# Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing

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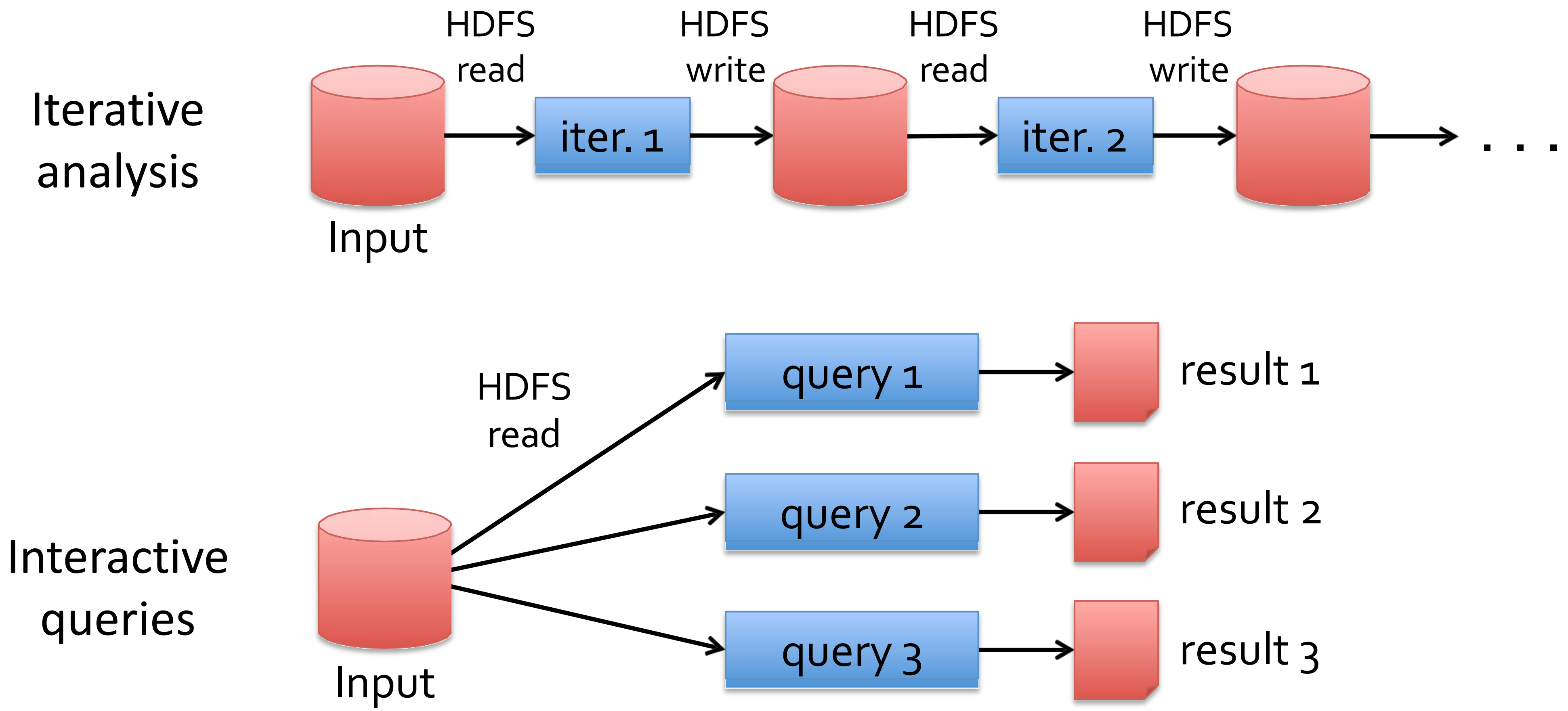
# Background

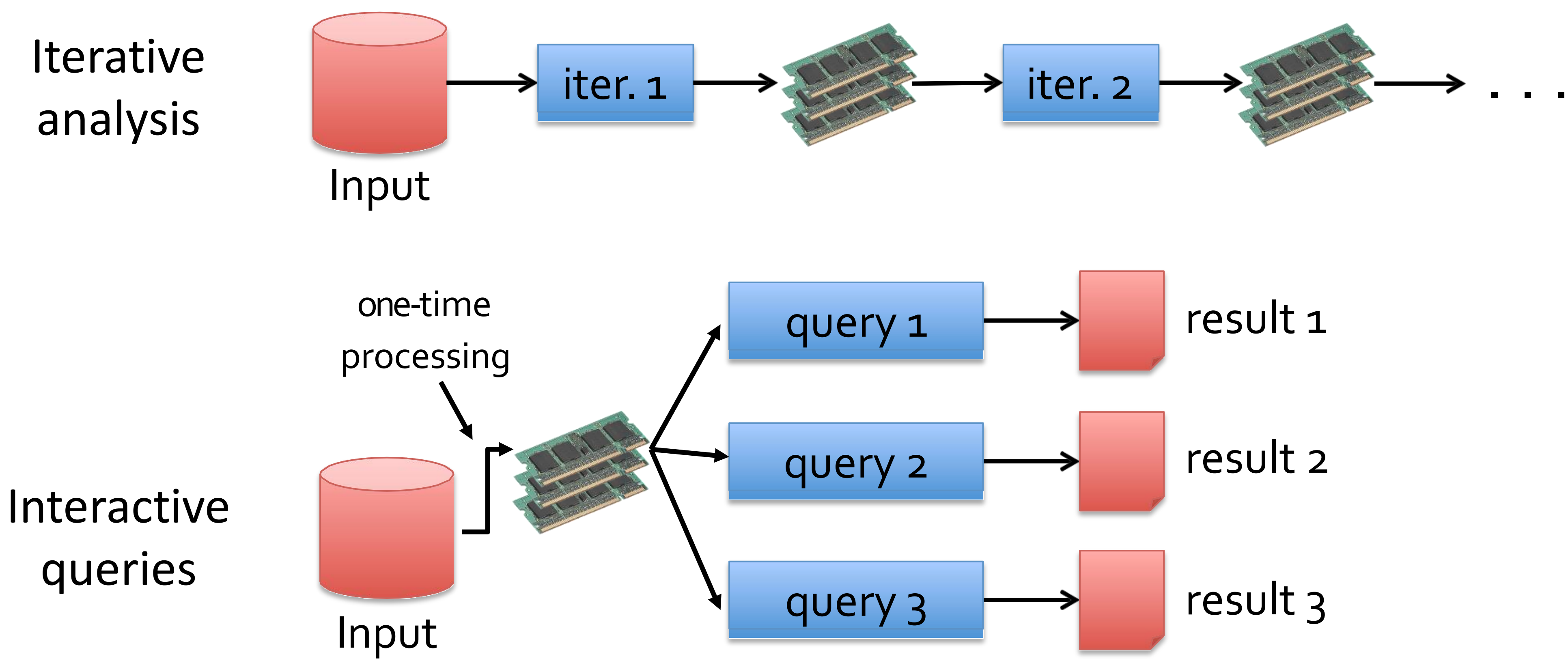
- MapReduce greatly simplified “big data” analysis on large, unreliable clusters
- But as soon as it got popular, users wanted more
  - More complex, iterative multi-stage applications
    - E.g., graph processing, machine learning
  - More interactive ad-hoc queries
- Why not use MapReduce?
  - Iterative and interactive queries require jobs to share data efficiently
  - With MapReduce, the only way to share data across jobs is through disks, which is slow

# MapReduce Example




Slow due to disk I/O and replication,
but necessary for fault tolerance

# Goal: Use Memory to Share Data




10-100× faster than network/disk,
but what about fault-tolerance?

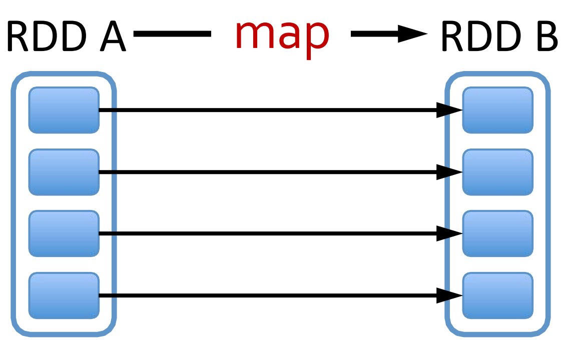
# Challenge With In-Memory Analytics

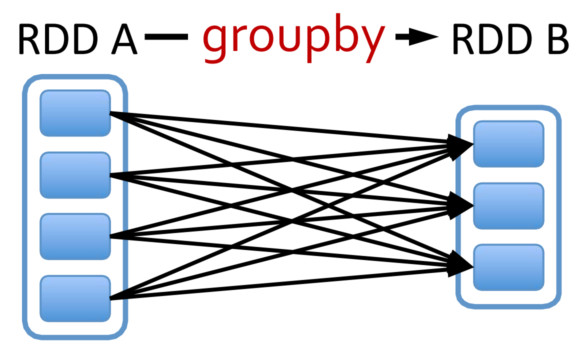
- How to design a distributed memory abstraction that is both efficient and fault-tolerant?

- Existing storage abstractions are based on fine-grained updates to mutable state
  - E.g., Databases, distributed shared memory, etc.
  - Require replicating data/logs for fault tolerance
    - Costly for data-intensive apps
    - 10-100x slower than memory writes

# Solution: Resilient Distributed Datasets (RDDs)

- RDDs are immutable, partitioned collections of records
- Support coarse-grained, deterministic , data-parallel transformations (map, filter, reduce, join, groupby, …)




- A restricted form of distributed memory abstraction that enables efficient fault-tolerance
  - During normal operation, log transformations (input logging)
  - On failure, re-execute the deterministic transformations needed to recover lost partitions of RDDs

# Generality of RDDs

- RDDs can express many parallel algorithms that apply the same operation to many items
- Unify many current programming models
    - Data flow models: MapReduce, Dryad, SQL, …
    - Specialized models for iterative apps: BSP (Pregel), iterative MapReduce (Haloop), …
- Support new applications beyond these models

# Spark Programming Interface

- Operations on RDDs
  - Transformations - create new RDDs
  - Actions - compute and output results
- Programmers can control partitioning
  - How data in RDD is partitioned across nodes
- Programmers can control persistence
  - Whether partitions are stored in RAM, disk, etc.

# Example: Log Mining

- Load error messages from a log into memory, then interactively search for various patterns

```
lines = spark.textFile("hdfs://...")

errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split('\t')(2))
messages.persist()

messages.filter(_.contains("foo")).count
messages.filter(_.contains("bar")).count
```

Base RDD

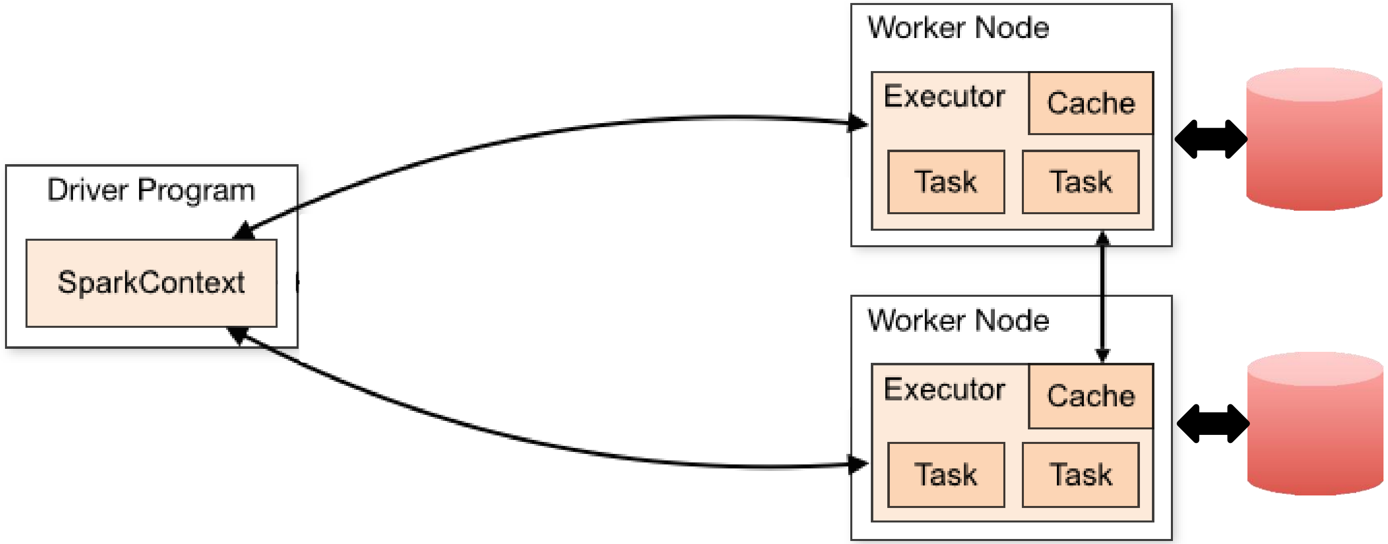
Transformed RDDs

Actions

Results: scaled to 1 TB of data in 5-7 seconds (vs 170 s for on-disk data)

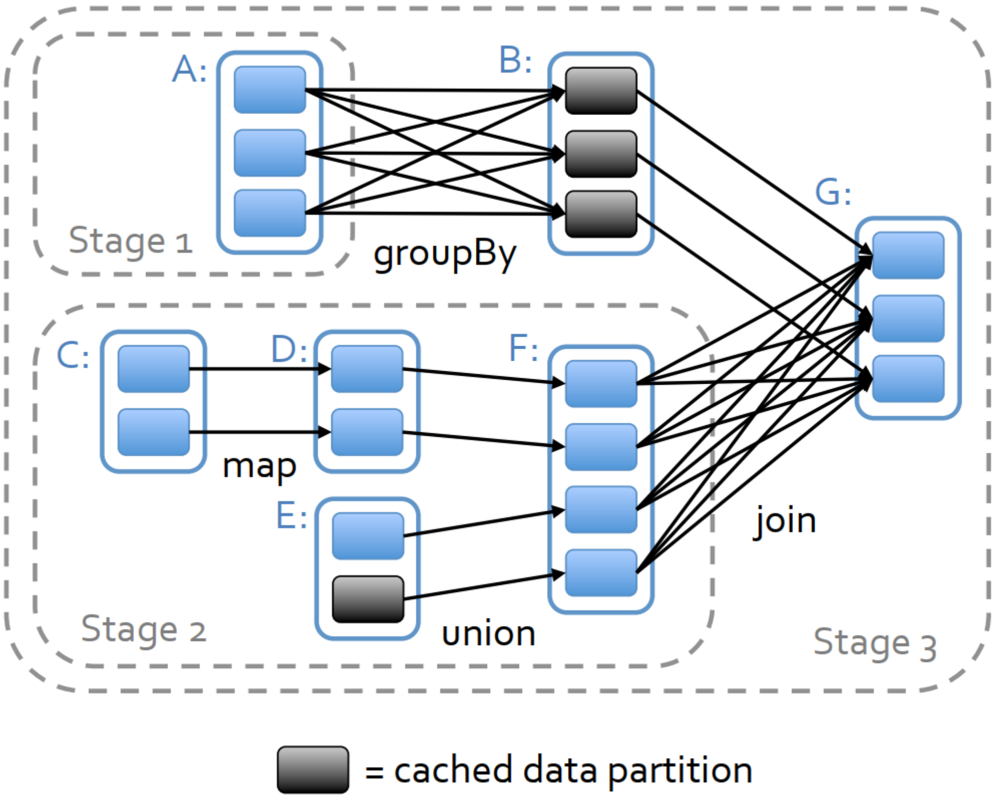
# Architecture

- Spark app runs a driver program (master) and one or more executor programs on worker nodes
- Executors access input data blocks, perform data transformations on data partitions, and store outputs
- A cluster manager allocates resources (e.g., worker nodes) to different Spark apps



# Implementation

- RDD nodes are grouped into stages
  - Stages are connected by shuffle-type operations (e.g., groupBy, reduce)
- Within each stage, transformations are:
  - Partition-aware
    - Avoids shuffles
  - Pipelined
    - Provides better locality



# Tracking Lineage

- RDDs track their lineage, i.e., the graph of transformations that built them

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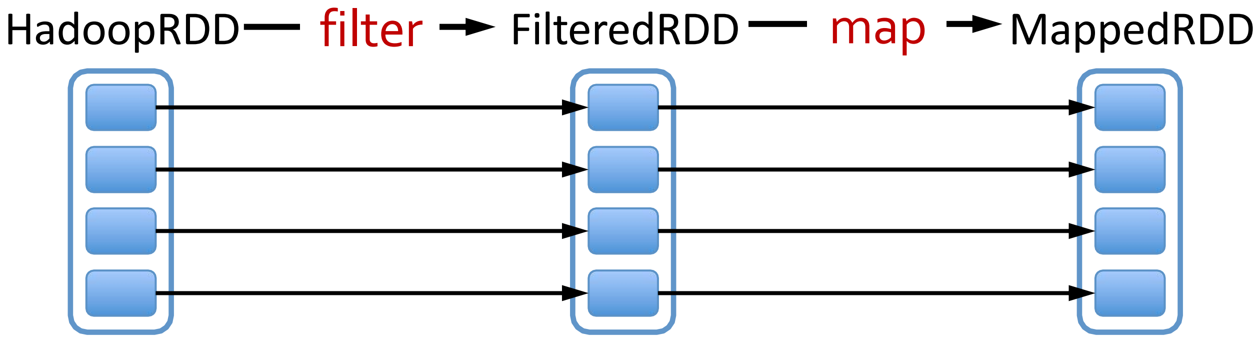

# Failure Recovery with Lineage

- Tracking lineage enables selectively recovering data partitions on failure

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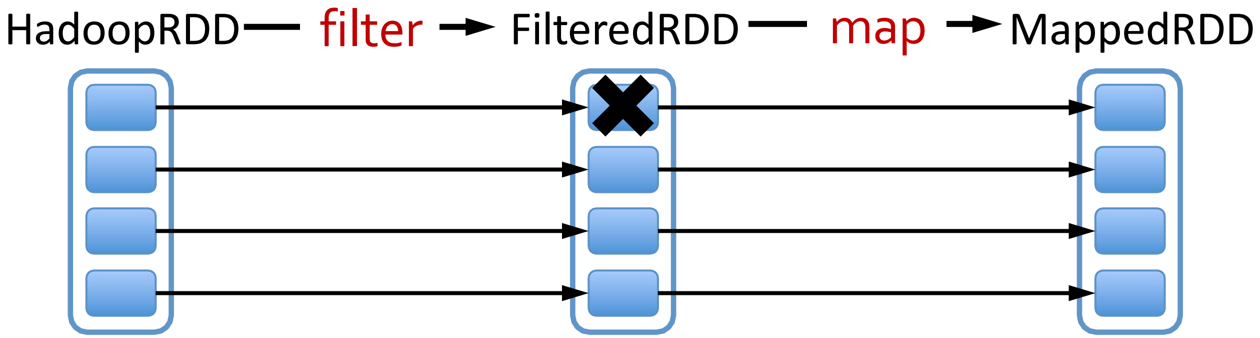

# Failure Recovery with Lineage

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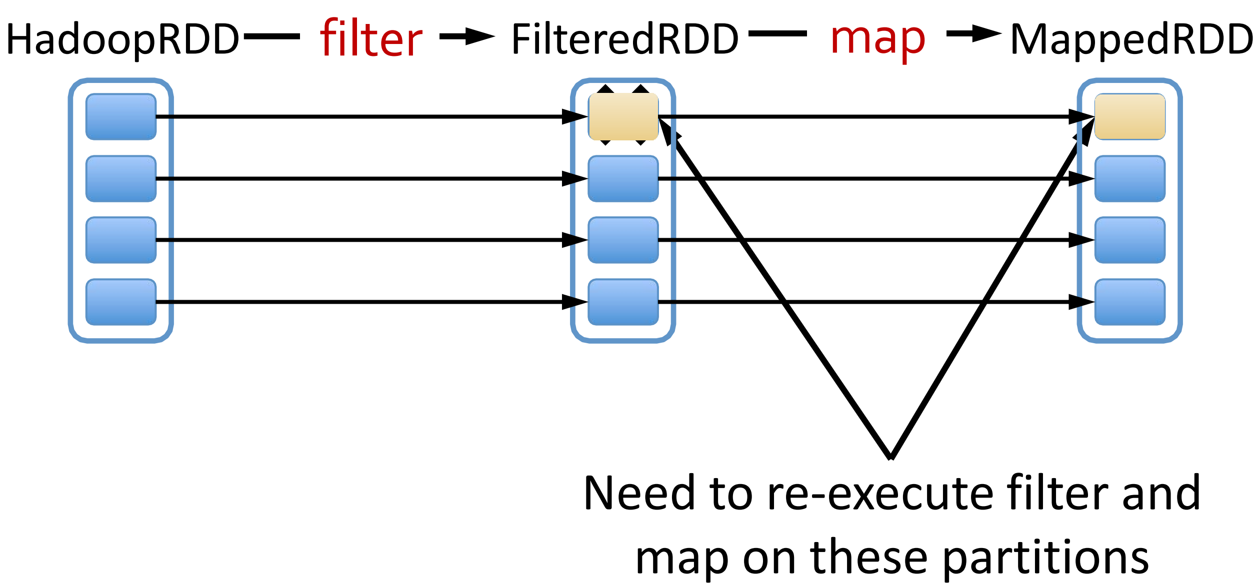
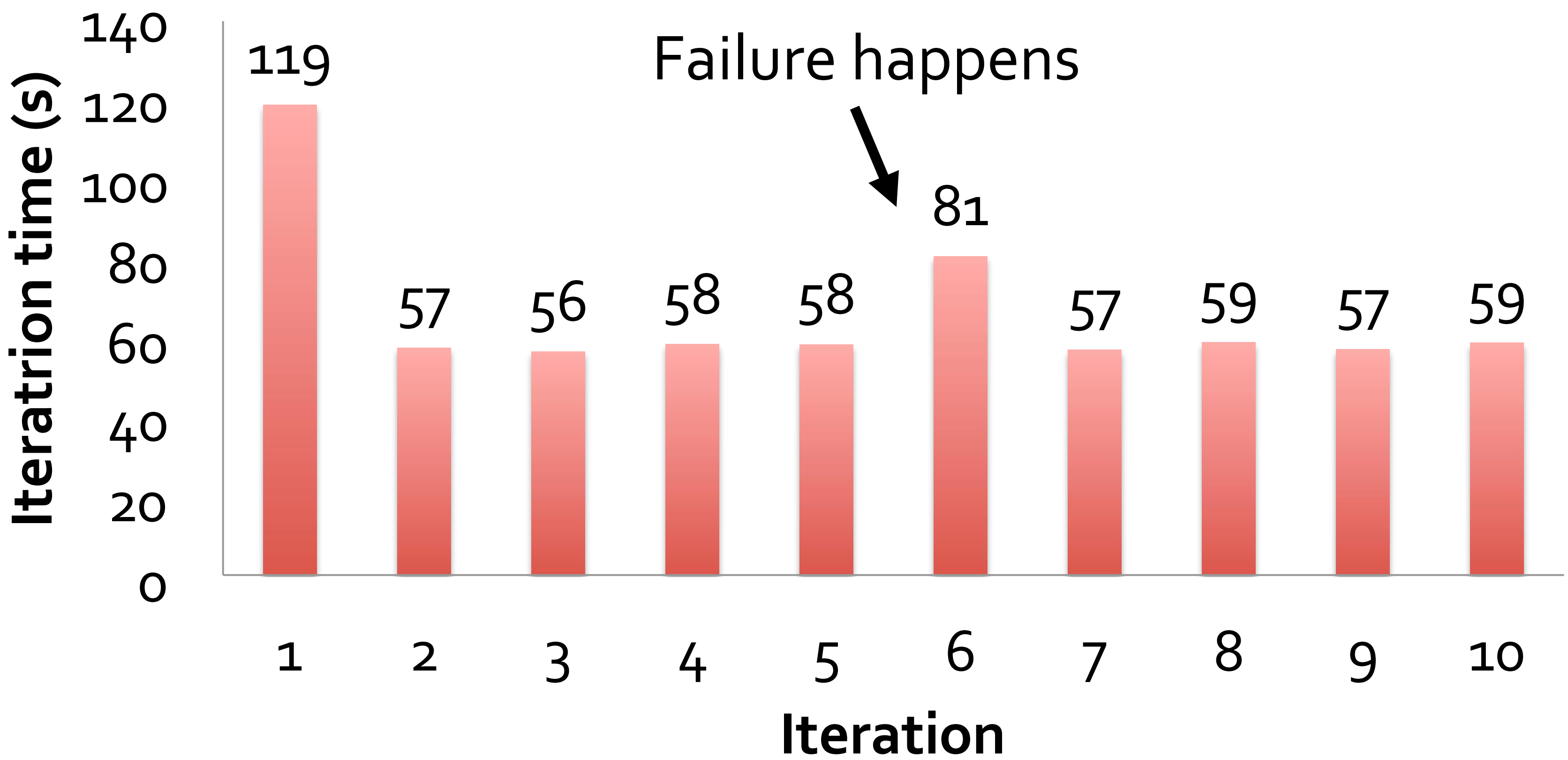


# Fault Recovery Results



# Example: PageRank (simplified)

- Start each page with a rank of 1
- On each iteration, update each page's rank to:

$$\Sigma_{i \in neighbors} (rank_i / |neighbors_i|)$$

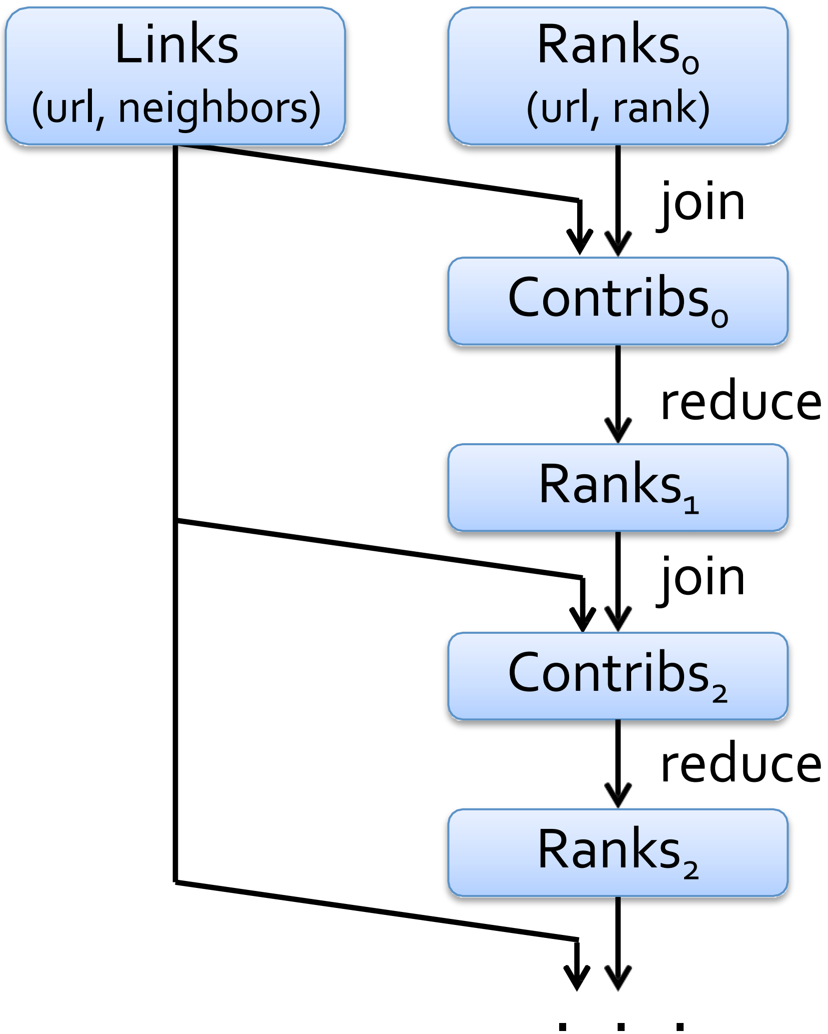
```
links = // RDD of (url, neighbors) pairs
ranks = // RDD of (url, rank) pairs

for (i <- 1 to ITERATIONS) {
  // map operation
  contribs = links.join(ranks).flatMap {
    (url, (nbrs, rank)) =>
        nbrs.map(neighbor => (neighbor, rank/nbrs.size))
  }
  // shuffle operation
  ranks = contribs.reduceByKey(_ + _)
}
```

# Example: PageRank

```
// input: RDD of (url, outgoing neighbors) pairs
links = {(url1, (url2, url3, url4)),
         (url2, (url3, url4)),
         (url3, (url4)),
         (url4, ())}

// output at start of iteration: RDD of (url, rank) pairs
ranks = {(url1, R1),
         (url2, R2),
         (url3, R3),
         (url4, R4)}

// contributions from incoming neighbors
contribs = {(url2, R1/3), (url3, R1/3), (url4, R1/3),
            (url3, R2/2), (url4, R2/2),
            (url4, R3/1)}

// shuffle operation, output at end of iteration
ranks = {(url2, R1/3), (url3, R1/3+R2/2), (url4, R1/3+R2/2+R3/1)}
```

# Optimizing Placement

- `links` & `ranks` are repeatedly joined
- Can co-partition them to avoid shuffles
  - E.g., hash by URL
  - Can also use app knowledge, e.g., partition by domain name



# PageRank, Optimized Placement

```
// input: RDD of (url, outgoing neighbors) pairs
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// output at start of iteration: RDD of (url, rank) pairs
ranks = {(url1, R1),
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// contributions from incoming neighbors
contribs = {(url2, R1/3), (url3, R1/3), (url4, R1/3),
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// shuffle operation, output at end of iteration
ranks = {(url2, R1/3), (url3, R1/3+R2/2), (url4, R1/3+R2/2+R3/1)}
```
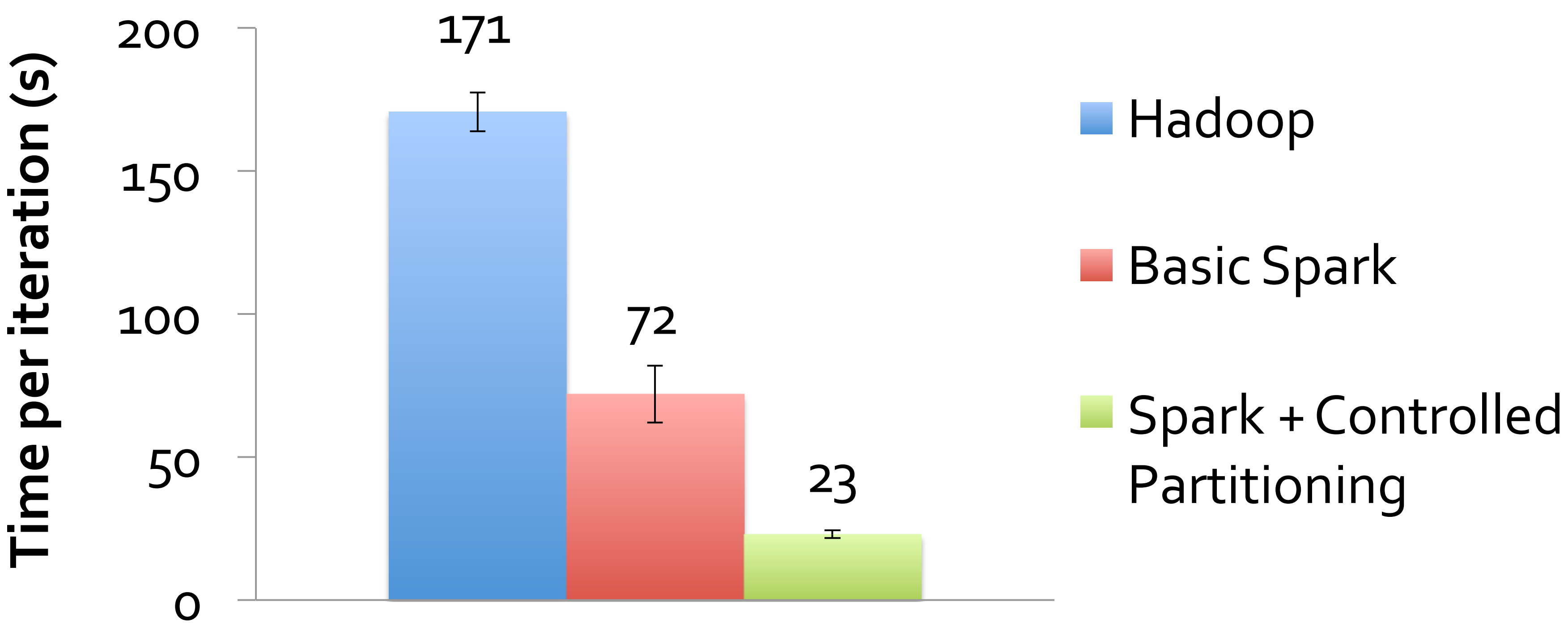

# PageRank Performance



# Conclusion

- RDDs offer a simple and efficient programming model for a broad range of applications
- Leverage the coarse-grained nature of many parallel algorithms for low-overhead recovery

# Discussion

# Q1

- Why does Spark require using immutable data structures and deterministic transformations?

# Q2

- Why does the paper argue that Spark has minimal cost when nothing fails? Is this correct?

# Q3

- What are the types of applications for which Spark is suitable?

# Q4

- What are the types of applications for which Spark is not suitable?

# Q5

- What problems can arise when transformations cause skew? How can these problems be handled?