MapReduce and Spark (and MPI) (Lecture 22, cs262a)

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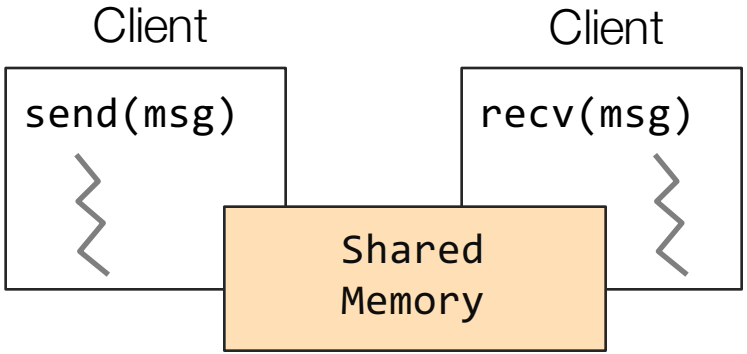
Context (1970s—1990s)

Supercomputers the pinnacle of computation

- Solve important science problems, e.g.,
  - Airplane simulations
  - Weather prediction
  - …
- Large national racing for most powerful computers
- In quest for increasing power → large scale distributed/parallel computers (1000s of processors)

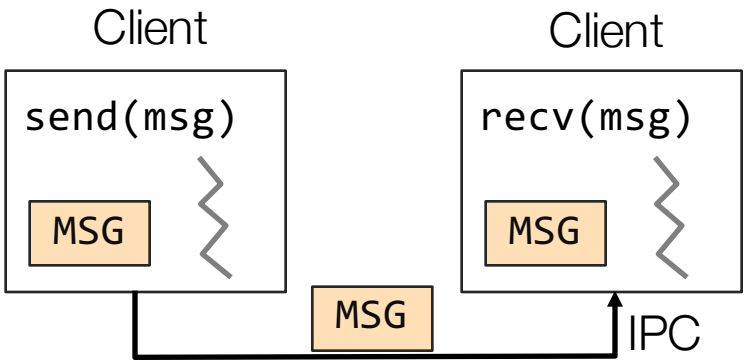
Question: how to program these supercomputers?

Shared memory vs. Message passing



Shared memory: all multiple processes to share data via memory

Applications must locate and and map shared memory regions to exchange data



Message passing: exchange data explicitly via IPC

Application developers define protocol and exchanging format, number of participants, and each exchange

Shared memory vs. Message passing

Easy to program; just like a single multi-threaded machines

Hard to write high perf. apps:

- Cannot control which data is local or remote (remote mem. access much slower)

Hard to mask failures

Message passing: can write very high perf. apps

Hard to write apps:

- Need to manually decompose the app, and move data

Need to manually handle failures

MPI

MPI - Message Passing Interface

- Library standard defined by a committee of vendors, implementers, and parallel programmers
- Used to create parallel programs based on message passing

Portable: one standard, many implementations

- Available on almost all parallel machines in C and Fortran
- De facto standard platform for the HPC community

Groups, Communicators, Contexts

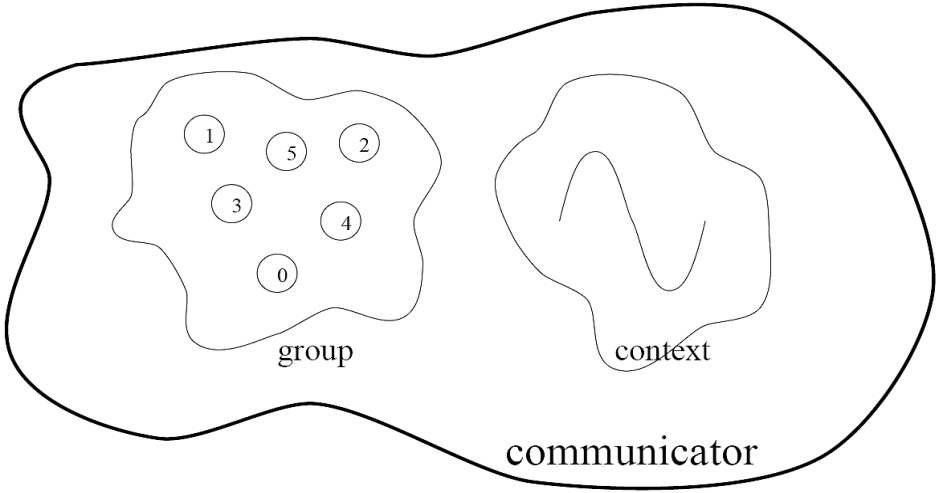
Group: a fixed ordered set of *k* processes, i.e., 0, 1, .., k-1

Communicator: specify scope of communication

- Between processes in a group
- Between two disjoint groups

Context: partition of comm. space

- A message sent in one context cannot be received in another context



This image is captured from: "Writing Message Passing Parallel Programs with MPI", Course Notes,
Edinburgh Parallel Computing Centre
The University of Edinburgh

Synchronous vs. Asynchronous Message Passing

A synchronous communication is not complete until the message has been received

An asynchronous communication completes before the message is received

Communication Modes

Synchronous: completes once ack is received by sender

Asynchronous: 3 modes

- Standard send: completes once the message has been sent, which may or may not imply that the message has arrived at its destination
- Buffered send: completes immediately, if receiver not ready, MPI buffers the message locally
- Ready send: completes immediately, if the receiver is ready for the message it will get it, otherwise the message is dropped silently

Blocking vs. Non-Blocking

Blocking, means the program will not continue until the communication is completed

- Synchronous communication
- Barriers: wait for every process in the group to reach a point in execution

Non-Blocking, means the program will continue, without waiting for the communication to be completed

MPI library

Huge (125 functions)

Basic (6 functions)

MPI Basic

Many parallel programs can be written using just these six functions, only two of which are non-trivial;

- MPI_INIT
- MPI_FINALIZE
- MPI_COMM_SIZE
- MPI_COMM_RANK
- MPI_SEND
- MPI_RECV

Skeleton MPI Program (C)

```c
#include <mpi.h>

main(int argc, char** argv)
{
    MPI_Init(&argc, &argv);

    /* main part of the program */

    /* Use MPI function call depend on your data
     * partitioning and the parallelization architecture
     */
    MPI_Finalize();
}
```

A minimal MPI program (C)

```c
#include “mpi.h”
#include <stdio.h>
int main(int argc, char *argv[])
{
  MPI_Init(&argc, &argv);
  printf(“Hello, world!\n”);
  MPI_Finalize();
  return 0;
}
```

A minimal MPI program (C)

`#include` “`mpi.h`” provides basic MPI definitions and types.

MPI_Init starts MPI

MPI_Finalize exits MPI

Notes:

- Non-MPI routines are local; this “printf” run on each process
- MPI functions return error codes or MPI_SUCCESS

Improved Hello (C)

```c
#include <mpi.h>
#include <stdio.h>
int main(int argc, char *argv[])
{
    int rank, size;
    MPI_Init(&argc, &argv);
    /* rank of this process in the communicator */
    MPI_Comm_rank(MPI_COMM_WORLD, &rank);
    /* get the size of the group associates to the communicator */
    MPI_Comm_size(MPI_COMM_WORLD, &size);
    printf("I am %d of %d\n", rank, size);
    MPI_Finalize();
    return 0;
}
```

Improved Hello (C)

```
/* Find out rank, size */
int world_rank, size;
MPI_Comm_rank(MPI_COMM_WORLD, &world_rank);
MPI_Comm_size(MPI_COMM_WORLD, &size);
int number;
if (world_rank == 0)
  number = -1;
  MPI_Send(&number, 1, MPI_INT, 1, 0, MPI_COMM_WORLD);
} else if (world_rank == 1) {
  MPI_Recv(&number, 1, MPI_INT, 0, 0, MPI_COMM_WORLD, MPI_STATUS_IGNORE);
  printf("Process 1 received number %d from process 0\n", number);
}
```

Number of elements

Rank of destination

Tag to identify message

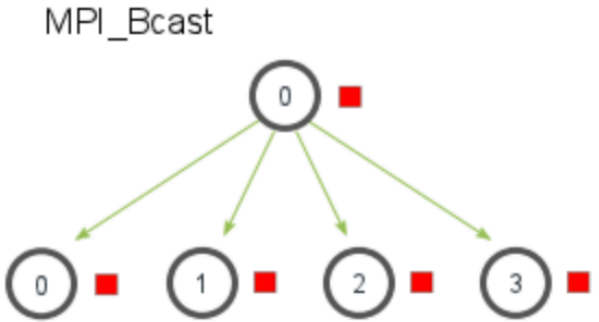
Default communicator

Rank of source

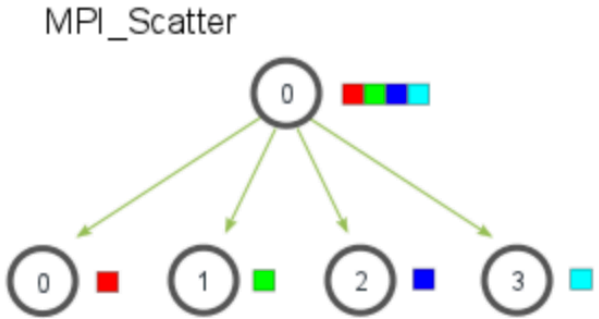
Status

Many other functions…

MPI_Bcast: send same piece of data to all processes in the group



MPI_Scatter: send different pieces of an array to different processes (i.e., partition an array across processes)

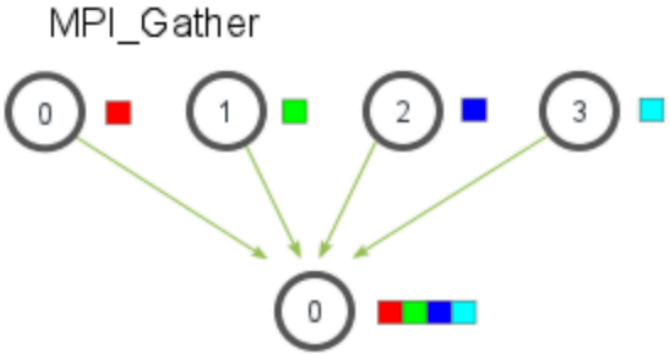


From: http://mpitutorial.com/tutorials/mpi-scatter-gather-and-allgather/

Many other functions…

MPI_Gather: take elements from many processes and gathers them to one single process

- E.g., parallel sorting, searching



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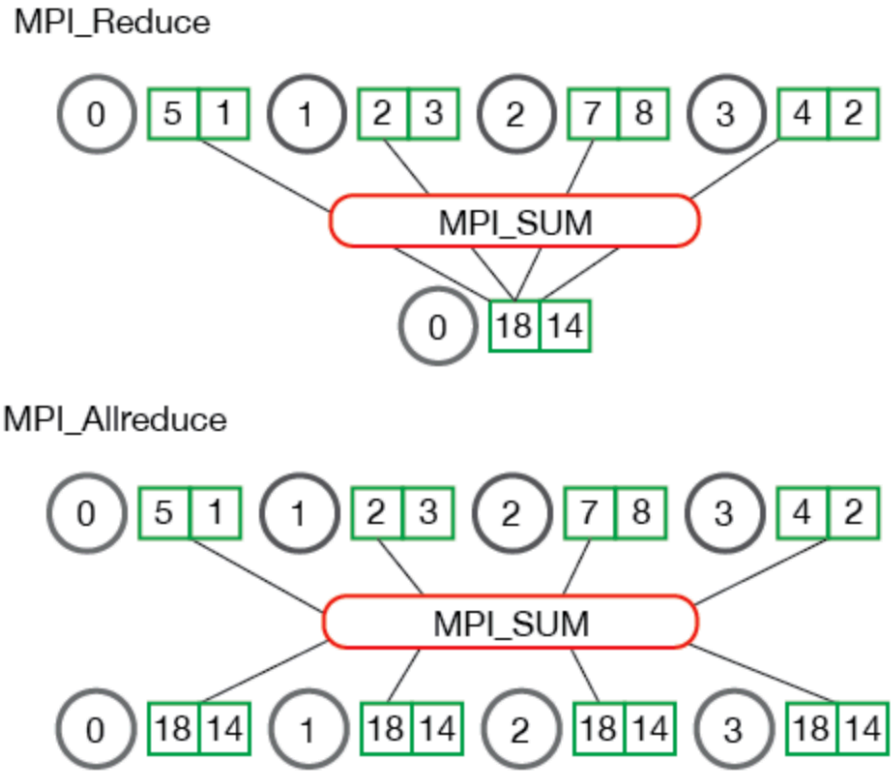
Many other functions…

MPI_Reduce: takes an array of input elements on each process and returns an array of output elements to the root process given a specified operation

MPI_Allreduce: Like MPI_Reduce but distribute results to all processes



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MPI Discussion

Gives full control to programmer

- Exposes number of processes
- Communication is explicit, driven by the program

Assume

- Long running processes
- Homogeneous (same performance) processors

Little support for failures, no straggler mitigation

Summary: achieve high performance by hand-optimizing jobs but requires experts to do so, and little support for fault tolerance

Today's Papers

MapReduce: Simplified Data Processing on Large Clusters, Jeffrey Dean and Sanjay Ghemawat, OSDI'04

http://static.googleusercontent.com/media/research.google.com/en//archive/mapreduce-osdi04.pdf

Spark: Cluster Computing with Working Sets,

Matei Zaharia, Mosharaf Chowdhury, Michael J. Franklin, Scott Shenker, Ion Stoica, NSDI'12

https://people.csail.mit.edu/matei/papers/2010/hotcloud_spark.pdf

Context (end of 1990s)

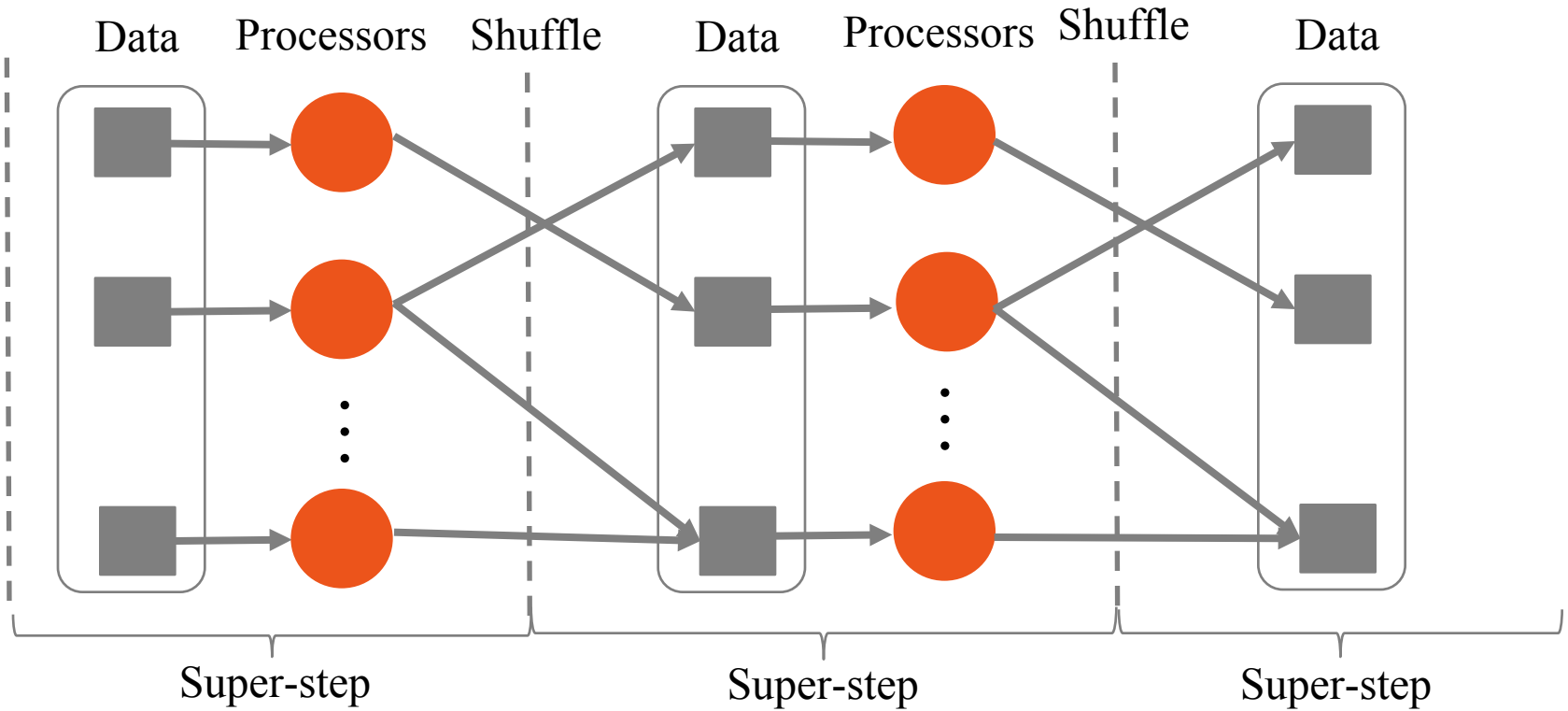
Internet and World Wide Web taking off

Search as a killer applications

- Need to index and process huge amounts of data
- Supercomputers very expensive; also designed for computation intensive workloads vs data intensive workloads

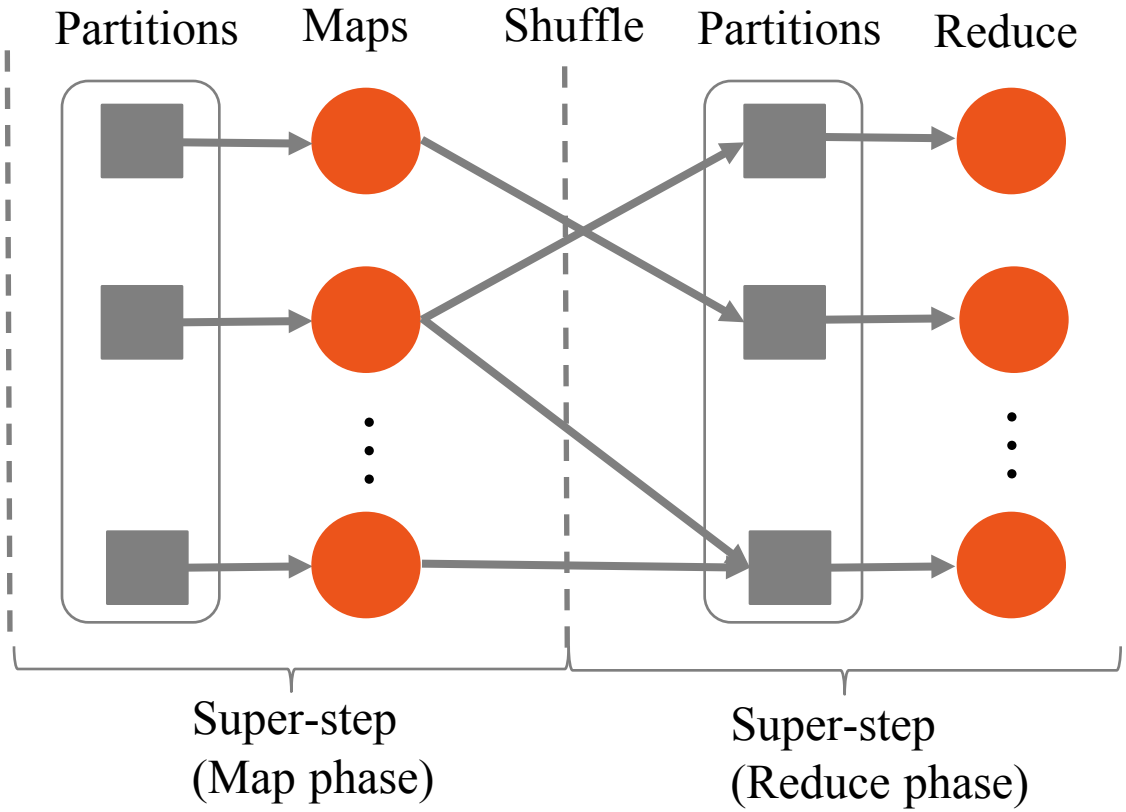
Data processing: highly parallel

Bulk Synchronous Processing (BSP) Model*

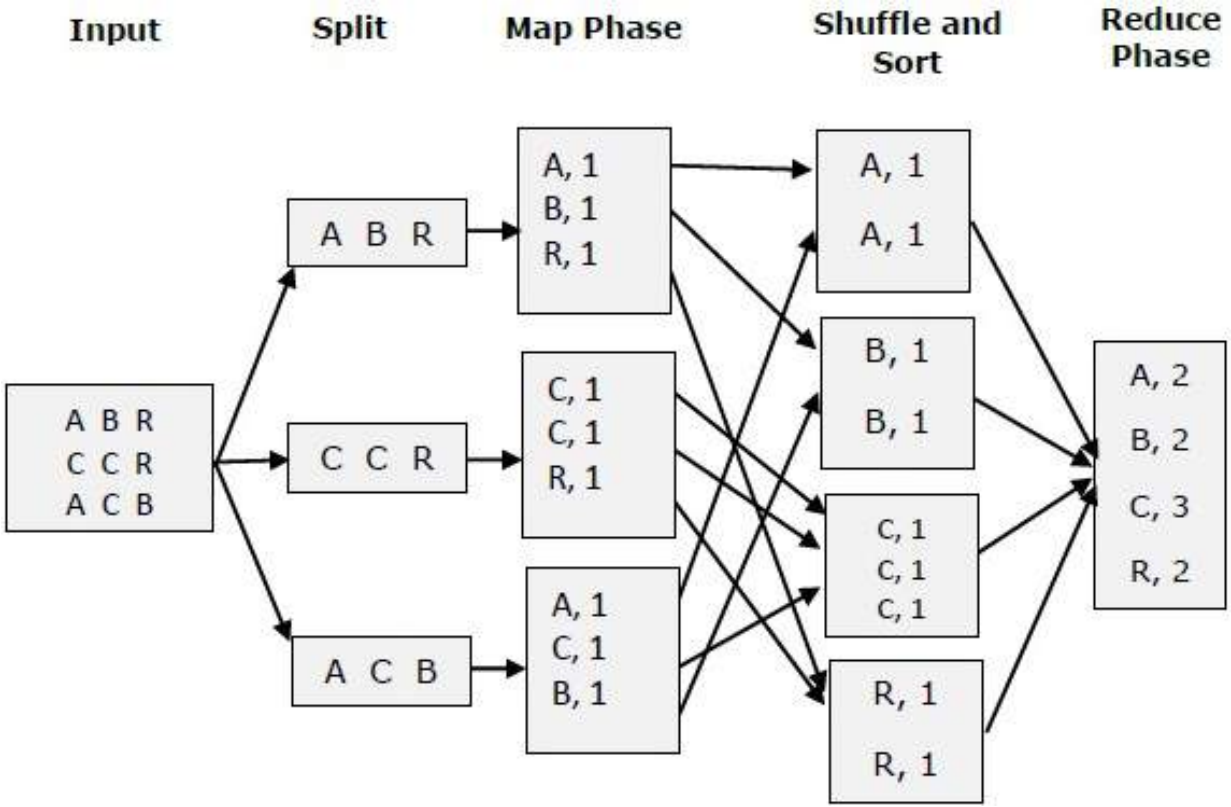


*Leslie G. Valiant, A bridging model for parallel computation, Communications of the ACM, Volume 33 Issue 8, Aug. 1990

MapReduce as a BSP System



Example: Word Count



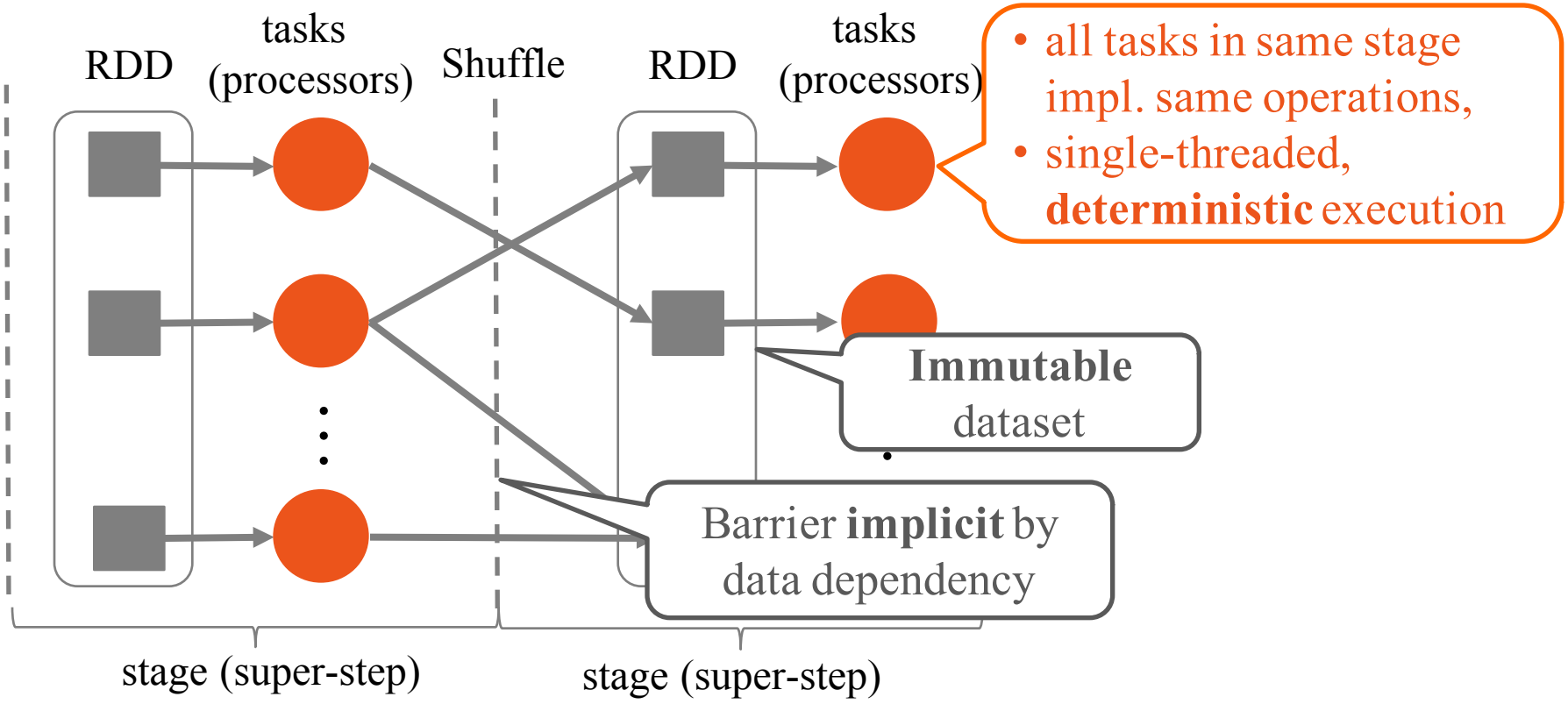
Context (2000s)

MapReduce and Hadoop de facto standard for big data processing → great for batch jobs

… but not effective for

- Interactive computations
- Iterative computations

Spark, as a BSP System



Spark, really a generalization of MapReduce

DAG computation model vs two stage computation model (Map and Reduce)

Tasks as threads vs. tasks as JVMs

Disk-based vs. memory-optimized

So for the rest of the lecture, we'll talk mostly about Spark

More context (2009): Application Trends

Iterative computations, e.g., Machine Learning

- More and more people aiming to get insights from data

Interactive computations, e.g., ad-hoc analytics

- SQL engines like Hive and Pig drove this trend

More context (2009): Application Trends

Despite huge amounts of data, many working sets in big data clusters fit in memory

2009: Application Trends

Memory (GB)	Facebook (% jobs)	Microsoft (% jobs)	Yahoo! (% jobs)
8	69	38	66
16	74	51	81
32	96	82	97.5
64	97	98	99.5
128	98.8	99.4	99.8
192	99.5	100	100
256	99.6	100	100

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Operations on RDDs

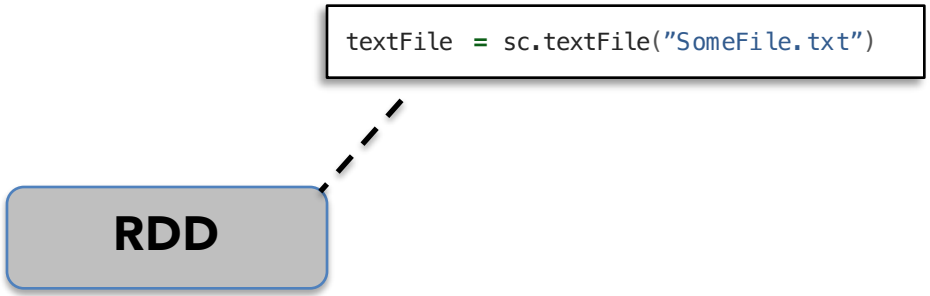
Transformations f(RDD) => RDD

- Lazy (not computed immediately)
- E.g., “map”, “filter”, “groupBy”

Actions:

- Triggers computation
- E.g. “count”, “collect”, “saveAsTextFile”

Working With RDDs



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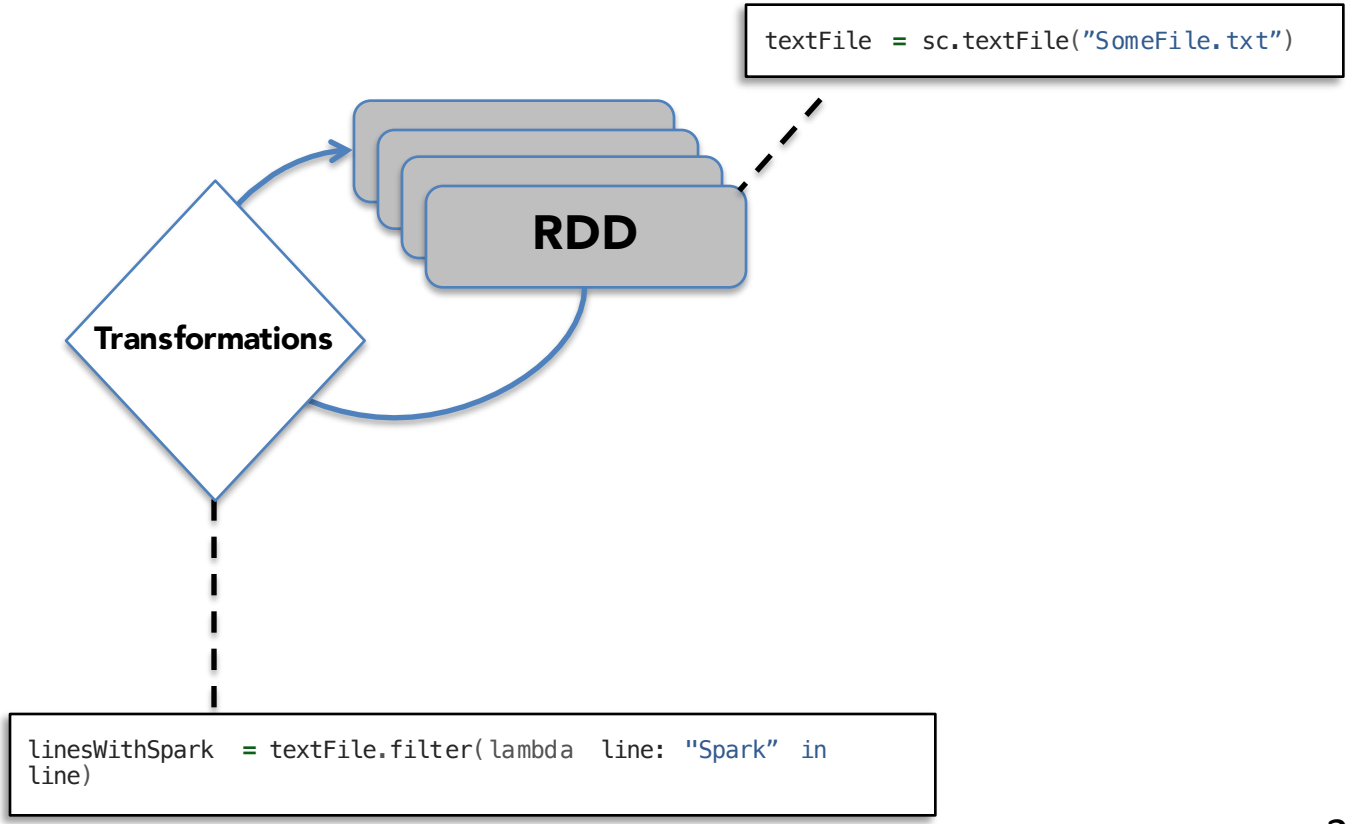

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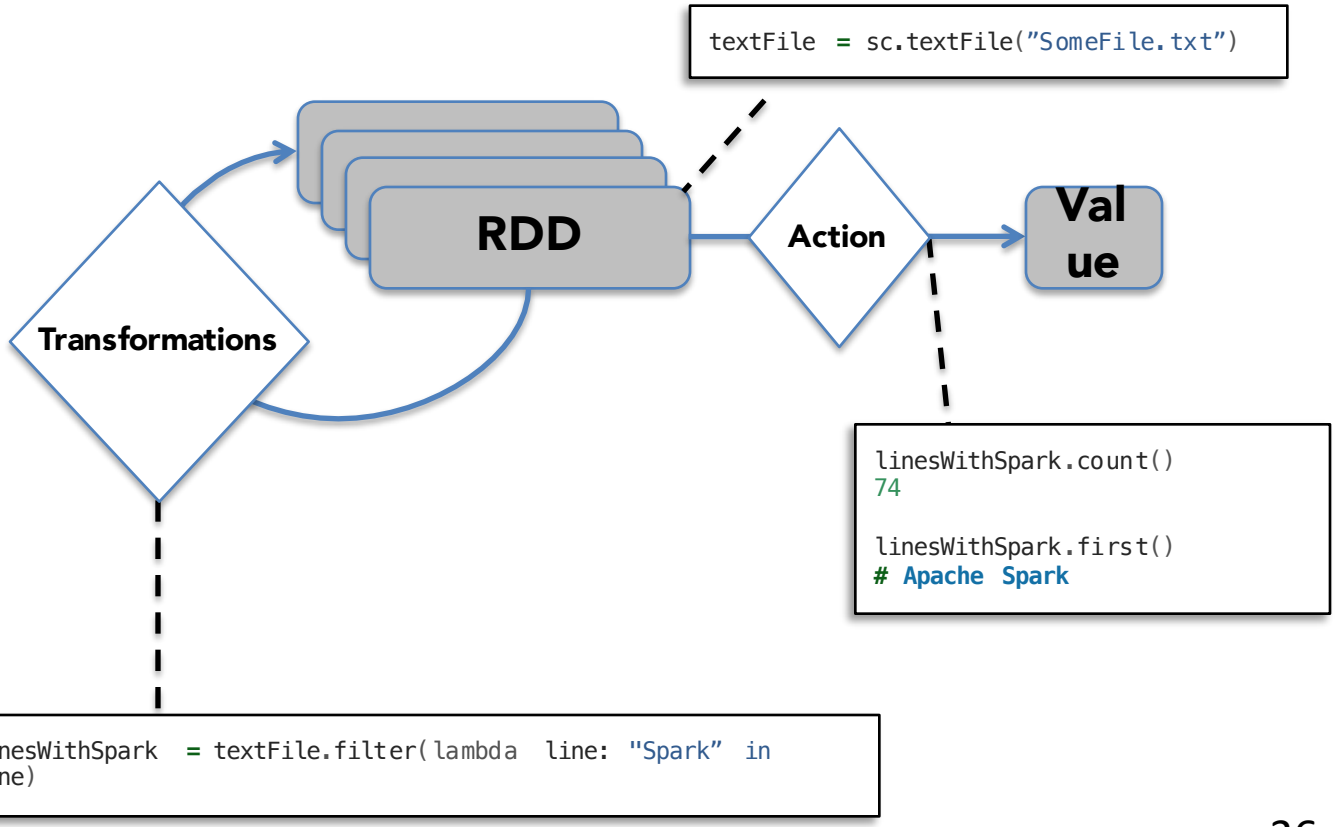

Example: Log Mining

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

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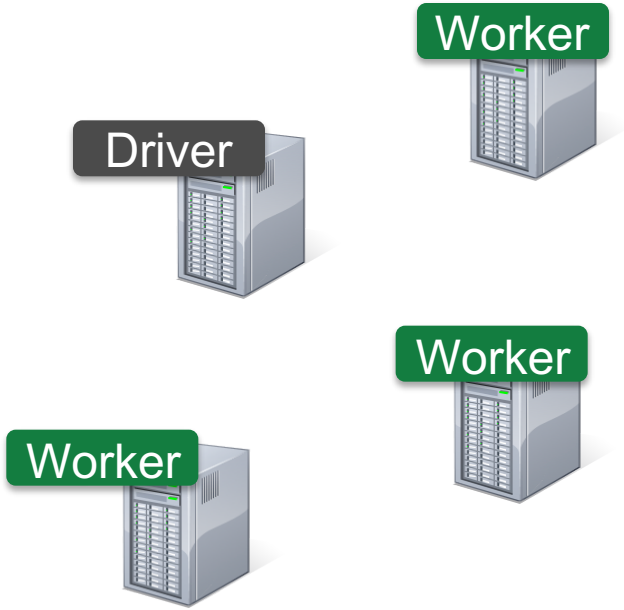

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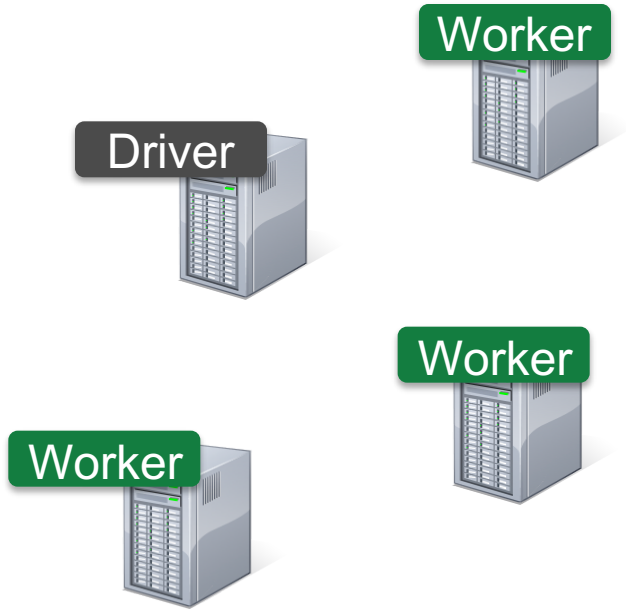

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Base RDD

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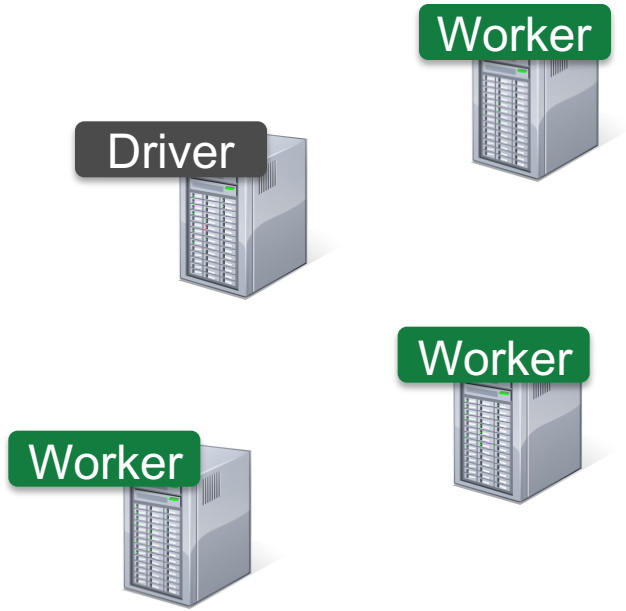

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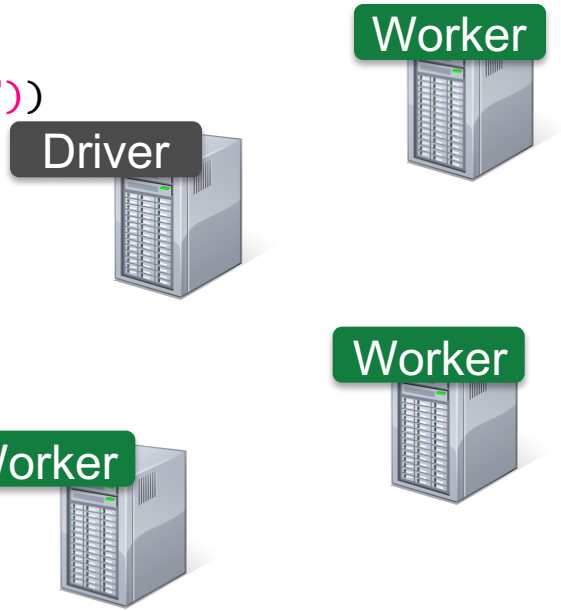

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Transformed RDD

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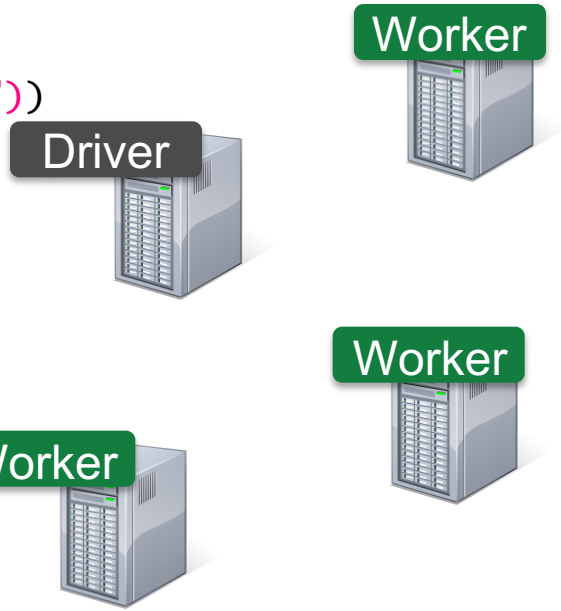

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messages.cache()

messages.filter(lambda s: "mysql" in s).count()
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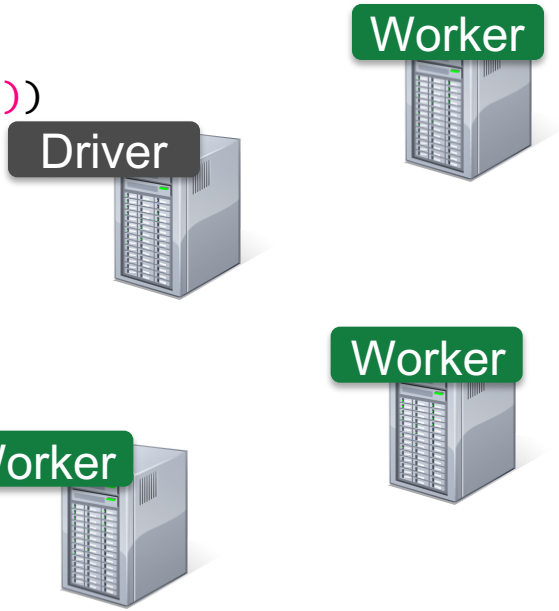

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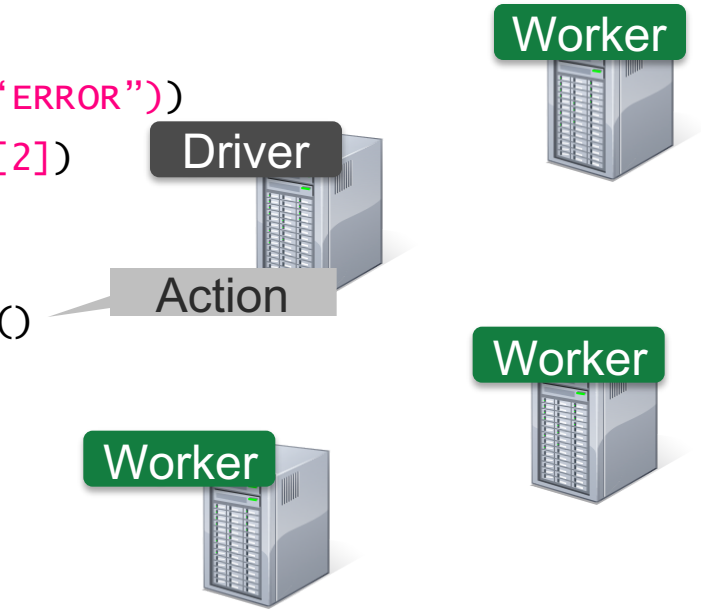

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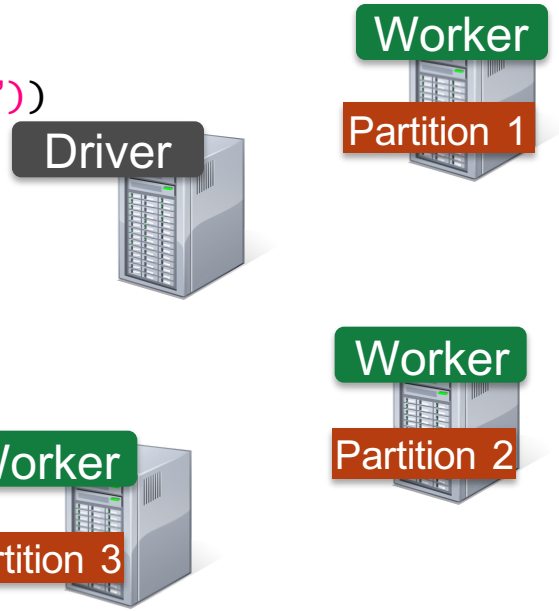

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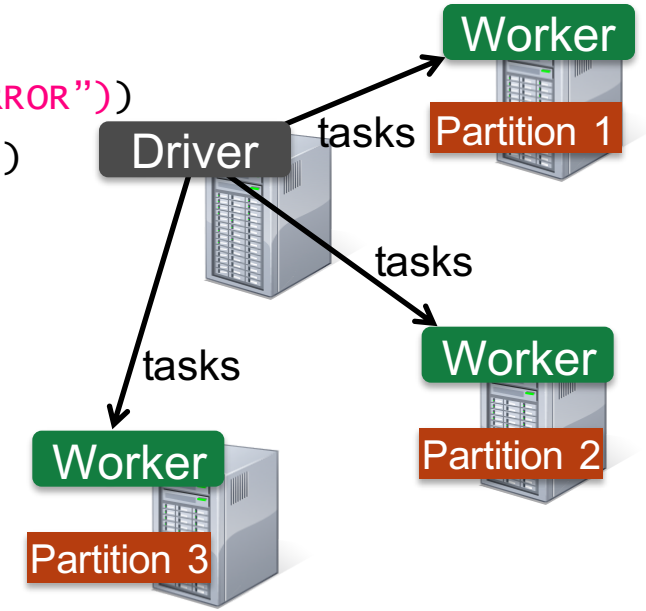

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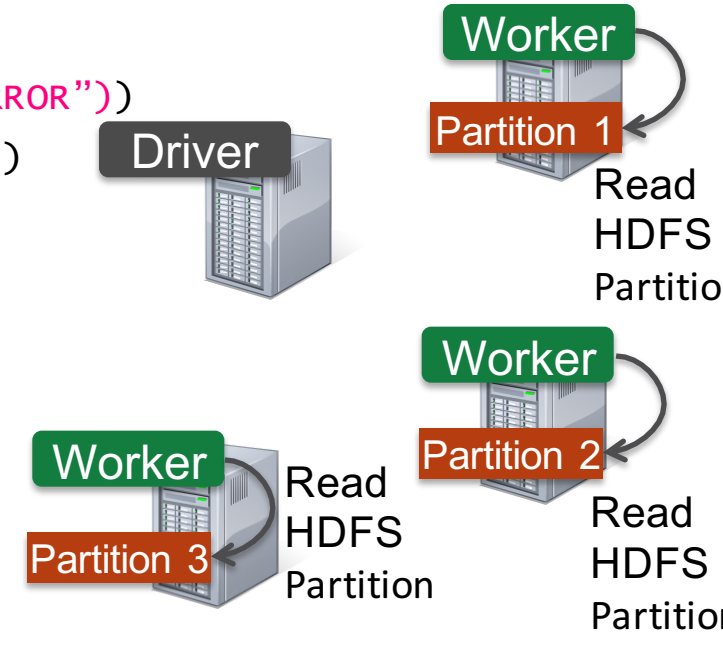

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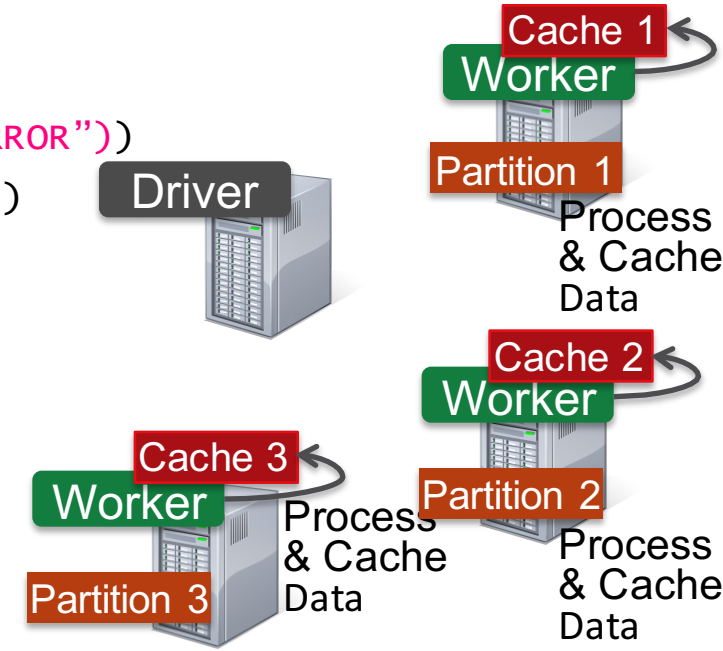

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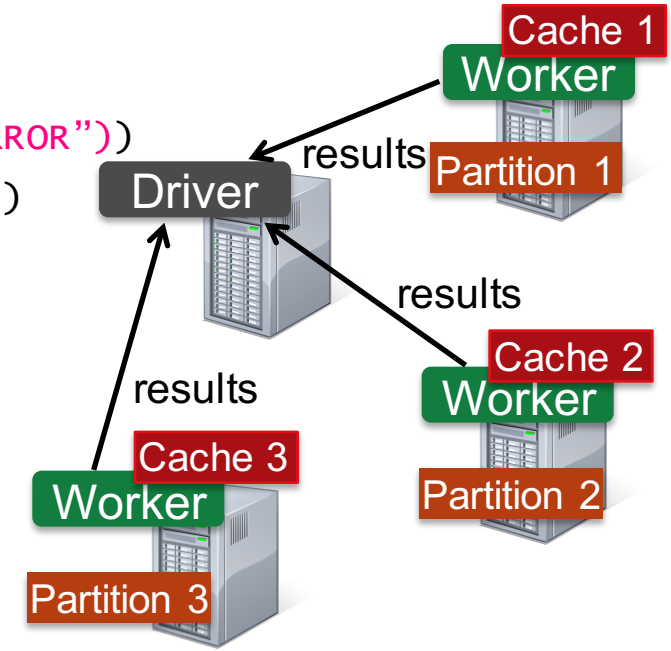

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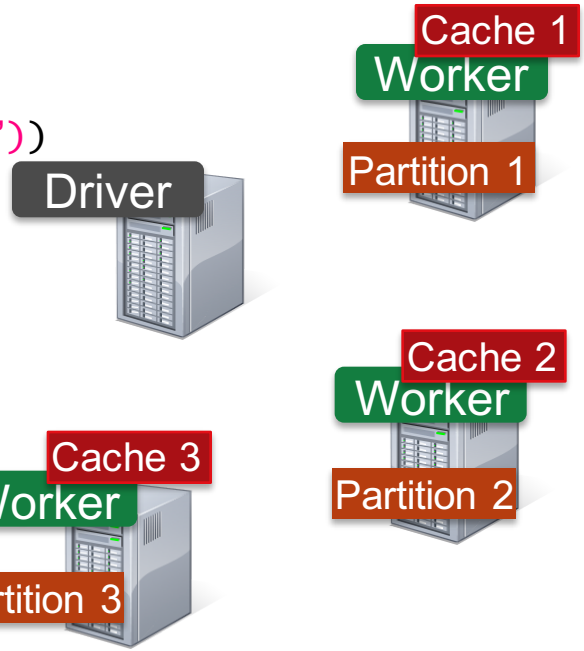

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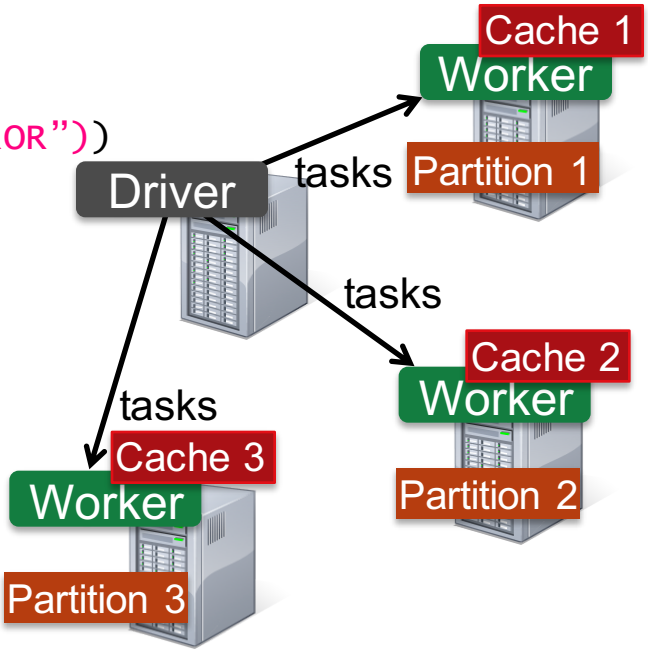

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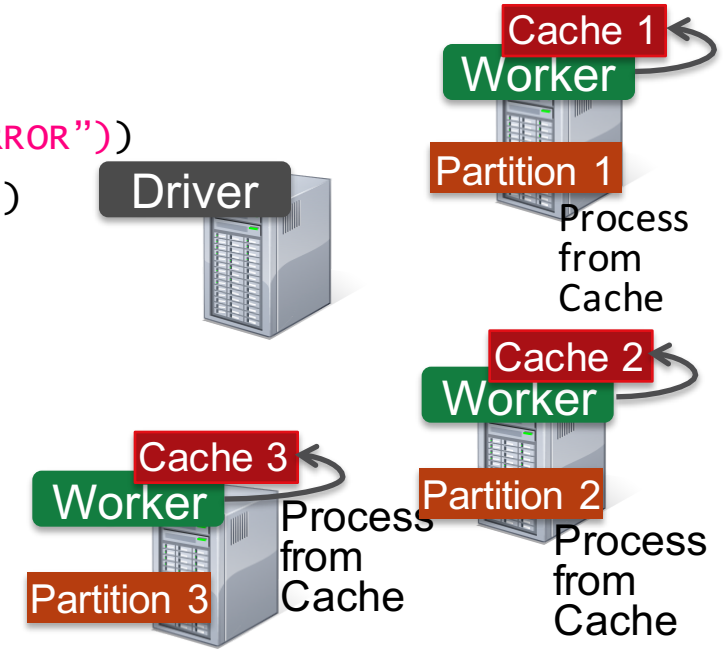

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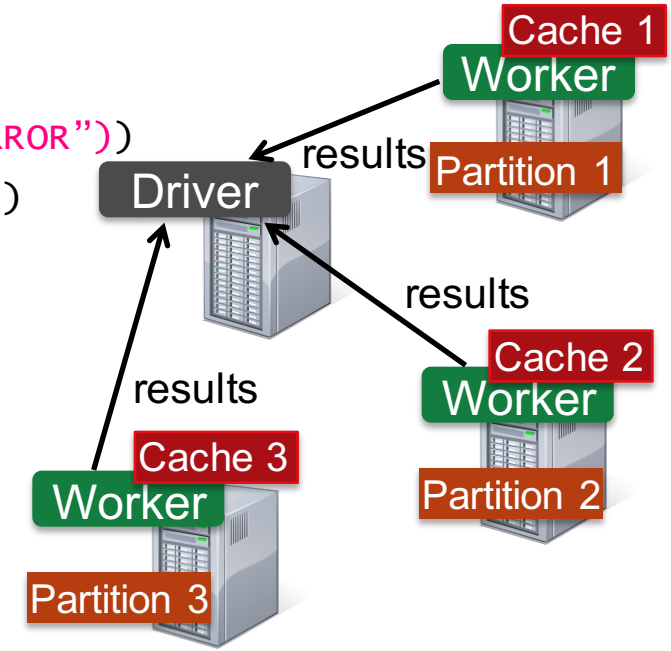

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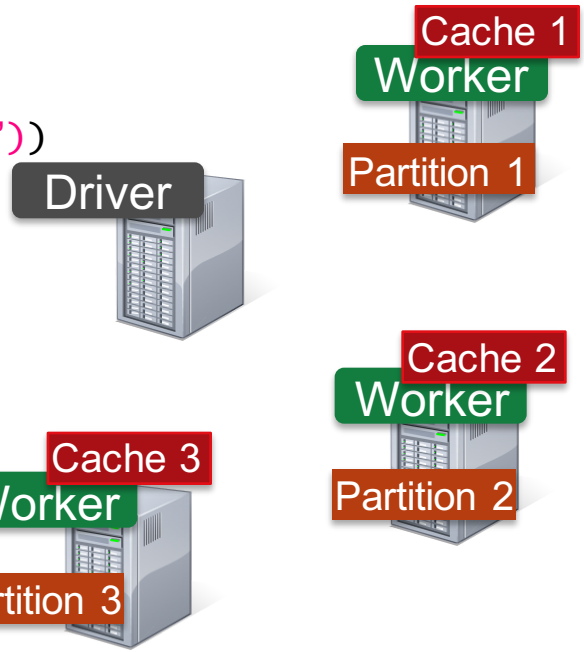
lines = spark.textFile("hdfs://...")
errors = lines.filter(lambda s: s.startswith("ERROR"))
messages = errors.map(lambda s: s.split("\t")[2])
messages.cache()

messages.filter(lambda s: "mysql" in s).count()
messages.filter(lambda s: "php" in s).count()
```



Cache your data ➔ Faster Results

Full-text search of Wikipedia

- 60GB on 20 EC2 machines
- 0.5 sec from mem vs. 20s for on-disk

Language Support

Python

```
lines = sc.textFile(...)
lines.filter(lambda s: "ERROR" in s).count()
```

Scala

```
val lines = sc.textFile(...)
lines.filter(x => x.contains("ERROR")).count()
```

Java

```
JavaRDD<String> lines = sc.textFile(...);
lines.filter(new Function<String, Boolean>() {
  Boolean call(String s) {
    return s.contains("error");
  }
}).count();
```

Standalone Programs

Python, Scala, & Java

Interactive Shells

Python & Scala

Performance

Java & Scala are faster due to static typing

…but Python is often fine

Expressive API

`map`

`reduce`

Expressive API

```
map
filter
groupBy
sort
union
join
leftOuterJoin
rightOuterJoin
```

```
reduce
count
fold
reduceByKey
groupByKey
cogroup
cross
zip
```

```
sample
take
first
partitionBy
mapWith
pipe
save    ...
```

Fault Recovery: Design Alternatives

Replication:

- Slow: need to write data over network
- Memory inefficient

Backup on persistent storage:

- Persistent storage still (much) slower than memory
- Still need to go over network to protect against machine failures

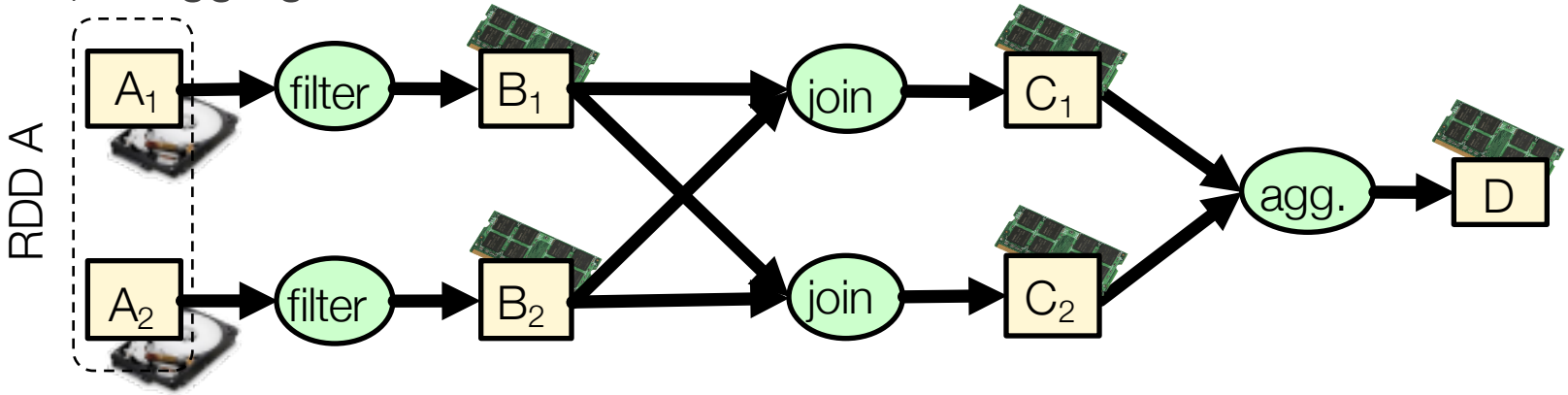
Spark choice:

- Lineage: track seq. of operations to efficiently reconstruct lost RRD partitions
- Enabled by determinist execution and data immutability

Fault Recovery Example

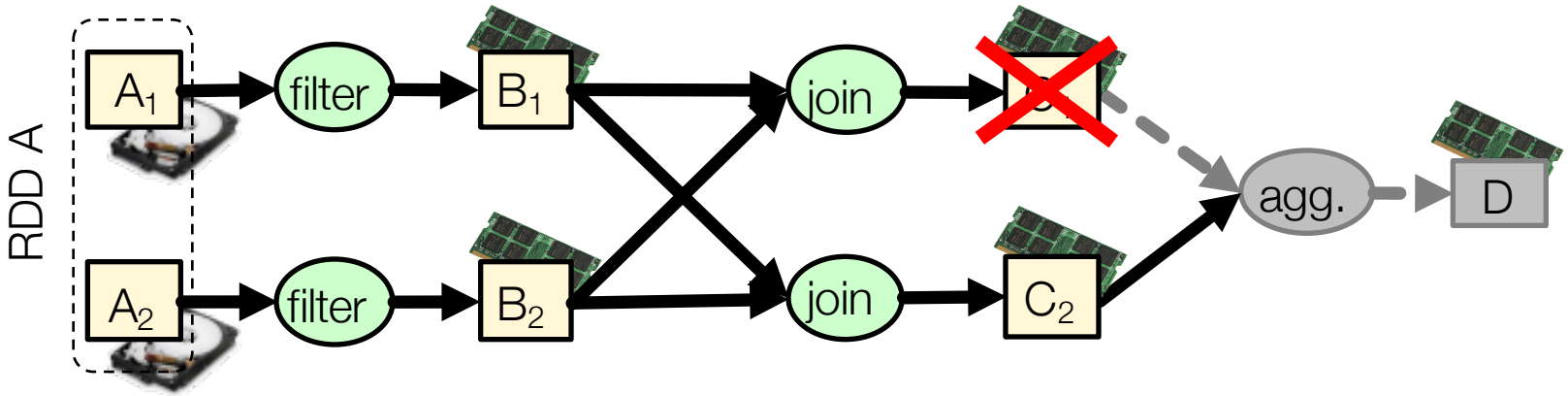
Two-partition RDD A={A_1, A_2} stored on disk

1) filter and cache → RDD B
2) join→ RDD C
3) aggregate → RDD D



Fault Recovery Example

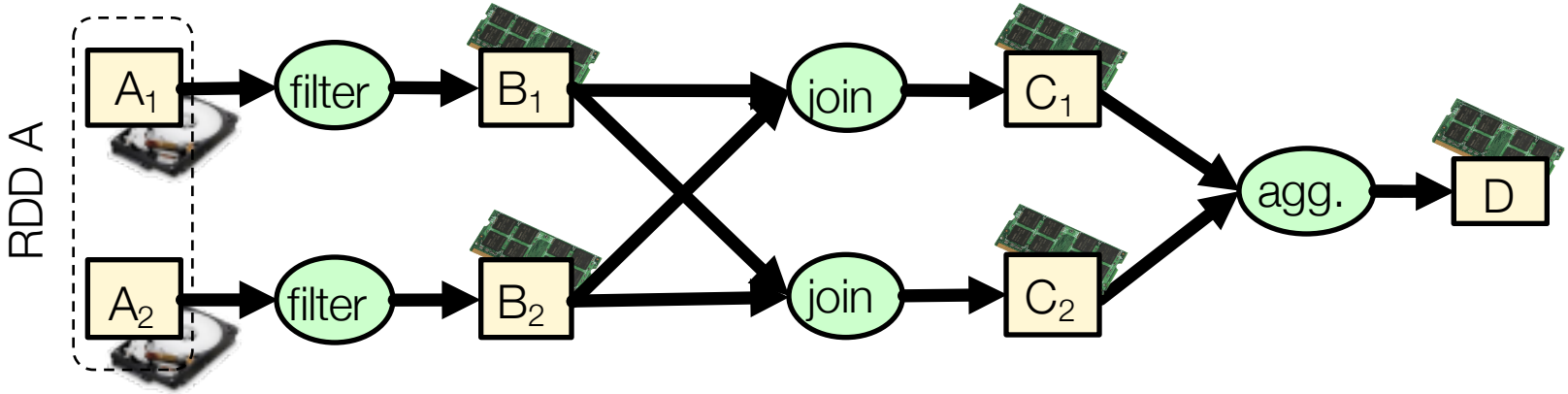
C_1 lost due to node failure before "aggregate" finishes



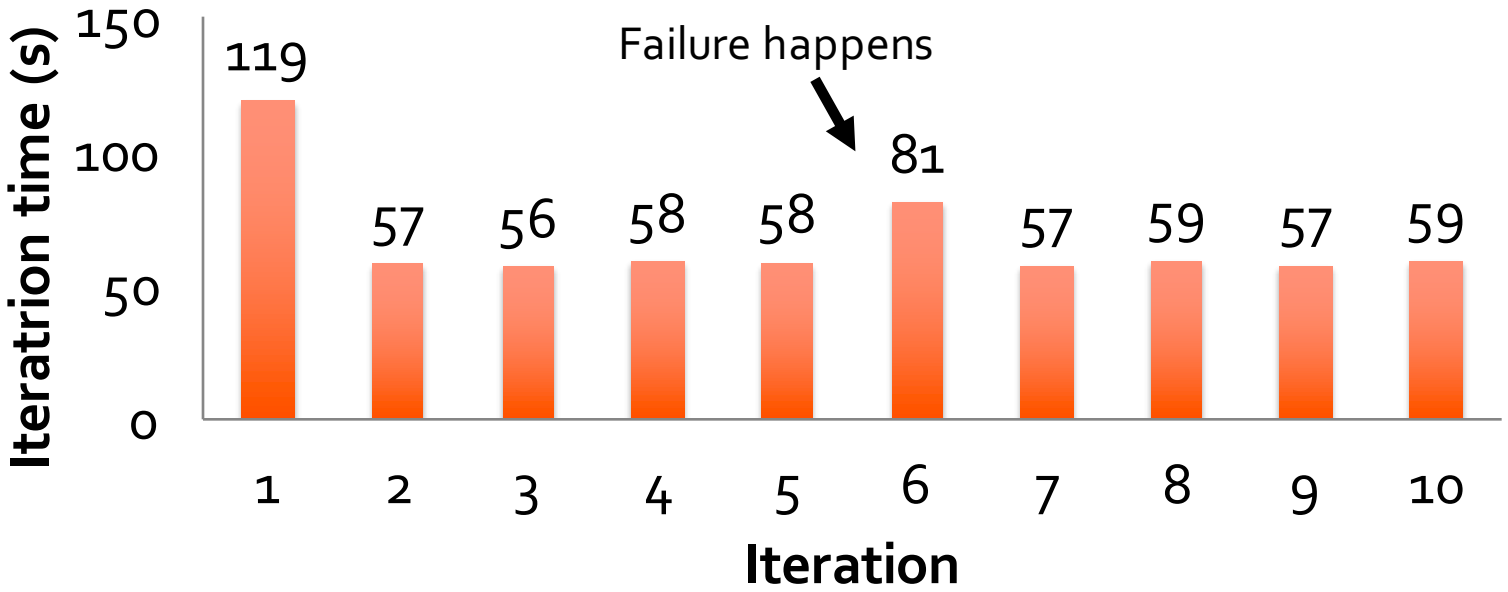
Fault Recovery Example

C_1 lost due to node failure before reduce finishes

Reconstruct C_1, eventually, on different node



Fault Recovery Results



Spark Streaming: Motivation

Process large data streams at second-scale latencies

- Site statistics, intrusion detection, online ML

To build and scale these apps users want

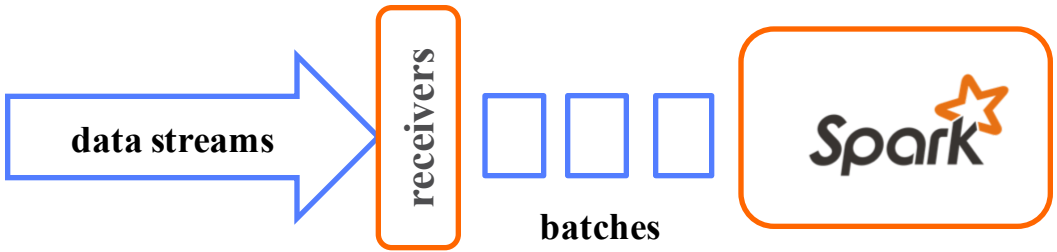
- **Fault-tolerance:** both for crashes and stragglers
- **Exactly one semantics**
- **Integration:** with offline analytical stack

Spark Streaming

Data streams are chopped into batches

- A batch is an RDD holding a few 100s ms worth of data

Each batch is processed in Spark



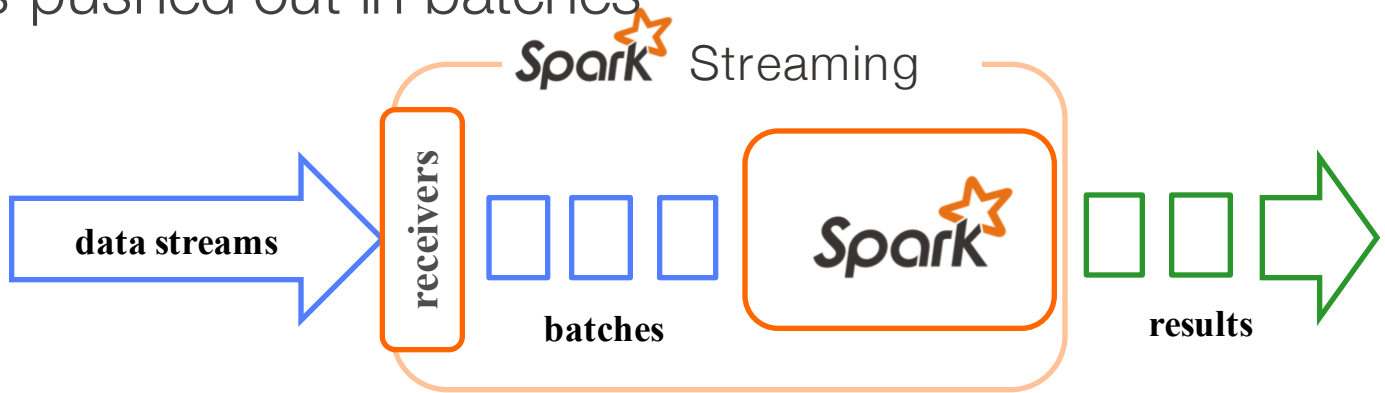
How does it work?

Data streams are chopped into batches

- A batch is an RDD holding a few 100s ms worth of data

Each batch is processed in Spark

Results pushed out in batches



Streaming Word Count

```
val lines = context.socketTextStream("localhost", 9999)
val words = lines.flatMap(_.split(" "))
val wordCounts = words.map(x => (x, 1)).reduceByKey(_ + _)
wordCounts.print()
ssc.start()
```

create DStream from data over socket

split lines into words

count the words

print some counts on screen

start processing the stream

Word Count

```
object NetworkWordCount {
  def main(args: Array[String]) {
    val sparkConf = new SparkConf().setAppName("NetworkWordCount")
    val context = new StreamingContext(sparkConf, Seconds(1))

    val lines = context.socketTextStream("localhost", 9999)
    val words = lines.flatMap(_.split(" "))
    val wordCounts = words.map(x => (x, 1)).reduceByKey(_ + _)

    wordCounts.print()
    ssc.start()
    ssc.awaitTermination()
  }
}
```

Word Count

Spark Streaming

```
object NetworkWordCount {
  def main(args: Array[String]) {
    val sparkConf = new SparkConf().setAppName("NetworkWordCount")
    val context = new StreamingContext(sparkConf, Seconds(1))

    val lines = context.socketTextStream("localhost", 9999)
    val words = lines.flatMap(_.split(" "))
    val wordCounts = words.map(x => (x, 1)).reduceByKey(_ + _)

    wordCounts.print()
    ssc.start()
    ssc.awaitTermination()
  }
}
```

Storm

```
public class WordCountTopology {
  public static class SplitSentence extends ShellBolt implements IRichBolt {

    public SplitSentence() {
      super("python", "splitsentence.py");
    }

    @Override
    public void declareOutputFields(OutputFieldsDeclarer declarer) {
      declarer.declare(new Fields("word"));
    }

    @Override
    public Map<String, Object> getComponentConfiguration(){
      return null;
    }
  }

  public static class WordCount extends BaseBasicBolt {
    Map<String, Integer> counts = new HashMap<String, Integer>();

    @Override
    public void execute(Tuple tuple, BasicOutputCollector collector) {
      String word = tuple.getString(0);
      Integer count = counts.get(word);
      if (count == null)
        count = 0;
      count++;
      counts.put(word, count);
      collector.emit(new Values(word, count));
    }

    @Override
    public void declareOutputFields(OutputFieldsDeclarer declarer) {
      declarer.declare(new Fields("word", "count"));
    }
  }

  public static void main(String[] args) throws Exception {

    TopologyBuilder builder = new TopologyBuilder();

    builder.setSpout("spout", new RandomSentenceSpout(), 5);

    builder.setBolt("split", new SplitSentence(), 8).shuffleGrouping("spout");
    builder.setBolt("count", new WordCount(), 12).fieldsGrouping("split", new
Fields("word"));

    Config conf = new Config();
    conf.setDebug(true);


    if (args != null && args.length > 0) {
      conf.setNumWorkers(3);

      StormSubmitter.submitTopologyWithProgressBar(args[0], conf, builder.createTopology());
    }
    else {
      conf.setMaxTaskParallelism(3);

      LocalCluster cluster = new LocalCluster();
      cluster.submitTopology("word-count", conf, builder.createTopology());

      Thread.sleep(10000);

      cluster.shutdown();
    }
```

Spark 2.0

Dataframes/datasets instead of RDDs

- Like tables in SQL
- Far more efficient:
  - Can directly access any field (dramatically reduce I/O and serialization/deserialization)
  - Can use column oriented access

Dataframe APIs (e.g., Python, R, SQL) use same optimizer: Catalyst

New libraries or old libraries revamped to use dataframe APIs

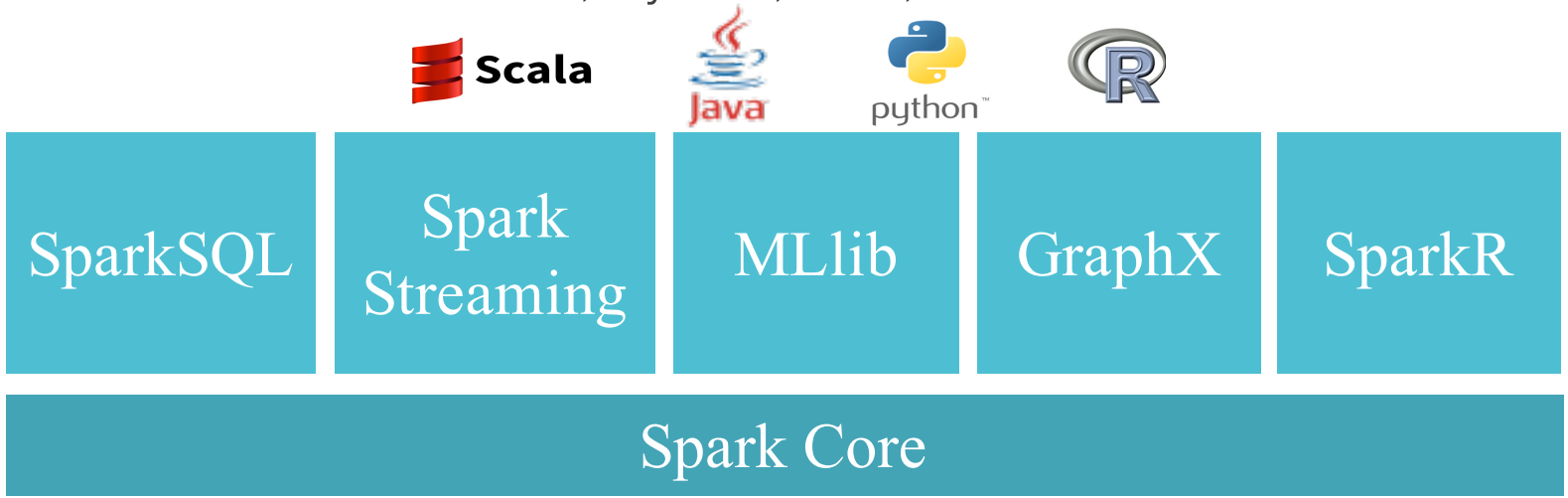
- Spark Streaming → Structured Streaming
- GraphX

General

Unifies ***batch, interactive, streaming*** workloads

Easy to build sophisticated applications

- Support iterative, graph-parallel algorithms
- Powerful APIs in Scala, Python, Java, R



Summary

MapReduce and later Spark jump-started Big Data processing

Lesson learned

- Simple design, simple computation model can go a long way
- Scalability, fault-tolerance first, performance next
  - With Dataframes and SparkSQL now Spark implements DB like optimizations which significantly increase performance

Discussion

	OpenMP/Cilk	MPI	MapReduce / Spark
Environment, Assumptions	Single node, multiple core, shared memory	Supercomputers Sophisticate programmers High performance Hard to scale hardware	Commodity clusters Java programmers Programmer productivity Easier, faster to scale up cluster
Computation Model	Fine-grained task parallelism	Message passing	Data flow / BSP
Strengths	Simplifies parallel programming on multi-cores	Can write very fast asynchronous code	Fault tolerance
Weaknesses	Still pretty complex, need to be careful about race conditions	Fault tolerance Easy to end up with non-deterministic code (if not using barriers)	Not as high performance as MPI