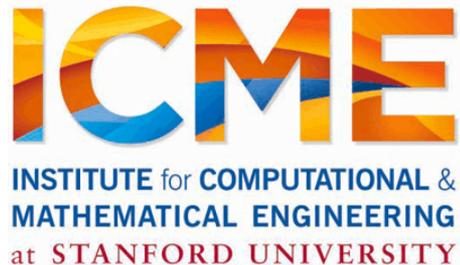


Communication Patterns

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Outline

Shipping code to the cluster

Shuffling

Broadcasting

Other programming languages

Outline

Shipping code to the cluster

Life of a Spark Program

- 1) Create some input RDDs from external data or parallelize a collection in your driver program.
- 2) Lazily **transform** them to define new RDDs using transformations like `filter()` or `map()`
- 3) Ask Spark to `cache()` any intermediate RDDs that will need to be reused.
- 4) Launch **actions** such as `count()` and `collect()` to kick off a parallel computation, which is then optimized and executed by Spark.

Example Transformations

`map()`

`intersection()`

`cartesion()`

`flatMap()`

`distinct()`

`pipe()`

`filter()`

`groupByKey()`

`coalesce()`

`mapPartitions()`

`reduceByKey()`

`repartition()`

`mapPartitionsWithIndex()`

`sortByKey()`

`partitionBy()`

`sample()`

`join()`

`...`

`union()`

`cogroup()`

`...`

Example Actions

`reduce()`

`collect()`

`count()`

`first()`

`take()`

`takeSample()`

`saveToCassandra()`

`takeOrdered()`

`saveAsTextFile()`

`saveAsSequenceFile()`

`saveAsObjectFile()`

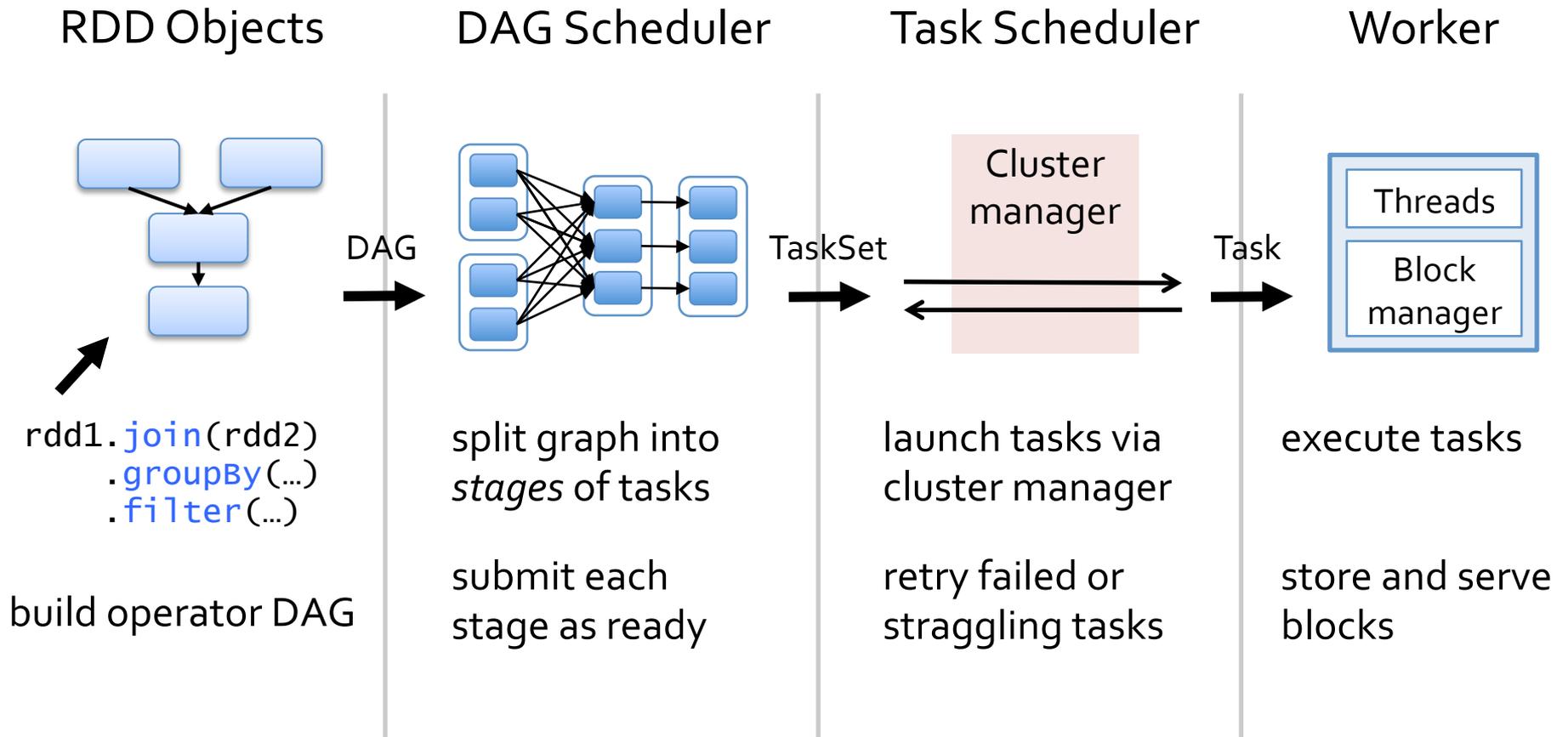
`countByKey()`

`foreach()`

`...`

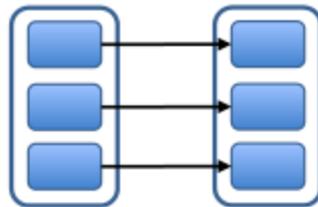
Sending your code to the cluster

RDD → Stages → Tasks

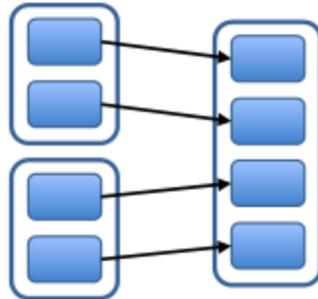


Communication Patterns

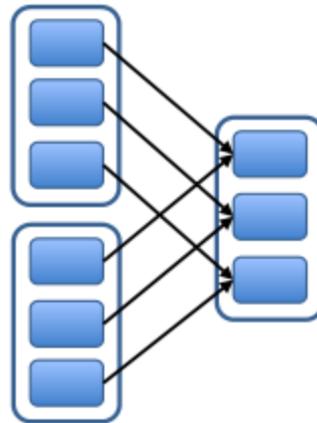
Narrow Dependencies:



map, filter

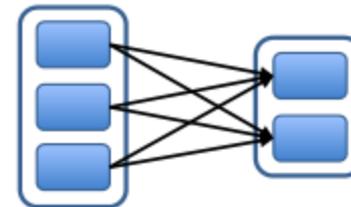


union

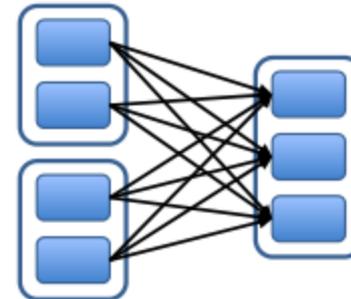


join with inputs
co-partitioned

Wide Dependencies:

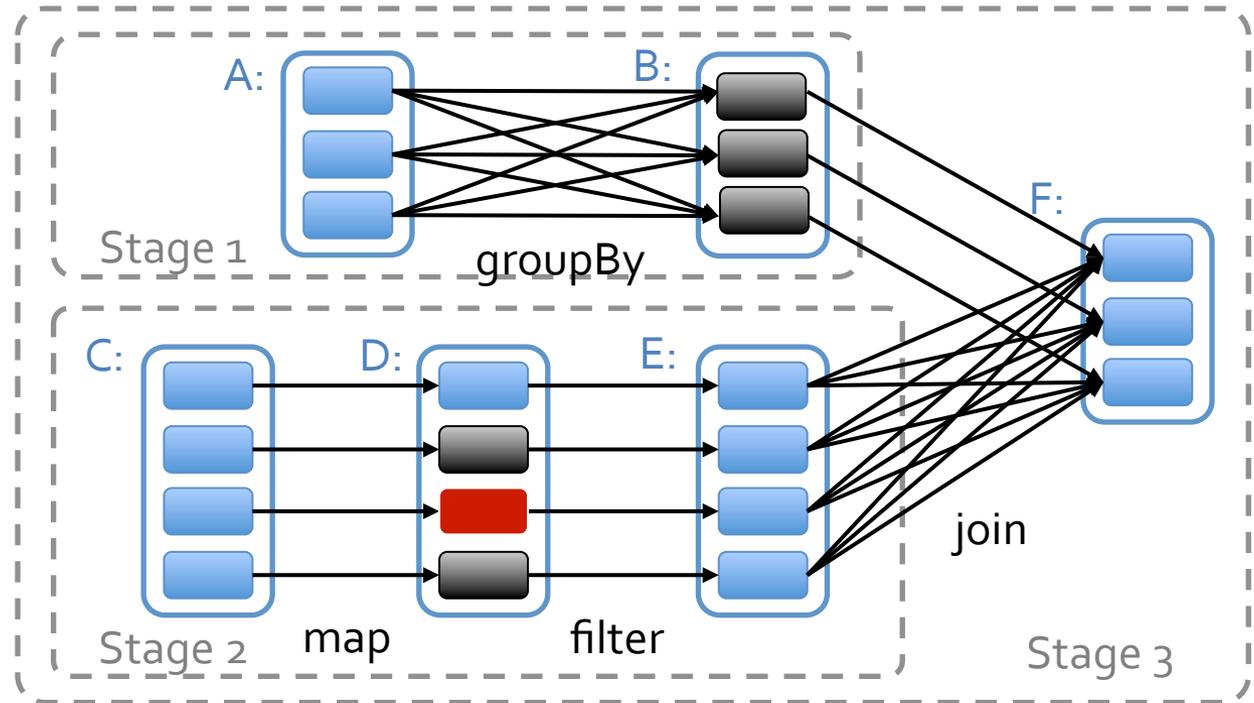
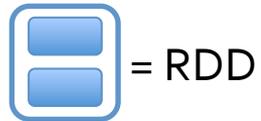


groupByKey



join with inputs not
co-partitioned

Example Stages



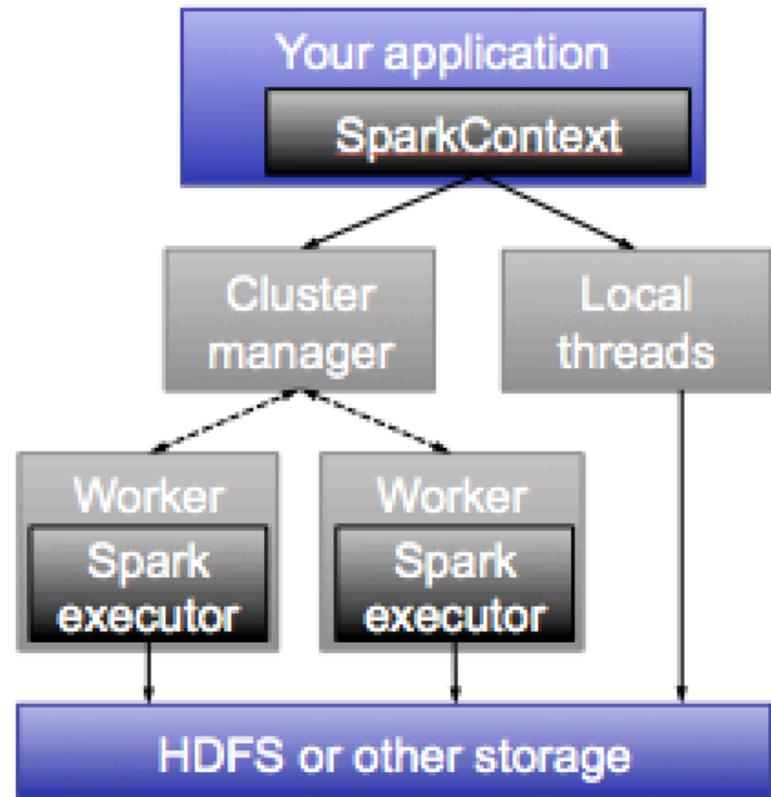
Talking to Cluster Manager

Manager can be:

YARN

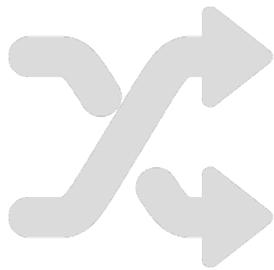
Mesos

Spark Standalone



Shuffling

Shuffle



=

groupByKey

sortByKey

reduceByKey

Sort: use advances in sorting single-machine memory-disk operations for all-to-all communication

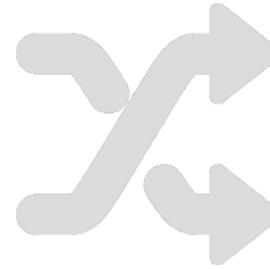
Sorting

Distribute Timsort, which is already well-adapted to respecting disk vs memory

Sample points to find good boundaries

Each machines sorts locally and builds an index

Sorting (shuffle)



	Hadoop World Record	Spark 100 TB *	Spark 1 PB
Data Size	102.5 TB	100 TB	1000 TB
Elapsed Time	72 mins	23 mins	234 mins
# Nodes	2100	206	190
# Cores	50400	6592	6080
# Reducers	10,000	29,000	250,000
Rate	1.42 TB/min	4.27 TB/min	4.27 TB/min
Rate/node	0.67 GB/min	20.7 GB/min	22.5 GB/min
Sort Benchmark Daytona Rules	Yes	Yes	No
Environment	dedicated data center	EC2 (i2.8xlarge)	EC2 (i2.8xlarge)

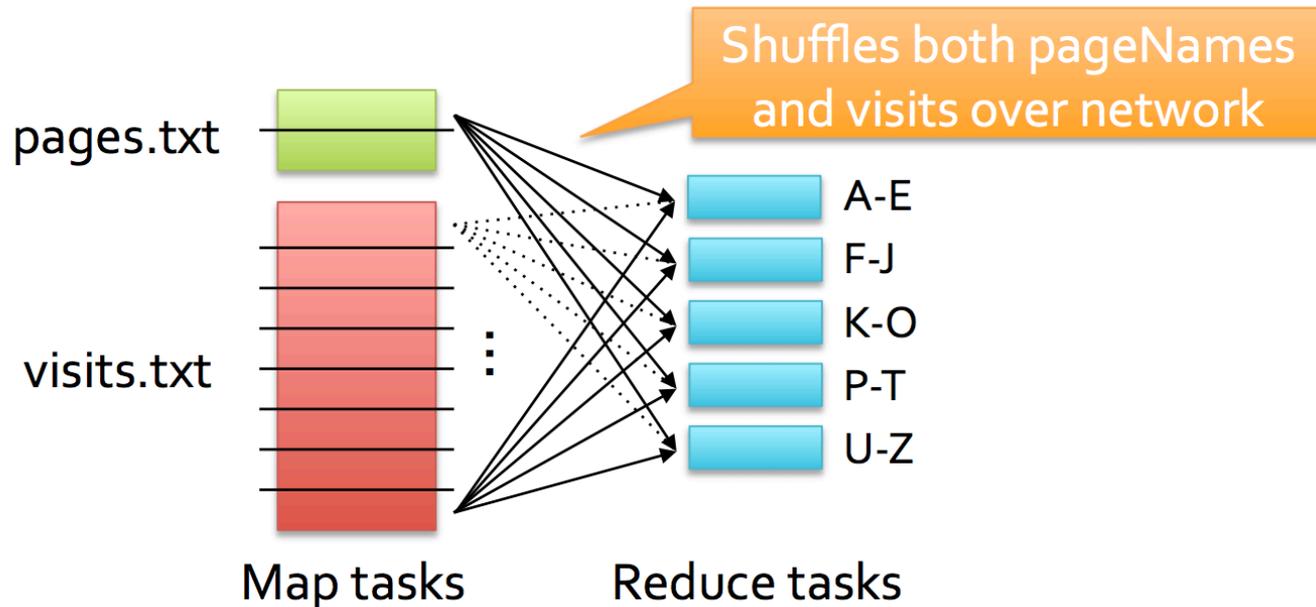
Distributed TimSort

Example Join

```
// Load RDD of (URL, name) pairs  
val pageNames = sc.textFile("pages.txt").map(...)
```

```
// Load RDD of (URL, visit) pairs  
val visits = sc.textFile("visits.txt").map(...)
```

```
val joined = visits.join(pageNames)
```



Broadcasting

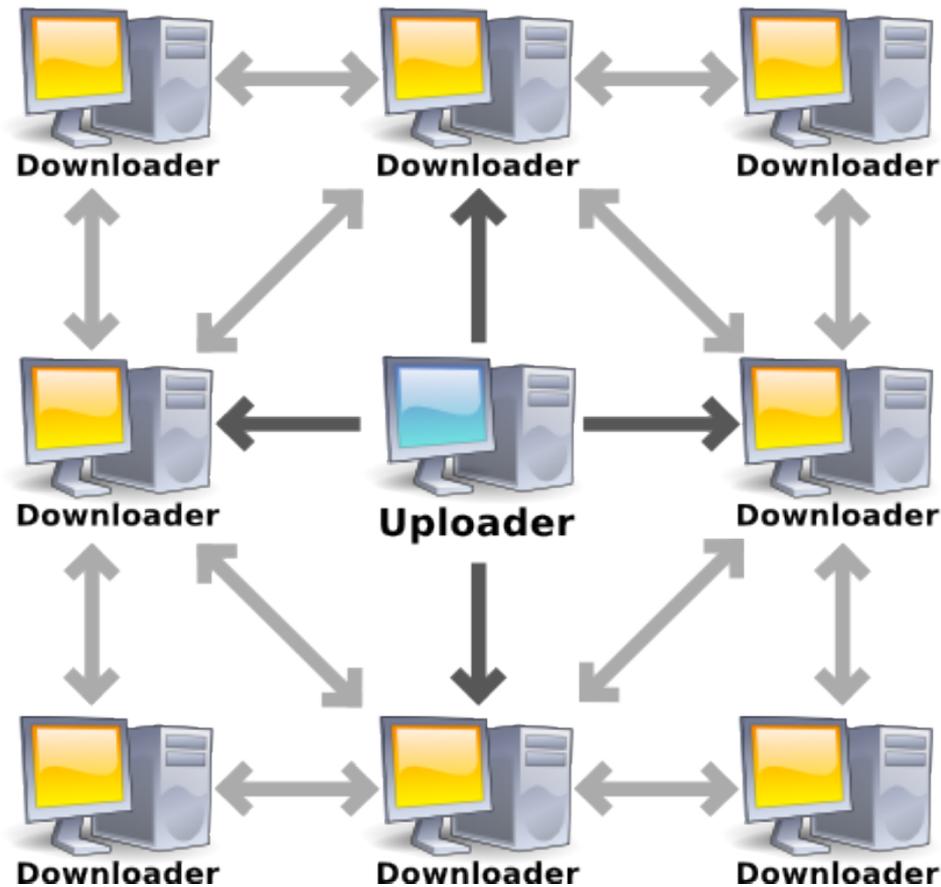
Broadcasting

Often needed to propagate current guess for optimization variables to all machines

The exact wrong way to do it is with “one machines feeds all” – use bit-torrent instead

Needs $\log(n)$ rounds of communication

Bit-torrent Broadcast



Broadcast Rules

Create with `SparkContext.broadcast(initialVal)`

Access with `.value` inside tasks (first task on each node to use it fetches the value)

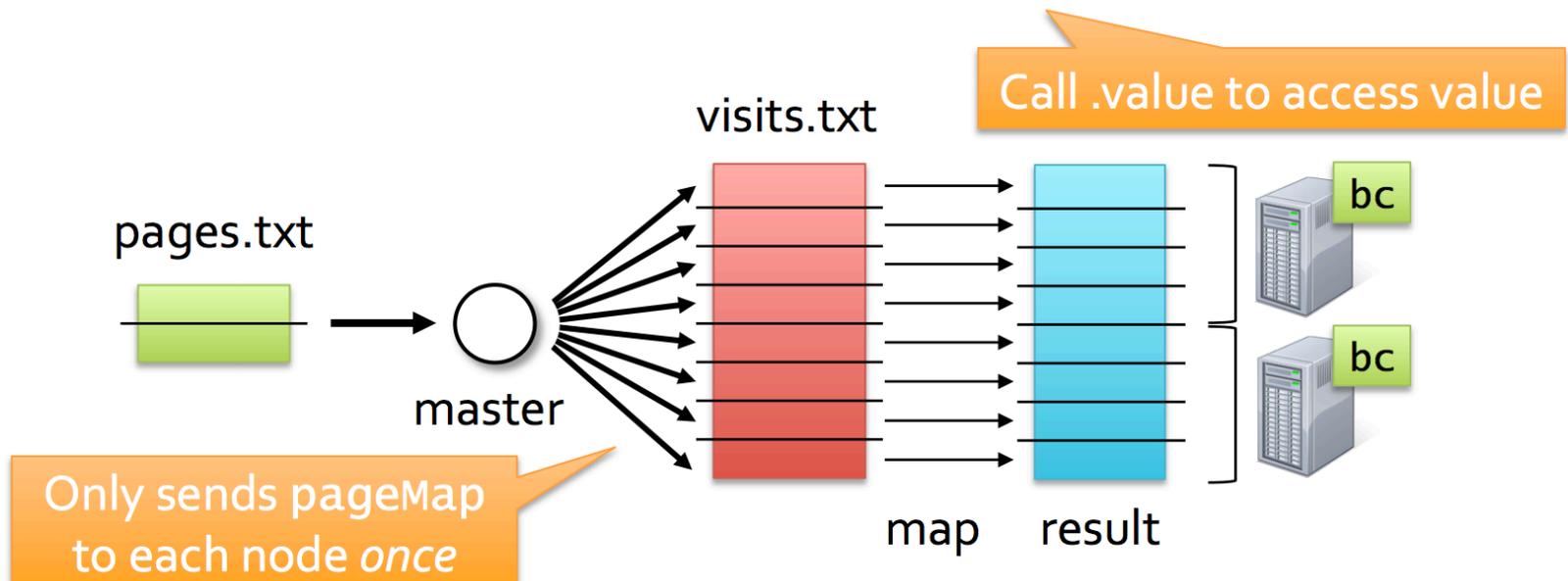
Cannot be modified after creation

Replicated Join

```
val pageNames = sc.textFile("pages.txt").map(...)
val pageMap = pageNames.collect().toMap()
val bc = sc.broadcast(pageMap)
val visits = sc.textFile("visits.txt").map(...)
val joined = visits.map(v => (v._1, (bc.value(v._1), v._2)))
```

Type is Broadcast[Map[...]]

Call .value to access value



Model Broadcast

$$w \leftarrow w - \alpha \cdot \sum_{i=1}^n g(w; x_i, y_i)$$

```
val points = spark.textFile(...).map(parsePoint).cache()
var w = Vector.zeros(d)
for (i <- 1 to numIterations) {
  val gradient = points.map { p =>
    (1 / (1 + exp(-p.y * w.dot(p.x))) - 1) * p.y * p.x
  }.reduce(_ + _)
  w -= alpha * gradient
}
```

Model Broadcast

$$w \leftarrow w - \alpha \cdot \sum_{i=1}^n g(w; x_i, y_i)$$

Call sc.broadcast

```
val points = spark.textFile(...).map(parsePoint).cache()
var w = Vector.zeros(d)
for (i <- 1 to numIterations) {
  val gradient = points.map { p =>
    (1 / (1 + exp(-p.y * w.dot(p.x)) - 1) * p.y * p.x
  ).reduce(_ + _)
  w -= alpha * gradient
}
```

Use via .value

Spark for Python (PySpark)

PySpark and Pipes

Spark core is written in Scala

PySpark calls existing scheduler, cache and networking layer (2K-line wrapper)

No changes to Python

