Introduction to Database Systems CSE 414

Lecture 20: Map-Reduce and Spark

Announcements

- HW6 is two parts
  - Running your Spark code locally
  - Running your Spark code on AWS
- Do all the local coding first, then run on AWS last.
- Useful: http://spark.apache.org/docs/latest/rdd-programming-guide.html

Typical Problems Solved by MR

- Read a lot of data
- Map: extract something you care about from each record
- Shuffle and Sort
- Reduce: aggregate, summarize, filter, transform
- Write the results

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

slide source: Jeff Dean

Data Model

Files!

A file = a bag of `(key, value)` pairs
Sounds familiar after HW5?

A MapReduce program:
- Input: a bag of `(inputkey, value)` pairs
- Output: a bag of `(outputkey, value)` pairs
  - outputkey is optional

Example

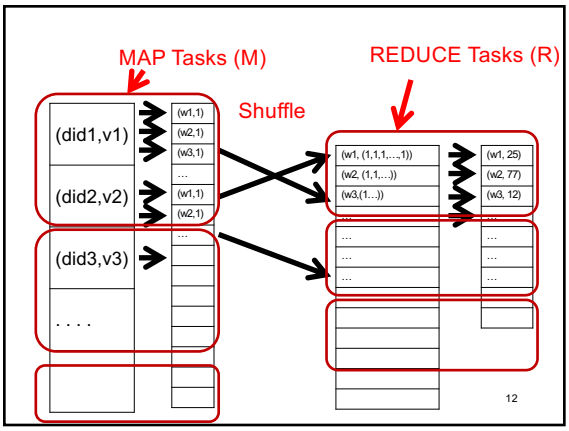
- Counting the number of occurrences of each word in a large collection of documents
- Each Document
  - The key = document id (did)
  - The value = set of words (word)

```
map(String key, String value):
  // key: document name
  // value: document contents
  for each word w in value:
      emitIntermediate(w, "1");
```

```
reduce(String key, Iterator values):
  // key: a word
  // values: a list of counts
  int result = 0;
    for each v in values:
      result += ParseInt(v);
  emit(AsString(result));
```

Workers

- A worker is a process that executes one task at a time
- Typically there is one worker per processor, hence 4 or 8 per node



Fault Tolerance

- If one server fails once every year…
  ... then a job with 10,000 servers will fail in less than one hour
- MapReduce handles fault tolerance by writing intermediate files to disk:
  - Mappers write file to local disk
  - Reducers read the files (=reshuffling); if the server fails, the reduce task is restarted on another server

Implementation

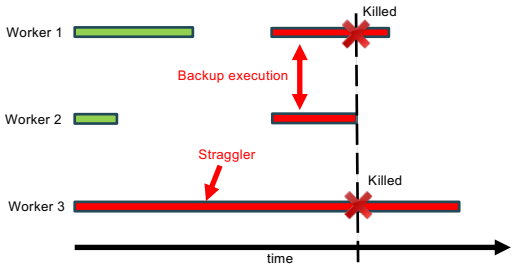
- There is one master node
- Master partitions input file into *M splits*, by key
- Master assigns *workers* (=servers) to the *M map tasks*, keeps track of their progress
- Workers write their output to local disk, partition into *R regions*
- Master assigns workers to the *R reduce tasks*
- Reduce workers read regions from the map workers' local disks

Interesting Implementation Details

Backup tasks:

- *Straggler* = a machine that takes unusually long time to complete one of the last tasks. E.g.:
  - Bad disk forces frequent correctable errors (30MB/s → 1MB/s)
  - The cluster scheduler has scheduled other tasks on that machine
- Stragglers are a main reason for slowdown
- Solution*: pre-emptive backup execution of the last few remaining in-progress tasks*

Straggler Example



Using MapReduce in Practice:

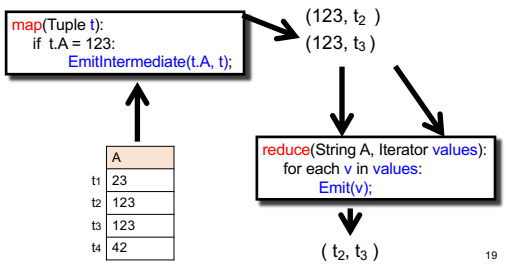
Implementing RA Operators in MR

Relational Operators in MapReduce

Given relations R(A,B) and S(B,C) compute:

- Selection: $\sigma_{A=123}(R)$
- Group-by: $\gamma_{A,sum(B)}(R)$
- ~~Join: $R \bowtie S$~~ (Saved for later)

Selection $\sigma_{A=123}(R)$



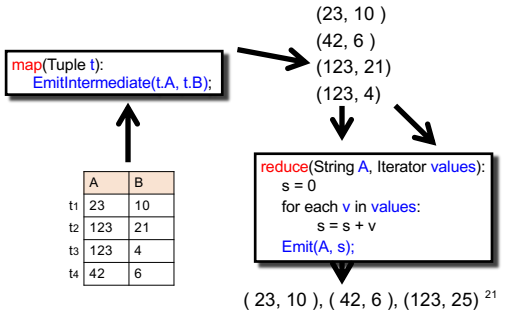
Selection $\sigma_{A=123}(R)$

```
map(Tuple t):
  if t.A = 123:
     EmitIntermediate(t.A, t);
```

~~reduce(String A, Iterator values):~~
~~for each v in values:~~
~~Emit(v);~~

No need for reduce.
But need system hacking in Hadoop to remove reduce from MapReduce

Group By $\gamma_{A,sum(B)}(R)$



Conclusions

- MapReduce offers a simple abstraction, and handles distribution + fault tolerance
- Speedup/scaleup achieved by allocating dynamically map tasks and reduce tasks to available server. However, skew is possible (e.g., one huge reduce task)
- Writing intermediate results to disk is necessary for fault tolerance, but very slow.
- Spark replaces this with "Resilient Distributed Datasets" = main memory + lineage

Spark

A Case Study of the MapReduce Programming Paradigm

HW6

- HW6 will ask you to write SQL queries and MapReduce tasks using Spark
- You will get to "implement" SQL using MapReduce tasks
  - Can you beat Spark's implementation?

Parallel Data Processing @ 2010

Spark

- Open source system from UC Berkeley
- Distributed processing over HDFS
- Differences from MapReduce (CSE 322):
  - Multiple steps, including iterations
  - Stores intermediate results in main memory
  - Closer to relational algebra (familiar to you)
- Details: http://spark.apache.org/examples.html

Spark

- Spark supports interfaces in Java, Scala, and Python
  - Scala: extension of Java with functions/closures
- We will illustrate use the Spark Java interface in this class
- Spark also supports a SQL interface (SparkSQL), and compiles SQL to its native Java interface

Programming in Spark

- A Spark program consists of:
  - Transformations (map, reduce, join…). Lazy
  - Actions (count, reduce, save...). Eager
- Eager: operators are executed immediately
- Lazy: operators are not executed immediately
  - A *operator tree* is constructed in memory instead
  - Similar to a relational algebra tree

Collections in Spark

- RDD<T> = an RDD collection of type T
  - Distributed on many servers, not nested
  - Operations are done in parallel
  - Recoverable via lineage; more later
  - We use JavaRDD in HW 6
- Seq<T> = a sequence
  - Local to one server, may be nested
  - Operations are done sequentially

Transformations:	
map(f : T -> U):	RDD<T> -> RDD<U>
mapToPair(f : T -> K, V):	RDD<T> -> RDD<K, V>
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

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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

Example

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

- Start with “ERROR”
- Contain the string “sqlite”

```
s = SparkSession.builder()...getOrCreate();

lines = s.read().textFile(“hdfs://logfile.log”);

errors = lines.filter(l -> l.startsWith(“ERROR”));

sqlerrors = errors.filter(l -> l.contains(“sqlite”));

sqlerrors.collect();
```


Example

Recall: anonymous functions
(lambda expressions) starting in Java 8

```
errors = lines.filter(l -> l.startsWith(“ERROR”));
```

is the same as:

```
class FilterFn implements Function<Row, Boolean>{
  Boolean call (Row l)
  { return l.startsWith(“ERROR”); }
}

errors = lines.filter(new FilterFn());
```


Example

Recall: anonymous functions
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Example

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

`s has type JavaRDD<String>`

- Start with “ERROR”
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Given a large log file hdfs://logfile.log retrieve all lines that:

- Start with "ERROR"
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`s has type JavaRDD<String>`

```
s = SparkSession.build...e();

lines = s.read().textFi...logfile.log");

errors = lines.filter(l -> l.startsWith("ERROR"));

sqlerrors = errors.filter(l...");

sqlerrors.collect();
```

Transformation: Not executed yet…

Action: triggers execution of entire program

Example

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

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

```
s = SparkSession.builder()...getOrCreate();

sqlerrors = s.read().textFile("hdfs://logfile.log")
             .filter(l -> l.startsWith("ERROR"))
             .filter(l -> l.contains("sqlite"))
             .collect();
```

"Call chaining" style

Example

The RDD s:


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sqlerrors = s.read().textFile("hdfs://logfile.log")
             .filter(l -> l.startsWith("ERROR"))
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```


Example

The RDD s:

Parallel step 1


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```
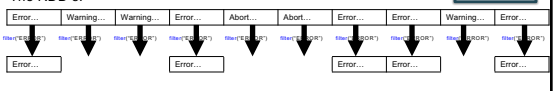


Example

The RDD s:

Parallel step 1

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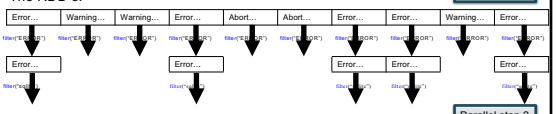
Example

The RDD s:

Parallel step 1

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```

Fault Tolerance

- When a job is executed on x100 or x1000 servers, the probability of a failure is high
- Example: if a server fails once/year, then a job with 10000 servers fails once/hour
- Different solutions:
  - Parallel database systems: restart. Expensive.
  - MapReduce: write everything to disk, redo. Slow.
  - Spark: redo only what is needed. Efficient.

Resilient Distributed Datasets

- RDD = Resilient Distributed Dataset
  - Distributed, immutable and records 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

Persistence

```
lines = s.read().textFile("hdfs://logfile.log");
errors = lines.filter(l->l.startsWith("ERROR"));
sqlerrors = errors.filter(l->l.contains("sqlite"));
sqlerrors.collect();
```

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

Persistence

RDD:


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errors = lines.filter(l->l.startsWith("ERROR"));
sqlerrors = errors.filter(l->l.contains("sqlite"));
sqlerrors.collect();
```

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

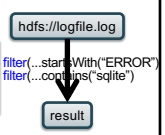
```
lines = s.read().textFile("hdfs://logfile.log");
errors = lines.filter(l->l.startsWith("ERROR"));
errors.persist();
sqlerrors = errors.filter(l->l.contains("sqlite"));
sqlerrors.collect()
```

New RDD

Spark can recompute the result from errors

Persistence

RDD:

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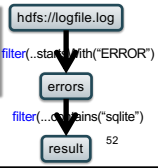
New RDD



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

```
R = strm.read().textFile("R.csv").map(parseRecord).persist();
S = strm.read().textFile("S.csv").map(parseRecord).persist();
```

Parses each line into an object

persisting on disk

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

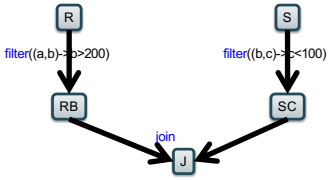
SELECT count(*) FROM R, S
WHERE R.B > 200 and S.C < 100 and R.A = S.A

Example

```
R = strm.read().textFile("R.csv").map(parseRecord).persist();
S = strm.read().textFile("S.csv").map(parseRecord).persist();
RB = R.filter(t -> t.b > 200).persist();
SC = S.filter(t -> t.c < 100).persist();
J = RB.join(SC).persist();
J.count();
```

transformations

action



Recap: 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 sequence
  - Local to a server, may be nested

Transformations:	
map(f : T -> U):	RDD<T> -> RDD<U>
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Spark 2.0

The DataFrame and Dataset Interfaces

DataFrames

- Like RDD, also an immutable distributed collection of data
- Organized into *named columns* rather than individual objects
  - Just like a relation
  - Elements are untyped objects called `Row`'s
- Similar API as RDDs with additional methods
  - ```
    people = spark.read().textFile(…);
    ageCol = people.col("age");
    ageCol.plus(10); // creates a new DataFrame
    ```


Datasets

- Similar to DataFrames, except that elements must be typed objects
- E.g.: `Dataset<People>` rather than `Dataset<Row>`
- Can detect errors during compilation time
- DataFrames are aliased as `Dataset<Row>` (as of Spark 2.0)
- You will use both Datasets and RDD APIs in HW6

Datasets API: Sample Methods

- Functional API
  - `agg(Column expr, Column... exprs)`
    Aggregates on the entire Dataset without groups.
  - `groupBy(String col1, String... cols)`
    Groups the Dataset using the specified columns, so that we can run aggregation on them.
  - `join(Dataset<?> right)`
    Join with another DataFrame.
  - `orderBy(Column... sortExprs)`
    Returns a new Dataset sorted by the given expressions.
  - `select(Column... cols)`
    Selects a set of column based expressions.
- "SQL" API
  - ```
    SparkSession.sql("select * from R");
    ```
- Look familiar?

Conclusions

- Parallel databases
  - Predefined relational operators
  - Optimization
  - Transactions
- MapReduce
  - User-defined map and reduce functions
  - Must implement/optimize manually relational ops
  - No updates/transactions
- Spark
  - Predefined relational operators
  - Must optimize manually
  - No updates/transactions