CSE544
Data Management

Lectures 16-17
Parallel Query Processing

Announcements

- Project proposal due on Friday
  - Please follow the suggestions on the Web: title/name, description, system, data, plan
- HW4 due on Tuesday

Supplier(sno,sname,scity,sstate)
Supply(sno,pno,price)

Hint on HW4

```
SELECT  x.sno, x.sname
FROM Supplier x
WHERE  x.sstate = 'WA'
    and s.sno not in
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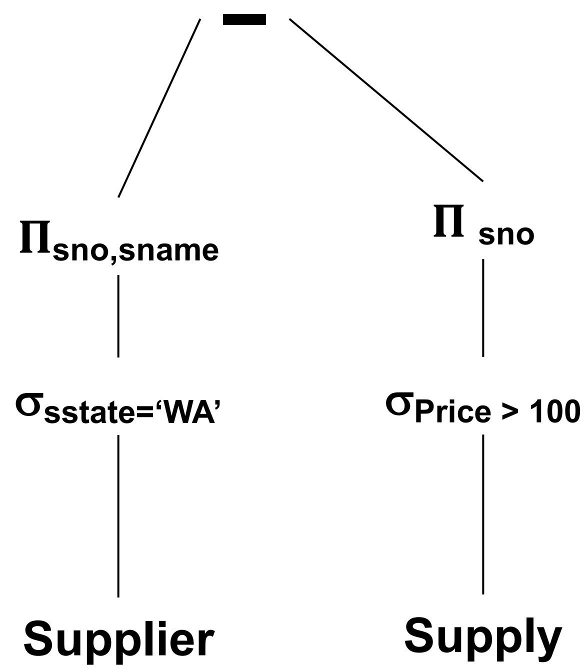

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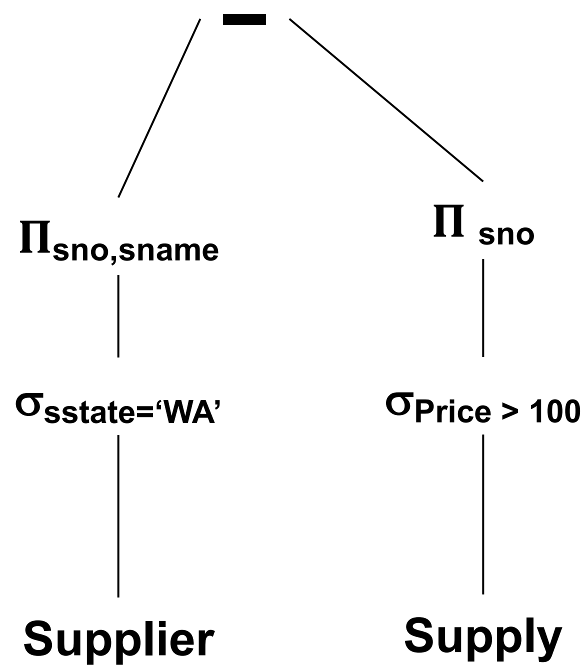

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why?

How do we fix it?

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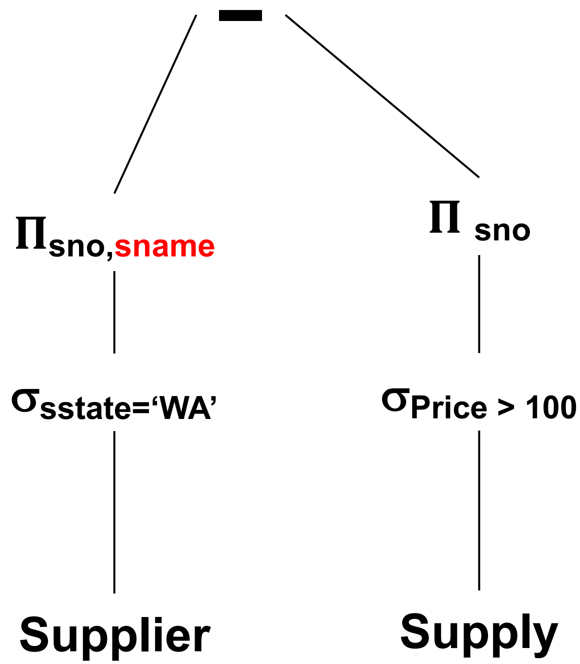

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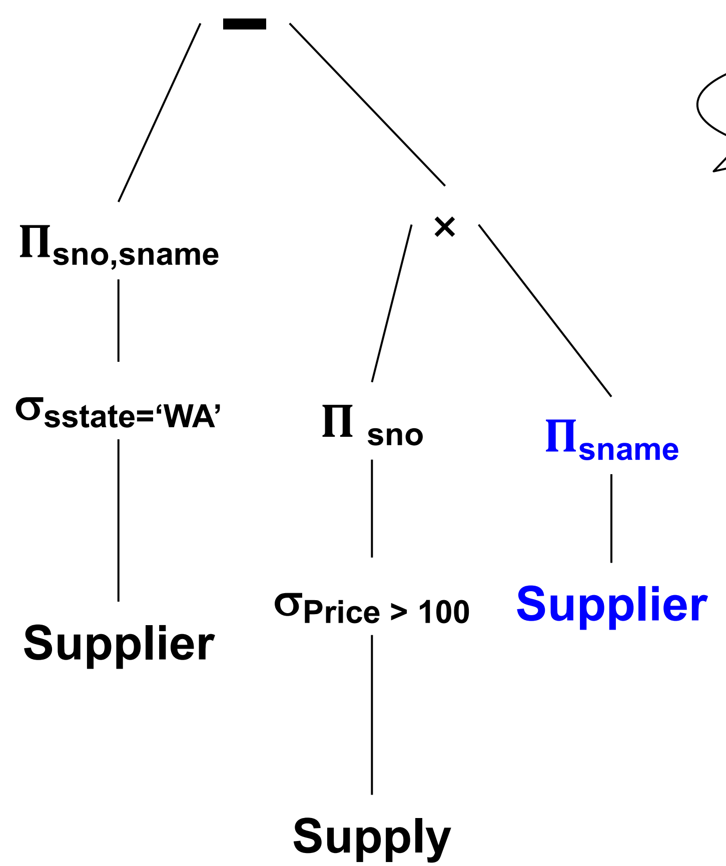

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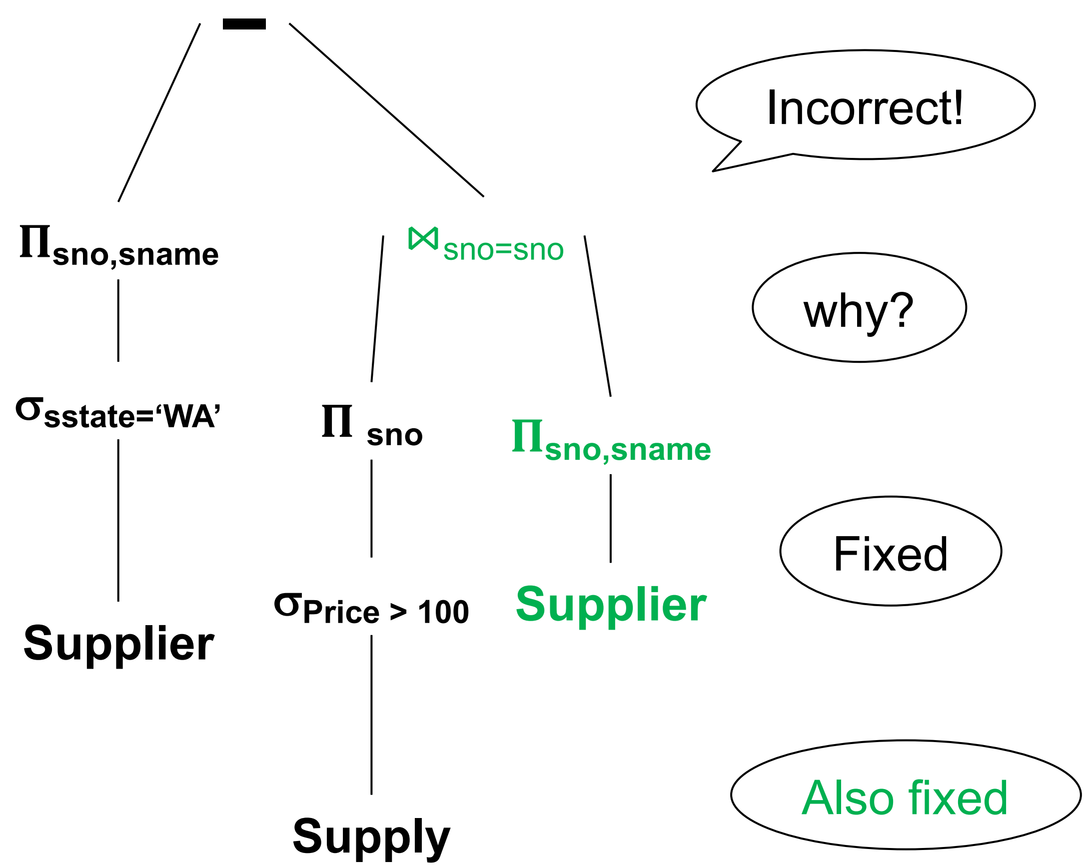


Outline

- MapReduce
- Spark
- Snowflake

References

Reading assignment Monday

- Jeffrey Dean and Sanjay Ghemawat, MapReduce: Simplified Data Processing on Large Clusters. OSDI'04

- Matei Zaharia, Mosharaf Chowdhury, Michael J. Franklin, Scott Shenker, Ion Stoica: Spark: Cluster Computing with Working Sets. HotCloud 2010

- Dageville et al.: The Snowflake Elastic Data Warehouse, SIGMOD'2016

Reading assignment Wednesday

MapReduce

Distributed File System (DFS)

- For very large files: TBs, PBs
- Each file partitioned into *chunks* (64MB)
- Each chunk replicated (≥3 times) – why?
- Implementations:
  - Google's DFS: GFS, proprietary
  - Hadoop's DFS: HDFS, open source

MapReduce

- Google:
  - Started around 2000
  - Paper published 2004
  - Discontinued September 2019
- Free variant: Hadoop

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

Data Model

Files!

A file = a bag of **(key, value)** pairs

Step 1: the MAP Phase

User provides the MAP-function:

- Input: **(input key, value)**
- Ouput: bag of **(intermediate key, value)**

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

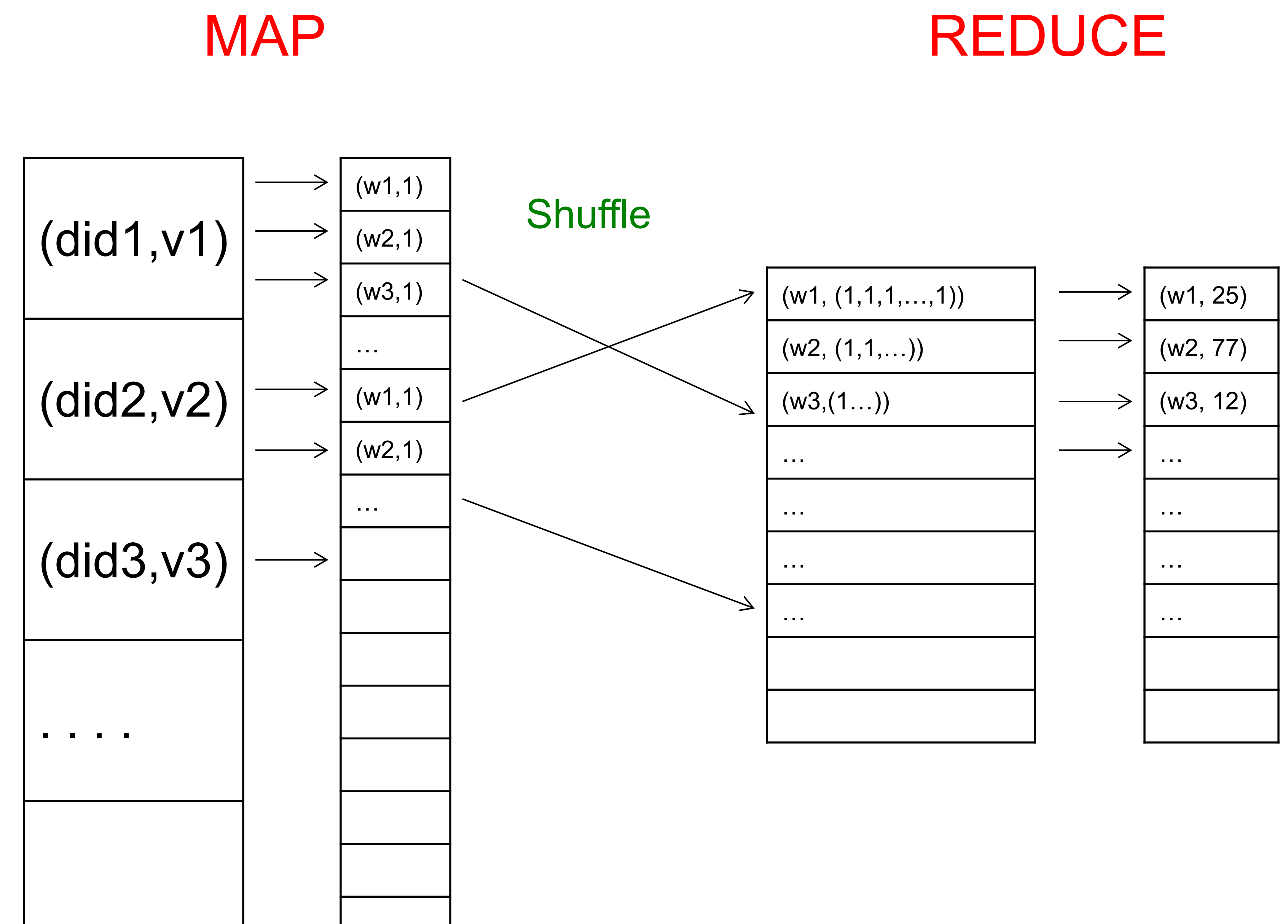
```
map(String key, String value):
    // key: document name
    // value: document contents
    for each word w in value:
     EmitIntermediate(w, "1");
```

```
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));
```

MapReduce = GroupBy-Aggregate

Occurrence(docID, word)

```
select    word, count(*)
from      Occurrence
group by  word
```


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)
…
…
…
…

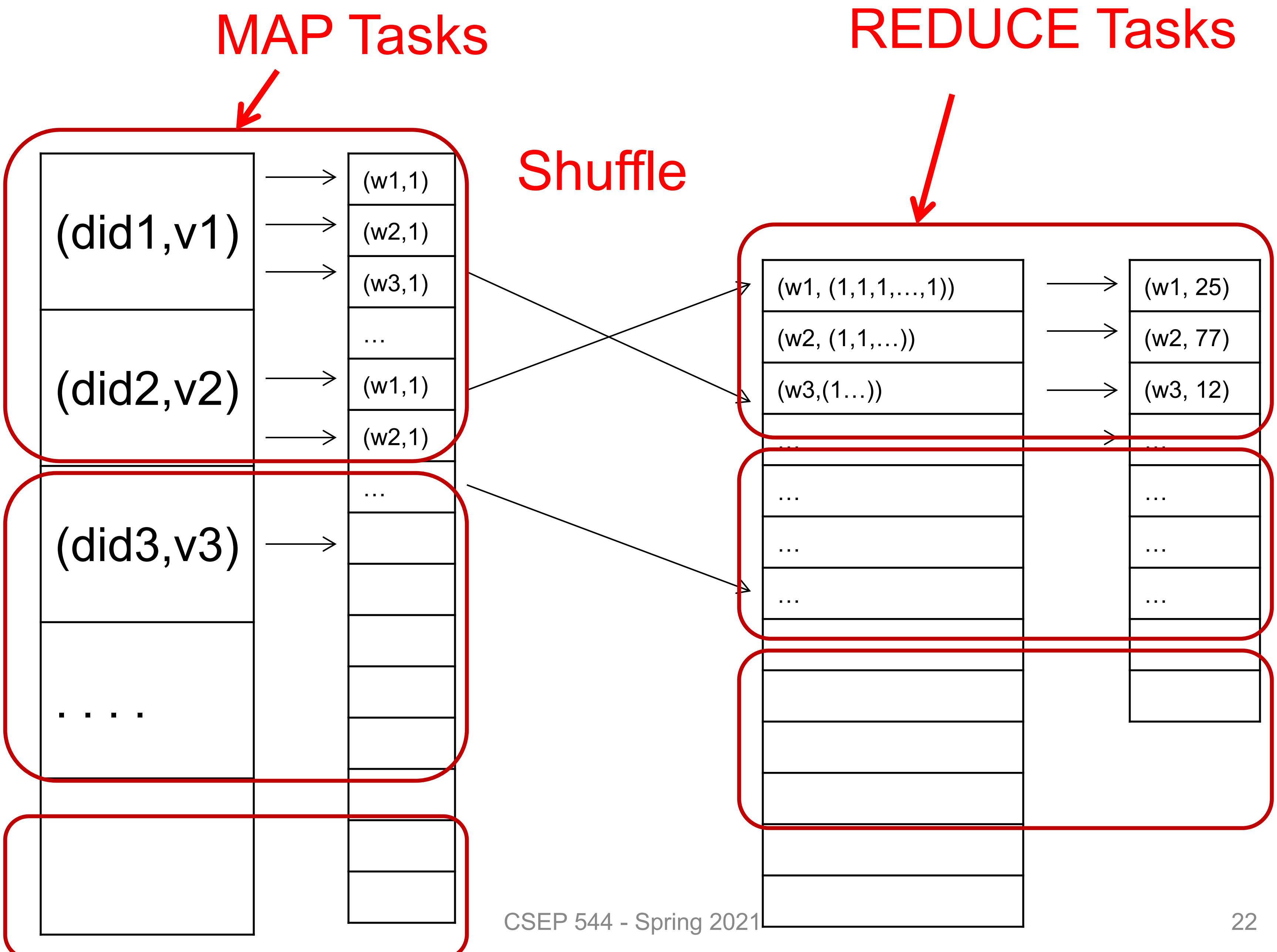
Jobs v.s. Tasks

- A MapReduce Job
  - One simple “query”, e.g. count words in docs
  - Complex queries may require many jobs
- A Map Task, or a Reduce Task
  - A group of instantiations of the map-, or reduce-function, to be scheduled on a single worker

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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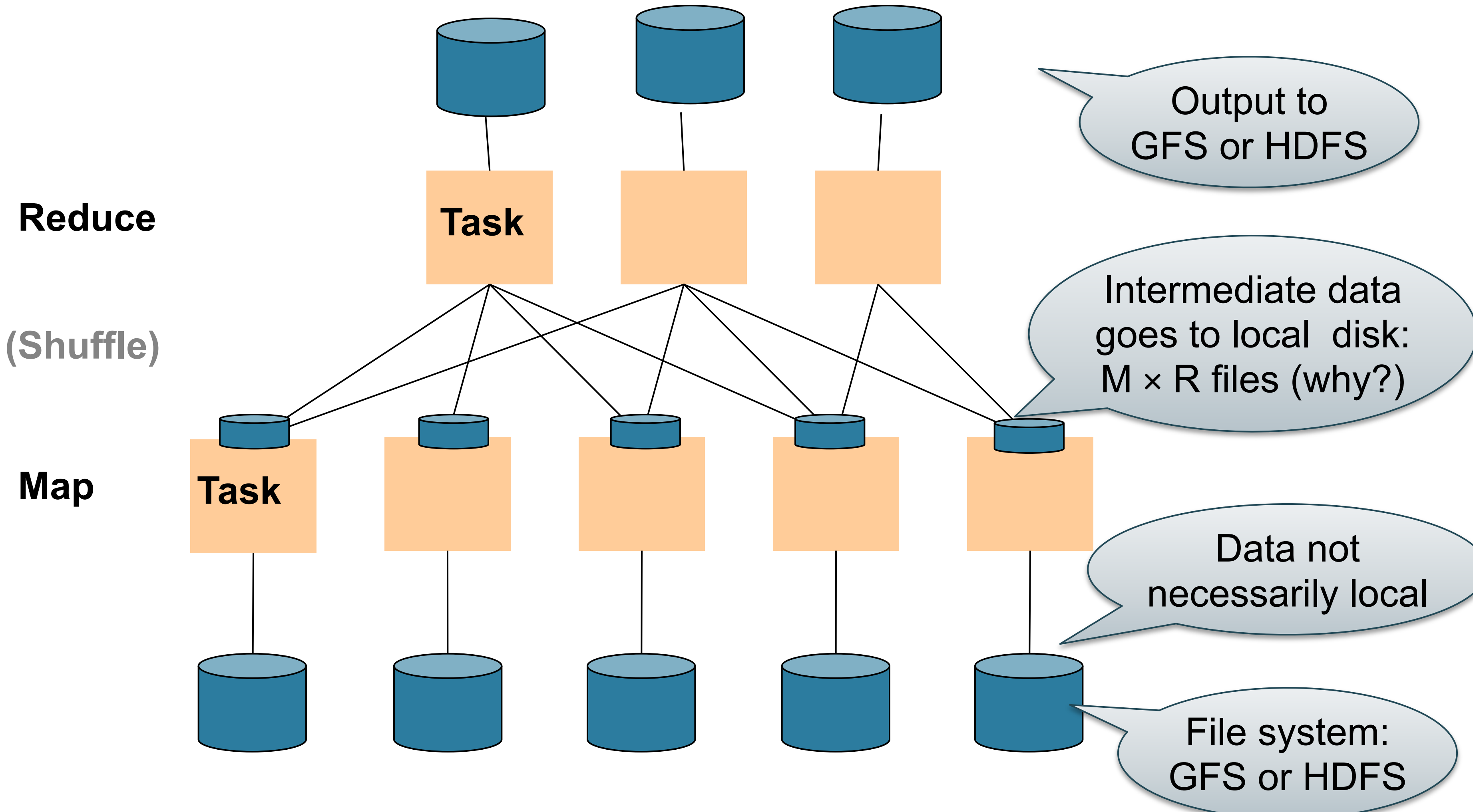
Fault Tolerance

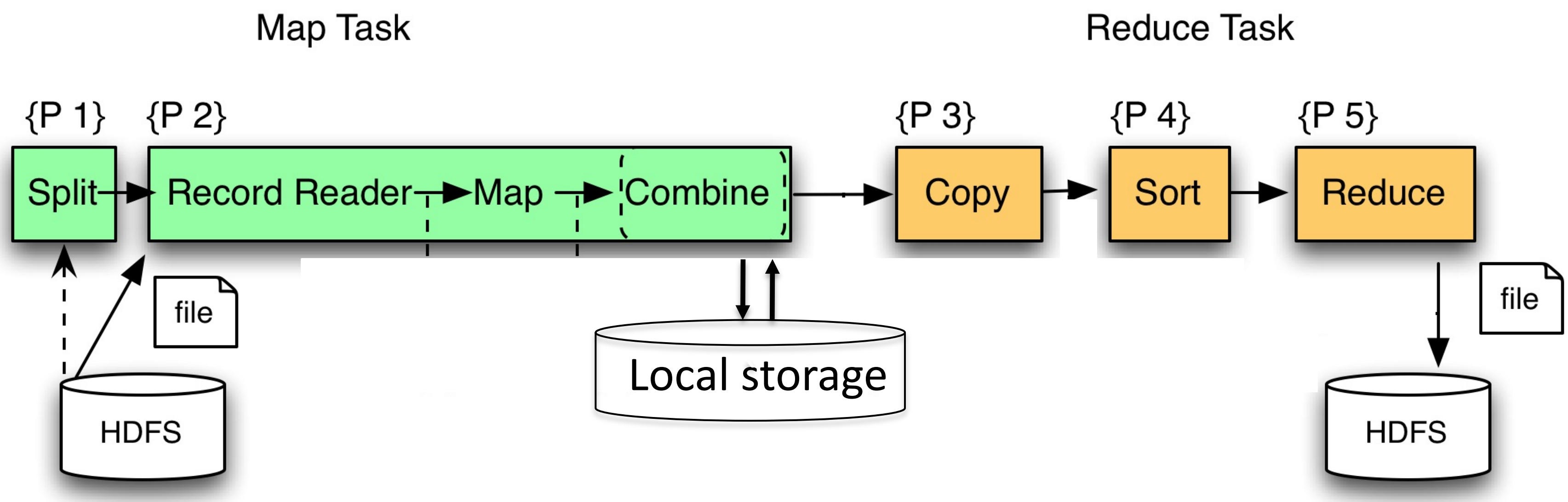
- If one server fails once every year…
  ... then a job on 10,000 servers fails in 1h

- MapReduce handles fault tolerance by writing intermediate files to disk:
  – Mappers write file to local disk
  – Reducers read the local files (=reshuffling);
  – If reducer fails, new work re-reads local files

MapReduce Execution Details



MapReduce Phases



Joins in MR

- One MR job = GROUP-BY/AGGREGATE
- Question: How do we implement a join?
- Answer:
  - Map function: groups by the join attribute
  - Reduce function: cartesian product

Joins in MR

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

```
map(String value):
    case value of:
      R(a,b,c): emit_Intermediate(a, R(a,b,c))
      S(d,e):    emit_Intermediate(d, S(d,e))
```

```
reduce(String key, Iterator values):
    local_R = [ ],  local_S = [ ];
    for each v in values:
      case R(a,b,c): local_R += v
      case S(d,e):   local_S += v
    emit( local_R x local_S );
```

MapReduce v.s. Databases

Blog* by DeWitt and Stonebraker

- Schemas are good
- Indexes
- Skew (MR mitigates it somewhat – how?)
- The M*R problem – what is it?
- Parallel databases uses push (to sockets) instead of pull – what's the point?

*Original blog deleted, cached version still here; slightly longer paper here.

Outline

- MapReduce
- Spark
- Snowflake

Spark

Spark

- Distributed processing over HDFS
- Multiple steps, including iterations
- Stores intermediate results in main memory
- Closer to relational algebra

Collections in Spark

- RDD<T> = an RDD collection of type T
  - Distributed
  - Not nested
  - Recoverable via lineage
- Seq<T> = a sequence
  - Local
  - May be nested

Programming in Spark

- Transformations (map, join…). Lazy
- Actions (count, reduce, save...). Eager

Example

Find in file hdfs://logfile.log the 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();
```

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“Call chaining” style

Example

The RDD s:

Error…	Warning…	Warning…	Error…	Abort…	Abort…	Error…	Error…	Warning…	Error…

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Example

Parallel step 1

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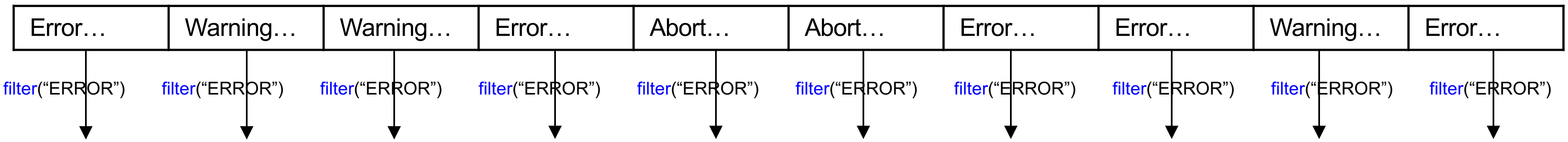


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Example

Parallel step 1

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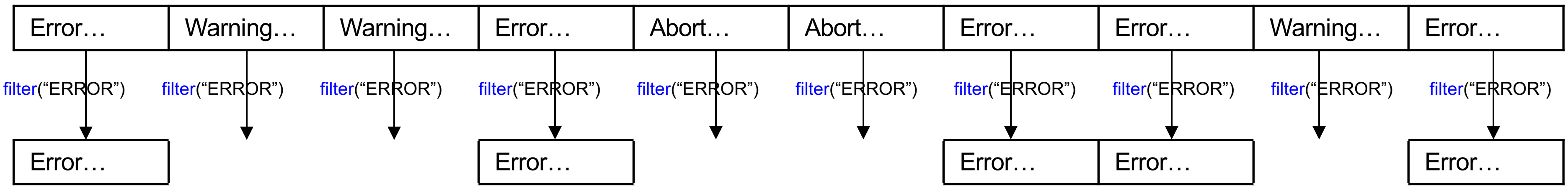


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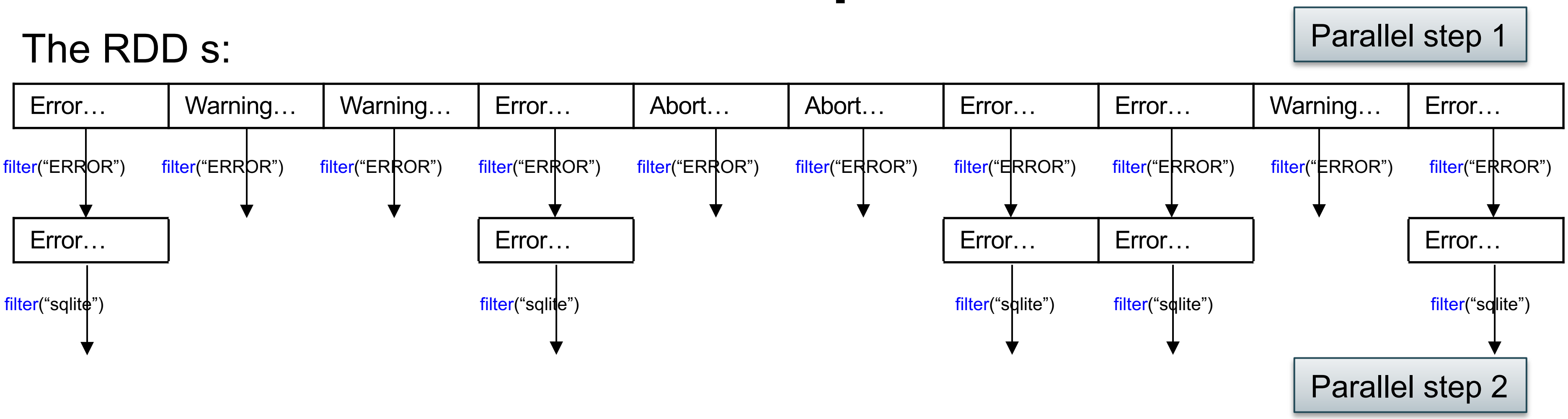


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Fault Tolerance

- 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 *lineage*
- Lineage = a relational algebra plan
- If a server crashes, recompute the lost partition of the RDD using the lineage

Persistence

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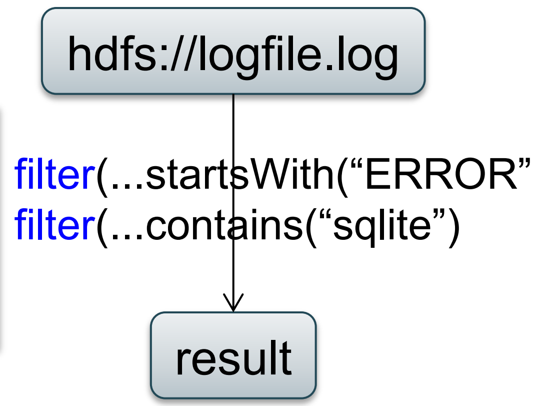
If any server fails before the end, then Spark must restart

Persistence

RDD:

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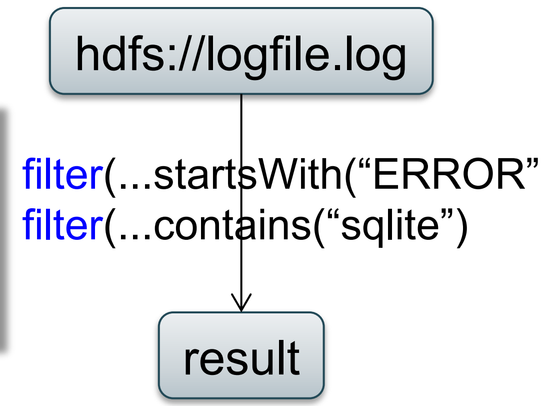


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If any server fails before the end, then Spark must restart

```
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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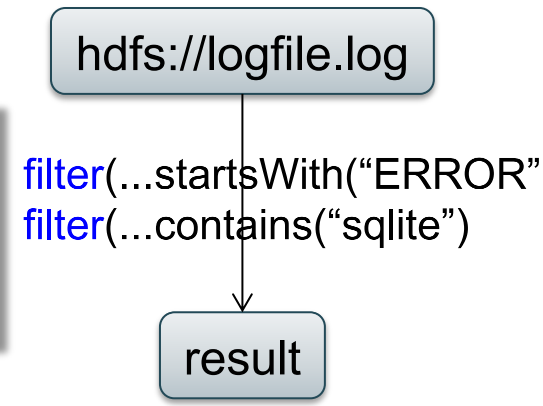

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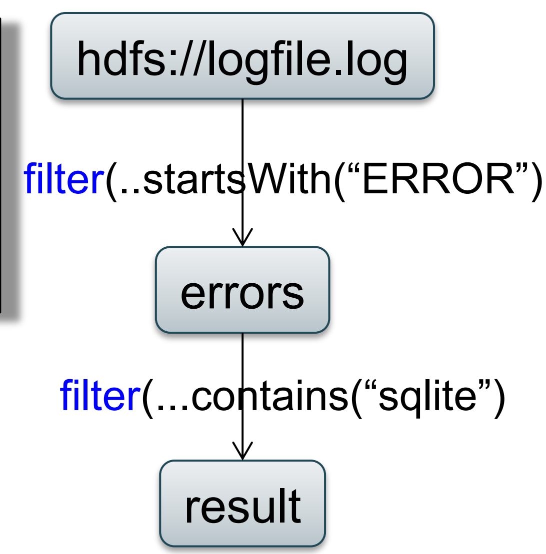


Spark can recompute the result from errors

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

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

Parses each line into an object

persist

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

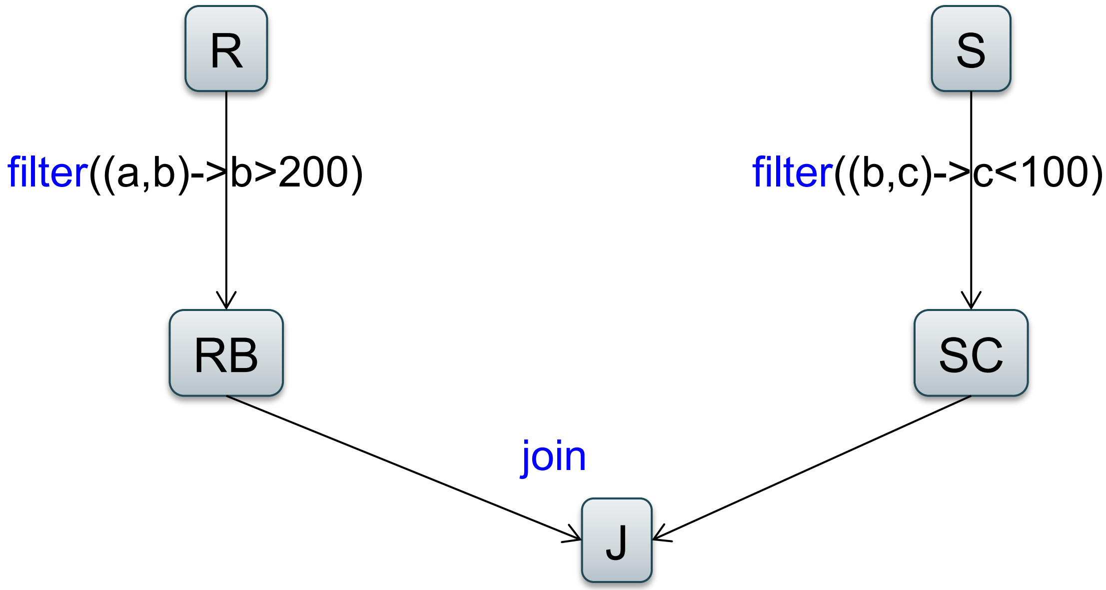
```
SELECT count(*)  FROM R, S
WHERE R.B > 200 and S.C < 100  and R.A = S.A
```

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



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

- DataFrames
  - Records, dynamically typed
- Datasets
  - Records, statically typed

Outline

- MapReduce
- Spark
- Snowflake

Snowflake

Snowflake

- It is an SaaS – what is this? Give other examples of types of cloud services…

Snowflake

- It is an SaaS – what is this? Give other examples of types of cloud services…
- SaaS = software as a service
- Other examples:
  - Platform as a service (PaaS): e.g. Amazon's EC
  - Infrastructure as a service (virtual machines)
  - Software as a Service
  - Function as a Service: Amazon's Lambda

Snowflake

- Describe Snowflake’s Data Storage

Snowflake

- Describe Snowflake's Data Storage

In class:

- S3:PUT/GET/DELETE
- Table → horizontal partition in *files*
- Blobs+PAX
- Temp storage→S3

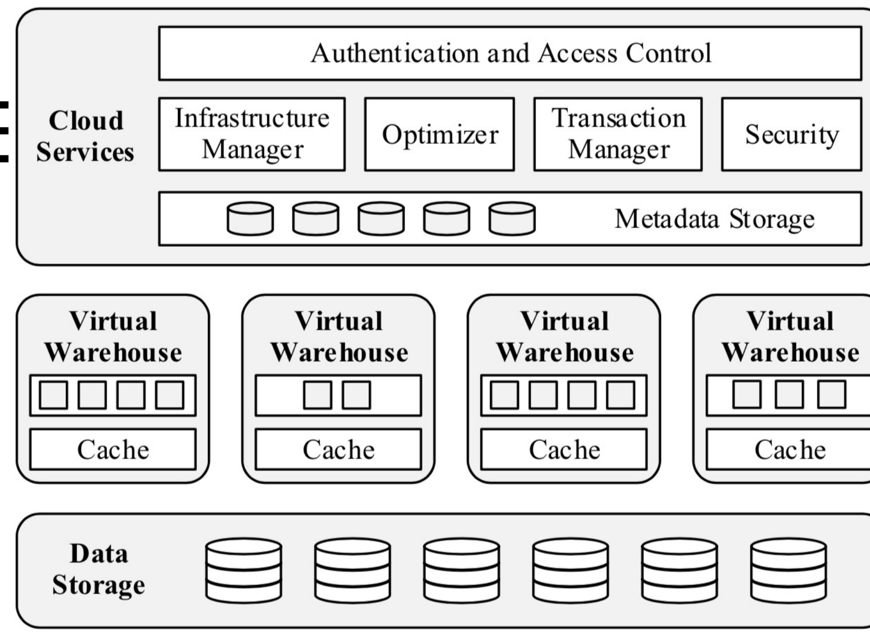


Figure 1: Multi-Cluster, Shared Data Architecture

Snowflake

- Describe Elasticity in Snowflake

- Describe failure handling in Snowflake

Snowflake

- Describe Elasticity in Snowflake
  - Virtual Warehouse (VW) serves one user
  - T-Shirt sizes: X-Small … XX-Large
  - Small query may run on subset of VW
- Describe failure handling in Snowflake

Snowflake

- Describe Elasticity in Snowflake
  - Virtual Warehouse (VW) serves one user
  - T-Shirt sizes: X-Small … XX-Large
  - Small query may run on subset of VW
- Describe failure handling in Snowflake
  - Restart the query
  - No partial retries (like MapReduce or Spark)

Snowflake

- Describe its execution engine

Snowflake

- Describe its execution engine
- Column-oriented (in class)
- Vectorized (“tuple batches” – in class)
- Push-based (in class)

Snowflake

- What does Snowflake use instead of indexes?

Snowflake

- What does Snowflake use instead of indexes?

- “Pruning”: for each file (recall: this is a horizontal partition of a table) and each attribute, it stores the min/max values in that column in that file; may skip files when not needed.

Conclusion

- Distributed data processing:
  - Spread the data to fit in main memory
  - Take advantage of parallelism
- “SQL is embarrassingly parallel”
  - Relational algebra: easy to parallelize
  - Hash-based algorithm suffer from skew