Good morning!

CS 744: RESILIENT DISTRIBUTED DATASETS

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Fall 2021

ADMINISTRIVIA

- Assignment 1: Due Sep 28, Tuesday at 10pm! → Code + report on Canvas
- Assignment 2: ML will be released Sep 29

- REMINDER: Submit your discussions
  - Within 24 hrs after end of class (11am next day) → Type it / Photo
  - Each student needs to submit

- Course project details: Next week

MOTIVATION: PROGRAMMABILITY

Most real applications require multiple MR steps

- Google indexing pipeline: 21 steps
- Analytics queries (e.g. sessions, top K): 2-5 steps
- Iterative algorithms (e.g. PageRank): 10's of steps

Data being read / written from GFS

Multi-step jobs create spaghetti code

- 21 MR steps → 21 mapper and reducer classes

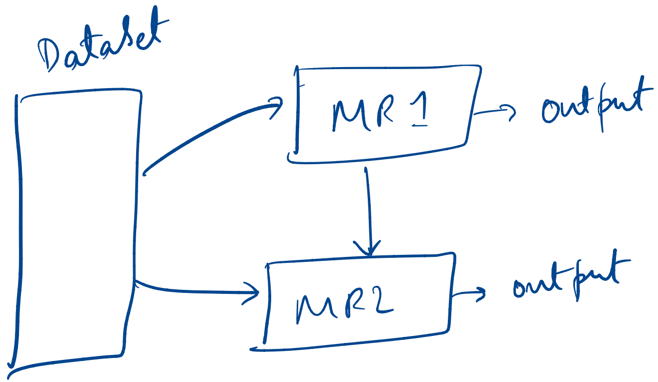
MOTIVATION: PERFORMANCE

MR only provides one pass of computation

- Must write out data to file system in-between

Expensive for apps that need to *reuse data*

- Multi-step algorithms (e.g. PageRank)
- Interactive data mining



PROGRAMMABILITY

Google MapReduce WordCount:

```
#include "mapreduce/mapreduce.h"

// User's map function
class SplitWords: public Mapper {
  public:
  virtual void Map(const MapInput& input)
  {
    const string& text = input.value();
    const int n = text.size();
    for (int i = 0; i < n; ) {
      // Skip past leading whitespace
      while (i < n && isspace(text[i]))
        i++;
      // Find word end
      int start = i;
      while (i < n && !isspace(text[i]))
        i++;
      if (start < i)
        Emit(text.substr(
            start,i-start),"1");
    }
  }
};

REGISTER_MAPPER(SplitWords);

// User's reduce function
class Sum: public Reducer {
  public:
  virtual void Reduce(ReduceInput* input)
  {
    // Iterate over all entries with the
    // same key and add the values
    int64 value = 0;
    while (!input->done()) {
      value += StringToInt(
                  input->value());
      input->NextValue();
    }
    // Emit sum for input->key()
    Emit(IntToString(value));
  }
};

REGISTER_REDUCER(Sum);

int main(int argc, char** argv) {
  ParseCommandLineFlags(argc, argv);
  MapReduceSpecification spec;
  for (int i = 1; i < argc; i++) {
    MapReduceInput* in= spec.add_input();
    in->set_format("text");
    in->set_filepattern(argv[i]);
    in->set_mapper_class("SplitWords");
  }

  // Specify the output files
  MapReduceOutput* out = spec.output();
  out->set_filebase("/gfs/test/freq");
  out->set_num_tasks(100);
  out->set_format("text");
  out->set_reducer_class("Sum");

  // Do partial sums within map
  out->set_combiner_class("Sum");

  // Tuning parameters
  spec.set_machines(2000);
  spec.set_map_megabytes(100);
  spec.set_reduce_megabytes(100);

  // Now run it
  MapReduceResult result;
  if (!MapReduce(spec, &result)) abort();
  return 0;
}
```

APACHE SPARK PROGRAMMABILITY

1. Fewer lines of code

2. Trace how operations are chained. Type checked!

3. Use of inline functions. Mimics local programs

```
val file = spark.textFile("hdfs://...")
val counts = file.flatMap(line => line.split(" "))
                 .map(word => (word, 1))
                 .reduceByKey(_ + _)

counts.save("out.txt")
```

Inline function

APACHE SPARK

Programmability: clean, functional API

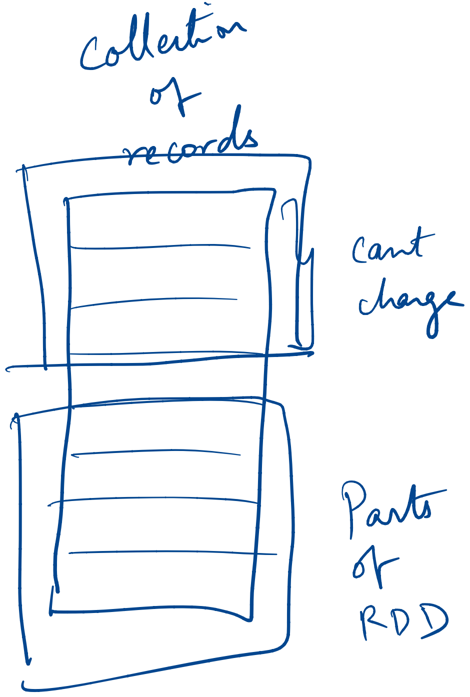
- Parallel transformations on collections
- 5-10x less code than MR
- Available in Scala, Java, Python and R

Performance

- In-memory computing primitives
- Optimization across operators

SPARK CONCEPTS

- Resilient distributed datasets (RDDs)
  - Immutable, partitioned collections of objects
  - May be cached in memory for fast reuse
- Operations on RDDs → Create from a file
  - *Transformations* (build RDDs)
  - *Actions* (compute results) → Integer on screen
    File save out
- Restricted shared variables
  - Broadcast, accumulators
    ↳ Counters



EXAMPLE: LOG MINING

Find error messages present in log files interactively

(Example: HTTP server logs)

RDD

```
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split('\t')(2))
messages.cache()
messages.filter(_.contains("foo")).count
```

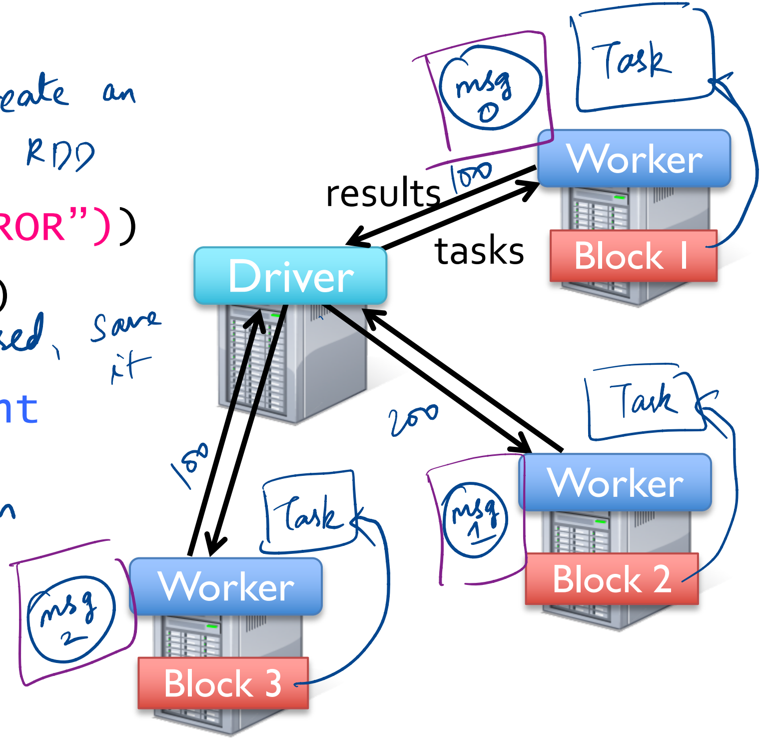
Create an RDD

→ when messages is processed, save it

Action

= 400

lines.filter(_.starts("INFO"))



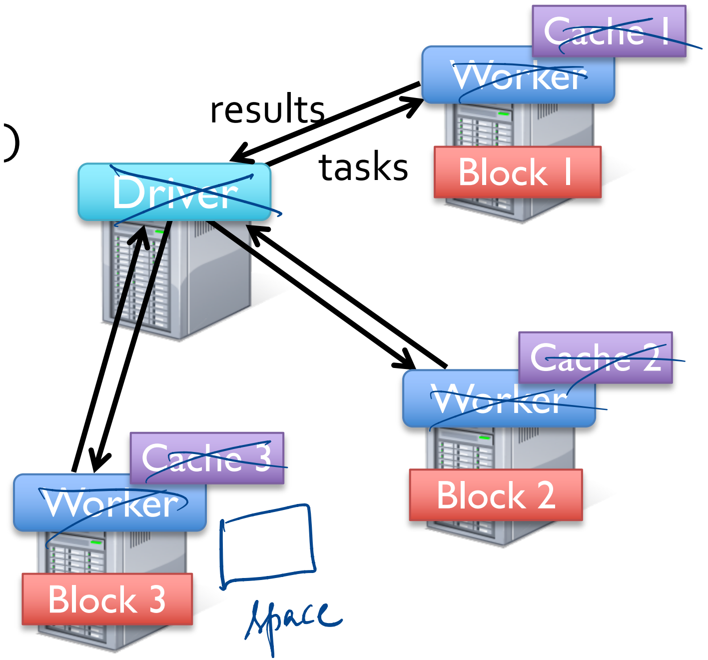
EXAMPLE: LOG MINING

Find error messages present in log files interactively

(Example: HTTP server logs)

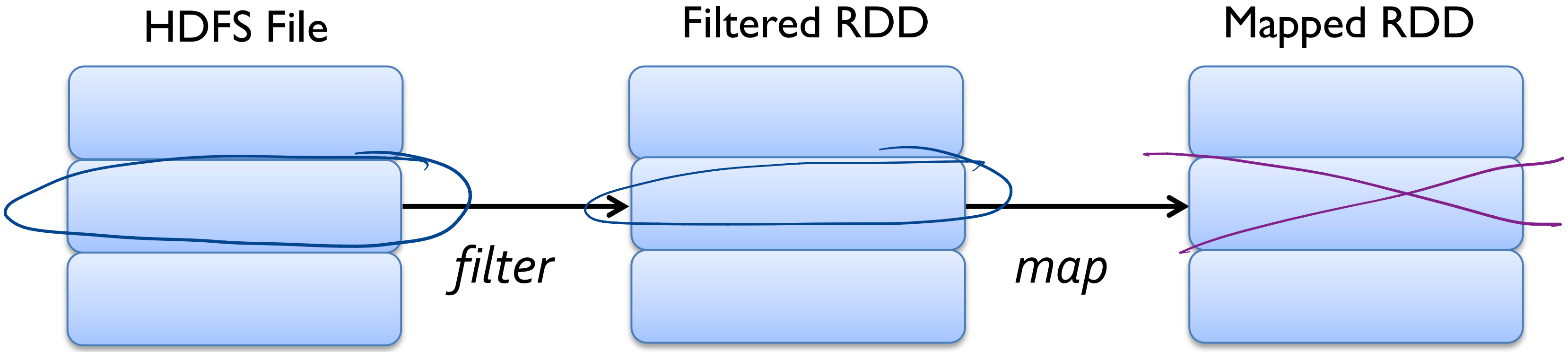
```
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split('\t')(2))
messages.cache()
messages.filter(_.contains("foo")).count
messages.filter(_.contains("bar")).count
. . .
```

Result: search 1 TB data in 5-7 sec
(vs 170 sec for on-disk data)



FAULT RECOVERY

```
messages = textFile(...).filter(_.startsWith("ERROR"))
                        .map(_.split('\t')(2))
```



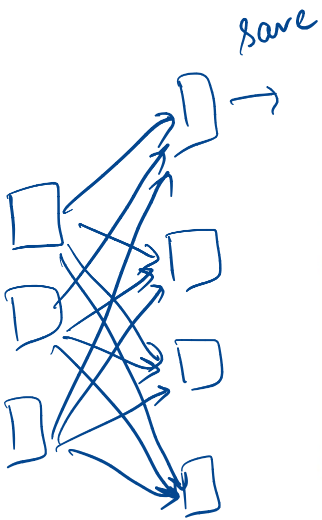
Lineage : History of transformations that created this RDD

Assumption input file is still available

OTHER RDD OPERATIONS

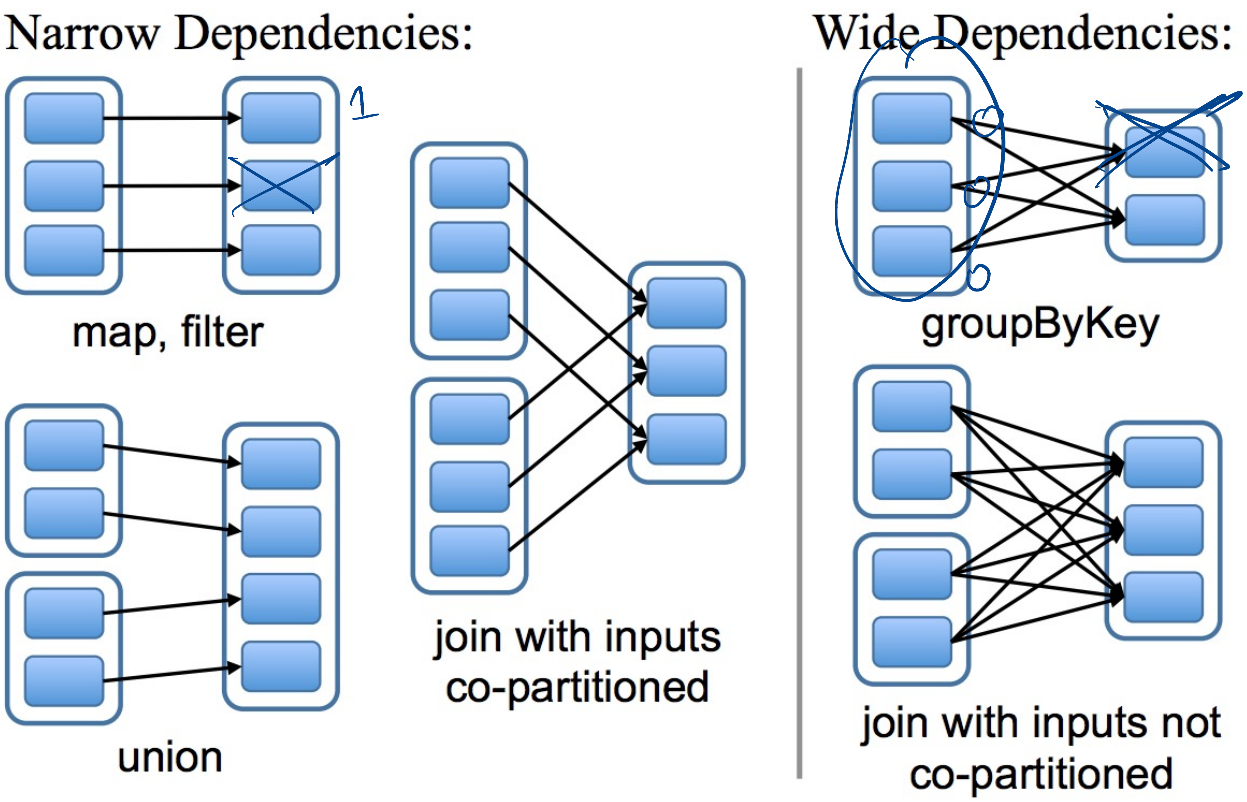
Transformations (define a new RDD)	map filter sample groupByKey reduceByKey cogroup	flatMap union join cross mapValues ...
Actions (output a result)	collect reduce take fold	count saveAsTextFile saveAsHadoopFile ...

DEPENDENCIES



shuffle

Intermediate files are on local disk



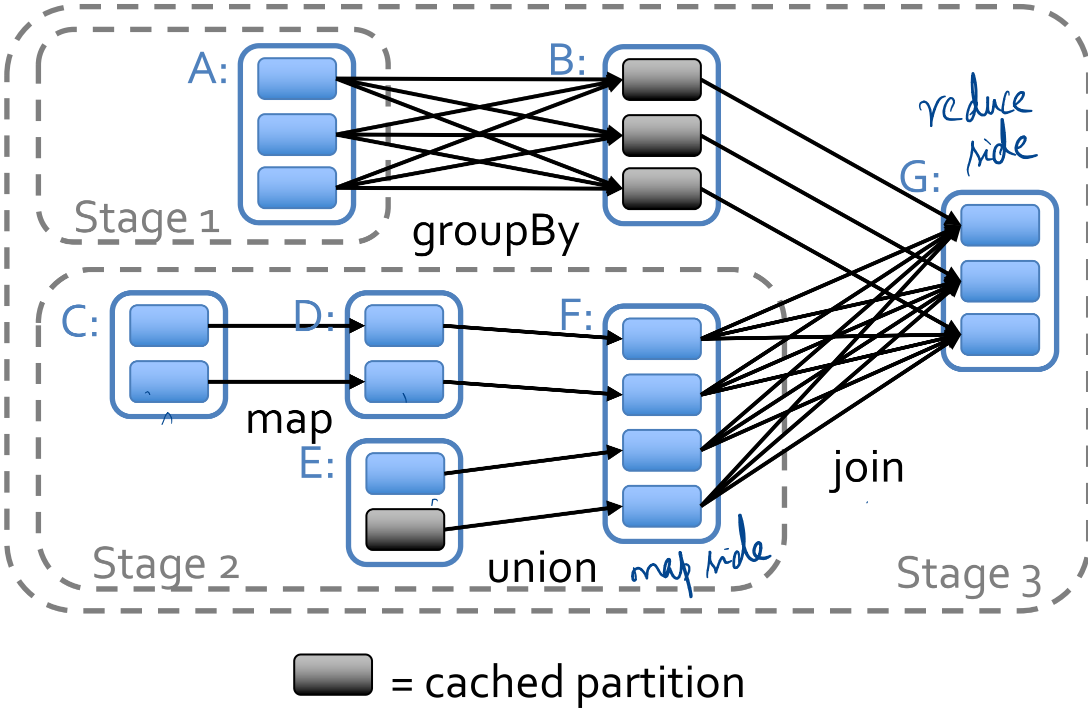
JOB SCHEDULER (1) → inside Driver

Captures RDD dependency graph

Pipelines functions into "stages"

↓

All narrow deps are coalesced inside a stage



JOB SCHEDULER (2)

Move computation to where data is cached

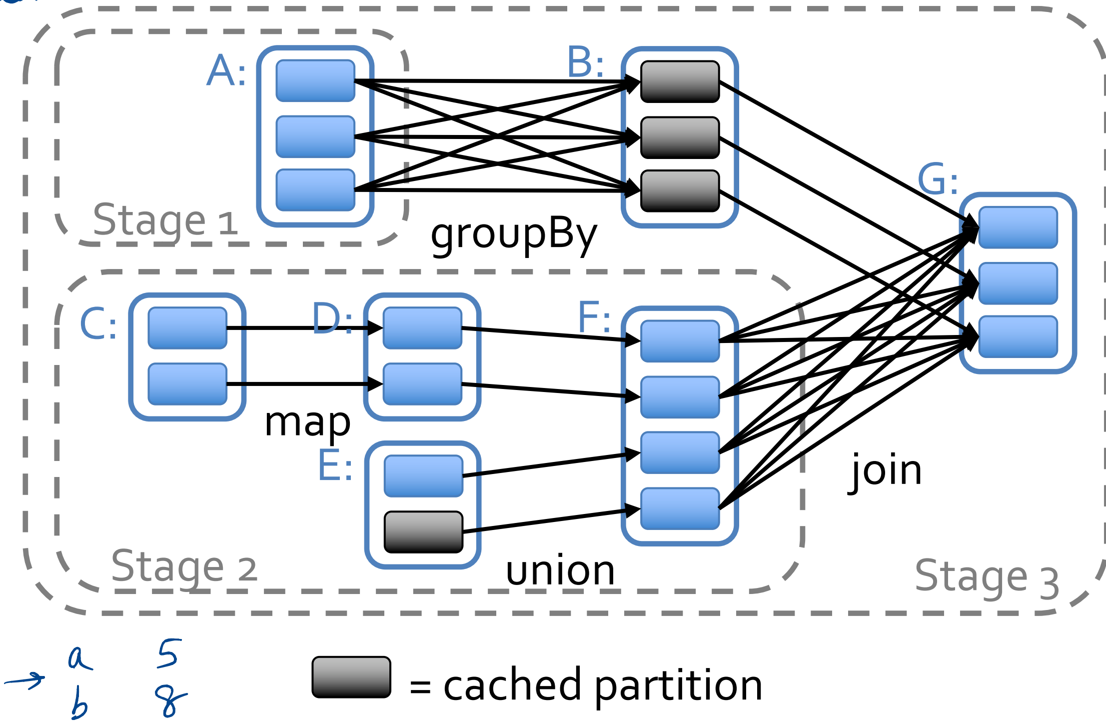
Cache-aware for data reuse, locality

Partitioning-aware to avoid shuffles

Join

rdd1	rdd2
a, 1	a, 4
b, 2	b, 6
c, 3	c, 7

Output → a 5, b 8, c 9



SUMMARY

Spark: Generalize MR programming model

Support in-memory computations with RDDs

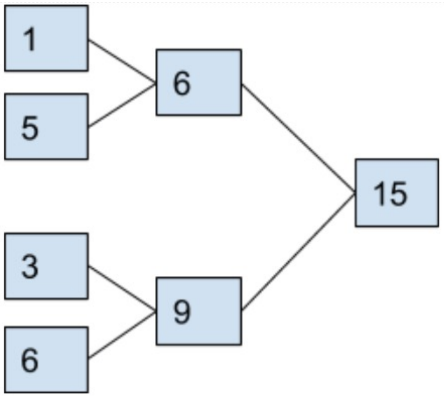
Job Scheduler: Pipelining, locality-aware

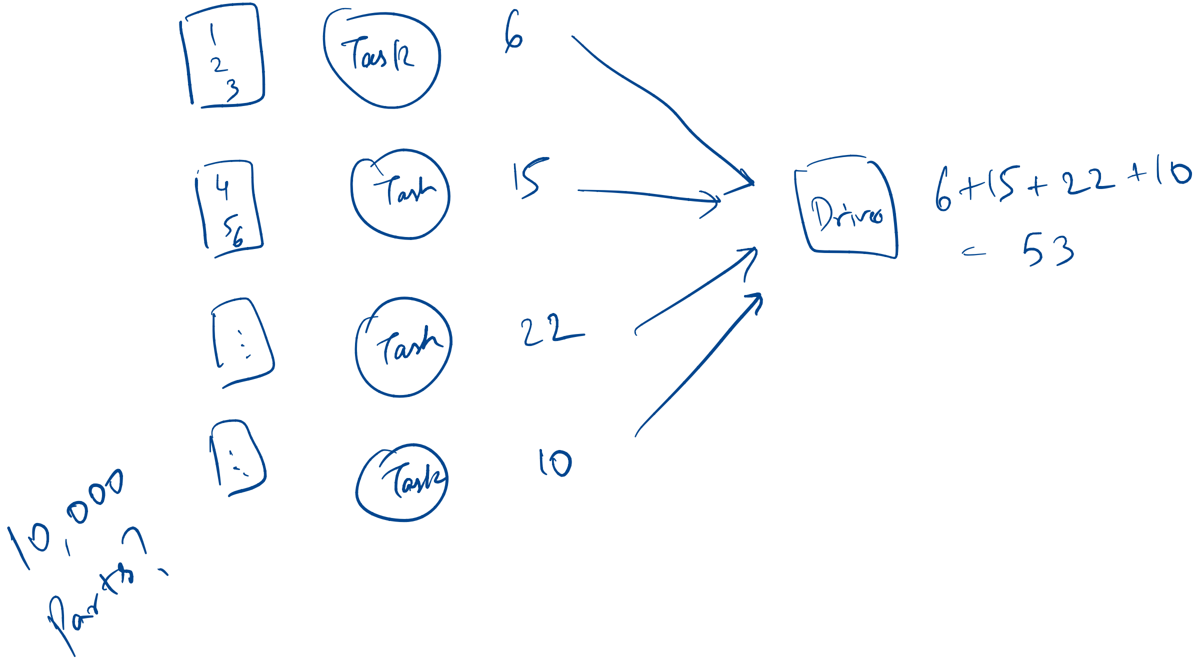
DISCUSSION

https://forms.gle/nPdJYq9D4nE4gtAD9

```
for (i <- 1 to numIters) {
      val modelBC = sc.broadcast(model)
      val grad = data.mapPartitions(iter => gradient(iter, modelBC.value))
      val aggGrad = grad.reduce(case(x, y) => add(x, y))
      model = computeUpdate(aggGrad, model)
}
```

How can we implement binary reduction tree in Spark?





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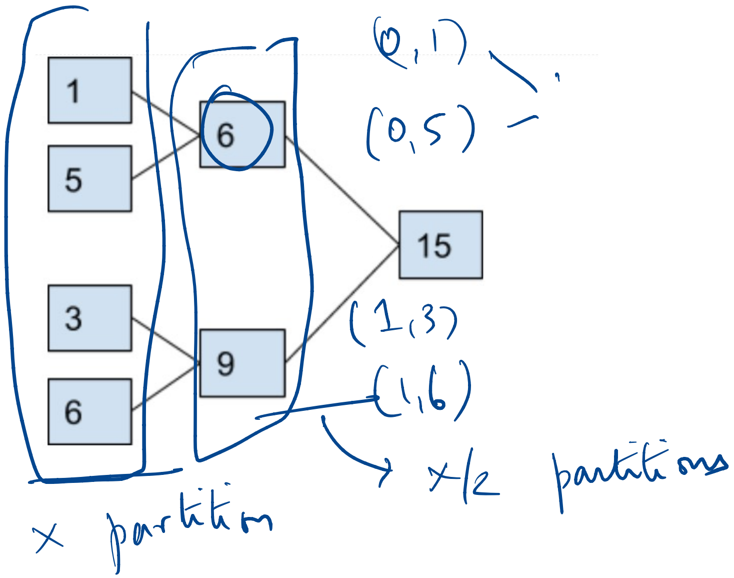
```

Tree Reduction

Assumption: Every task knows its partition Id



$\log_2 P$

Every iteration

Partition By (grouping on keys?)

Aggregate within partition

< Driver launches next >
stage

When would reduction trees be better than using `reduce` in Spark?
When would they not be ?

Very large number of partitions → good for treeReduce

If shuffles are expensive → use reduce.

NEXT STEPS

Next week: Resource Management

- Mesos
- DRF

Assignment 1 is due soon!

CHECKPOINTING

```
rdd = sc.parallelize(1 to 100, 2).map(x → 2*x)
rdd.checkpoint()
```