MapReduce and Spark

Parallel Data Programming

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Recap

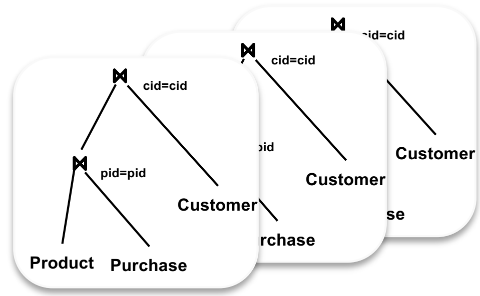
- We have discussed:
  - Single-node relational database systems
  - Parallel relational database systems
  - NoSQL databases

- What about parallel NoSQL databases?
  - That’s what we will discuss next!

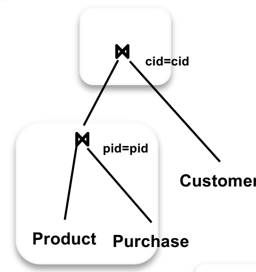
PARALLEL DATA PROCESSING IN THE 20TH CENTURY

Approaches to Parallel Relational Query Evaluation

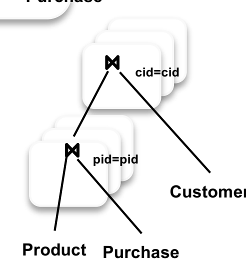
- Inter-query parallelism
  - One query per node
  - Good for transactional (OLTP) workloads



- Inter-operator parallelism
  - Operator per node
  - Good for analytical (OLAP) workloads



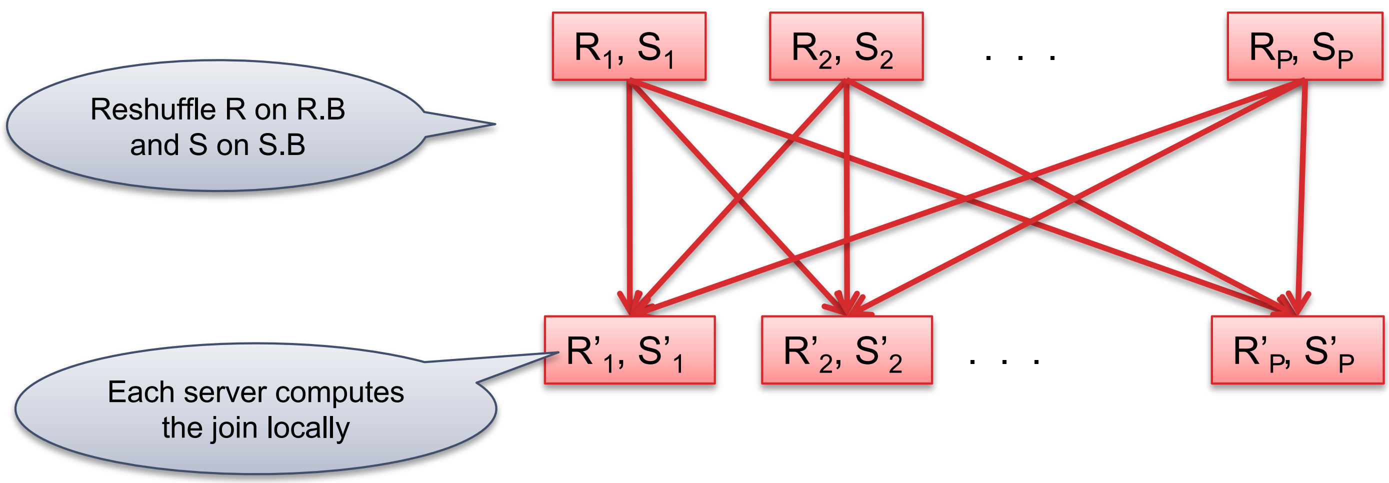
- Intra-operator parallelism
  - Operator on multiple nodes
  - Good for both?



We study only intra-operator parallelism: most scalable

Parallel Execution of RA Operators: Partitioned Hash-Join

- Data: R(K1, A, B), S(K2, B, C)
- Query: R(K1, A, B) $\bowtie$ S(K2, B, C)
  - Initially, both R and S are partitioned on K1 and K2



Data: R(K1,A, B), S(K2, B, C)

Query: R(K1,A,B) ⋈ S(K2,B,C)

Parallel Join Illustration

Partition

M1

R1

K1	B
1	20
2	50

S1

K2	B
101	50
102	50

M2

R2

K1	B
3	20
4	20

S2

K2	B
201	20
202	50

Shuffle on B

Local Join

M1

R1'

K1	B
1	20
3	20
4	20

⋈

S1'

K2	B
201	20

M2

R2'

K1	B
2	50

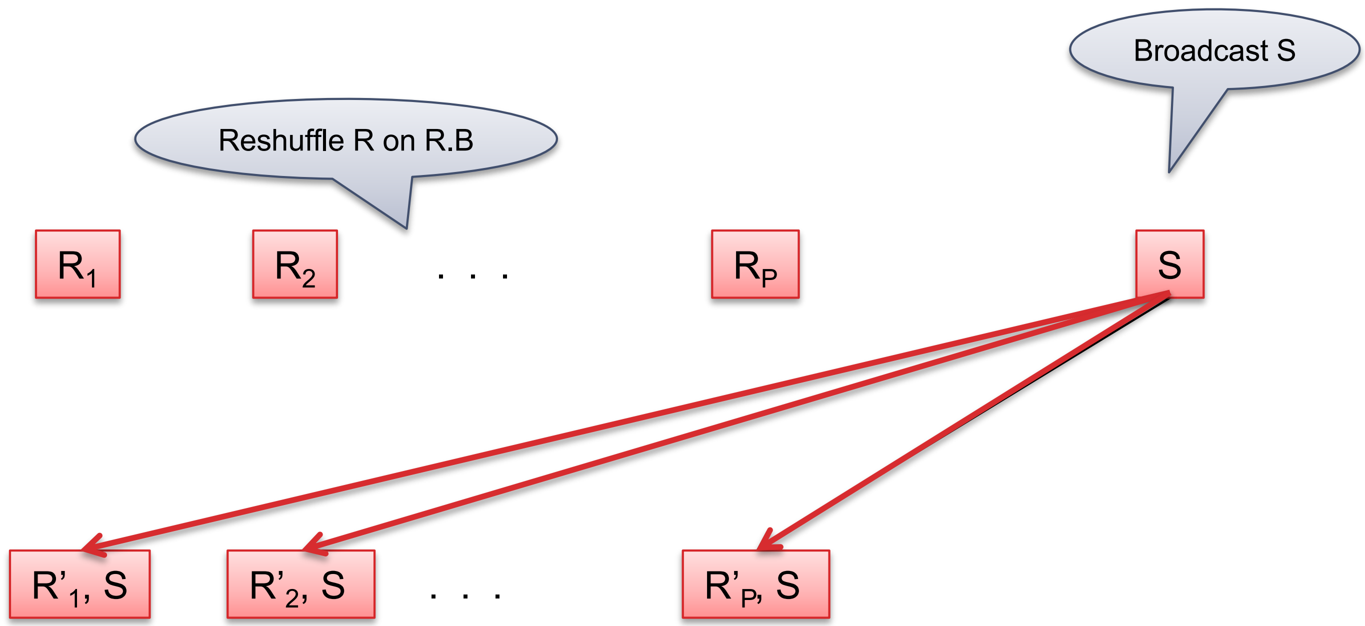
⋈

S2'

K2	B
101	50
102	50
202	50

Broadcast Join

Data: R(A, B), S(C, D)
Query: R(A,B) $\bowtie_{B=C}$ S(C,D)



Why would you want to do this?

Parallel Data Processing @ 2000

Optional Reading

- Original paper: https://www.usenix.org/legacy/events/osdi04/tech/dean.html
- Rebuttal to a comparison with parallel DBs: http://dl.acm.org/citation.cfm?doid=1629175.1629198
- Chapter 2 (Sections 1,2,3 only) of Mining of Massive Datasets, by Rajaraman and Ullman http://i.stanford.edu/~ullman/mmds.html

Motivation

- We learned how to parallelize relational database systems
- While useful, it might incur too much overhead if our query plans consist of simple operations
- MapReduce is a programming model for such computation
- First, let's study how data is stored in such systems

Distributed File System (DFS)

- For very large files: TBs, PBs
- Each file is partitioned into *chunks*, typically 64MB
- Each chunk is replicated several times (≥3), on different racks, for fault tolerance
- Implementations:
  - Google's DFS: GFS, proprietary
  - Hadoop's DFS: HDFS, open source

MapReduce

- Google: paper published 2004
- Free variant: Hadoop

- MapReduce = high-level programming model and implementation for large-scale parallel data processing

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

Project 6 anyone?

A MapReduce program:

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

Step 1: the MAP Phase

User provides the MAP-function:

- Input: `(input key, value)`
- Output: bag of `(intermediate key, value)`

System applies the map function in parallel to all `(input key, value)` pairs in the input file

Step 2: the REDUCE Phase

User provides the REDUCE function:

- Input: `(intermediate key, bag of values)`
- Output: bag of output `(values)`

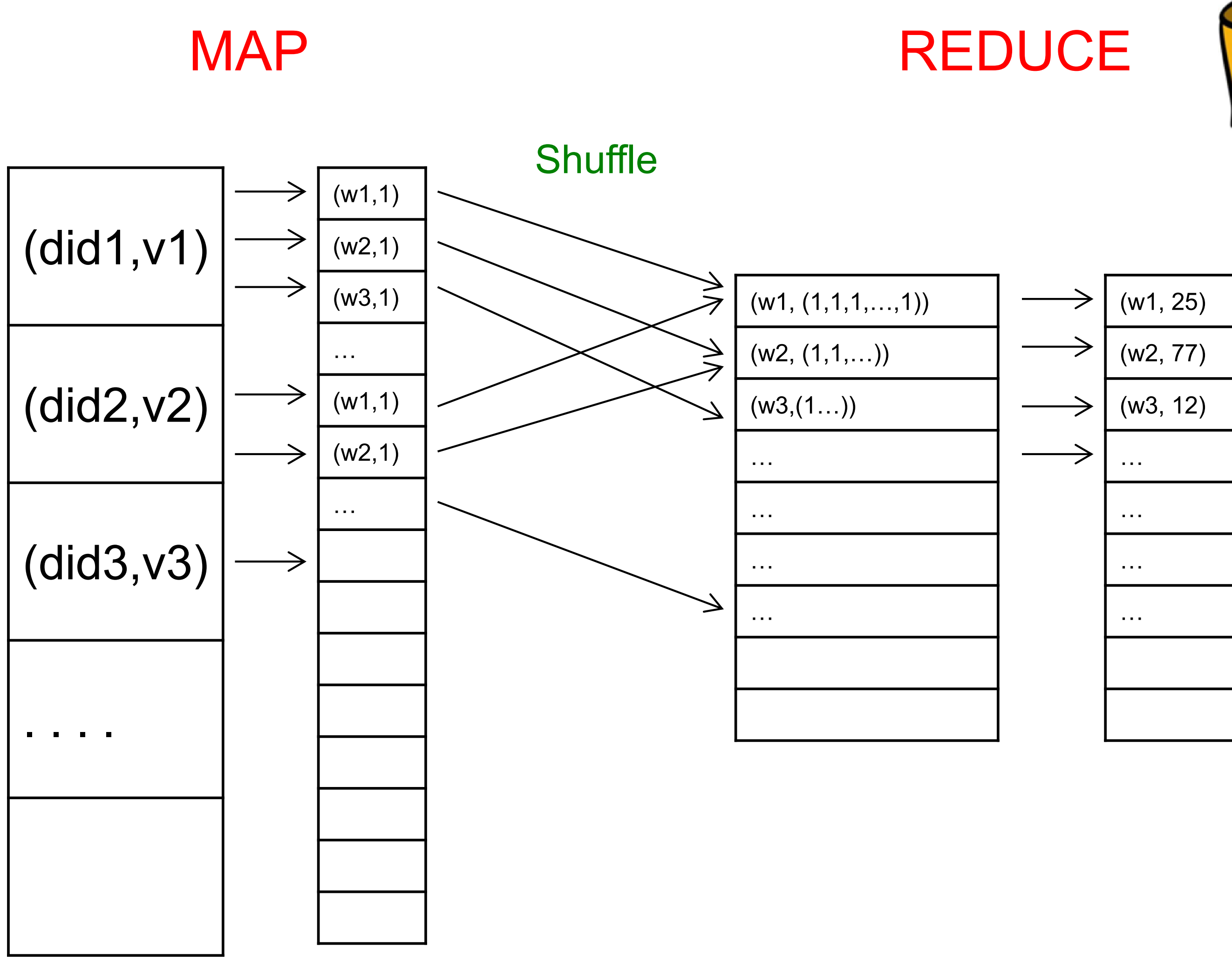
System groups all pairs with the same intermediate key, and passes the bag of values to the REDUCE function

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)

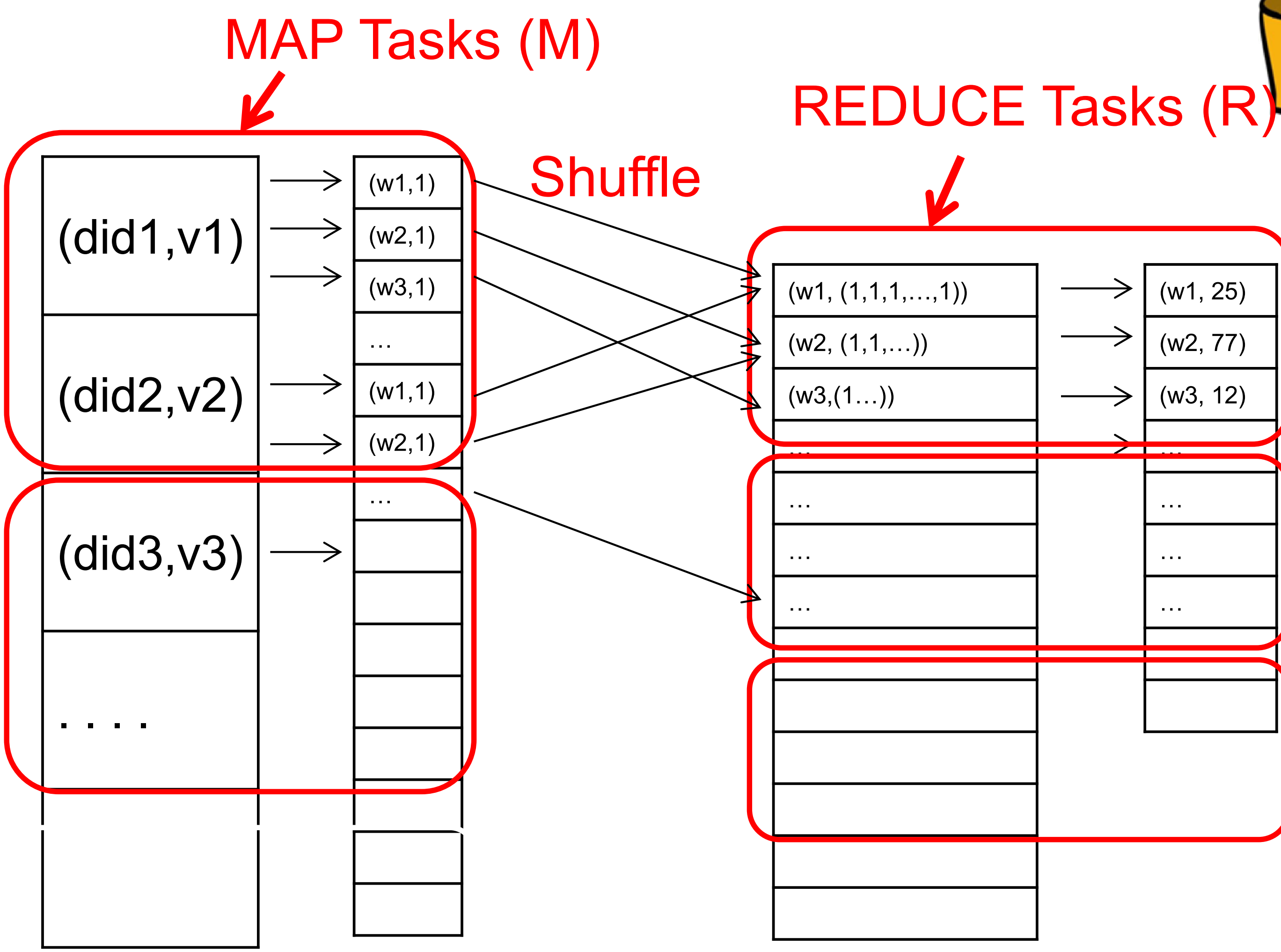
```
map(String key, String value):
   // key: document name
   // value: document contents
   for each word w in value:
        emitIntermediate(w, "1");
```

```
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));
```


MAP
REDUCE
Shuffle
(did1,v1)
(did2,v2)
(did3,v3)
. . . .
(w1,1)
(w2,1)
(w3,1)
…
(w1,1)
(w2,1)
…
(w1, (1,1,1,…,1))
(w2, (1,1,…))
(w3,(1…))
…
…
…
…
(w1, 25)
(w2, 77)
(w3, 12)
…
…
…
…

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


MAP Tasks (M)
REDUCE Tasks (R)
Shuffle
(did1,v1)
(did2,v2)
(did3,v3)
. . . .
(w1,1)
(w2,1)
(w3,1)
…
(w1,1)
(w2,1)
…
(w1, (1,1,1,…,1))
(w2, (1,1,…))
(w3,(1…))
…
…
…
…
(w1, 25)
(w2, 77)
(w3, 12)
…
…
…
…

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

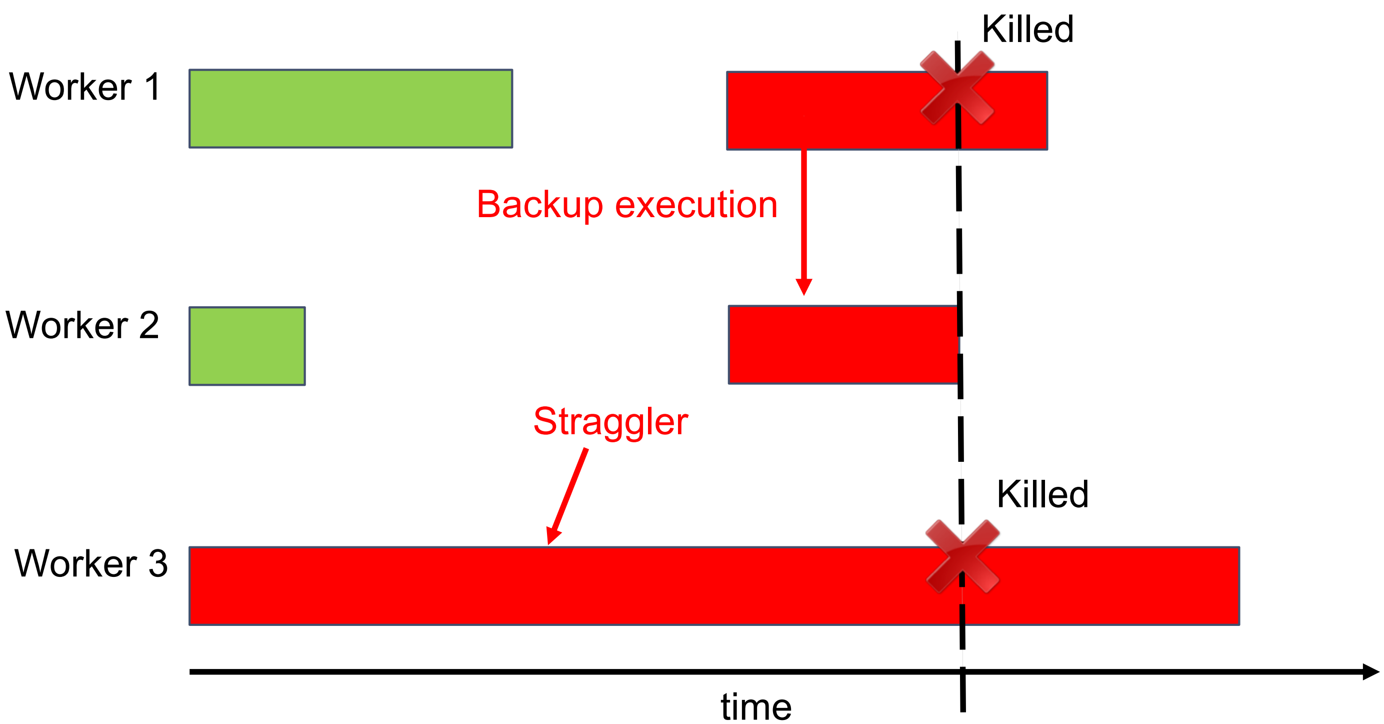
- There is one master node
- Master partitions input file into *M splits*, by key
- Master assigns *workers* (=servers) to the *M map tasks*, keeps track of their progress
- Workers write their output to local disk, partition into *R regions*
- Master assigns workers to the *R reduce tasks*
- Reduce 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: $\gamma_{A,\mathrm{sum}(B)}(R)$
- Join: $R \bowtie S$

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

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

(123, [t_2, t_3])

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

	A
t_1	23
t_2	123
t_3	123
t_4	42

(t_2, t_3)

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

```
map(Tuple t):
    EmitIntermediate(t.A, t.B);
```

(23, [t_1])
(42, [t_4])
(123, [t_2, t_3])

	A	B
t_1	23	10
t_2	123	21
t_3	123	4
t_4	42	6

```
reduce(String A, Iterator values):
    s = 0
    for each v in values:
        s = s + v
    Emit(A, s);
```

(23, 10), (42, 6), (123, 25)

Join

Let's review our parallel join algorithms:

- Partitioned hash-join
- Broadcast join

Partitioned Hash-Join

$R(A,B) \bowtie_{B=C} S(C,D)$

type

actual tuple

```
map(Tuple t):
    case t.relationName of
        'R': EmitIntermediate(t.B, ('R', t));
        'S': EmitIntermediate(t.C, ('S', t));
```

R

	A	B
t_1	23	10
t_2	123	21
t_3	123	4
t_4	42	6

S

	C	D
t_5	4	101
t_6	5	25
t_7	6	4
t_8	21	67

(10, [('R', t_1)])
(21, [('R', t_4), ('S', t_8)])
(4, [('R', t_3), ('S', t_5)])
(6, [('R', t_4), ('S', t_7)])
(5, [('S', t_6)])

```
reduce(String k, Iterator values):
    R = [ ];  S = [ ];
    for each v in values:
        case v.type of:
            'R':  R.append(v)
            'S':  S.append(v);
    for v1 in R, for v2 in S
        Emit(v1,v2);
```

(123, 21, 21, 67)
(123, 4, 4, 101)
(42, 6, 6, 4)

Broadcast Join

$R(A,B) \bowtie_{B=C} S(C,D)$

```
map(String value):
    readFromNetwork(S); /* over the network */
    hashTable = new HashTable()
    for each w in S:
        hashTable.insert(w.C, w)

    for each v in value:
        for each w in hashTable.find(v.B)
            Emit(v,w);
```

map should read several records of R: value = some group of tuples from R

Read entire table S, build a Hash Table

```
reduce(…):
    /* empty: map-side only */
```

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

- Automatically convert vanilla Java programs to MR: http://casper.uwplse.org

Parallel Data Processing @ 2010

Issues with MapReduce

- Difficult to write more complex queries
  - Everything has to be expressed as map-reduce

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

Spark

- Open source system developed right here!
- Distributed processing over HDFS
- Differences from MapReduce:
  - Multiple steps, including iterations
  - Stores intermediate results in main memory
  - Closer to relational algebra (familiar to you)
- Details: http://spark.apache.org

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

Data Model: Resilient Distributed Datasets

- RDD = Resilient Distributed Datasets
  - A distributed, immutable relation, together with its *lineage*
  - Lineage = expression that says how that relation was computed (e.g., 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 program consists of:
  - Transformations (map, reduceByKey, 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

What are the benefits of lazy execution?

THE RDD INTERFACE

Collections in Spark

- 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

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

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

- Start with “ERROR”
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lines, errors, sqlerrors have type JavaRDD<String>

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

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

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sqlerrors = errors.filter(l                     e”));

sqlerrors.collect();
```

Transformation:
Not executed yet…

Action:
triggers execution
of entire program

Example

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retrieve all lines that:

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

“Call chaining” style

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 collection with 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

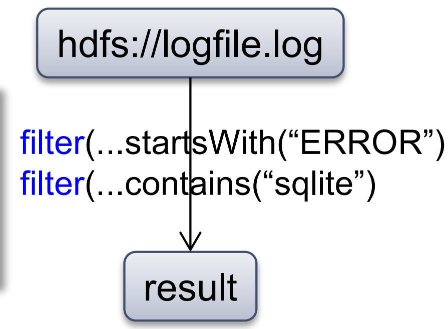
Persistence

```
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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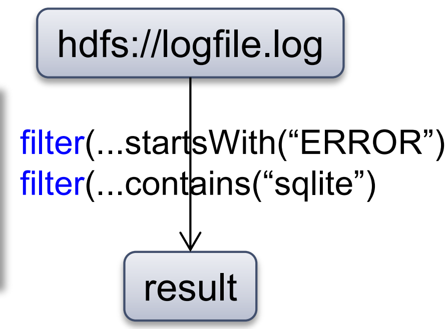


```
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errors = lines.filter(l->l.startsWith("ERROR"));
sqlerrors = errors.filter(l->l.contains("sqlite"));
sqlerrors.collect();
```

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()
```

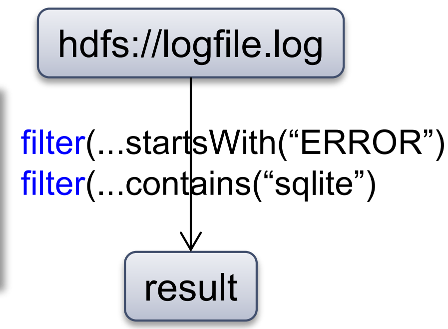
New RDD

Spark can recompute the result from errors

Persistence

RDD:

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



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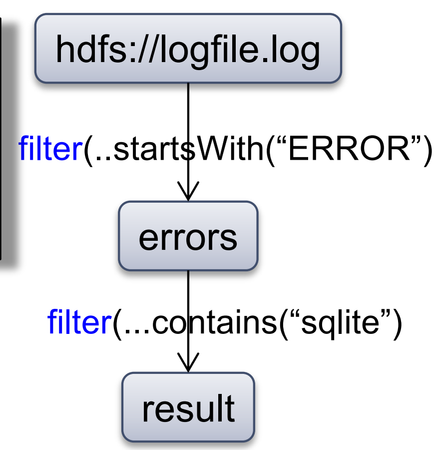
errors = lines.filter(l->l.startsWith("ERROR"));
errors.persist();
sqlerrors = errors.filter(l->l.contains("sqlite"));
sqlerrors.collect()
```

New RDD



Spark can recompute the result from errors

Example

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

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

Berkeley cs186

```
R = s.read().textFile(“R.csv”).map(parseRecord).persist();
S = s.read().textFile(“S.csv”).map(parseRecord).persist();
```

Parses each line into an object

persisting on disk

Example

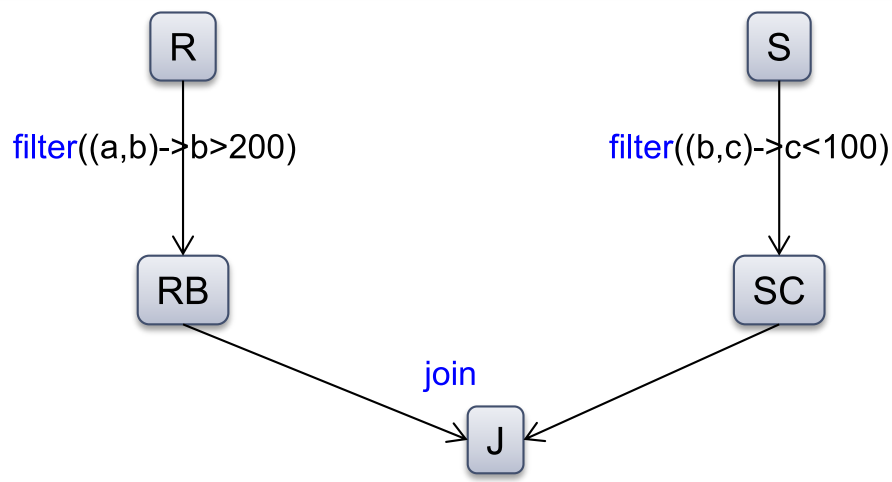
R(A,B)
S(A,C)

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

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

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)

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?

What Goes Around Comes Around

Michael Stonebraker
Joseph M. Hellerstein

Readings in Database Systems, 5th Edition

Abstract

This paper provides a summary of 35 years of data model proposals, grouped into 9 different eras. We discuss the proposals of each era, and show that there are only a few basic data modeling ideas, and most have been around a long time. Later proposals inevitably bear a strong resemblance to certain earlier proposals. Hence, it is a worthwhile exercise to study previous proposals.

In addition, we present the lessons learned from the exploration of the proposals in each era. Most current researchers were not around for many of the previous eras, and have limited (if any) understanding of what was previously learned. There is an old adage that he who does not understand history is condemned to repeat it. By presenting "ancient history", we hope to allow future researchers to avoid replaying history.

Conclusions

- Parallel databases
  - Predefined relational operators
  - Optimization
  - Transactions and recovery
- 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