Database Systems
CSE 344

Lecture 24: Spark

Announcements

- Final Exam in class Friday
  - 60min exam – focus will be on second half of class
  - Wednesday – review what's on the exam
  - Thursday section – more review

- HW Grades through HW6 are published
  - HW6 is out of 100 points but will be scaled to 21

Announcements

- Homework breakdown (50%) of grade
  - HW1 (sqlite) 20 pt
  - HW2 (sqlite) 20 pt
  - HW3 (sql sever) 27 pt
  - H4 (RA,RC,Datalog) 15pt
  - H6 (E/R BCNF) 21pt
  - HW7 30 pt

Lifecycle of a MR Program

1. Read a lot of data and parse into (key, value) pairs
2. Map: extract something you care about from each (key, value) pair
3. Shuffle output from mappers
   – done internally by implementation
4. Reduce: aggregate, summarize, filter, transform
5. Write the results to files

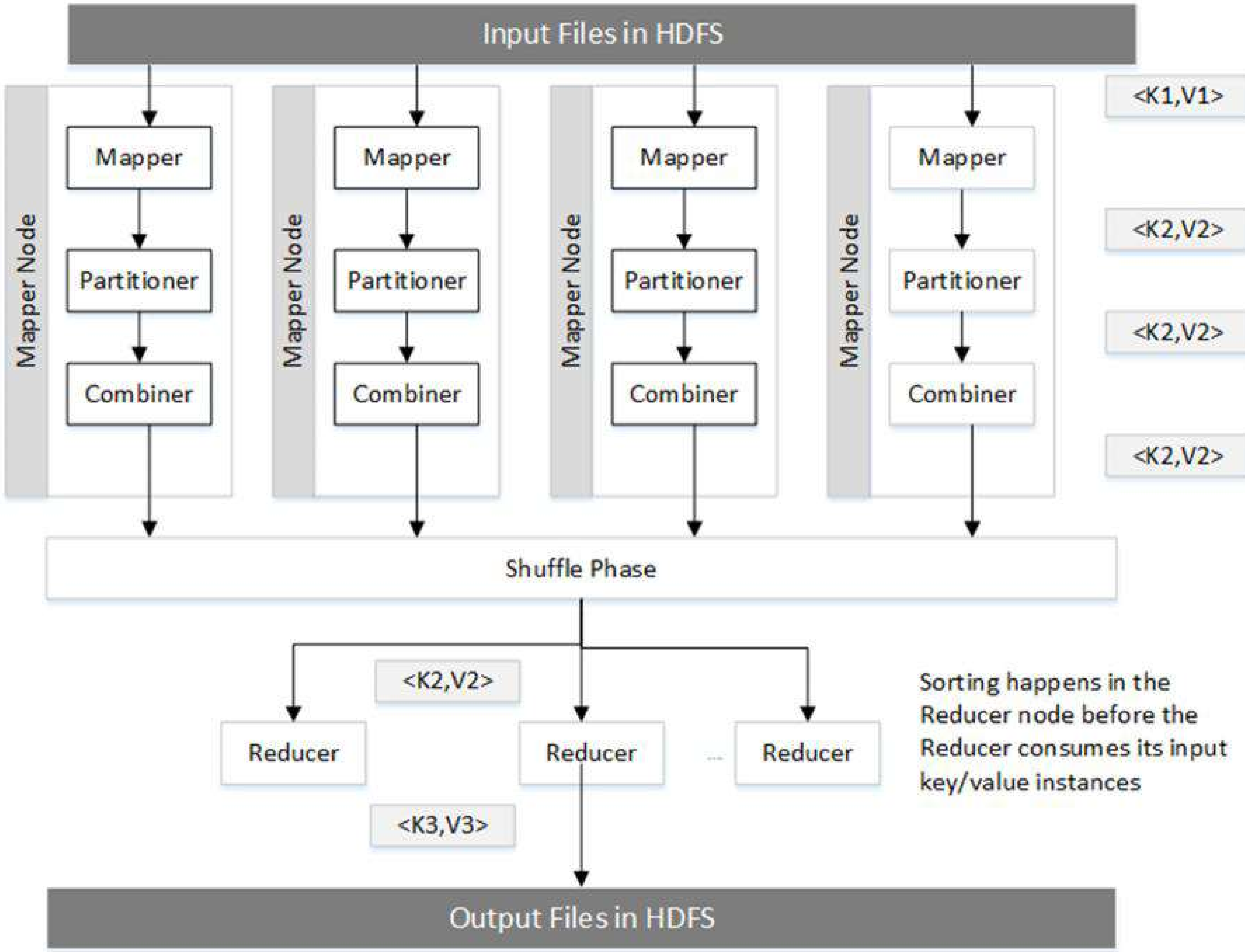
Paradigm stays the same,
change map and reduce
functions for different problems

Issues with MapReduce

- Difficult to write more complex queries

- Need multiple MapReduce jobs: dramatically slows down because it writes all results to disk

Over view of MapReduce



Spark

- Open source system from Berkeley
- Distributed processing over HDFS
- Differences from MapReduce:
  - Multiple steps, including iterations
  - Stores intermediate results in main memory
  - Supports SQL
- Details: http://spark.apache.org/examples.html
- Free Trail: https://community.cloud.databricks.com/

Spark Interface

- Spark supports a Scala interface
- Scala = ext of Java with functions/closures
  - will show Scala/Spark examples shortly…

- Spark also supports a SQL interface
- It compiles SQL into Scala
  - Best of both world: programmatic and SQL APIs

RDD

- RDD = Resilient Distributed Datasets
  - A distributed relation, together with its *lineage*
  - Lineage = expression that says how that relation was computed = a relational algebra plan
- Spark stores intermediate results as RDD
- If a server crashes, its RDD in main memory is lost. However, the driver (=master node) knows the lineage, and will simply recompute the lost partition of the RDD

Programming in Spark

- A Spark/Scala program consists of:
  - Transformations (map, reduce, join…). Lazy
  - Actions (count, reduce, save...). Eager

- RDD[T] = an RDD collection of type T
  - Partitioned, recoverable (through lineage), not nested
- Seq[T] = a Scala sequence
  - Local to a server, may be nested

Example

Given a large log file hdfs://logfile.log
retrieve all lines that:

- Start with "ERROR"
- Contain the string "sqlite"

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

errors = lines.filter(_.startsWith("ERROR"));

sqlerrors = errors.filter(_.contains("sqlite"));

sqlerrors.collect()
```

Example

for _ in errors:
  if _.startswith
    return True
return False

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Transformation:
Not executed yet…

Action:
triggers execution
of entire program

MapReduce Again…

Steps in Spark resemble MapReduce:

- col.filter(p) applies in parallel the predicate p to all elements x of the partitioned collection, and returns those x where p(x) = true
- col.map(f) applies in parallel the function f to all elements x of the partitioned collection, and returns a new partitioned collection

Scala Primer

- Functions with one argument:

  _.contains("sqlite")

  _ > 6

- Functions with more arguments

  (x => x.contains("sqlite"))

  (x => x > 6)

  ((x,y) => x+3*y)

- Closures (functions with variable references):

  var x = 5;   rdd.filter(_ > x)

  var s = "sqlite"; rdd.filter(x => x.contains(s))

Persistence

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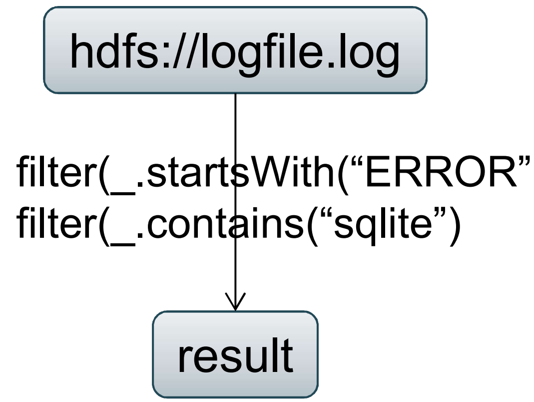
If any server fails before the end, then Spark must restart

Persistence

RDD:

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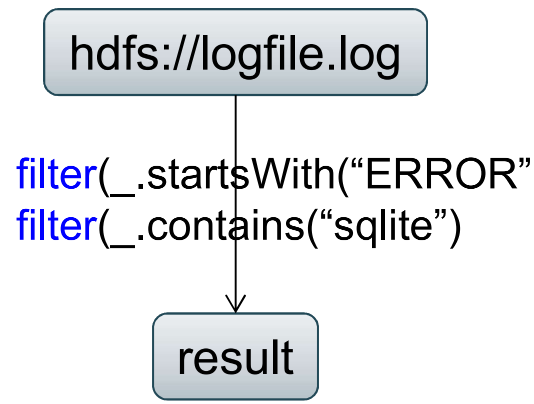


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sqlerrors.collect()
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If any server fails before the end, then Spark must restart

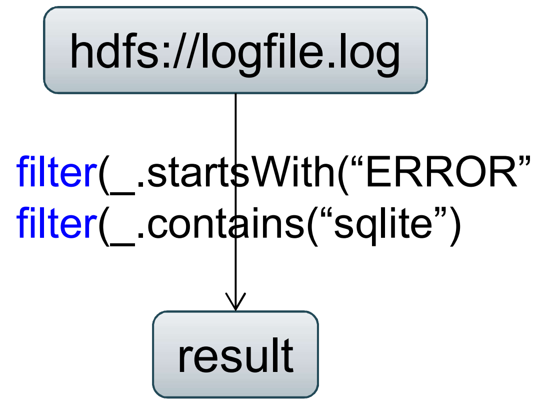
```
lines = spark.textFile(“hdfs://logfile.log”);
errors = lines.filter(_.startsWith(“ERROR”));
errors.persist()
sqlerrors = errors.filter(_.contains(“sqlite”));
sqlerrors.collect()
```

New RDD

Spark can recompute the result from errors

Persistence

RDD:

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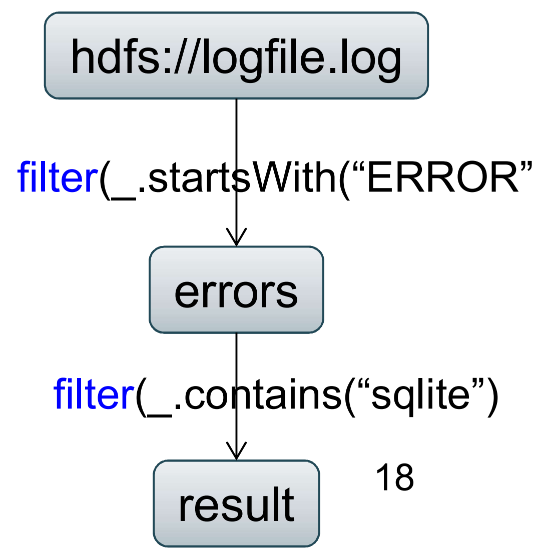


Spark can recompute the result from errors

R(A,B)
S(A,C)

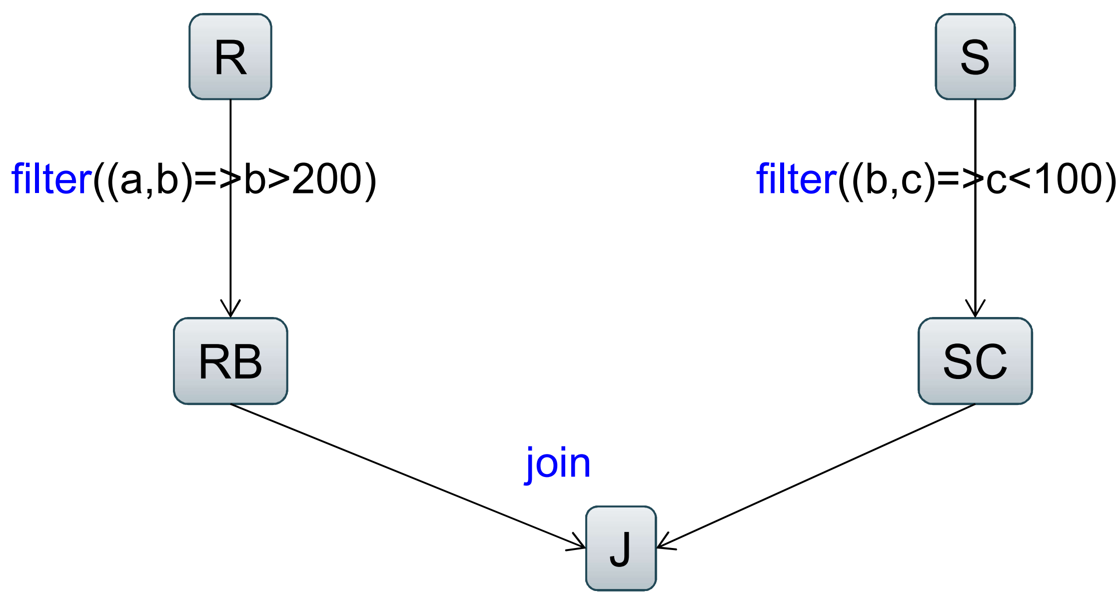
```
SELECT count(*)  FROM R, S
WHERE R.B > 200 and S.C < 100  and R.A = S.A
```

Example

→ text ⇒ csv row

```
R = spark.textFile("R.csv").map(parseRecord).persist()
S = spark.textFile("S.csv").map(parseRecord).persist()
RB = R.filter((a,b) => b > 200).persist()
SC = S.filter((a,c) => c < 100).persist()
J = RB.join(SC).persist()
J.count();
```

cache in memory



Programming in Spark

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Transformations:	
map(f : T => U):	RDD[T] => RDD[U] Size is equal
flatMap(f: T => Seq[U]):	RDD[T] => RDD[U]
filter(f:T=>Bool):	RDD[T] => RDD[T]
groupByKey():	RDD[(K,V)] => RDD[(K,Seq[V])]
reduceByKey(F:(V,V) => V):	RDD[(K,V)] => RDD[(K,V)]
union():	(RDD[T],RDD[T]) => RDD[T]
join():	(RDD[(K,V)],RDD[(K,W)]) => RDD[(K,(V,W))]
cogroup():	(RDD[(K,V)],RDD[(K,W)]) => RDD[(K,(Seq[V],Seq[W]))]
crossProduct():	(RDD[T],RDD[U]) => RDD[(T,U)]

Actions:	
count():	RDD[T] => Long
collect():	RDD[T] => Seq[T]
reduce(f:(T,T)=>T):	RDD[T] => T
save(path:String):	Outputs RDD to a storage system e.g. HDFS

MapReduce ~> Spark

- input into an RDD
- map phase becomes .flatMap
- shuffle & sort becomes .groupByKey
- reduce becomes another .flatMap
- save output to HDFS

Spark APIs

```java
JavaRDD<String> textFile = sc.textFile("hdfs://...");
JavaPairRDD<String, Integer> counts = textFile
    .flatMap(s -> Arrays.asList(s.split(" "))
    .iterator()) .mapToPair(word -> new Tuple2<>(word, 1))
     .reduceByKey((a, b) -> a + b);
counts.saveAsTextFile("hdfs://...");
```

Java

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

Scala

SQL ~> Spark

- You know enough to execute SQL on Spark!
- Idea: (1) SQL to RA + (2) RA on Spark
  - $\boldsymbol{\sigma}$ = filter $\sigma_{a=10}$ filter(_ < 10)
  - $\boldsymbol{\pi}$ = map
  - $\boldsymbol{\gamma}$ = groupByKey
  - $\times$ = crossProduct
  - $\bowtie$ = join
- Spark SQL does small optimizations to RA
- Also chooses btw broadcast and parallel joins

Spark APIs: SQL

```
// Register the DataFrame as a SQL temporary view
df.createOrReplaceTempView("people")

val sqlDF = spark.sql("SELECT * FROM people")
sqlDF.show()
// +----+-------+
// | age|   name|
// +----+-------+
// |null|Michael|
// |  30|   Andy|
// |  19| Justin|
// +----+-------+
```

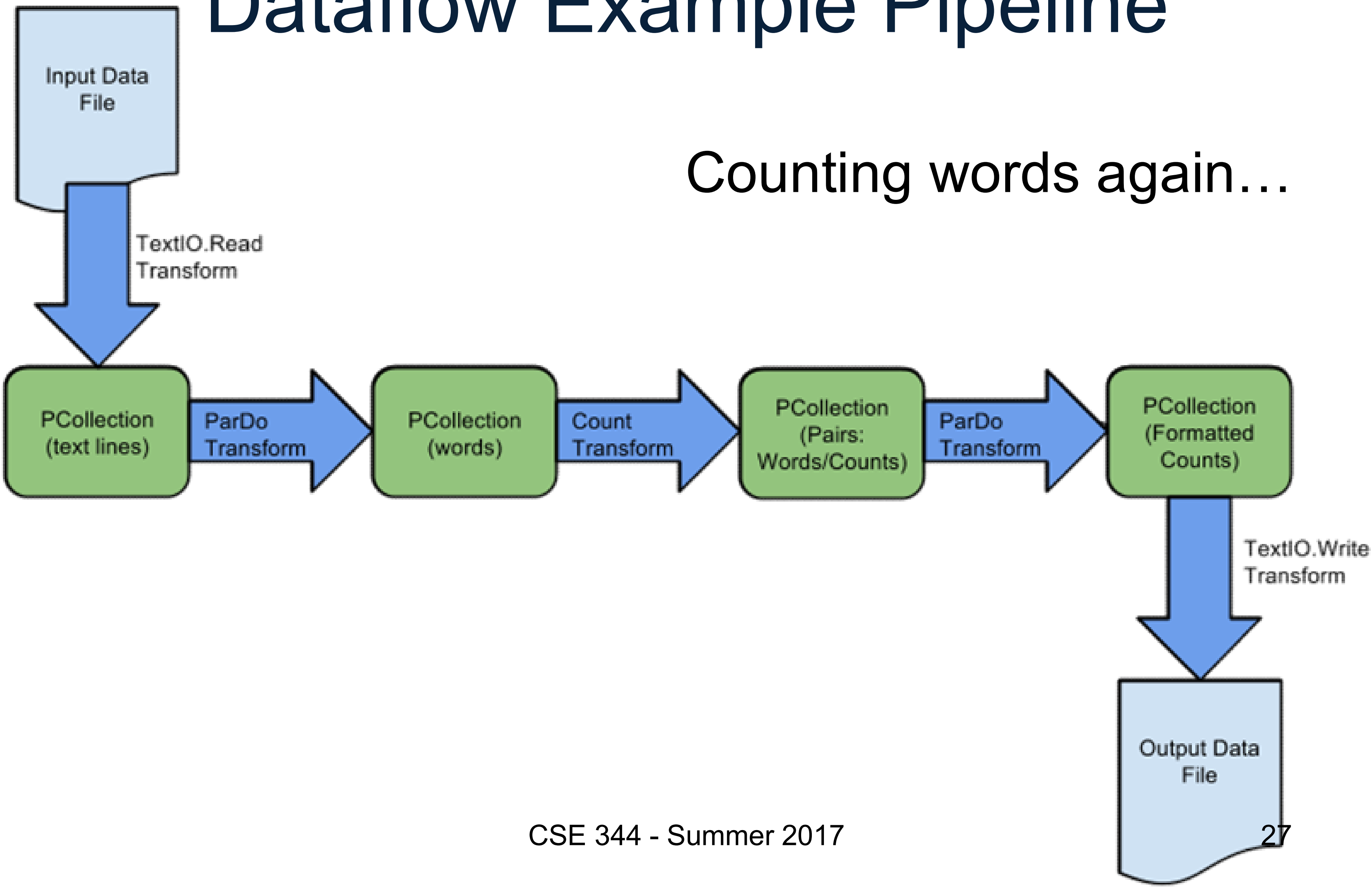
Google Dataflow

- Similar to Spark/Scala
- Allows you to lazily build pipelines and then execute them

- Much simpler than multi-job MapReduce

Dataflow Example Pipeline

Counting words again…



Dataflow Example Code

Read lines into PCollection

```
Pipeline p = Pipeline.create(options);

p.apply(TextIO.Read.from(
    "gs://dataflow-samples/shakespeare/kinglear.txt"))

  .apply(ParDo.named("ExtractWords").of(new DoFn<String, String>() {
     @Override
     public void processElement(ProcessContext c) {
       for (String word : c.element().split("[^a-zA-Z']+")) {
         if (!word.isEmpty()) {
           c.output(word);
         }
       }
     }
  }))
```

map line to bag of words

Dataflow Example Code cont.

```
  .apply(Count.<String>perElement())
```

built-in routine to count occurrances

```
  .apply(MapElements.via(new SimpleFunction<KV<String, Long>, String>() {
    @Override
    public String apply(KV<String, Long> element) {
      return element.getKey() + ": " + element.getValue();
    }
  }))
```

(“foo”, 3) ~> “foo: 3”

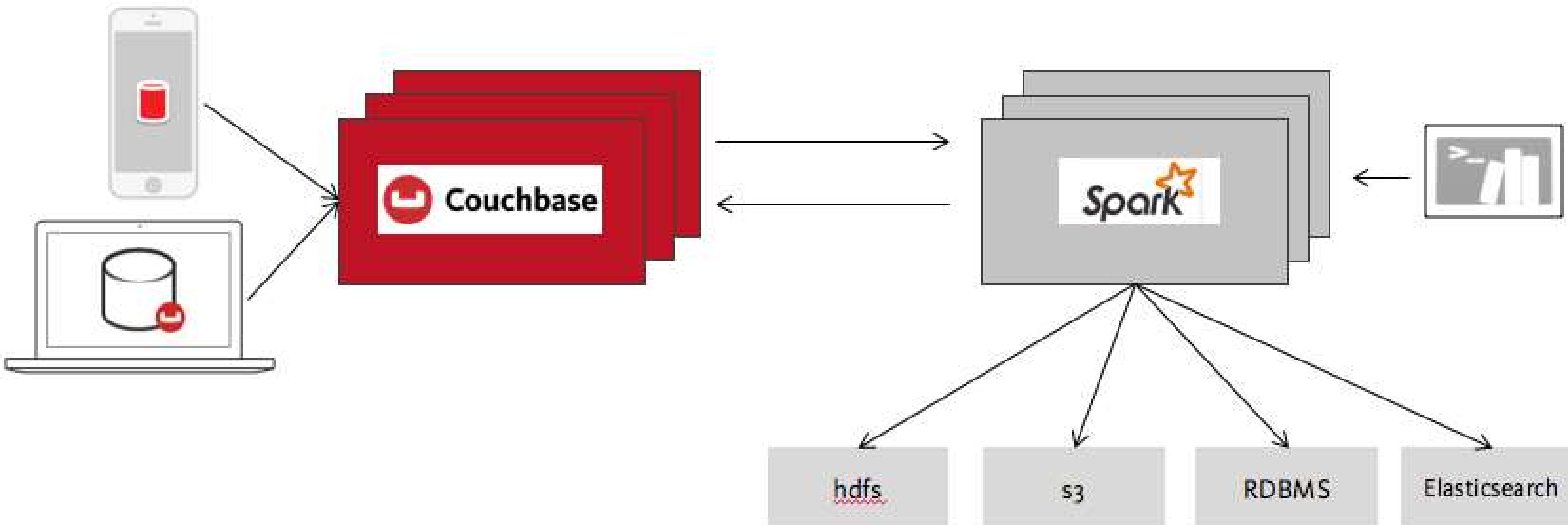
```
  .apply(TextIO.Write.to("gs://my-bucket/counts.txt"));

p.run();
```

execute now

Write results into GFS

Where is Spark Used



Summary

- Parallel databases order 10 nodes
  - Predefined relational operators
  - Optimization
  - Transactions
- MapReduce 10,000 nodes
  - User-defined map and reduce functions
  - Must implement/optimize manually relational ops
  - No updates/transactions
- Spark 10 nodes all memory
  - Predefined relational operators
  - Must optimize manually
  - No updates/transactions

Summary cont.

- All of these technologies use **dataflow engines**:
  - Google Dataflow (on top of MapReduce)
  - Spark (on top of Hadoop)
  - AsterixDB (on top of Hyracks)
- Spark & AsterixDB map SQL to a dataflow pipeline
  - SQL ~> RA ~> dataflow operators (group, join, map)
  - could do the same thing for Google Dataflow
- None of these systems optimize RA very well (as of 2015)
  - Spark has no indexes
  - AsterixDB has indexes but no statistics
- Future work should improve that