Motivation

Recall from first lecture that network bandwidth is ~100× as expensive as memory bandwidth

One way Spark avoids using it is through locality-aware scheduling for RAM and disk

Another important tool is controlling the *partitioning* of RDD contents across nodes

Spark PageRank

Given directed graph, compute node importance. Two RDDs:

» Neighbors (a sparse graph/matrix)

» Current guess (a vector)

Best representation for vector and matrix?

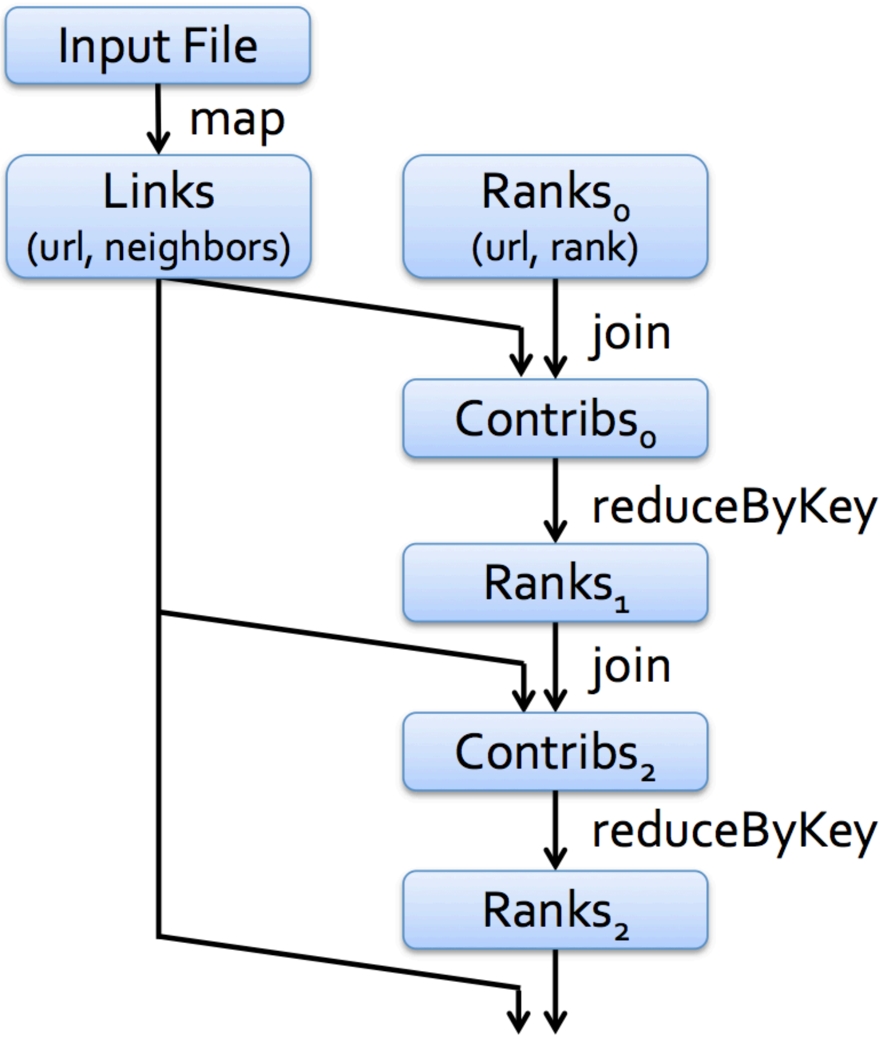
Example

1. Start each page at a rank of 1
2. On each iteration, have page p contribute $rank_p$ / $|neighbors_p|$ to its neighbors
3. Set each page's rank to 0.15 + 0.85 × contribs

```
val links = // RDD of (url, neighbors) pairs
var ranks = // RDD of (url, rank) pairs

for (i <- 1 to ITERATIONS) {
  val contribs = links.join(ranks).flatMap {
    case (url, (links, rank)) =>
      links.map(dest => (dest, rank/links.size))
  }
  ranks = contribs.reduceByKey(_ + _).mapValues(.15 + .85*_)
}
```

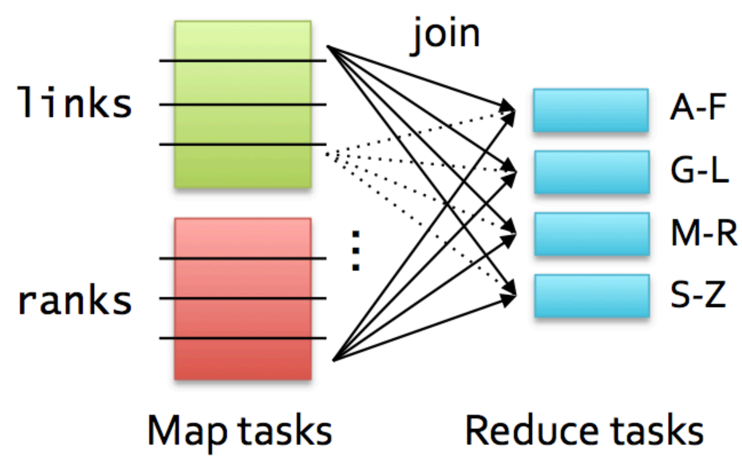
Execution



`links` and `ranks` are repeatedly joined

Each join requires a full shuffle over the network

» Hash both onto same nodes



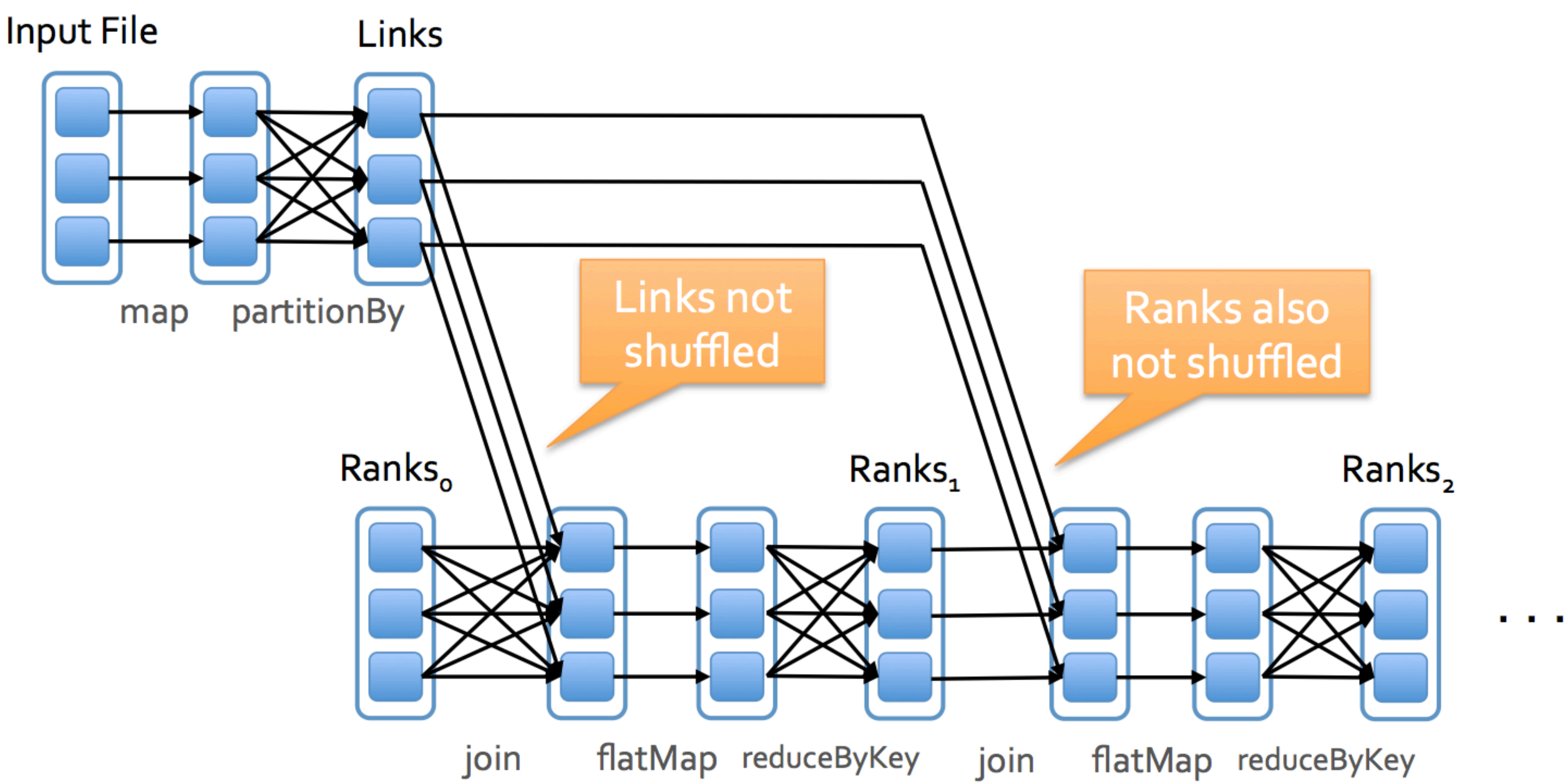
Solution

Pre-partition the `links` RDD so that links for URLs with the same hash code are on the same node

```
val ranks = // RDD of (url, rank) pairs
val links = sc.textFile(...).map(...)
                 .partitionBy(new HashPartitioner(8))

for (i <- 1 to ITERATIONS) {
  ranks = links.join(ranks).flatMap {
    (url, (links, rank)) =>
      links.map(dest => (dest, rank/links.size))
  }.reduceByKey(_ + _)
   .mapValues(0.15 + 0.85 * _)
}
```

New Execution



How it works

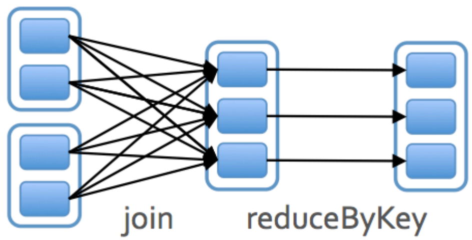
Each RDD has an optional Partitioner object

Any shuffle operation on an RDD with a Partitioner will respect that Partitioner

Any shuffle operation on two RDDs will take on the Partitioner of one of them, if one is set

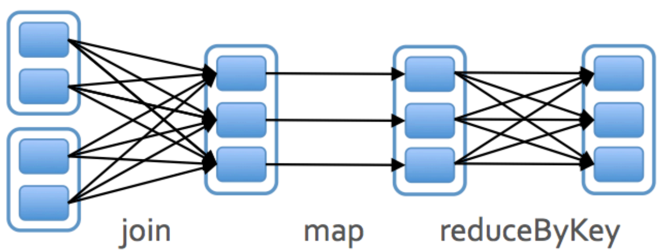
Examples

```
pages.join(visits).reduceByKey(...)
```



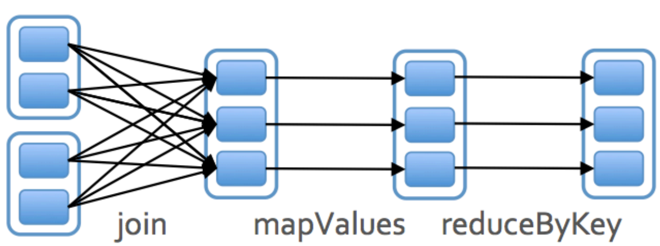
Output of join is already partitioned

```
pages.join(visits).map(...).reduceByKey(...)
```



map loses knowledge about partitioning

```
pages.join(visits).mapValues(...).reduceByKey(...)
```



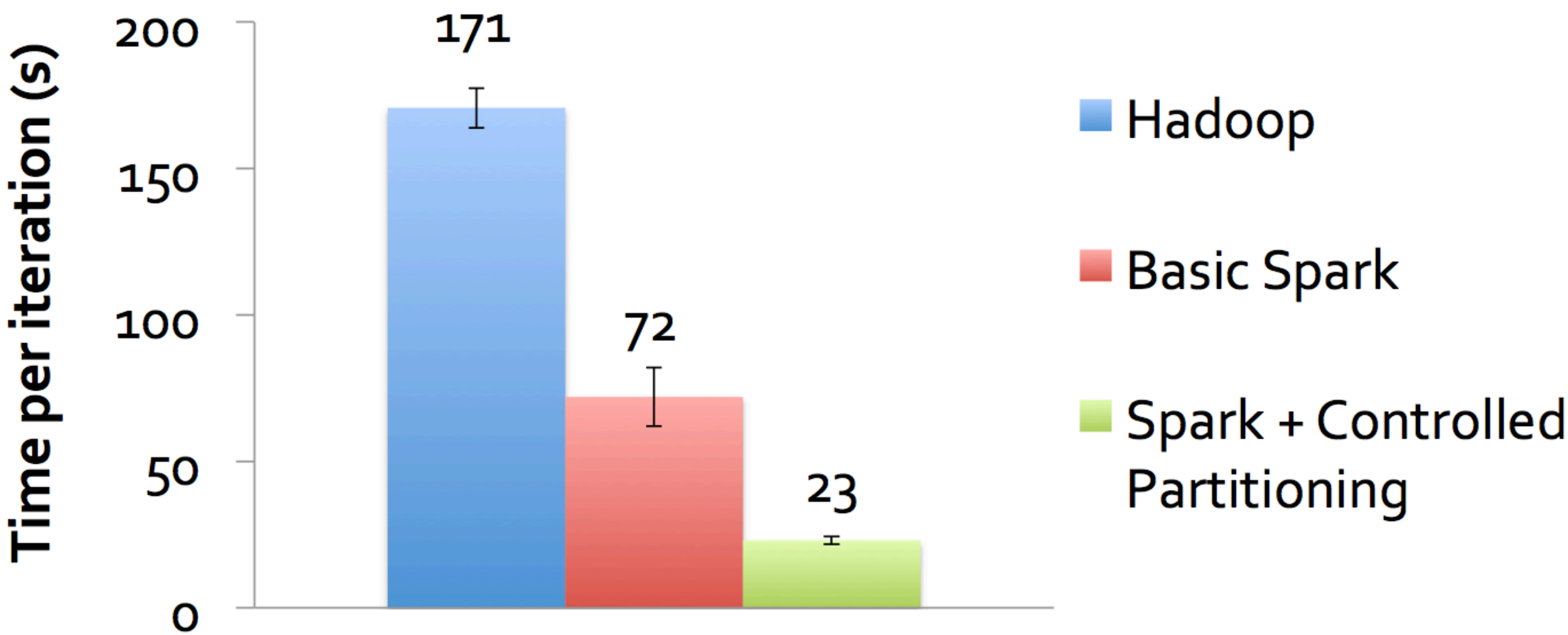
mapValues retains keys unchanged

Main Conclusion

Controlled partitioning can avoid unnecessary all-to-all communication, saving computation

Repeated joins generalizes to repeated Matrix Multiplication, opening many algorithms from Numerical Linear Algebra

Performance



Why it helps so much: `links` RDD is much bigger in bytes than ranks!

RDD partitioner

Use the `.partitioner` method on RDD

```
scala> val a = sc.parallelize(List((1, 1), (2, 2)))
scala> val b = sc.parallelize(List((1, 1), (2, 2)))
scala> val joined = a.join(b)

scala> a.partitioner
res0: Option[Partitioner] = None

scala> joined.partitioner
res1: Option[Partitioner] = Some(HashPartitioner@286d41c0)
```

Custom Partitioning

Can define your own subclass of `Partitioner` to leverage domain-specific knowledge

Example: in PageRank, hash URLs by domain name, because may links are internal

```
class DomainPartitioner extends Partitioner {
  def numPartitions = 20

  def getPartition(key: Any): Int =
    parseDomain(key.toString).hashCode % numPartitions

  def equals(other: Any): Boolean =
    other.isInstanceOf[DomainPartitioner]
}
```

Needed for Spark to tell when two partitioners are equivalent