Introduction to Data Management CSE 344

Lecture 26:

Parallel Databases and MapReduce

HW8

- MapReduce (Hadoop) w/ declarative language (Pig)
- Cluster will run in Amazon's cloud (AWS)
  - Give your credit card
  - Click, click, click… and you have a MapReduce cluster
- We will analyze a real 0.5TB graph
- Processing the entire data takes hours
  - Problems #1,#2,#3: queries on a subset only
  - Problem #4: entire data

Amazon Warning

- "We **HIGHLY** recommend you remind students to turn off any instances after each class/session – as this can quickly diminish the credits and start charging the card on file. **You are responsible for the overages.**"
- "AWS customers can now use **billing alerts** to help monitor the charges on their AWS bill. You can get started today by visiting your Account Activity page to enable monitoring of your charges. Then, you can set up a billing alert by simply specifying a bill threshold and an e-mail address to be notified as soon as your estimated charges reach the threshold."

Outline

- Today: Query Processing in Parallel DBs
- Next Lecture: Parallel Data Processing at Massive Scale (MapReduce)
  - Reading assignment:
    Chapter 2 (Sections 1,2,3 only) of Mining of Massive Datasets, by Rajaraman and Ullman
    http://i.stanford.edu/~ullman/mmds.html

Review

- Why parallel processing?
- What are the possible architectures for a parallel database system?
- What are speedup and scaleup?

Basic Query Processing: Quick Review in Class

Basic query processing on one node.

Given relations R(A,B) and S(B, C), no indexes, how do we compute:

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

Basic Query Processing: Quick Review in Class

Basic query processing on one node.

Given relations R(A,B) and S(B, C), no indexes, how do we compute:

- Selection: $\sigma_{A=123}(R)$
  - Scan file R, select records with A=123
- Group-by: $\gamma_{A,sum(B)}(R)$
  - Scan file R, insert into a hash table using attr. A as key
  - When a new key is equal to an existing one, add B to the value
- Join: $R \bowtie S$
  - Scan file S, insert into a hash table using attr. B as key
  - Scan file R, probe the hash table using attr. B

Parallel Query Processing

How do we compute these operations on a shared-nothing parallel db?

- Selection: $\sigma_{A=123}(R)$ (that's easy, won't discuss…)
- Group-by: $\gamma_{A,sum(B)}(R)$
- Join: $R \bowtie S$

Before we answer that: how do we store R (and S) on a shared-nothing parallel db?

Horizontal Data Partitioning

Data:

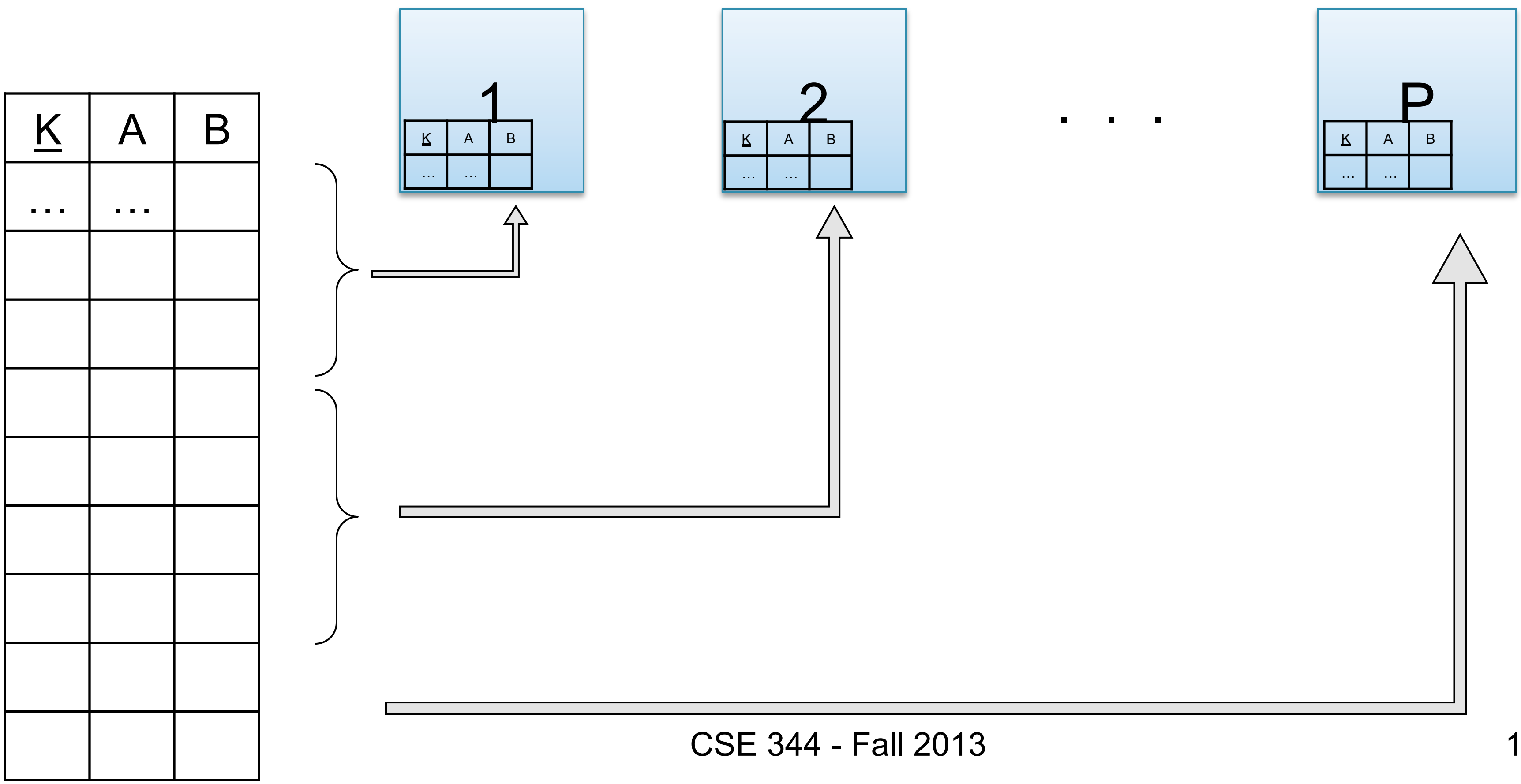
K	A	B
…	…	

Servers:

Horizontal Data Partitioning

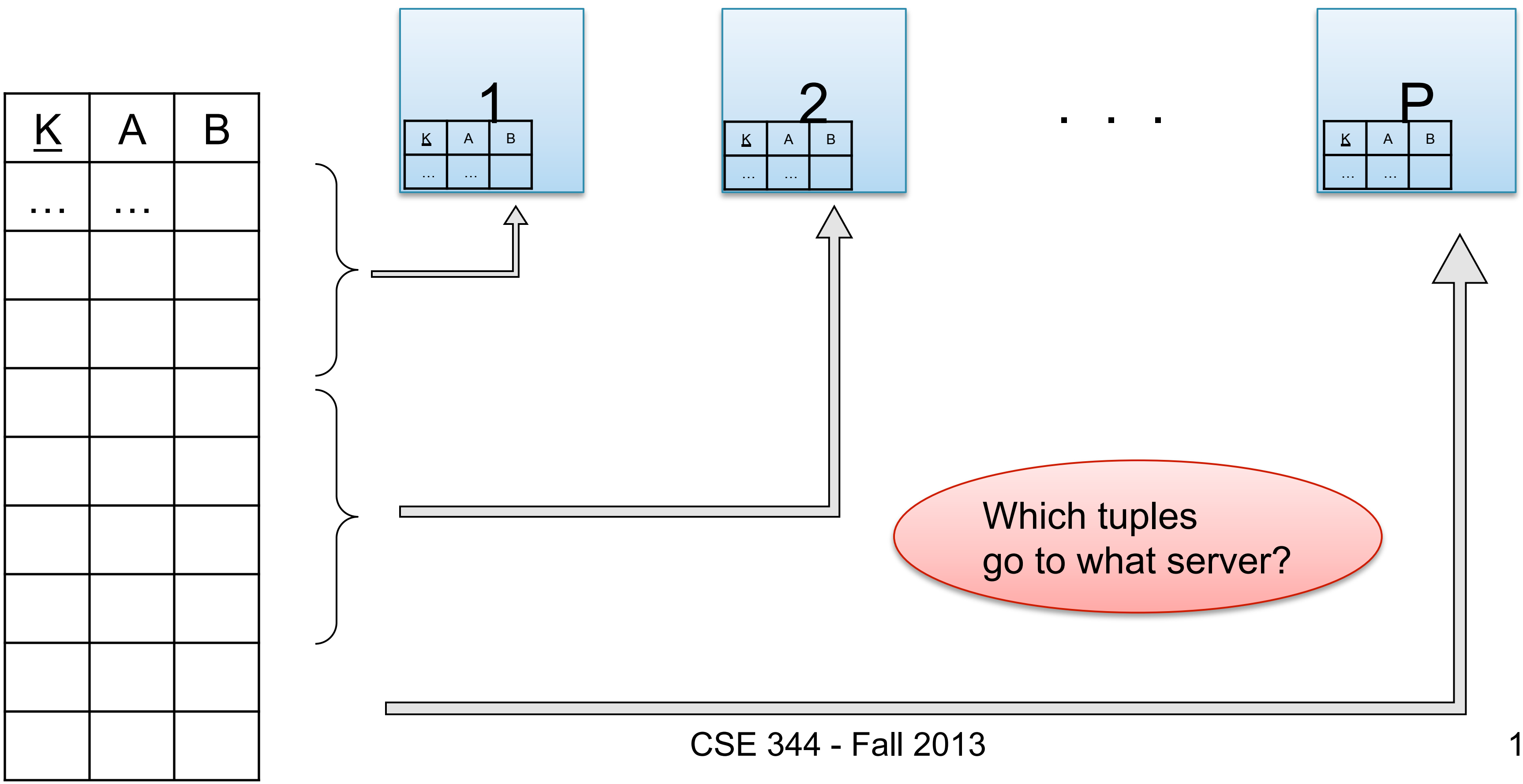
Data:

Servers:



Horizontal Data Partitioning

Data: Servers:



Horizontal Data Partitioning

- Block Partition:
  - Partition tuples arbitrarily s.t. size(R_1)≈ … ≈ size(R_P)
- Hash partitioned on attribute A:
  - Tuple t goes to chunk i, where i = h(t.A) mod P + 1
- Range partitioned on attribute A:
  - Partition the range of A into $-\infty = v_0 < v_1 < \ldots < v_P = \infty$
  - Tuple t goes to chunk i, if $v_{i-1} < t.A < v_i$

Parallel GroupBy

Data: R(K,A,B,C)

Query: $\gamma_{A,sum(C)}(R)$

Discuss in class how to compute in each case:

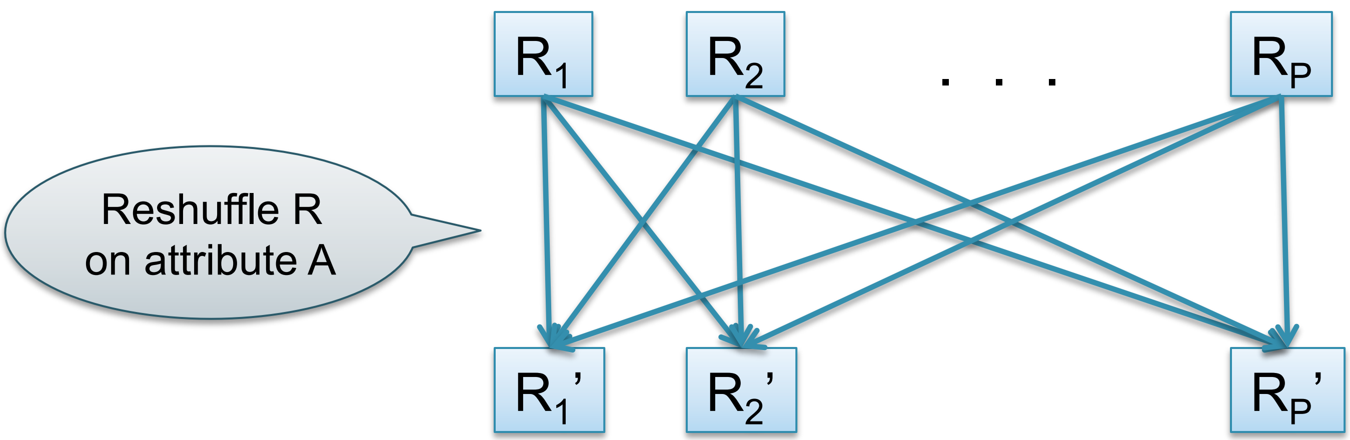
- R is hash-partitioned on A
- R is block-partitioned
- R is hash-partitioned on K

Parallel GroupBy

Data: R(K,A,B,C)

Query: $\gamma_{A,sum(C)}(R)$

- R is block-partitioned or hash-partitioned on K



Parallel Join

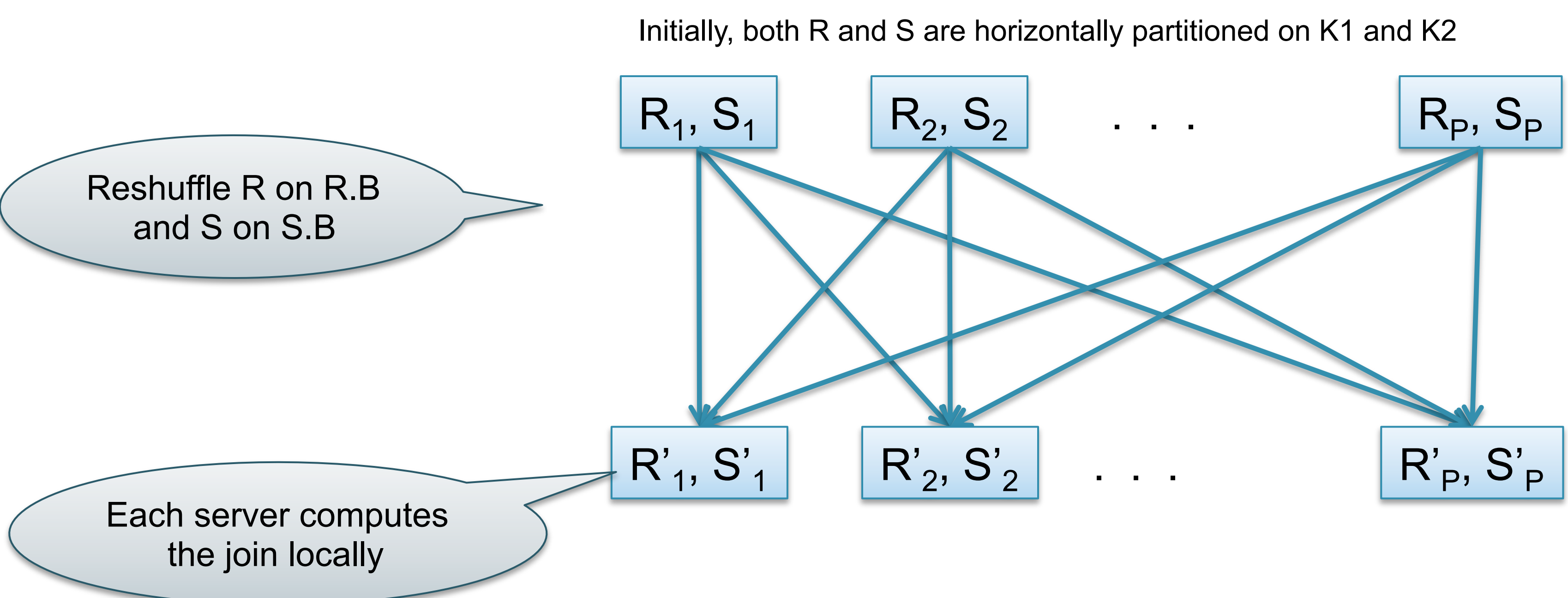
- Data: R(<u>K1</u>,A, B), S(<u>K2</u>, B, C)
- Query: R(<u>K1</u>,A,B) $\bowtie$ S(<u>K2</u>,B,C)

Initially, both R and S are horizontally partitioned on K1 and K2

R_1, S_1	R_2, S_2	R_P, S_P

Parallel Join

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



Speedup and Scaleup

- Consider:
  - Query: $\gamma_{A,sum(C)}(R)$
  - Runtime: dominated by reading chunks from disk
- If we double the number of nodes P, what is the new running time?

- If we double both P and the size of R, what is the new running time?

Speedup and Scaleup

- Consider:
  - Query: $\gamma_{A,sum(C)}(R)$
  - Runtime: dominated by reading chunks from disk
- If we double the number of nodes P, what is the new running time?
  - Half (each server holds ½ as many chunks)
- If we double both P and the size of R, what is the new running time?
  - Same (each server holds the same # of chunks)

Uniform Data v.s. Skewed Data

- Let R(<u>K</u>,A,B,C); which of the following partition methods may result in skewed partitions?

- Block partition

- Hash-partition
  - On the key K
  - On the attribute A

Uniform Data v.s. Skewed Data

- Let R(<u>K</u>,A,B,C); which of the following partition methods may result in skewed partitions?

- Block partition

Uniform

- Hash-partition
  - On the key K
  - On the attribute A

Assuming good hash function

Uniform

May be skewed

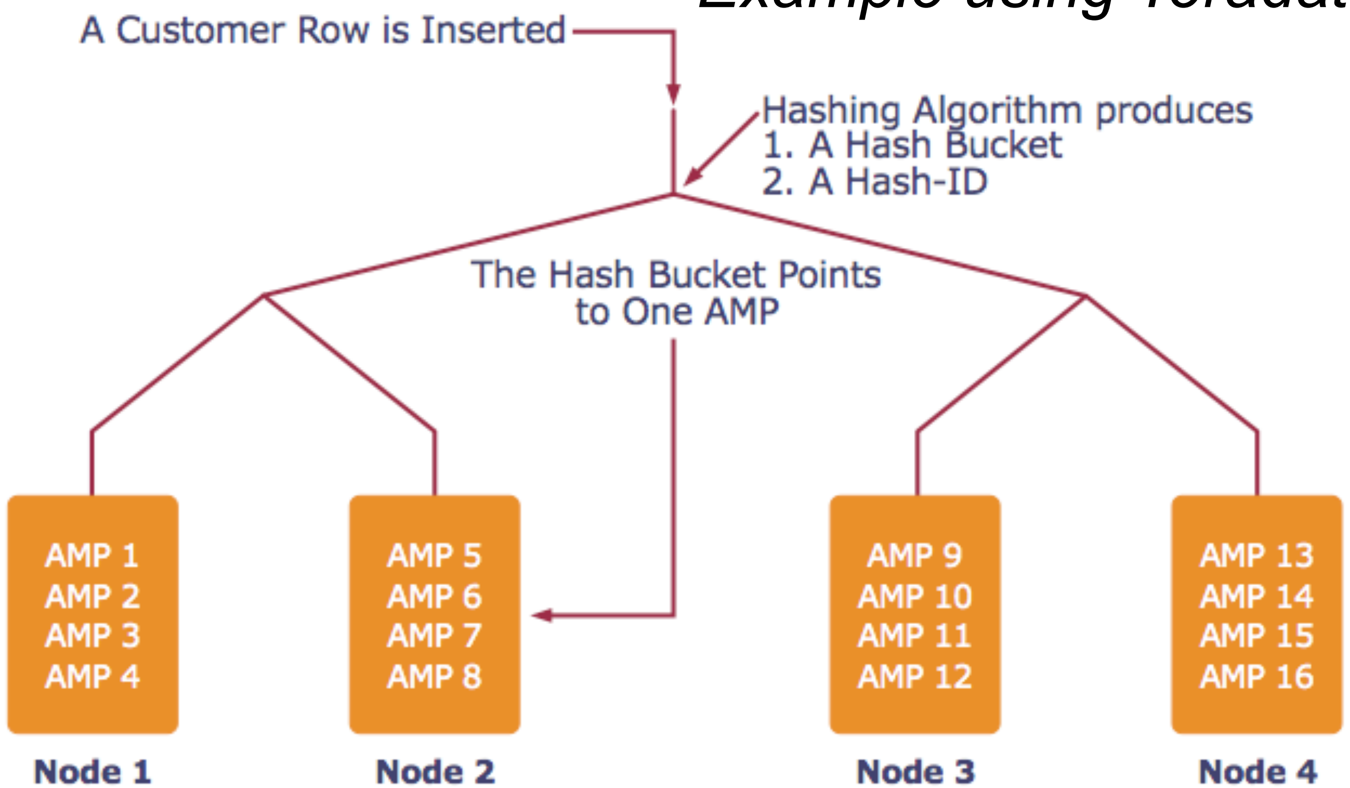
E.g. when all records have the same value of the attribute A, then all records end up in the same partition

Parallel DBMS

- Parallel query plan: tree of parallel operators
  Intra-operator parallelism
  - Data streams from one operator to the next
  - Typically all cluster nodes process all operators
- Can run multiple queries at the same time
  Inter-query parallelism
  - Queries will share the nodes in the cluster
- Notice that user does not need to know how his/her SQL query was processed

Loading Data into a Parallel DBMS

Example using Teradata System

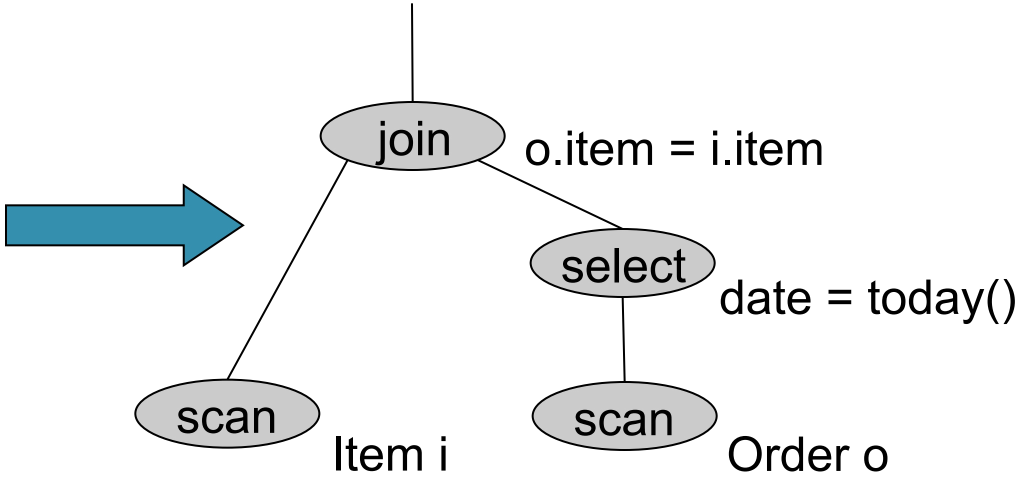


AMP = "Access Module Processor" = unit of parallelism

Example Parallel Query Execution

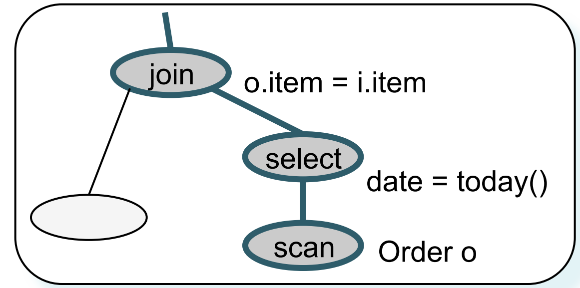
Find all orders from today, along with the items ordered

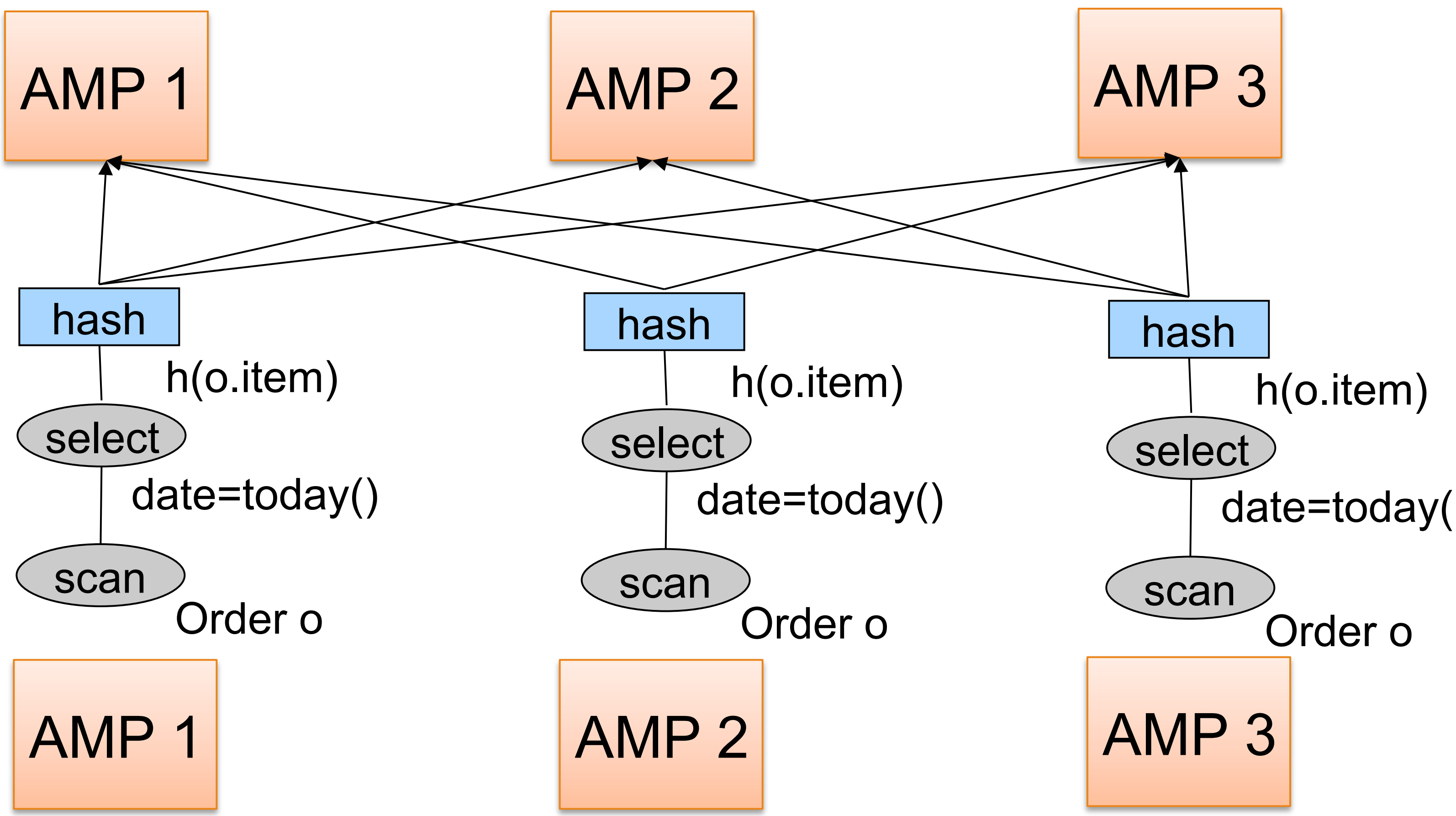
```
SELECT *
  FROM Order o, Line i
 WHERE o.item = i.item
   AND o.date = today()
```



Order(<u>oid</u>, item, date), Line(item, …)

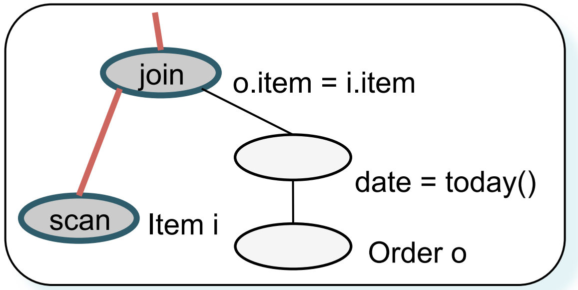
Example Parallel Query Execution

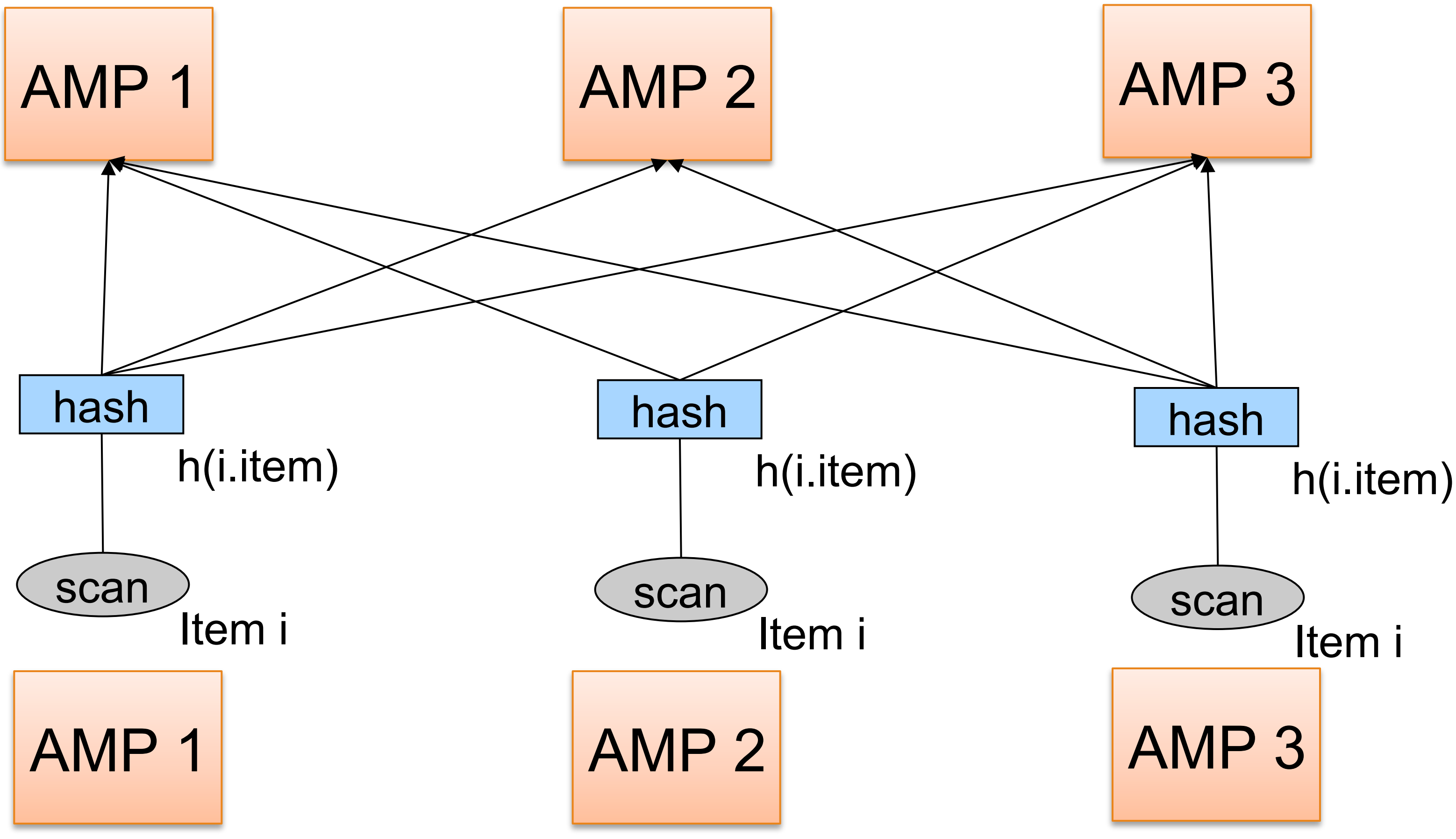




Order(oid, item, date), Line(item, …)

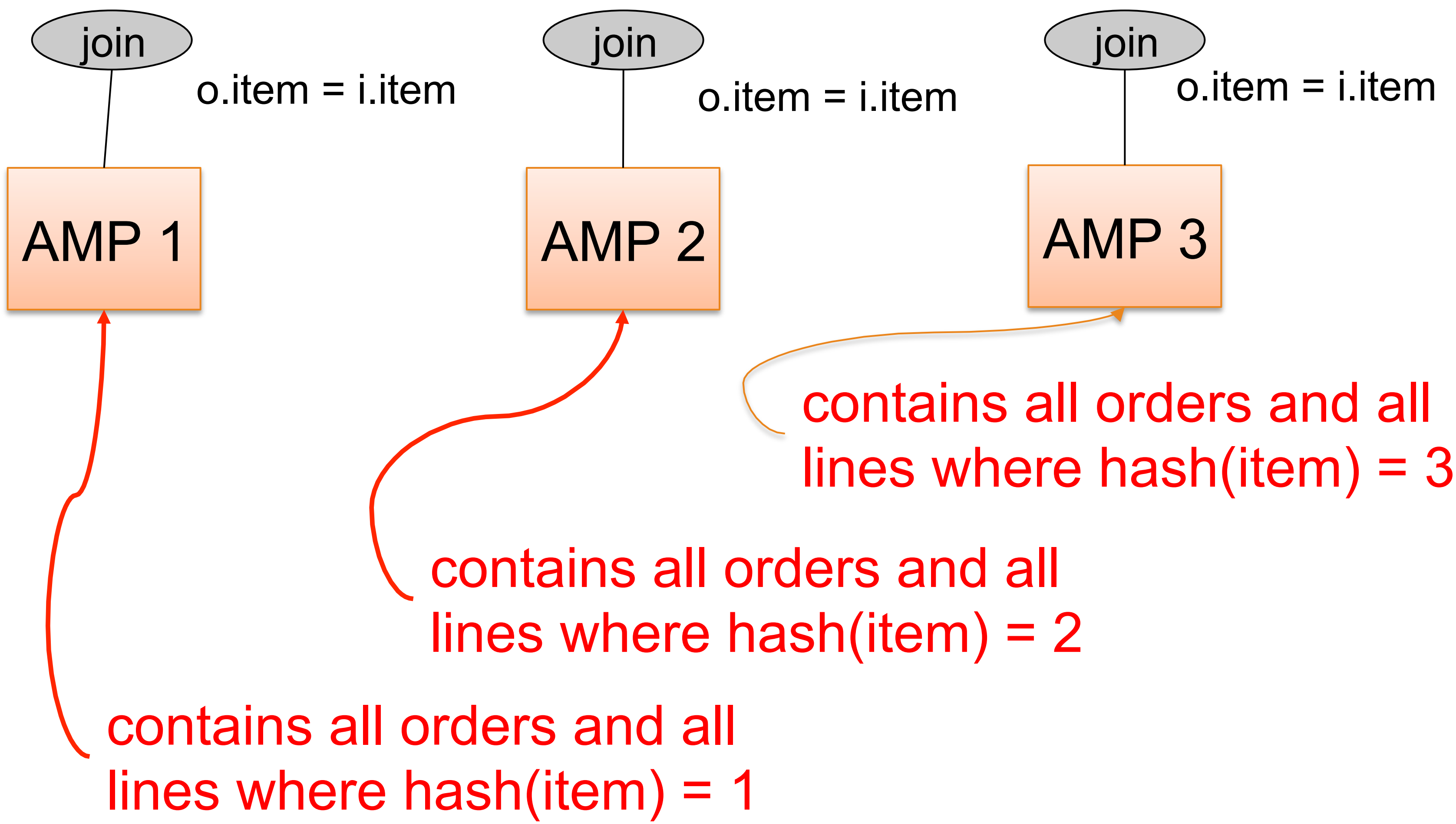
Example Parallel Query Execution





Order(<u>oid</u>, item, date), Line(item, …)

Example Parallel Query Execution



Parallel Dataflow Implementation

- Use relational operators unchanged

- Add a special *shuffle* operator
  - Handle data routing, buffering, and flow control
  - Inserted between consecutive operators in the query plan
  - Two components: ShuffleProducer and ShuffleConsumer
  - Producer pulls data from operator and sends to n consumers
    - Producer acts as driver for operators below it in query plan
  - Consumer buffers input data from n producers and makes it available to operator through getNext interface

- You will use this extensively in 444

Parallel Data Processing at Massive Scale

Data Centers Today

- Large number of commodity servers, connected by high speed, commodity network
- Rack: holds a small number of servers
- Data center: holds many racks

Data Processing at Massive Scale

- Want to process petabytes of data and more
- Massive parallelism:
  - 100s, or 1000s, or 10000s servers
  - Many hours
- Failure:
  - If medium-time-between-failure is 1 year
  - Then 10000 servers have one failure / hour

Distributed File System (DFS)

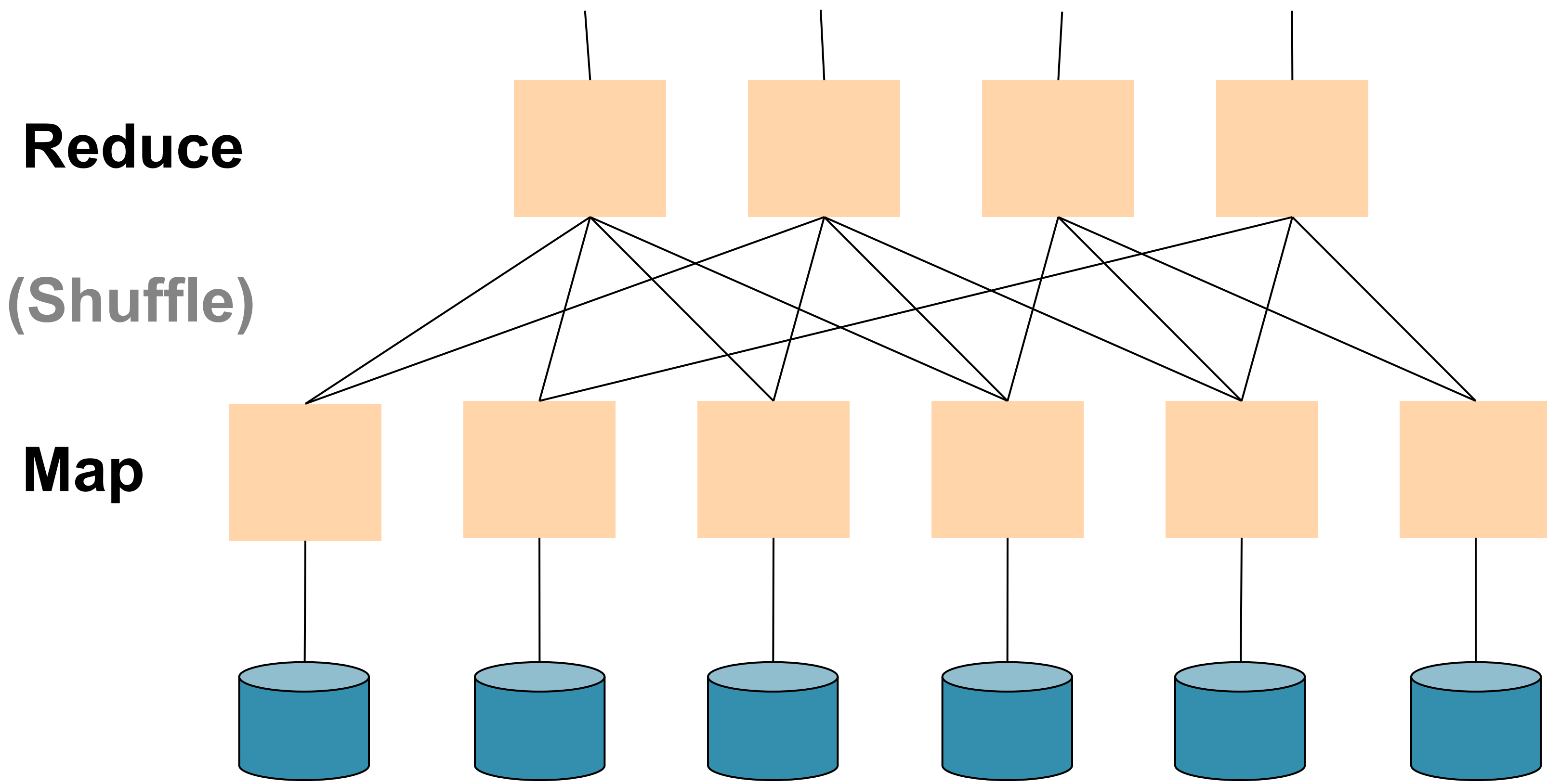
- For very large files: TBs, PBs
- Each file is partitioned into *chunks*, typically 64MB
- Each chunk is replicated several times (≥3), on different racks, for fault tolerance
- Implementations:
  - Google's DFS: GFS, proprietary
  - Hadoop's DFS: HDFS, open source

MapReduce

- Google: paper published 2004
- Free variant: Hadoop

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

Observation: Your favorite parallel algorithm…



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

Outline stays the same,
map and reduce change to fit the problem

slide source: Jeff Dean

Data Model

Files !

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

A MapReduce program:

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

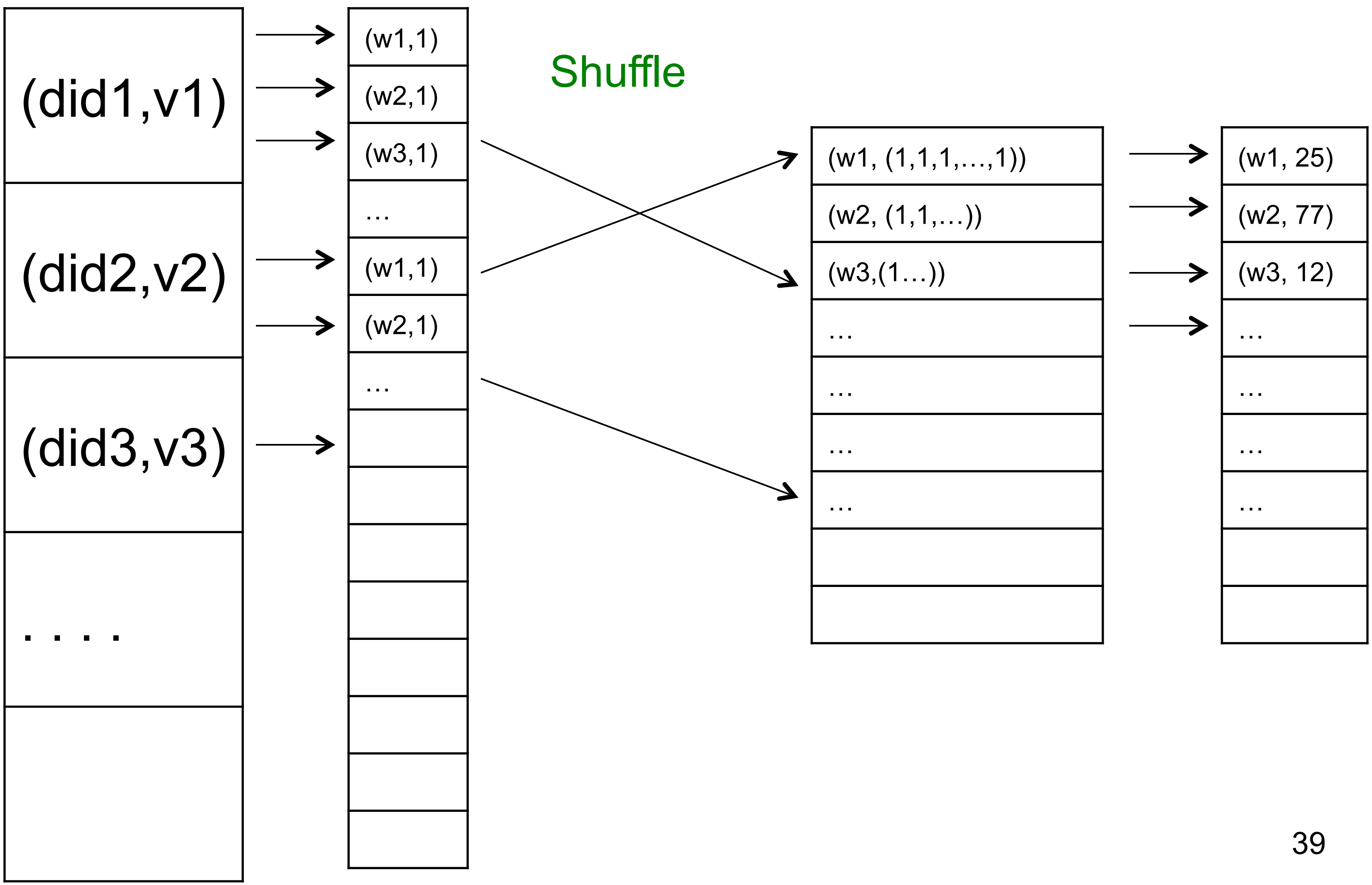
- Counting the number of occurrences of each word in a large collection of documents
- Each Document
  - The key = document id (did)
  - The value = set of words (word)

```
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



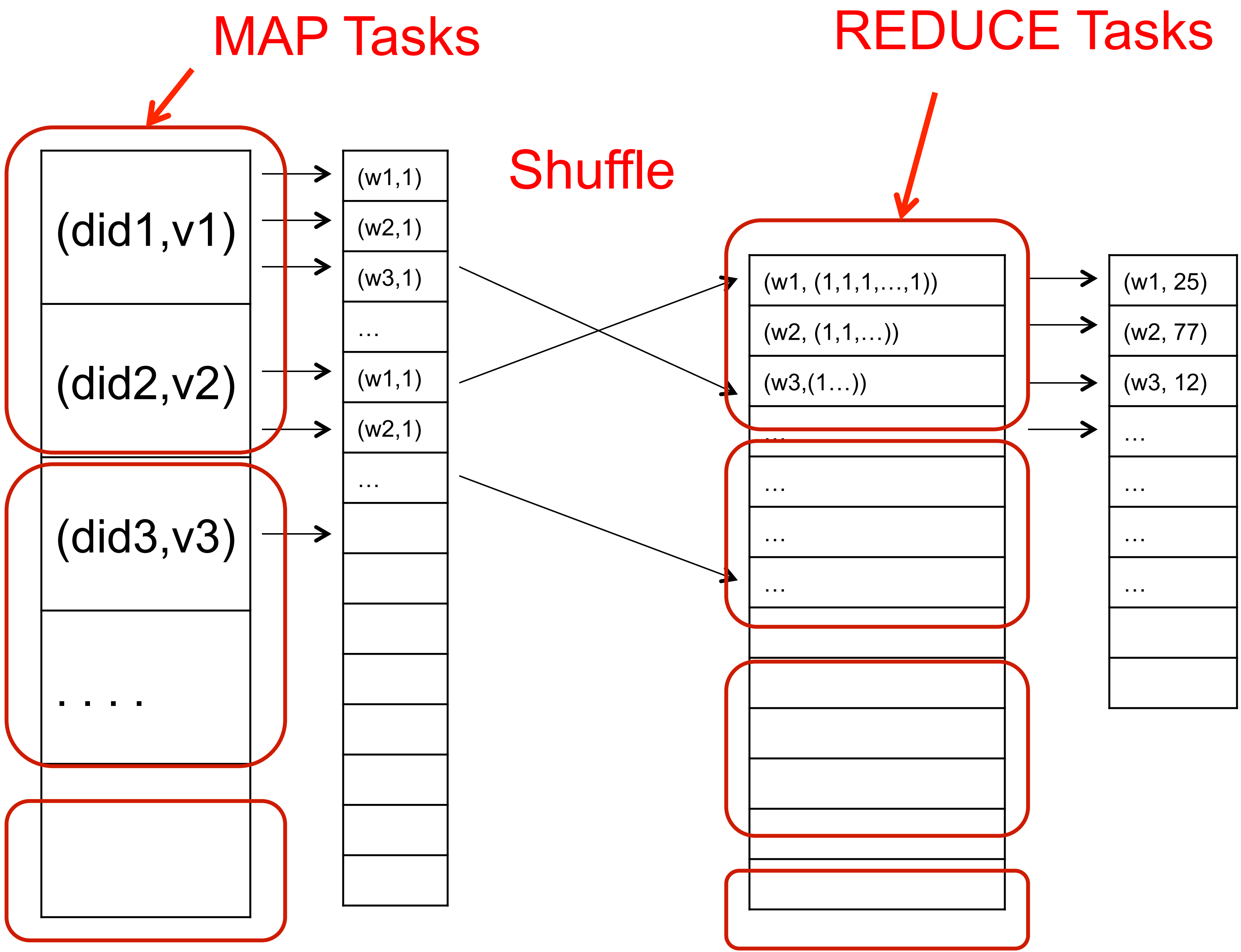
Shuffle
(did1,v1)
(did2,v2)
(did3,v3)
. . . .
(w1,1)
(w2,1)
(w3,1)
…
(w1,1)
(w2,1)
…
(w1, (1,1,1,…,1))
(w2, (1,1,…))
(w3,(1…))
…
…
…
…
(w1, 25)
(w2, 77)
(w3, 12)
…
…
…
…

Jobs v.s. Tasks

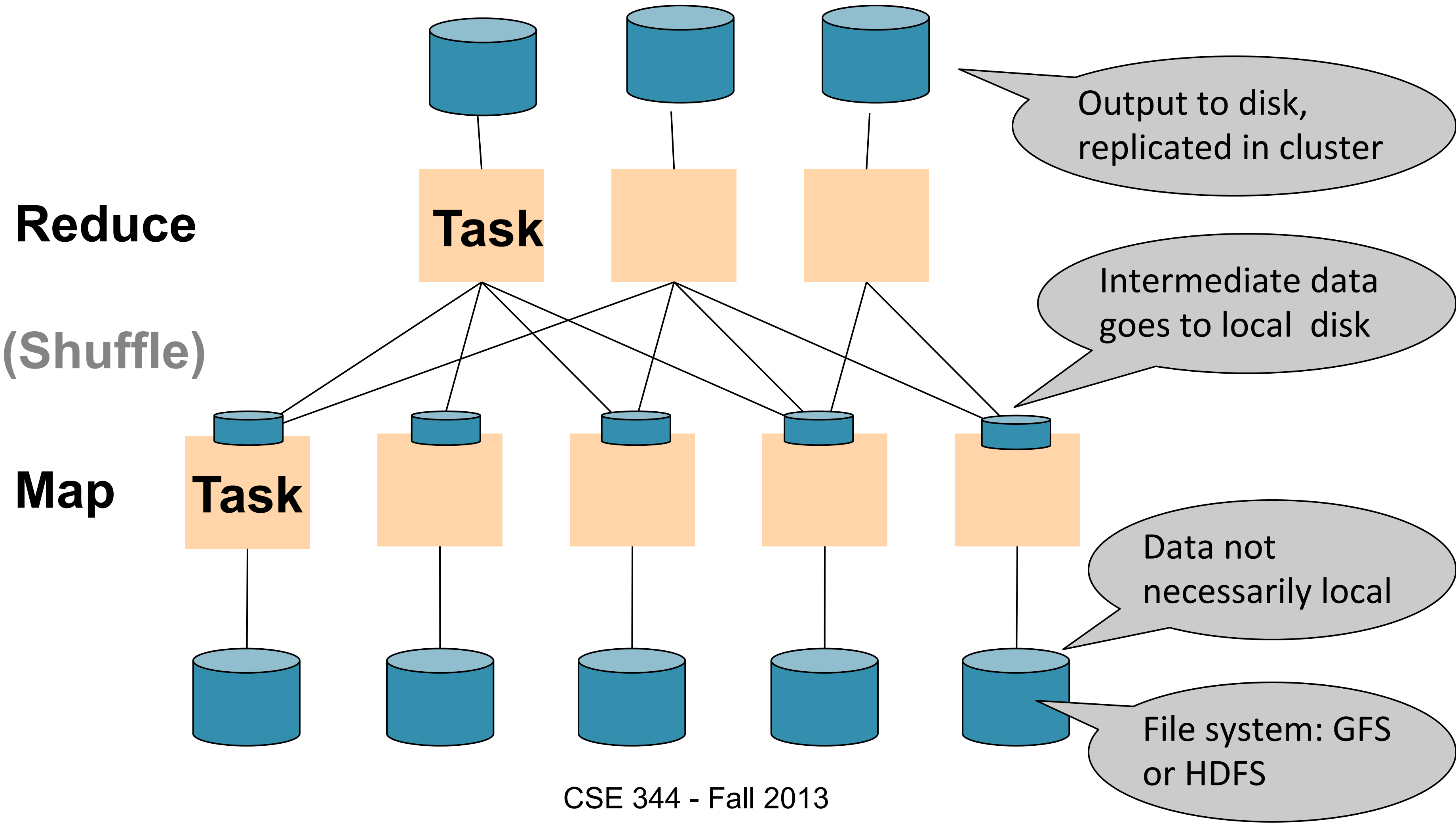
- A MapReduce Job
  - One single “query”, e.g. count the words in all docs
  - More complex queries may consists of multiple jobs
- A Map Task, or a Reduce Task
  - A group of instantiations of the map-, or reduce-function, which are scheduled on a single worker

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

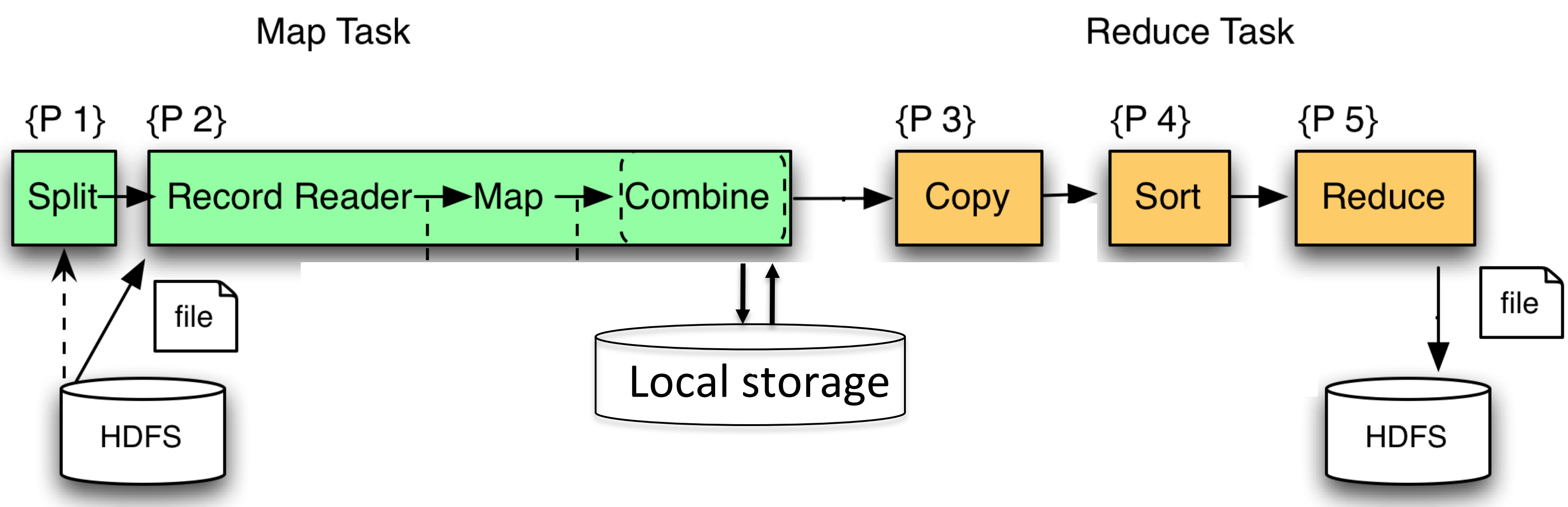

MAP Tasks
REDUCE Tasks
Shuffle
(did1,v1)
(did2,v2)
(did3,v3)
. . . . .
(w1,1)
(w2,1)
(w3,1)
…
(w1,1)
(w2,1)
…
(w1, (1,1,1,…,1))
(w2, (1,1,…))
(w3,(1…))
…
…
…
…
(w1, 25)
(w2, 77)
(w3, 12)
…
…
…
…

MapReduce Execution Details

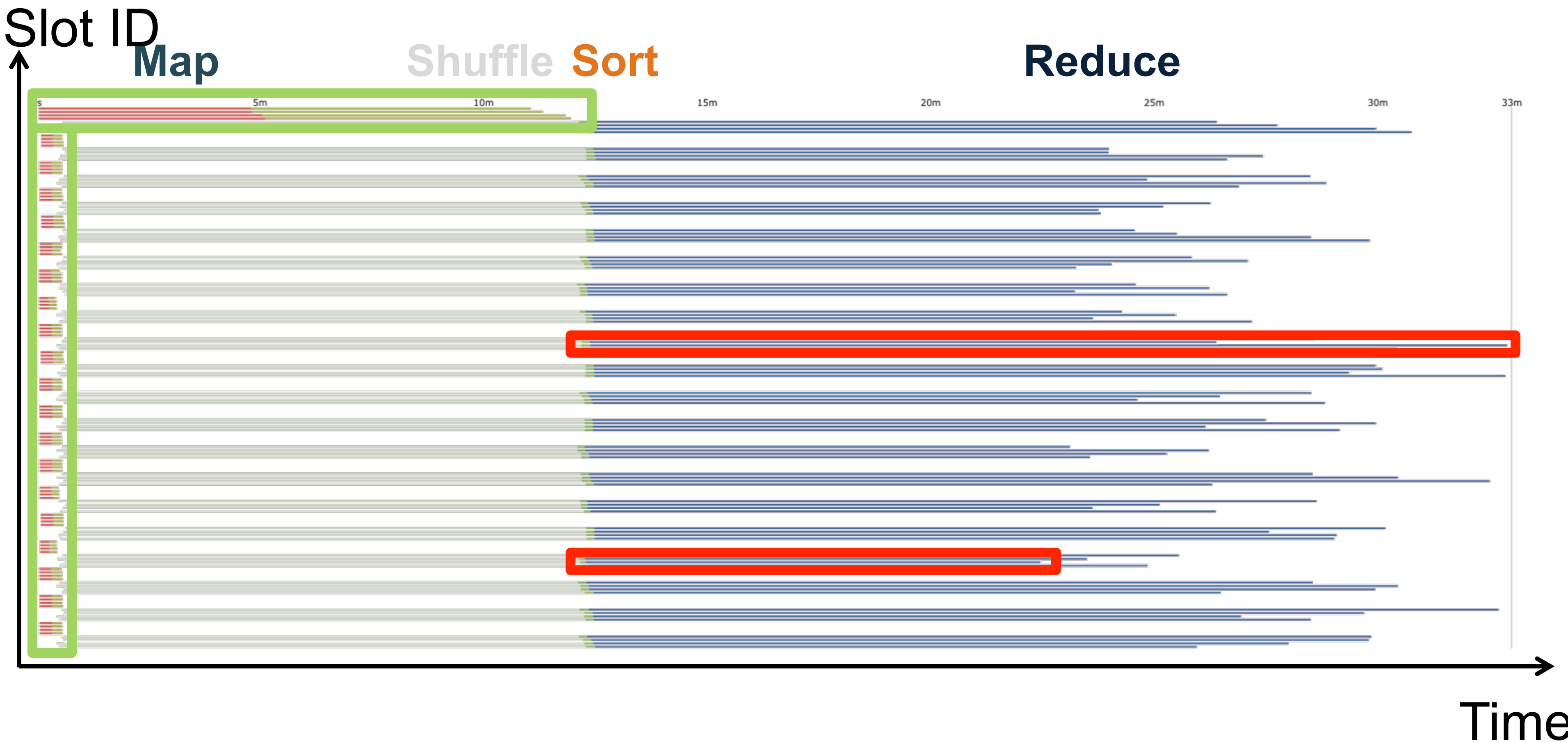


MR Phases

- Each Map and Reduce task has multiple phases:



Example: CloudBurst



CloudBurst. Lake Washington Dataset (1.1GB). 80 Mappers 80 Reducers.

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

Worker failure:

- Master pings workers periodically,
- If down then reassigns the task to another worker

Interesting Implementation Details

Backup tasks:

- *Straggler* = a machine that takes unusually long time to complete one of the last tasks. Eg:
  - 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*

MapReduce Summary

- Hides scheduling and parallelization details
- However, very limited queries
  - Difficult to write more complex queries
  - Need multiple MapReduce jobs
- Solution: declarative query language

Declarative Languages on MR

- PIG Latin (Yahoo!)
  - New language, like Relational Algebra
  - Open source
- HiveQL (Facebook)
  - SQL-like language
  - Open source
- SQL / Tenzing (Google)
  - SQL on MR
  - Proprietary

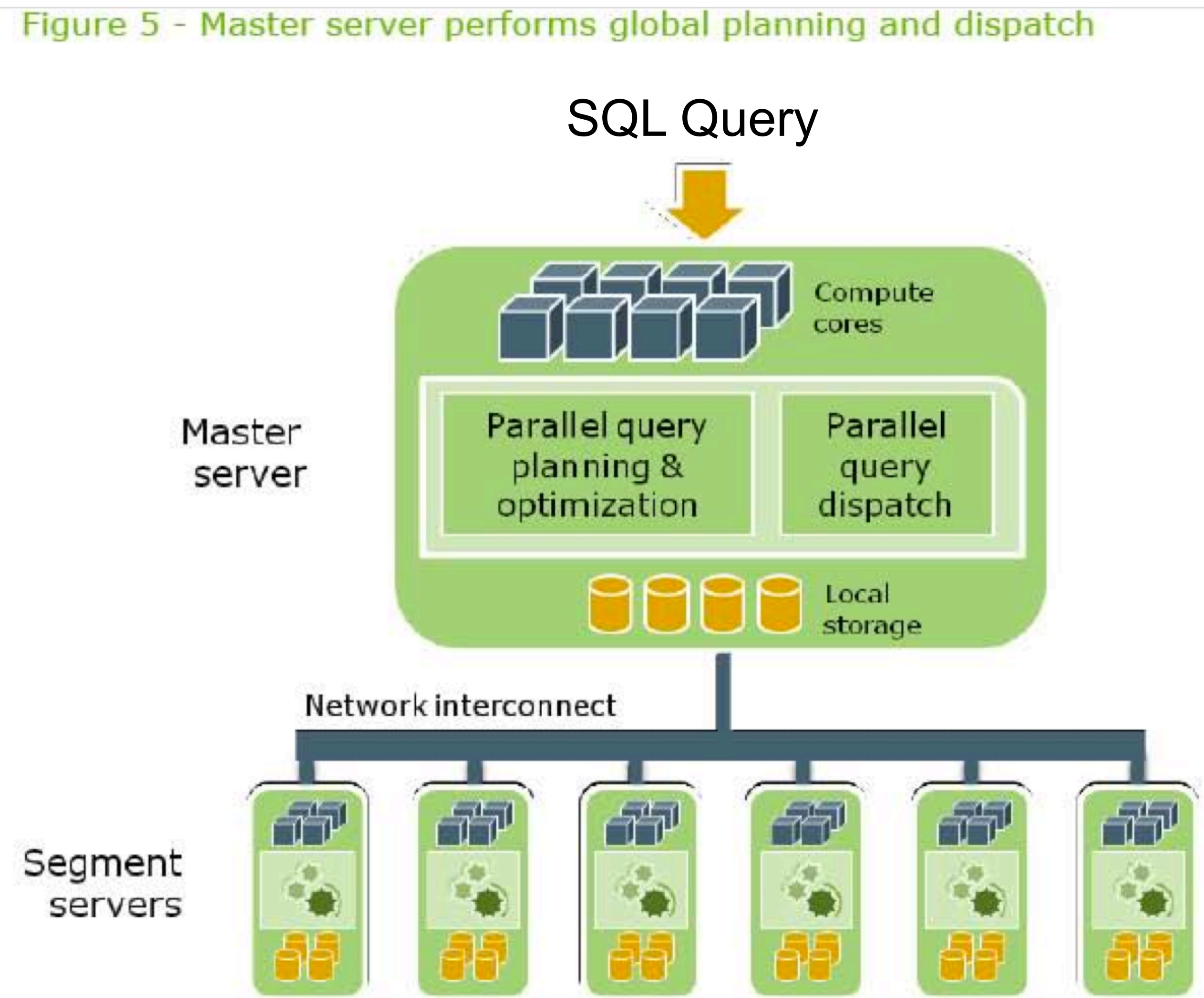
Parallel DBMS vs MapReduce

- Parallel DBMS
  - Relational data model and schema
  - Declarative query language: SQL
  - Many pre-defined operators: relational algebra
  - Can easily combine operators into complex queries
  - Query optimization, indexing, and physical tuning
  - Streams data from one operator to the next without blocking
  - Can do more than just run queries: Data management
    - Updates and transactions, constraints, security, etc.

Parallel DBMS vs MapReduce

- MapReduce
  - Data model is a file with key-value pairs!
  - No need to "load data" before processing it
  - Easy to write user-defined operators
  - Can easily add nodes to the cluster (no need to even restart)
  - Uses less memory since processes one key-group at a time
  - Intra-query fault-tolerance thanks to results on disk
  - Intermediate results on disk also facilitate scheduling
  - Handles adverse conditions: e.g., stragglers
  - Arguably more scalable… but also needs more nodes!

Review: Parallel DBMS



From: Greenplum Database Whitepaper