CS 744: BIG DATA SYSTEMS

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ADMINISTRIVIA

- Assignment 1: Due Oct 1
- Project
  - Ideas posted on Piazza
  - Meetings on Oct 4 / Oct 5

DISCUSSION: 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

Multi-step jobs create spaghetti code

- 21 MR steps → 21 mapper and reducer classes

DISCUSSION: 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

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 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();
```

SPARK PROGRAMMABILITY

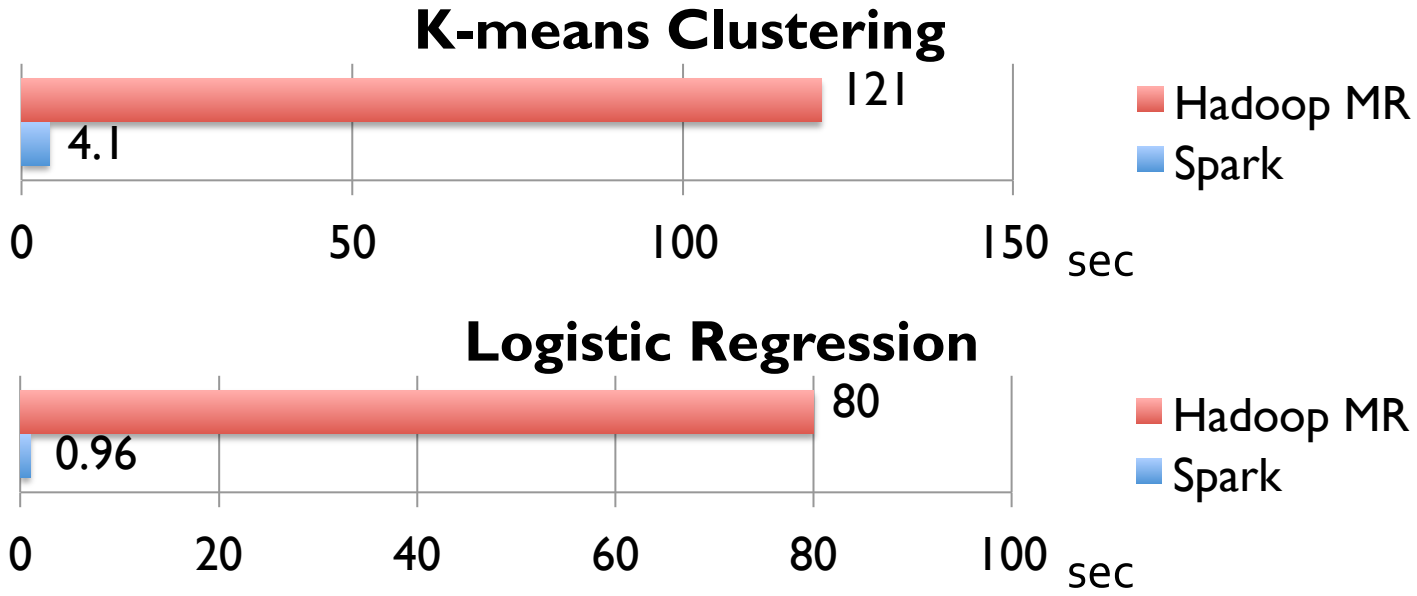
Spark WordCount:

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

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

SPARK PERFORMANCE

Iterative algorithms:



SPARK CONCEPTS

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

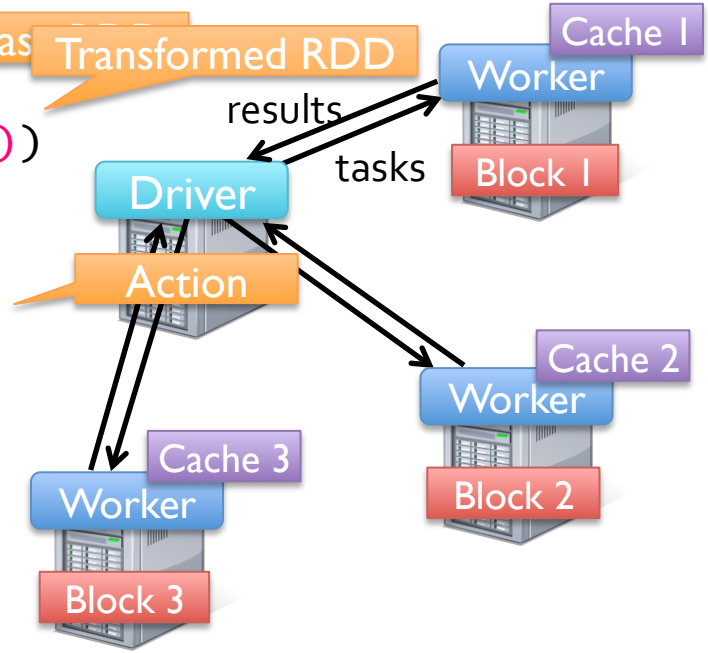
EXAMPLE: LOG MINING

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
. . .
```

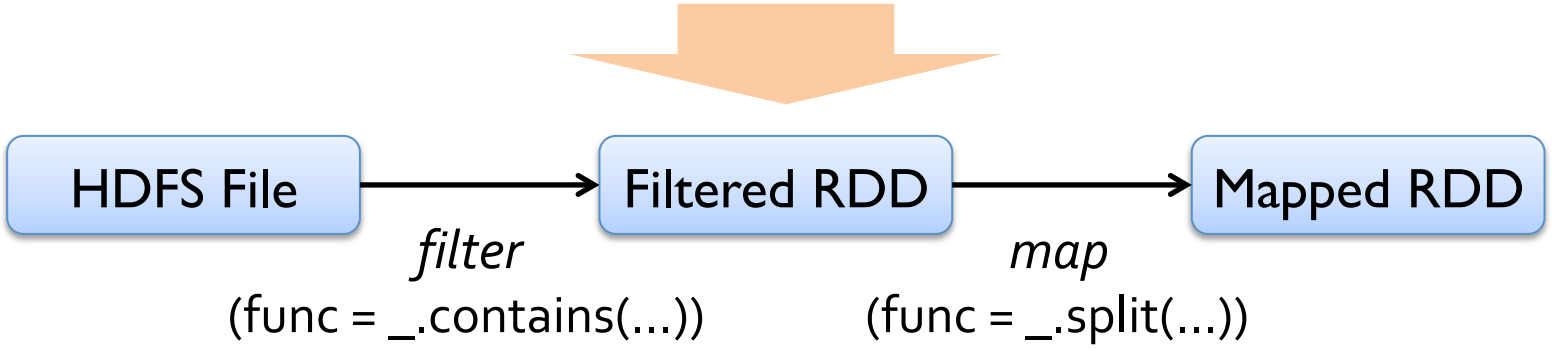
Result: search 1 TB data in 5-7 sec
(vs 170 sec for on-disk data)



FAULT RECOVERY

RDDs track *lineage* information that can be used to efficiently reconstruct lost partitions

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



SHARED VARIABLES

RDD operations: use local variables from scope

Two other kinds of shared variables:

- Broadcast Variables
- Accumulators

BROADCAST VARIABLES

```
val data = spark.textFile(...).map(readPoint).cache()

// Random Projection
val M = Matrix.random(N)

var w = Vector.random(D)

for (i <- 1 to ITERATIONS) {
  val gradient = data.map(p =>
    (1 / (1 + exp(-p.y*(w.dot(p.x.dot(M))))) - 1)
    * p.y * p.x
  ).reduce(_ + _)
  w -= gradient
}

println("Final w: " + w)
```

Large Matrix

Problem:
M re-sent to all nodes in each iteration

BROADCAST VARIABLES

```
val data = spark.textFile(...).map(readPoint).cache()

// Random Projection
Val M = spark.broadcast(Matrix.random(N))

var w = Vector.random(D)

for (i <- 1 to ITERATIONS) {
  val gradient = data.map(p =>
    (1 / (1 + exp(-p.y*(w.dot(p.x.dot(M.value))))) - 1)  * p.y *
   p.x
  ).reduce(_ + _)
  w -= gradient
}

println("Final w: " + w)
```

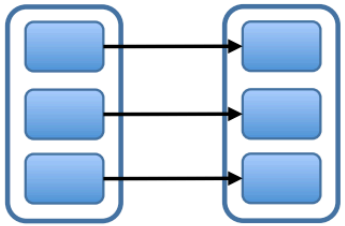
Solution: mark M as broadcast variable

OTHER RDD OPERATIONS

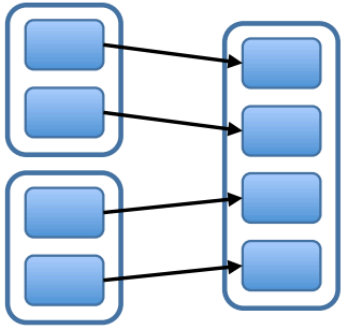
Transformations (define a new RDD)	map filter sample groupByKey reduceByKey cogroup	flatMap union join cross mapValues ...
Actions (output a result)	collect reduce take fold	count saveAsTextFile saveAsHadoopFile ...

DEPENDENCIES

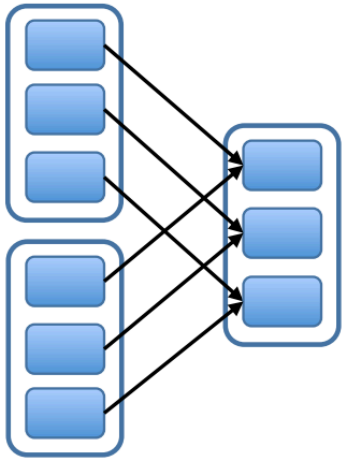
Narrow Dependencies:



map, filter

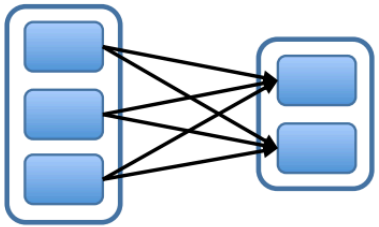


union

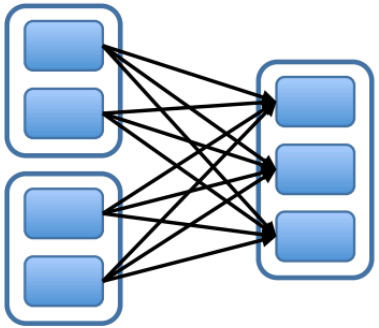


join with inputs co-partitioned

Wide Dependencies:



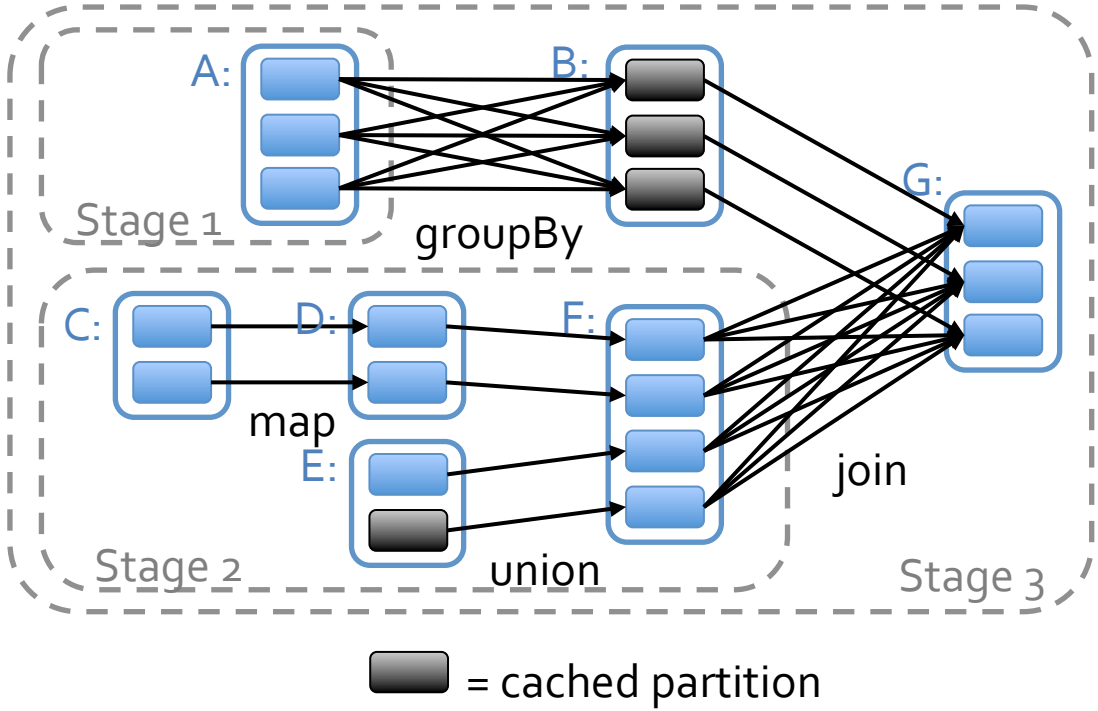
groupByKey



join with inputs not co-partitioned

JOB SCHEDULER

- Captures RDD dependency graph
- Pipelines functions into "stages"
- Cache-aware for data reuse & locality
- Partitioning-aware to avoid shuffles



SPARK ADOPTION

Open source Apache Project, > 1000 contributors

Extensions to SQL, Streaming, Graph processing

Unified Platform for Big Data Applications

QUESTIONS / DISCUSSION ?