(df("age") > 21).show()
// age name
// 30 Andy

// Count people by age
df.groupBy("age").count().show()
// age count
// null 1
// 19 1
// 30 1
```


Running SQL Queries Programmatically

- ▶ Running **SQL queries programmatically** and returns the result as a DataFrame.
- ▶ Using the `sql` function on a `SQLContext`.

```
val sqlContext = ... // An existing SQLContext
val df = sqlContext.sql("SELECT * FROM table")
```

Converting RDDs into DataFrames

- ▶ Inferring the schema using [reflection](#).

```
// Define the schema using a case class.
case class Person(name: String, age: Int)

// Create an RDD of Person objects and register it as a table.
val people = sc.textFile(...).map(_.split(","))
                .map(p => Person(p(0), p(1).trim.toInt)).toDF()
people.registerTempTable("people")

// SQL statements can be run by using the sql methods provided by sqlContext.
val teenagers = sqlContext
    .sql("SELECT name, age FROM people WHERE age >= 13 AND age <= 19")

// The results of SQL queries are DataFrames.
teenagers.map(t => "Name: " + t(0)).collect().foreach(println)
teenagers.map(t => "Name: " + t.getAs[String]("name")).collect()
                .foreach(println)
```

Spark Streaming

- ▶ 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
 - ...

- ▶ Database Management Systems (DBMS): **data-at-rest** analytics
 - **Store** and **index** data before processing it.
 - Process data only when **explicitly** asked by the users.

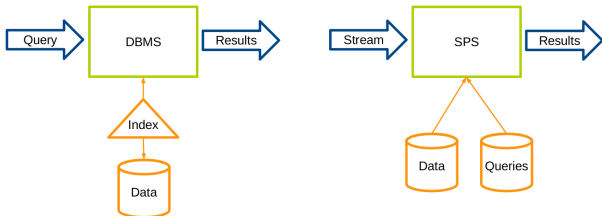
Stream Processing Systems

- ▶ Database Management Systems (DBMS): **data-at-rest** analytics
 - Store and index data before processing it.
 - Process data only when explicitly asked by the users.

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

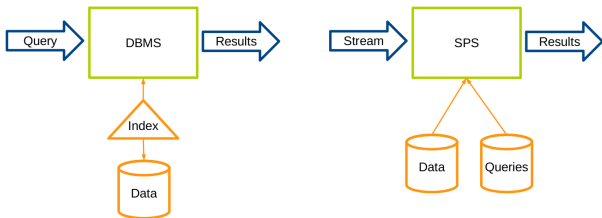
DBMS vs. SPS (1/2)

- ▶ **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**.

Spark Streaming

- ▶ Run a streaming computation as a **series** of very **small, deterministic batch** jobs.



Spark Streaming

- ▶ Run a streaming computation as a **series** of very **small, deterministic batch** jobs.
 - **Chop up** the live stream into batches of **X** seconds.



Spark Streaming

- ▶ Run a streaming computation as a **series** of very **small, deterministic batch** jobs.
 - **Chop up** the live stream into batches of **X** seconds.
 - Spark treats each batch of data as **RDDs** and processes them using **RDD operations**.



Spark Streaming

- ▶ Run a streaming computation as a **series** of very **small, deterministic batch** jobs.
 - **Chop up** the live stream into batches of **X** seconds.
 - Spark treats each batch of data as **RDDs** and processes them using **RDD operations**.
 - Finally, the processed results of the RDD operations are returned in **batches**.



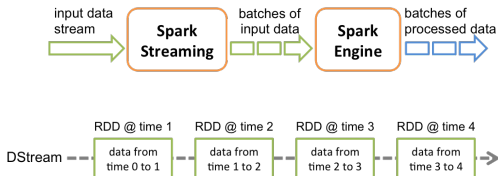
Spark Streaming

- ▶ Run a streaming computation as a **series** of very **small, deterministic batch** jobs.
 - **Chop up** the live stream into batches of **X** seconds.
 - Spark treats each batch of data as **RDDs** and processes them using **RDD operations**.
 - Finally, the processed results of the RDD operations are returned in **batches**.
 - Discretized Stream Processing (**DStream**)



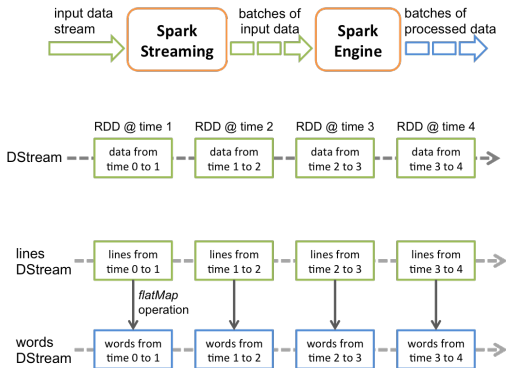
DStream

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



DStream

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



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

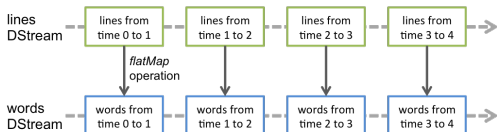
DStream Transformation Example

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

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

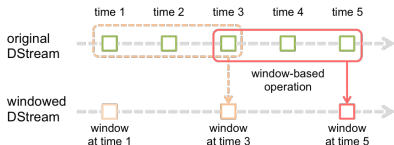
val words = lines.flatMap(_.split(" "))
val pairs = words.map(word => (word, 1))
val wordCounts = pairs.reduceByKey(_ + _)

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

```
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")

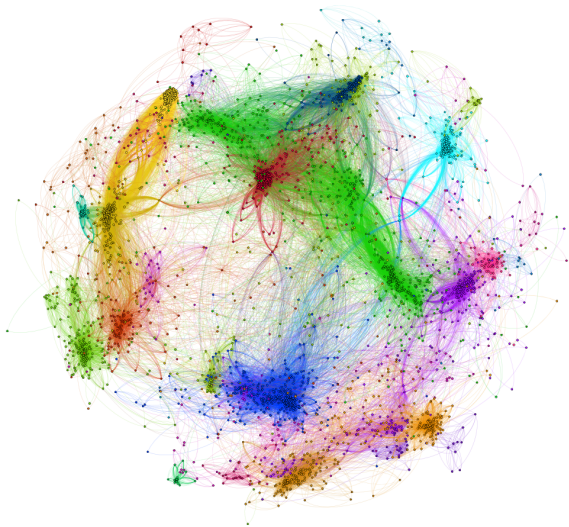
  // Do word count on DataFrame using SQL and print it
  val wordCountsDataFrame =
    sqlContext.sql("select word, count(*) as total from words group by word")
  wordCountsDataFrame.show()
}
```


GraphX

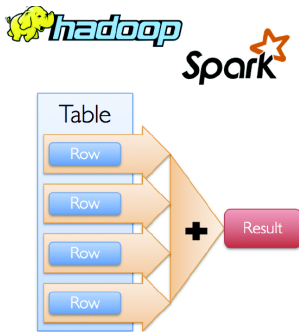


- ▶ **Graphs** provide a **flexible abstraction** for describing relationships between **discrete objects**.
- ▶ Many problems can be **modeled by graphs** and solved with appropriate **graph algorithms**.

Large Graph



Can we use platforms like [MapReduce](#) or [Spark](#), which are based on **data-parallel** model, for large-scale graph proceeding?

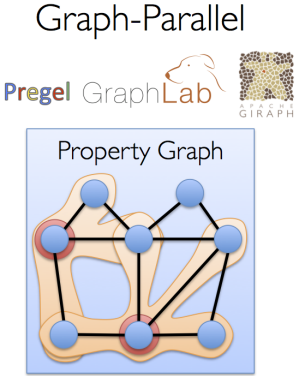
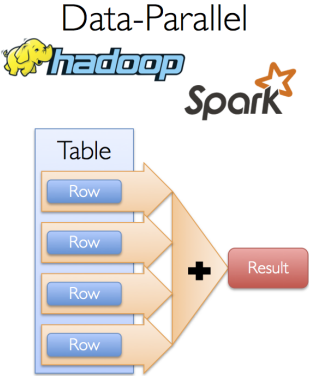


Graph-Parallel Processing

- ▶ **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)

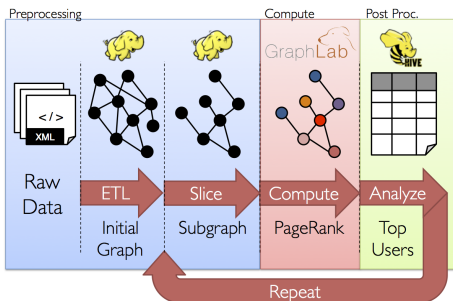


Data-Parallel vs. Graph-Parallel Computation (2/3)

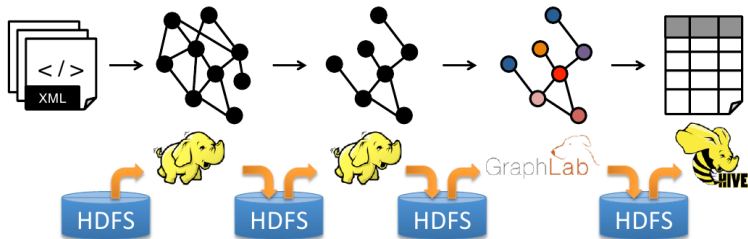
- ▶ **Graph-parallel** computation: **restricting** the types of computation to achieve **performance**.

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**.

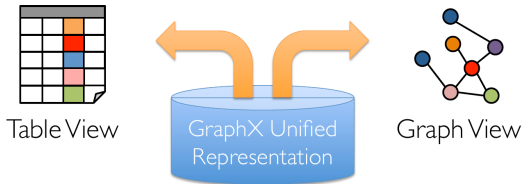


Data-Parallel vs. Graph-Parallel Computation (3/3)

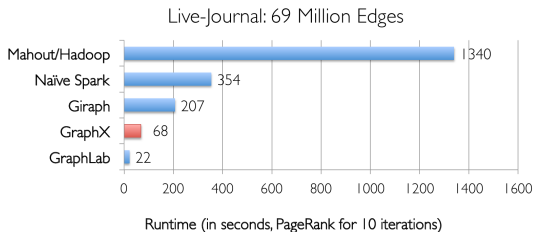


- ▶ **Moving** between **table** and **graph** views of the **same physical data**.
- ▶ **Inefficient**: extensive **data movement** and **duplication** across the network and file system.

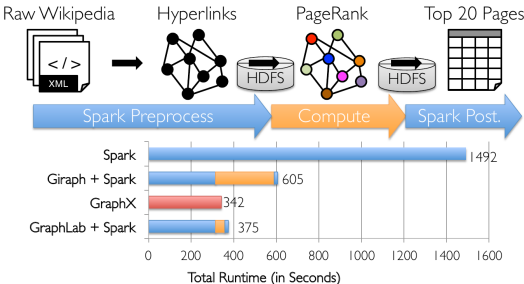
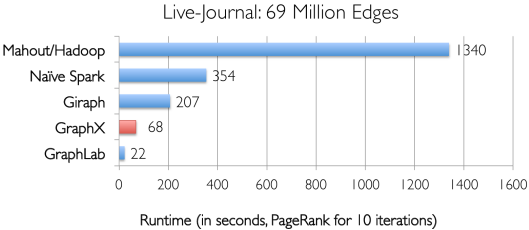
- ▶ Unifies **data-parallel** and **graph-parallel** systems.
- ▶ **Tables** and **Graphs** are **composable views** of the same physical data.
- ▶ Implemented on top of **Spark**.



GraphX vs. Data-Parallel/Graph-Parallel Systems



GraphX vs. Data-Parallel/Graph-Parallel Systems

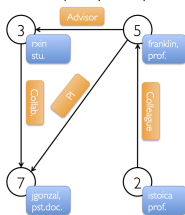


Property Graph

► Represented using **two** Spark **RDDs**:

- **Edge collection**: VertexRDD
- **Vertex collection**: EdgeRDD

Property Graph



Vertex Table

Id	Property (V)
3	(non, student)
7	(gonzal, 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

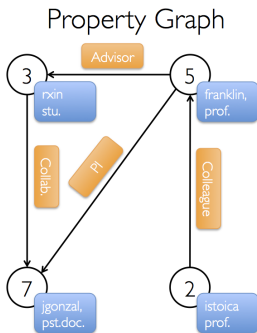
```
// VD: the type of the vertex attribute
// ED: the type of the edge attribute
class Graph[VD, ED] {
  val vertices: VertexRDD[VD]
  val edges: EdgeRDD[ED]
}
```

Triplets

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



Example Property Graph (1/3)



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

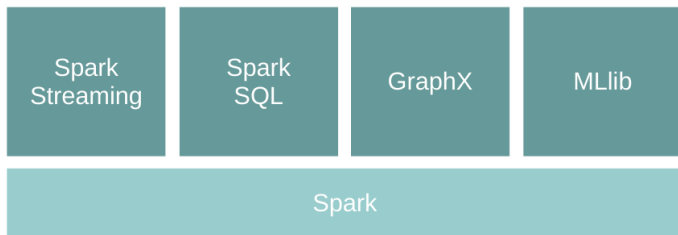
```
def aggregateMessages[Msg: ClassTag](
  sendMsg: EdgeContext[VD, ED, Msg] => Unit, // map
  mergeMsg: (Msg, Msg) => Msg, // reduce
  tripletFields: TripletFields = TripletFields.All):
  VertexRDD[Msg]
```

```
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



Questions?