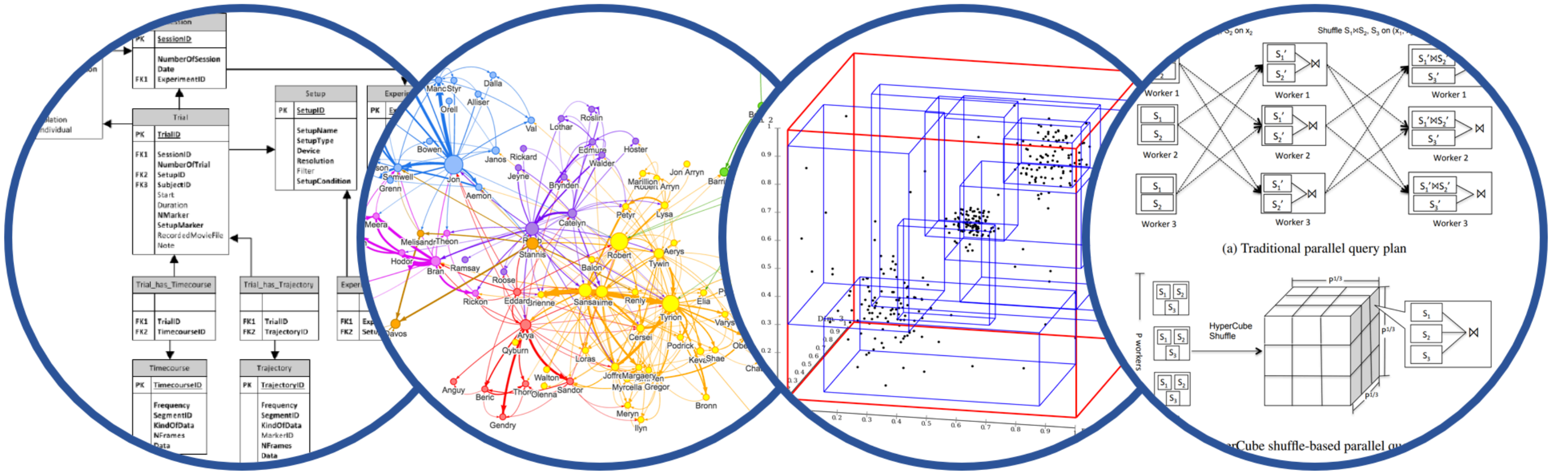

Database System Internals

MapReduce

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Summary of Aries

Redo is physical:

- Replay history
- Idempotent
- Efficient
- Redo in Aries is done for *all* TXN, including active
- Undo the active TXN in the next phase

Summary of Aries

Undo is logical

- Can be done selectively for single TXN
- Not idempotent: must prevent second execution
- But what if CRASH during UNDO?
- Solution: CLR records the *physical* op; these are standard REDO records, hence idempotent

Parallel Data Processing

OLAP: Online Analytical Processing

- Big queries: joins, group-by, large data
- No updates
- Use parallelism/distribution to improve performance
- Challenge: optimize ONE query

OLTP: Online Transaction Processing

- Big data, but simple query: many simple updates
- Distribute data to support large workloads
- Challenge: ACID or something weaker

This lecture

Data model? Relational

Scaleup goal? OLAP

Architecture? Shared-Nothing

This lecture

Data model? Relational → text/kv-pairs

Scaleup goal? OLAP

Architecture? Shared-Nothing

References

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

- Mining of Massive Datasets, by Rajaraman and Ullman, http://i.stanford.edu/~ullman/mmds.html
  - Map-reduce (Section 20.2);
  - Chapter 2 (Sections 1,2,3 only)

A Note

- MapReduce is obsolete now
  Interesting only from a historical perspective

- It has had an important influence, still visible today, but newer systems do a better job at adopting traditional database principles:
  - Spark
  - Snowflake – standard highly distributed SQL

Map Reduce Review

- Google: [Dean 2004]
- Open source implementation: Hadoop

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

MapReduce Motivation

- Not designed to be a DBMS
- But to simplify task of writing parallel programs
  - Simple programming model that applies to many problems
- Hides messy details in runtime library:
  - Automatic parallelization
  - Load balancing
  - Network and disk transfer optimizations
  - Handling of machine failures
  - Robustness

content in part from: Jeff Dean

Data Processing at Massive Scale

- Massive parallelism:
  - 100s, or 1000s, or 10000s servers (think data center)
  - Many hours

- Failure:
  - If medium-time-between-failure is 1 year
  - Then 10000 servers have one failure / hour

Data Storage: GFS/HDFS

- MapReduce job input is a file

- Distributed file system:
  - GFS: Google File System
  - HDFS: Hadoop File System

- File is split into “blocks” or “chunks”: 64MB or so
- Blocks are replicated & stored on random machines
- Files are append only

MapReduce: 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 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:
  - Original MR paper: bag of output `(values)`
  - Hadoop: bag of `(output key, values)`

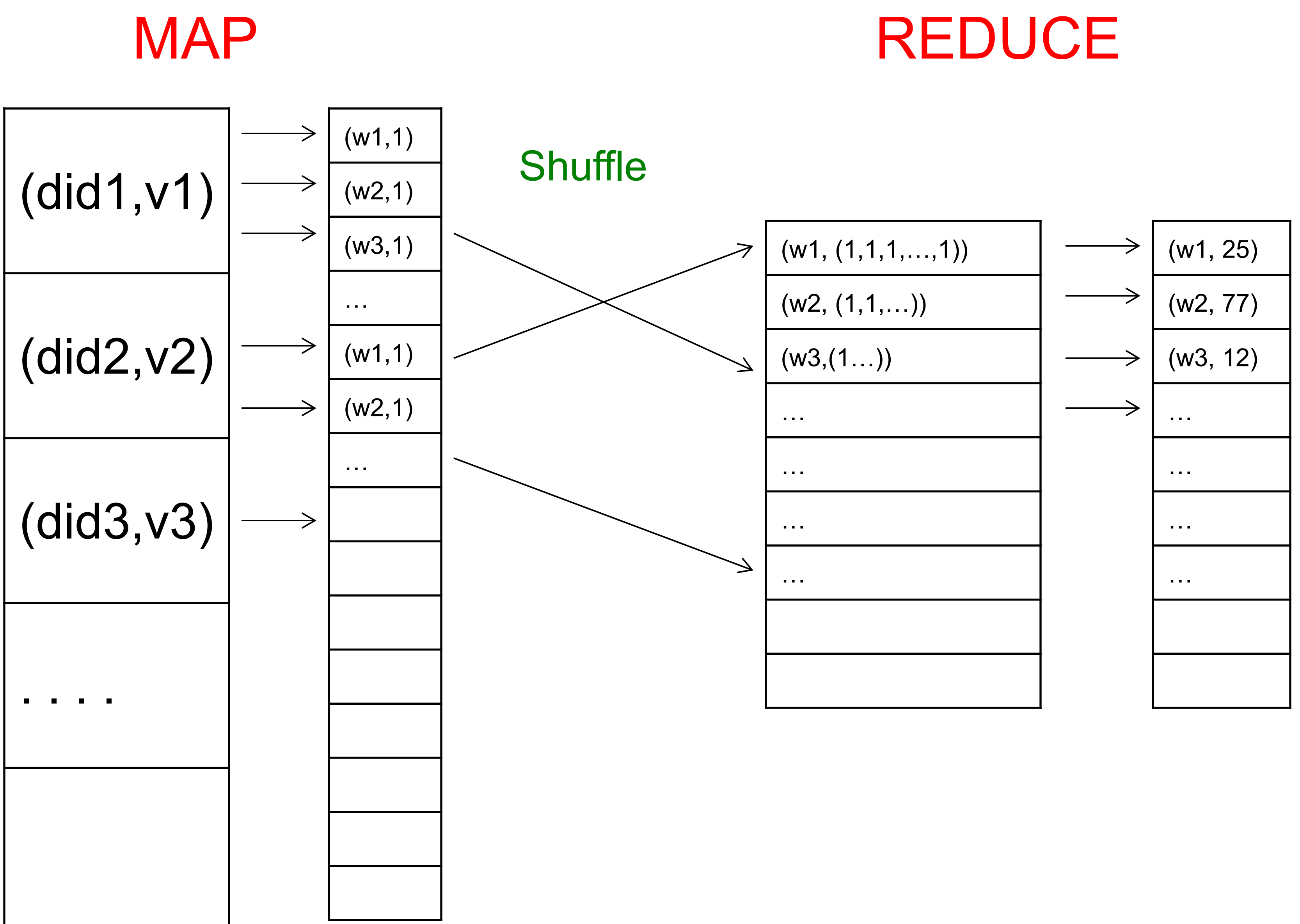
System groups all pairs with the same intermediate key, and passes the bag of values to REDUCE

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));
```

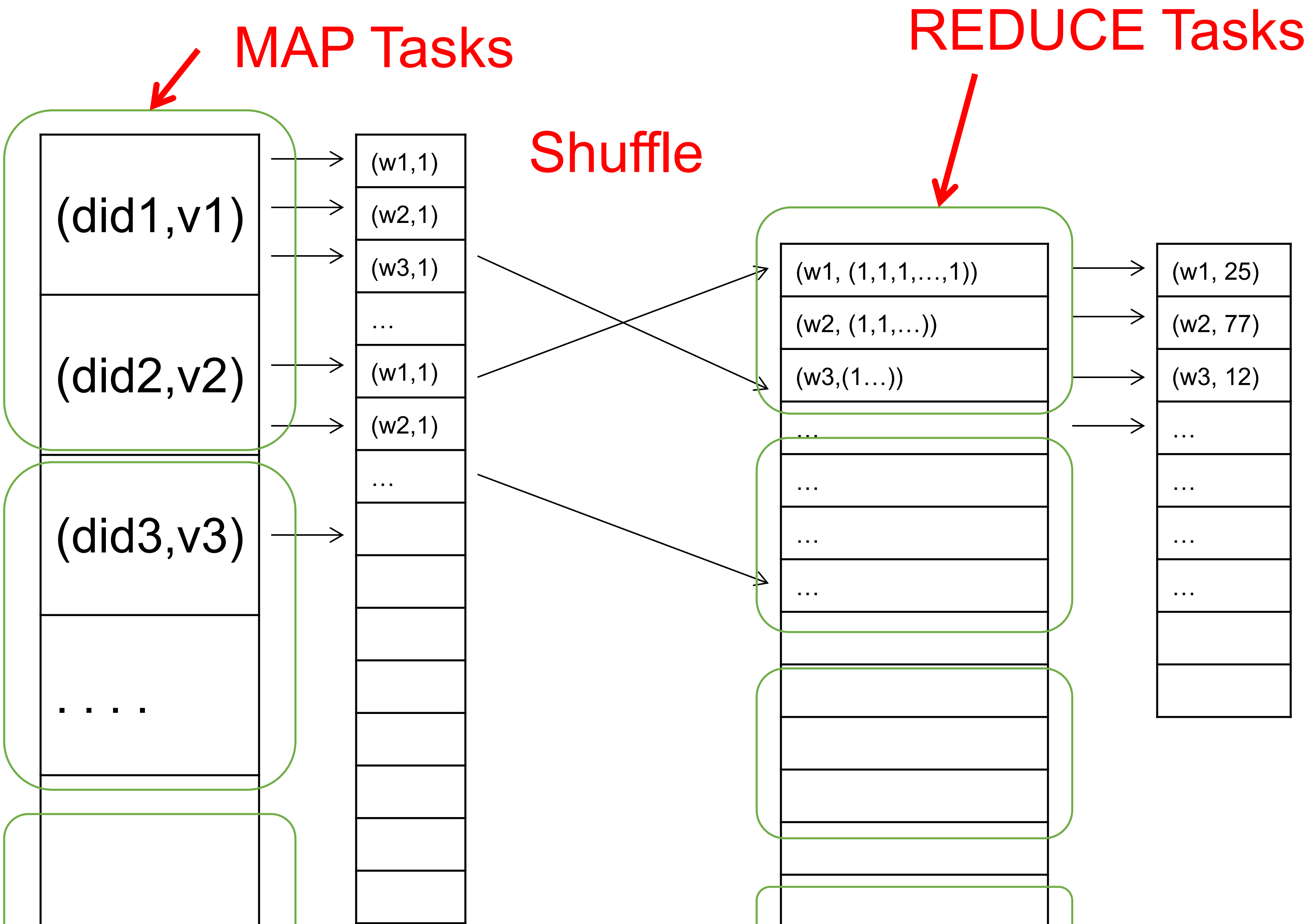

MAP
REDUCE
(did1,v1)
(did2,v2)
(did3,v3)
. . . .
(w1,1)
(w2,1)
(w3,1)
…
(w1,1)
(w2,1)
…
Shuffle
(w1, (1,1,1,…,1))
(w2, (1,1,…))
(w3,(1…))
…
…
…
…
(w1, 25)
(w2, 77)
(w3, 12)
…
…
…
…

Jobs vs. 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
- Often talk about "slots"
  - E.g., Each server has 2 map slots and 2 reduce slots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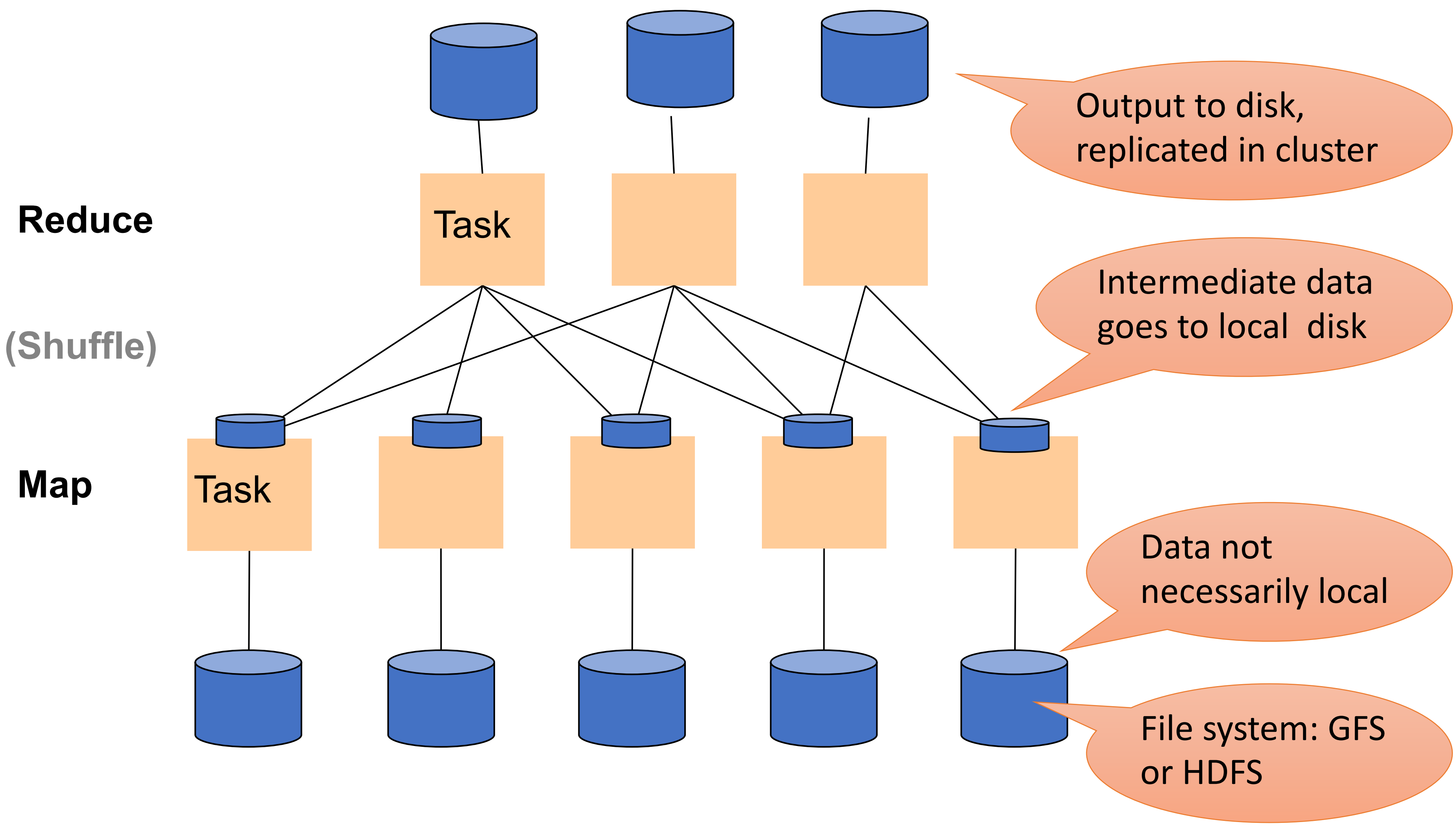
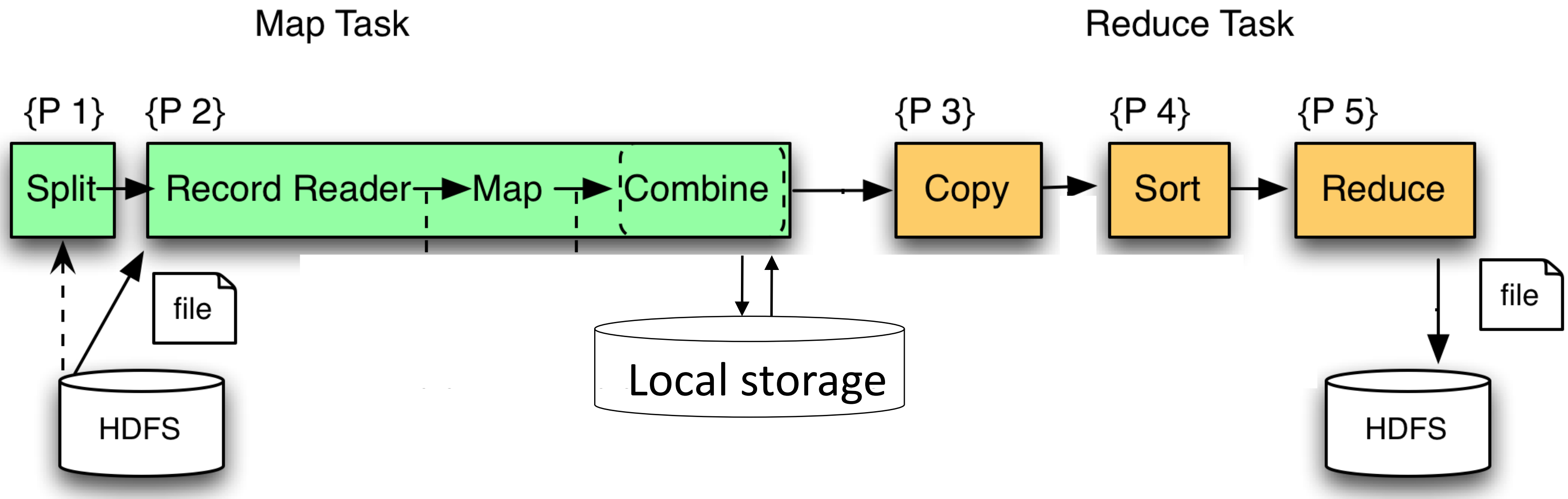
Parallel MapReduce Details



MapReduce Implementation

- There is one master node
- Input file gets partitioned further into *M′ splits*
  - Each split is a contiguous piece of the input file
  - By default splits correspond to blocks
- Master assigns *workers* (=servers) to the *M′ map tasks*, keeps track of their progress
- Workers write their output to local disk
- Output of each map task is partitioned into *R regions*
- Master assigns workers to the *R reduce tasks*
- Reduce workers read regions from the map workers′ local disks

MapReduce Phases



Interesting Implementation Details

- Worker failure:
  - Master pings workers periodically,
  - If down then reassigns its task to ***another* worker**
  - (≠ a parallel DBMS restarts whole query)

- How many map and reduce tasks:
  - Larger is better for load balancing
  - But more tasks also add overheads
  - (≠ parallel DBMS spreads ops across all nodes)

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*

The State of MapReduce Systems

- Lots of extensions to address limitations
  - Capabilities to write DAGs of MapReduce jobs
  - Declarative languages
  - Ability to read from structured storage (e.g., indexes)
  - Etc.
- Most companies use both types of engines (MR and DBMS), with increased integration
- New systems emerged which improve over MapReduce: e.g. Spark

Relational Queries over MR

- Query → query plan
- Each operator → one MapReduce job

GroupBy in MapReduce

Doc(key, word)

MapReduce IS A GroupBy!

MAP=GROUP BY, REDUCE=Aggregate

```
SELECT word, sum(1)
FROM Doc
GROUP BY word
```

Joins in MapReduce

- If MR is GROUP-BY plus AGGREGATE, then how do we compute $R(A,B) \bowtie S(B,C)$ using MR?

Joins in MapReduce

- If MR is GROUP-BY plus AGGREGATE, then how do we compute R(A,B) ⋈ S(B,C) using MR?

- Answer:
  - Map: group R by R.B, group S by S.B
    - Input = either a tuple R(a,b) or a tuple S(b,c)
    - Output = (b,R(a,b)) or (b,S(b,c)) respectively
  - Reduce:
    - Input = (b,{R(a1,b),R(a2,b),…,S(b,c1),S(b,c2),…})
    - Output = {R(a1,b),R(a2,b),…} × {S(b,c1),S(b,c2),…}
    - In practice: improve the reduce function (next…)

Join in MR

Users(name, age)
Pages(userName, url)

```
Users = load 'users' as (name, age);
Pages = load 'pages' as (userName, url);
Jnd = join Users by name, Pages by userName;
```

```
map([String key], String value):
    // value.relation is either 'Users' or 'Pages'
    if value.relation='Users':
     EmitIntermediate(value.name, (1, value));
    else // value.relation='Pages':
     EmitIntermediate(value.userName, (2, value));
```

```
reduce(String user, Iterator values):
    Users = empty;  Pages = empty;
    for each v in values:
      if v.type = 1: Users.insert(v)
      else Pages.insert(v);
    for v1 in Users, for v2 in Pages
     Emit(v1,v2);
```

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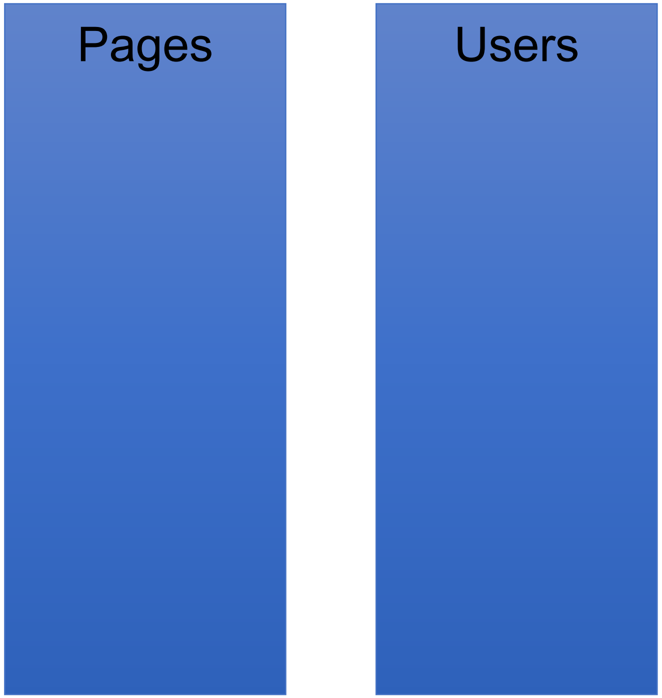

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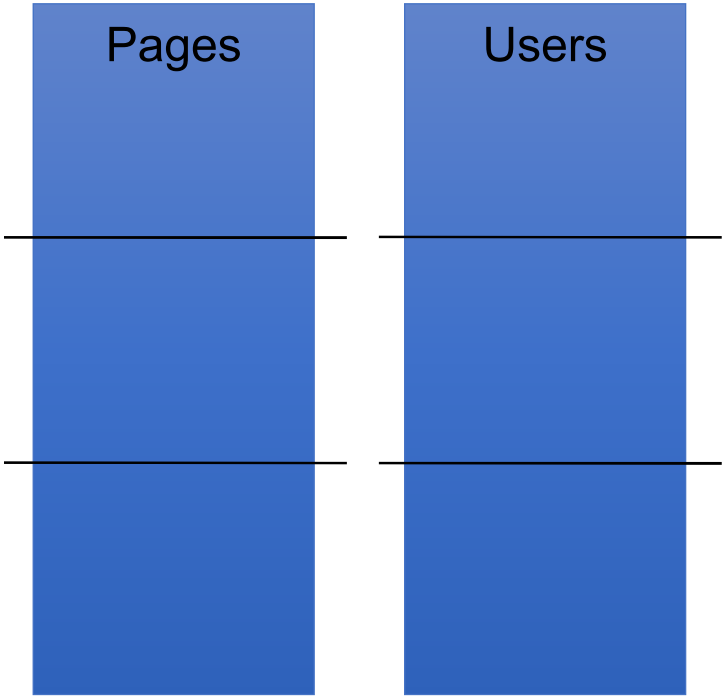

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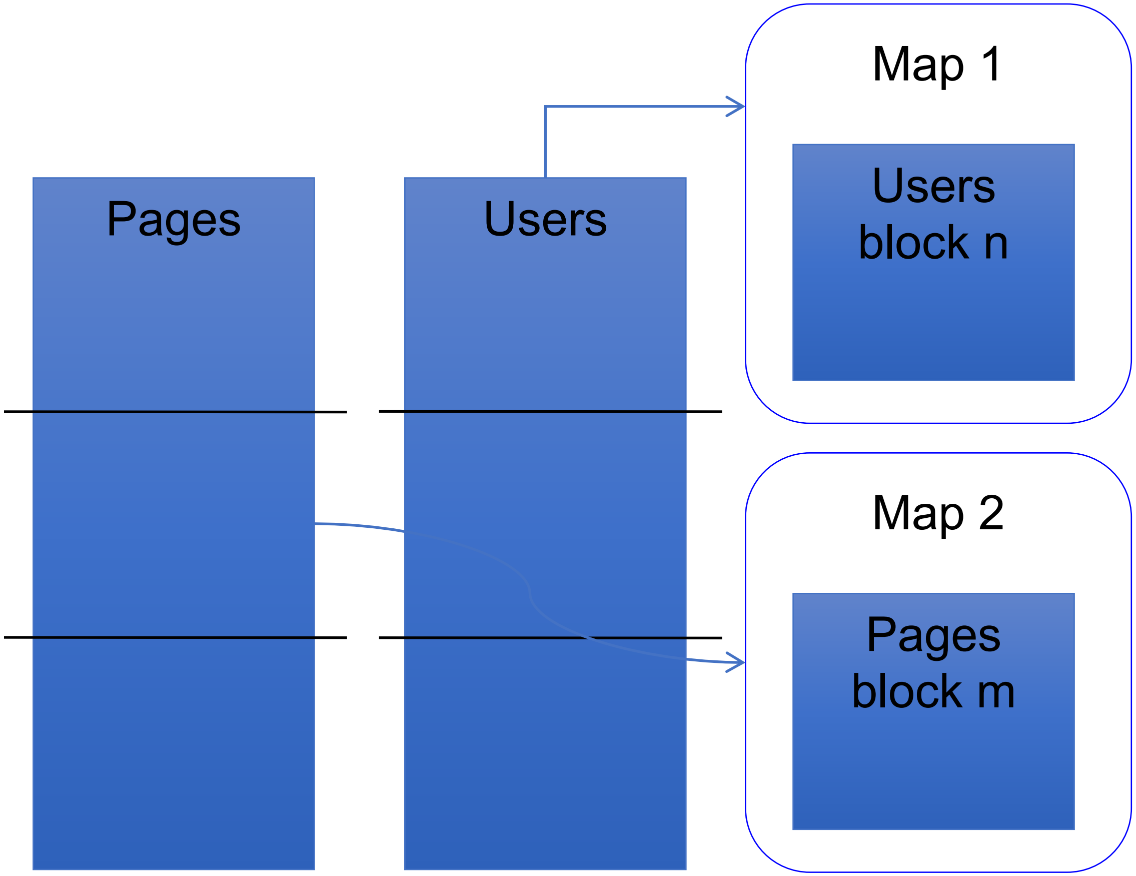

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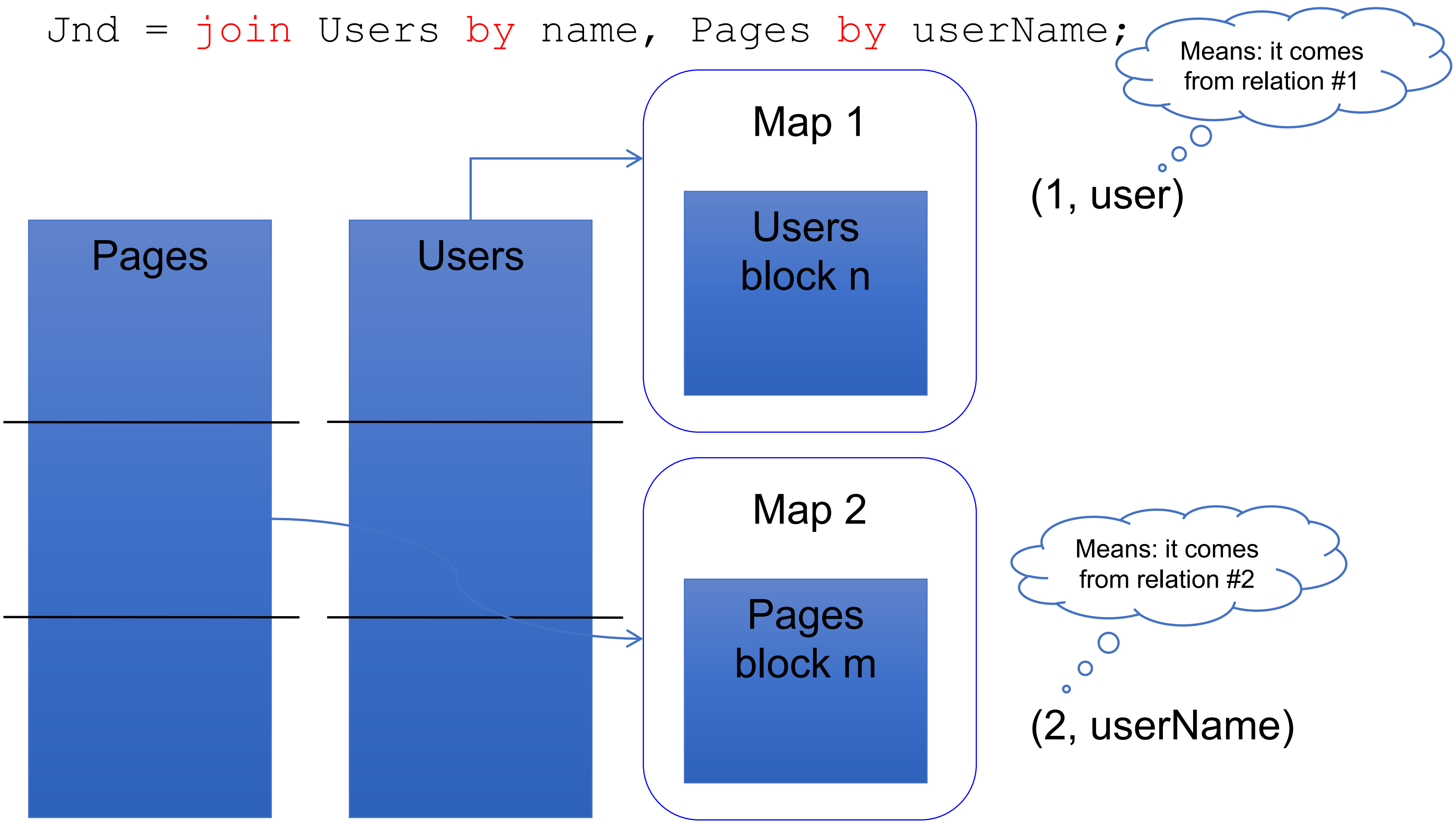

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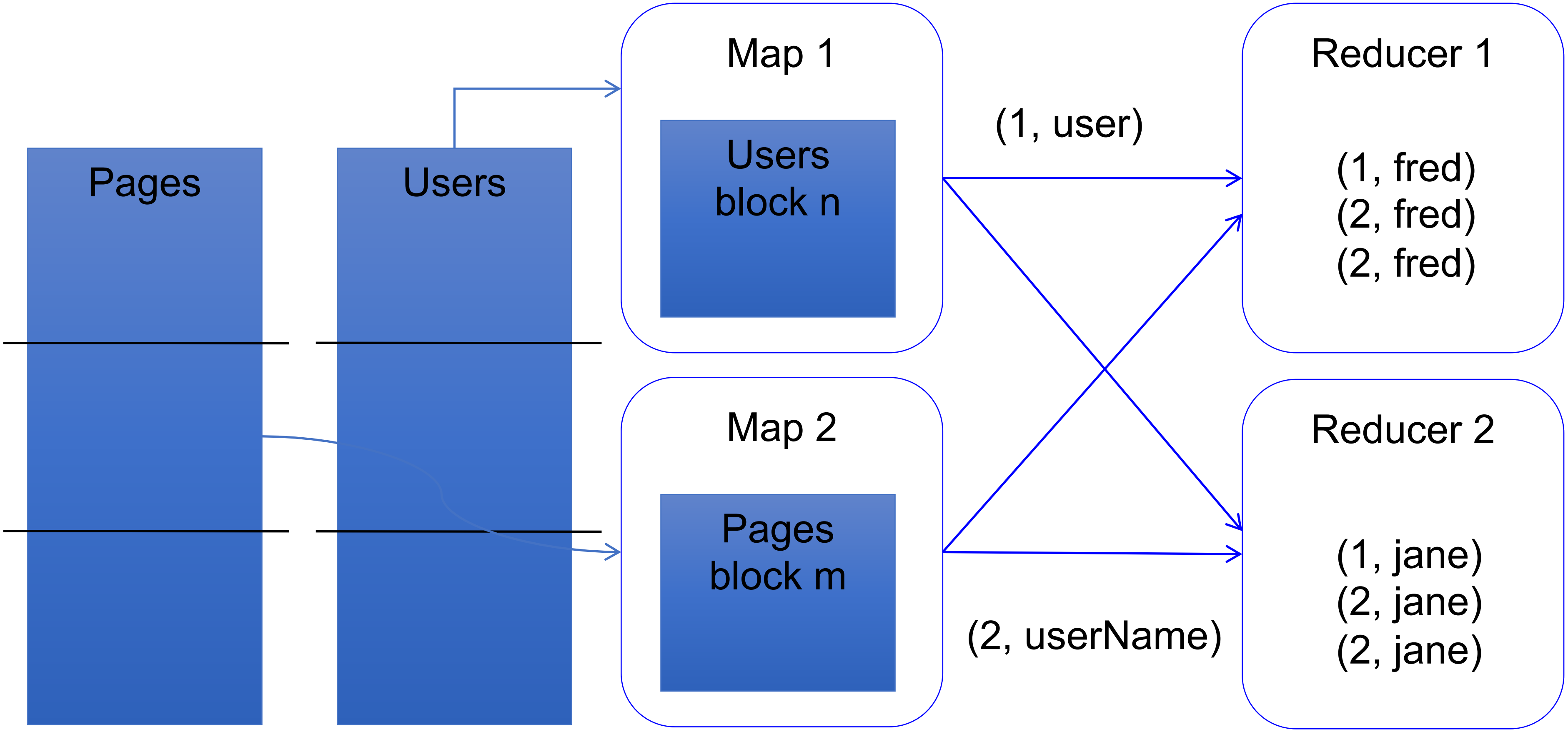

Parallel DBMS vs MapReduce

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.

MapReduce: A major step backwards by David DeWitt

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!**

MapReduce: A major step backwards by David DeWitt