Hello!

CS 744: RESILIENT DISTRIBUTED DATASETS

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Spring 2024

ADMINISTRIVIA

code & report

- Assignment 1: Due tonight! → 10pm. to Canvas
- Assignment 2: ML will be released later tonight / tomorrow

- 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

21 MR jobs

10 MapReduce jobs

Multi-step jobs create spaghetti code

- 21 MR steps → 21 mapper and reducer classes

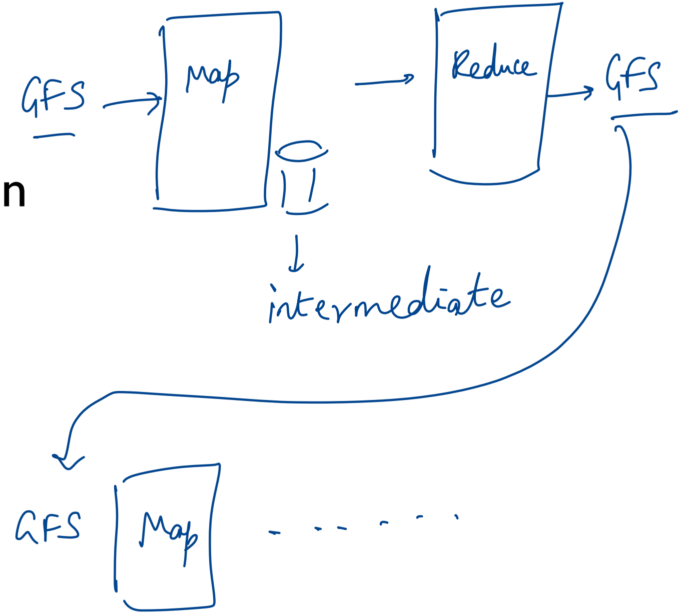
MOTIVATION: PERFORMANCE

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

new API

strings

richer set of operators

word count

Scala

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

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

fewer lines of code

chaining

Inline functions

String → Array[String]

LINQ → Language Integrated Queries

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

→ lead to faster programs

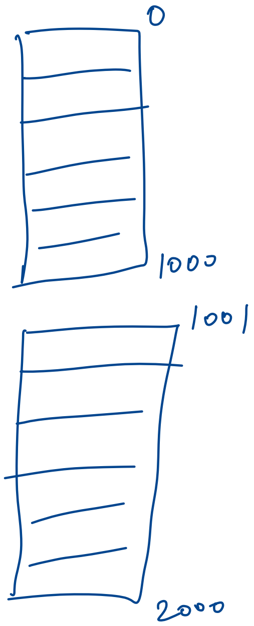
Immutable
↳ what was done to create it → Lineage

SPARK CONCEPTS

Partitioned Collections

- Resilient distributed datasets (RDDs)
  - Immutable, partitioned collections of objects
  - May be cached in memory for fast reuse
- Operations on RDDs
  - *Transformations* (build RDDs)
  - *Actions* (compute results)
- Restricted shared variables
  - Broadcast, accumulators

immutable
↓
Create once
read only



→ Programming more expressive

produce
Concrete results (not RDDs)

EXAMPLE: LOG MINING

Lazy execution

Find error messages present in log files interactively

(Example: HTTP server logs) → Distributed grep

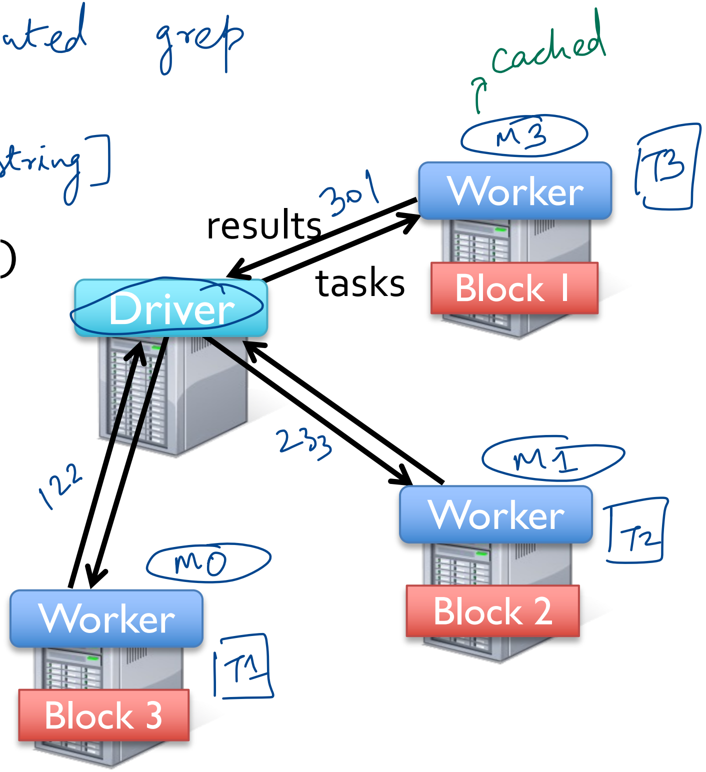
→ RDD

RDD [String]

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

→ Denotes to spark to save messages in memory =

Action



EXAMPLE: LOG MINING

Find error messages present in log files interactively

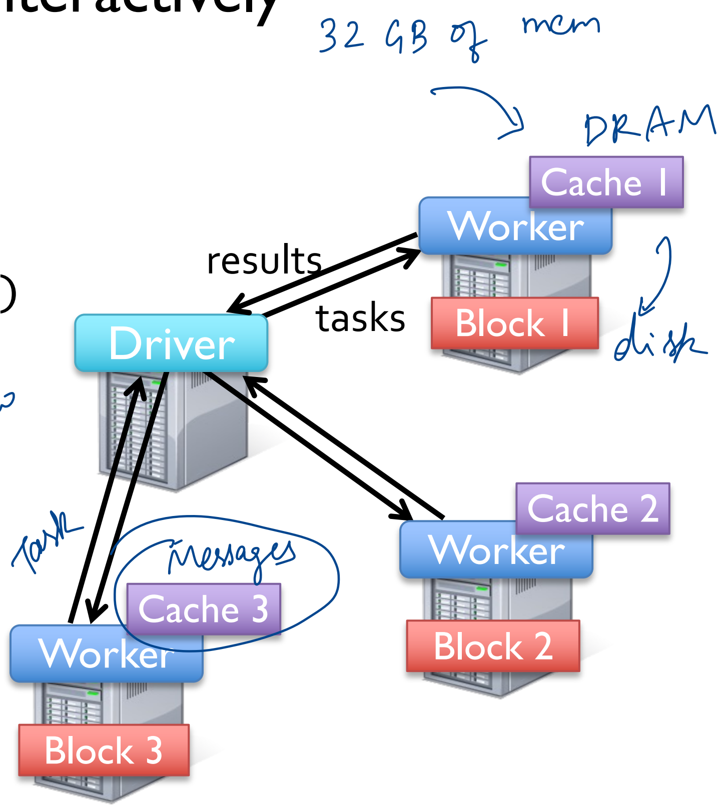
(Example: HTTP server logs)

skip

```
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
. . .
```

slow

faster



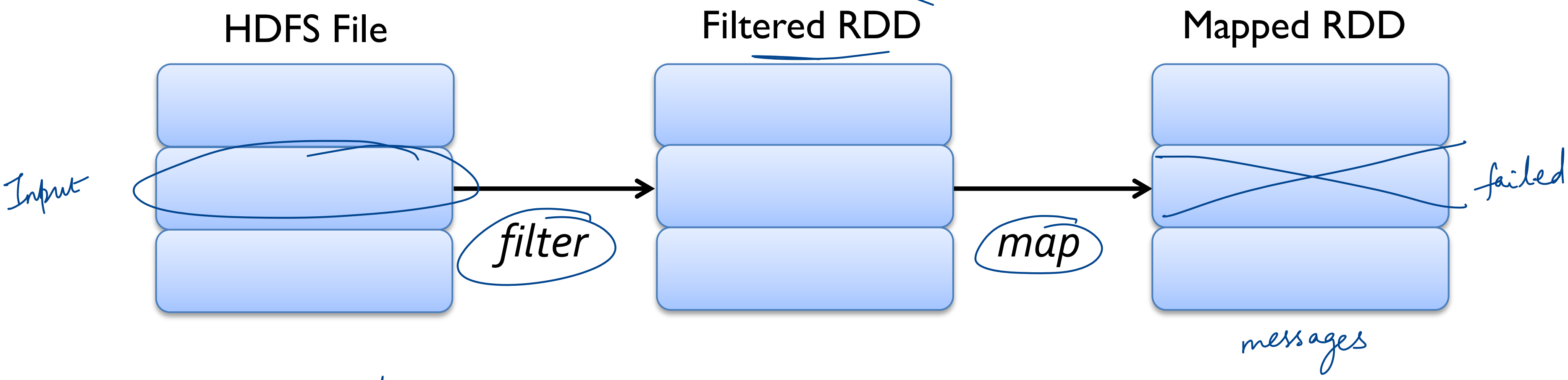
Result: search 1 TB data in 5-7 sec
(vs 170 sec for on-disk data)

Saving lineage

FAULT RECOVERY

Driver

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

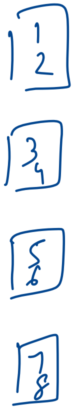


repeat

input
filter
map

to recreate the missing partition

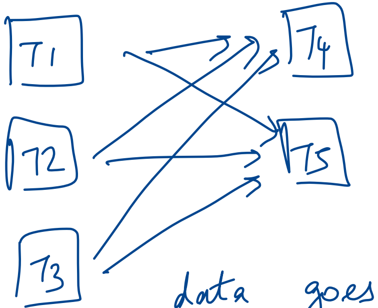
OTHER RDD OPERATIONS



.reduce(_ + _)

= 39

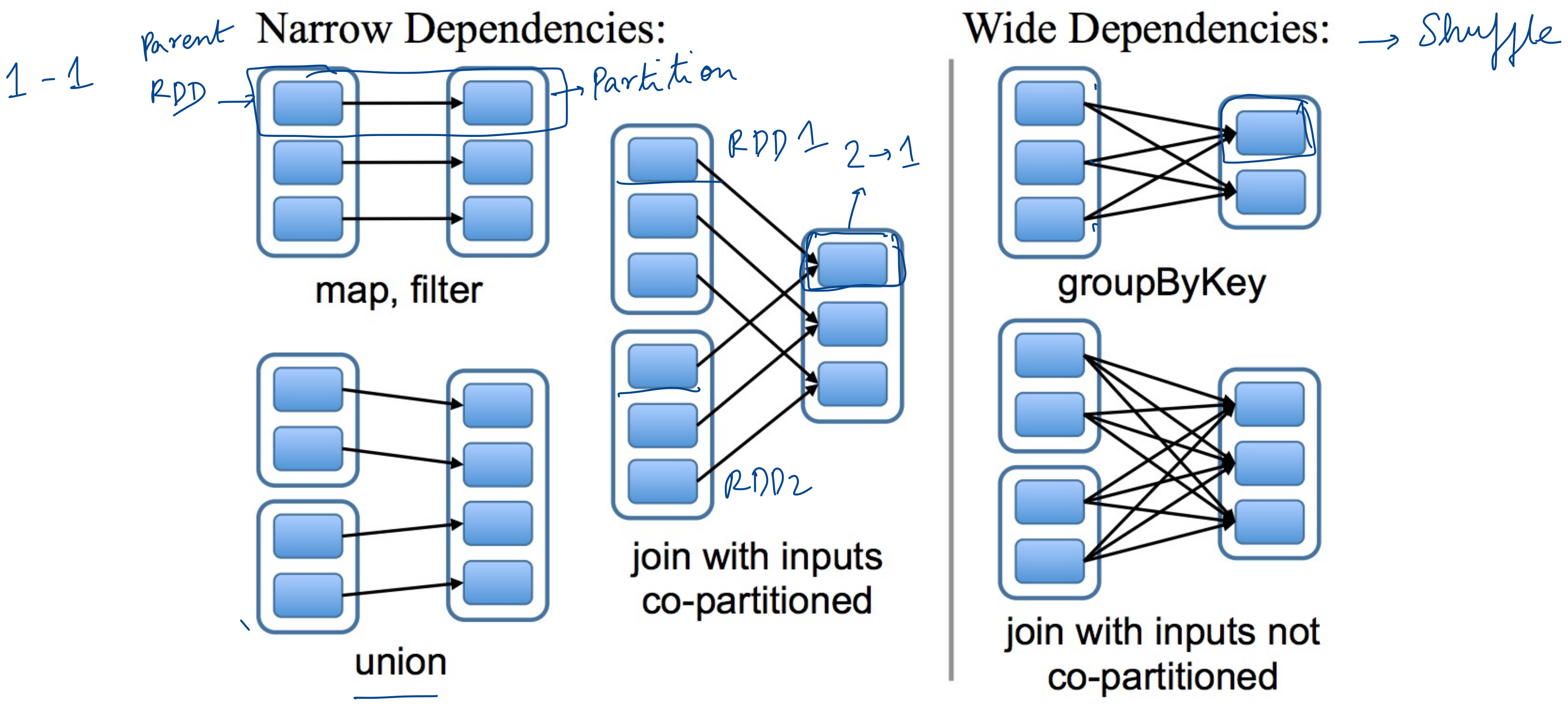
Driver



data goes all of {T1, T2, T3} to {T4, T5}

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



JOB SCHEDULER (1)

Intermediate files

↳ performance, reliability

↳ local disk

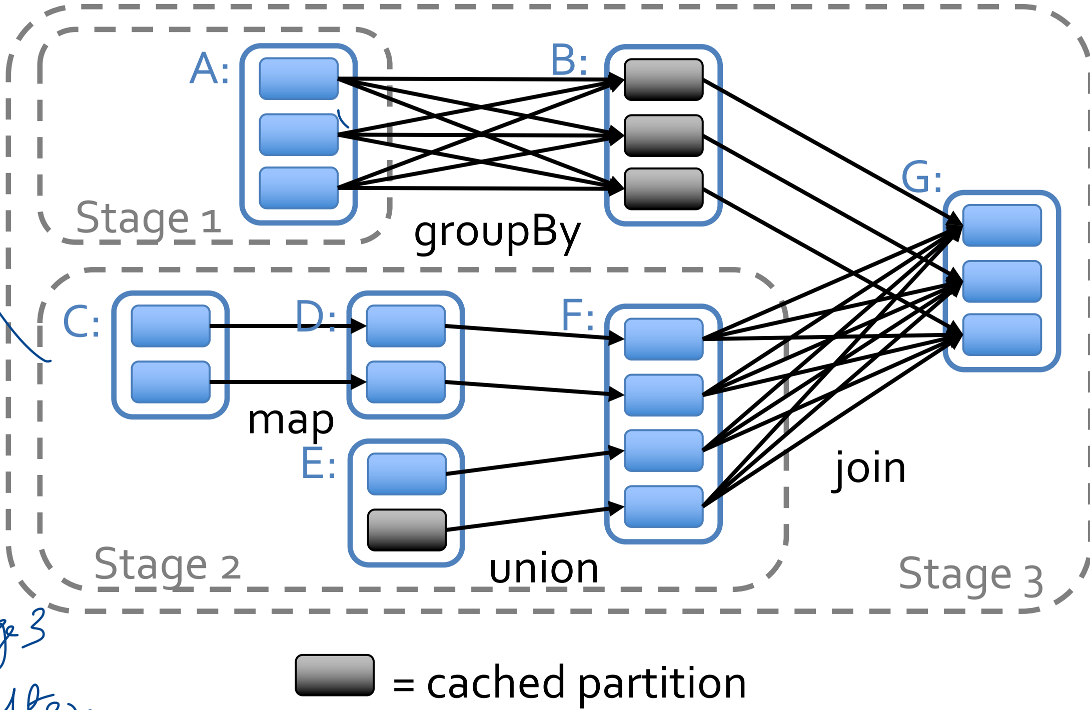
narrow dependencies are coalsced

Job.

Captures RDD dependency graph

Pipelines functions into "stages"

Stage boundaries are shuffle operations



Stage 1 and Stage 2 run in parallel

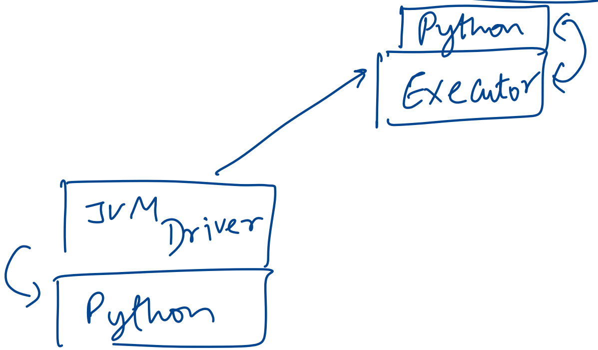
Stage 3 after

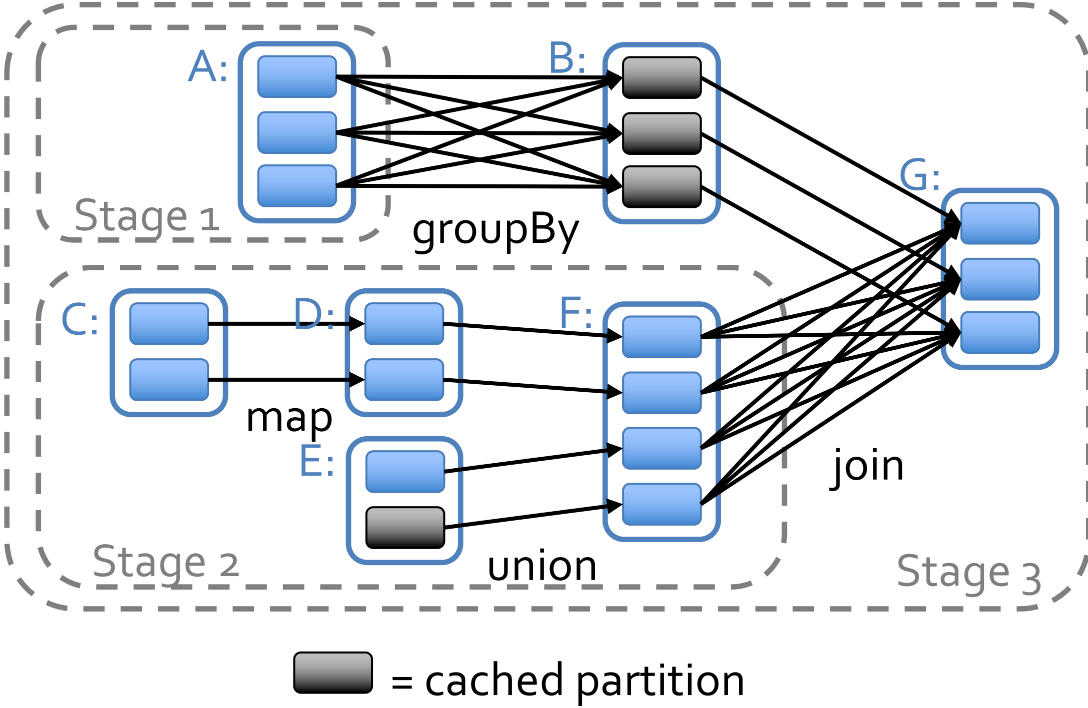
JOB SCHEDULER (2)

task input in-memory → run there
local disk → run there
any location

Cache-aware for data reuse, locality

Partitioning-aware to avoid shuffles





SUMMARY

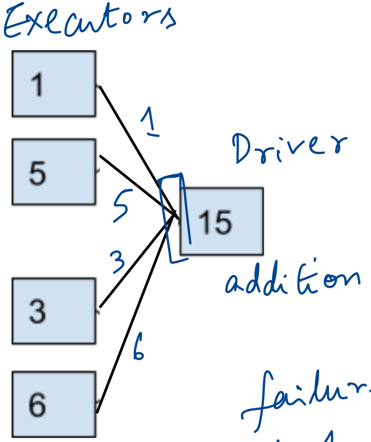
Spark: Generalize MR programming model

Support in-memory computations with RDDs

Job Scheduler: Pipelining, locality-aware

DISCUSSION

https://forms.gle/LB2Fu7vPrNy3oJKq6



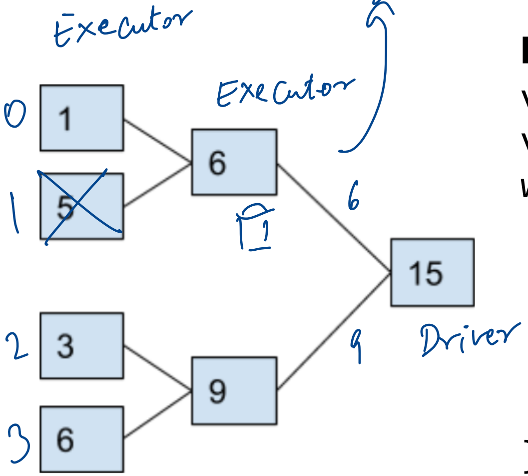

```
for (i <- 1 to numIters) {
    val modelBC = sc.broadcast(model)
    val grad = data.mapPartitions(iter => gradient(iter,
modelBC.value))
    val aggGrad = grad.reduce(case(x, y) => add(x, y))
    model = computeUpdate(aggGrad, model)
}
```

failure / straggler prob is higher ?

network bandwidth of driver

parallelizing the addition

large list lot of computation → Reduction tree



Binary Reduction Tree

```
var g = grad
var numPartitions = g.partitions.size
while (numPartitions > 1) {
   numPartitions = numPartitions / 2
   val part = new HashPartitioner(numPartitions)
   g = g.mapPartitionsWithIndex { case (partId, itr) =>
       Iterator.single(partId / 2, itr.next)
         }.reduceByKey(part, reduceFunc).values
}
```

When would reduction trees be better than using \`reduce\` in Spark?

When would reduction trees not be a good idea?

overhead

→ Task launch

→ Intermediate, reading network

latency

when data is small

failure / straggler probability

Partitioner / load balance

NEXT STEPS

Next week: Machine Learning

Assignment 1 is due TODAY!