CSE 344

JULY 25TH

MAP-REDUCE

ADMINISTRIVIA

- **Midterm on Friday**
  - 4 problems
  - similar content to previous exams
    - (but no parallel DBs)
  - cost formulas provided

- **HW6 released Saturday**
  - due next *Thursday*

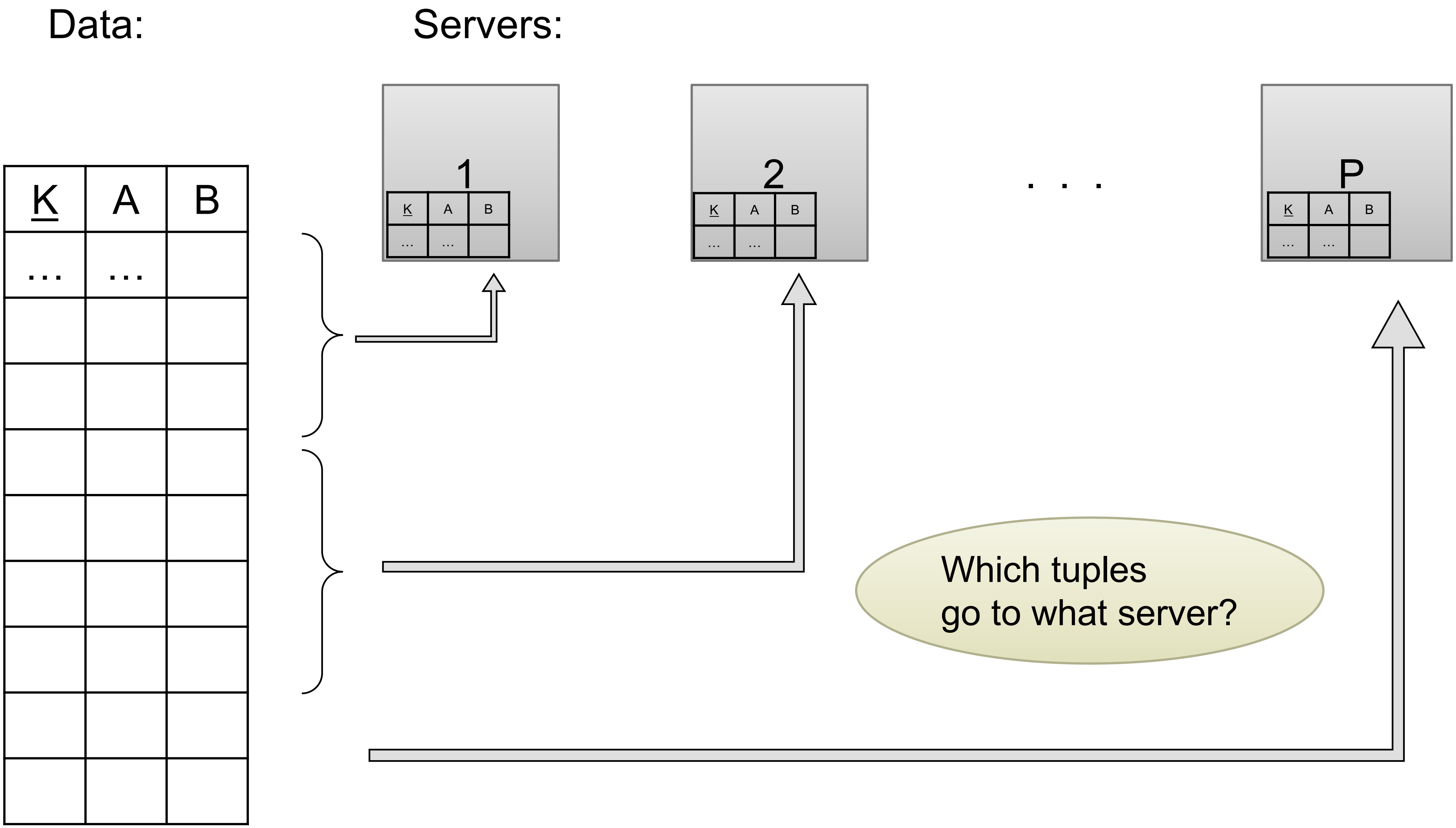
DISTRIBUTED QUERY PROCESSING

Data is horizontally partitioned on many servers

Operators may require data reshuffling

- move data to the machines that needs it
- this is the main new element in parallel query processing

HORIZONTAL DATA PARTITIONING



Data:

K	A	B
…	…	

Servers:

Which tuples
go to what server?

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
- Recall: calling hash fn's is free in this class

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 $v_{i-1} < t.A < v_i$

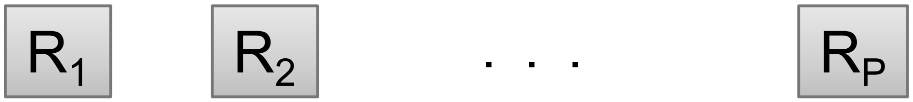
PARALLEL EXECUTION OF RA OPERATORS: SELECTION

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

Query: $\sigma_{A=c}(R)$

No change necessary

- Send query to every machine
- Each sends back its tuples that satisfy selection
- Result is the union of these



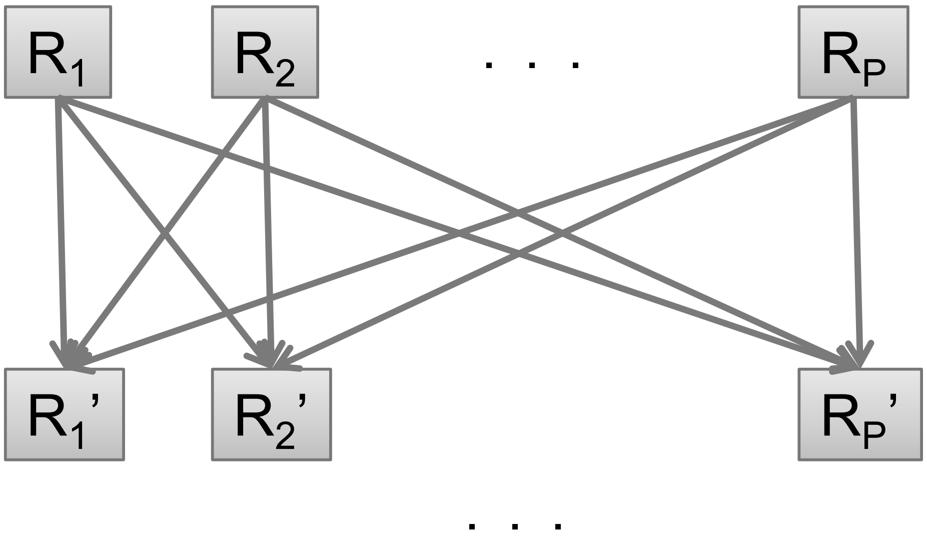
R_1 R_2 . . . R_P

PARALLEL EXECUTION OF RA OPERATORS: GROUPING

Data: R($\underline{K}$,A,B,C)

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

R is block-partitioned or hash-partitioned on K



Reshuffle R on attribute A

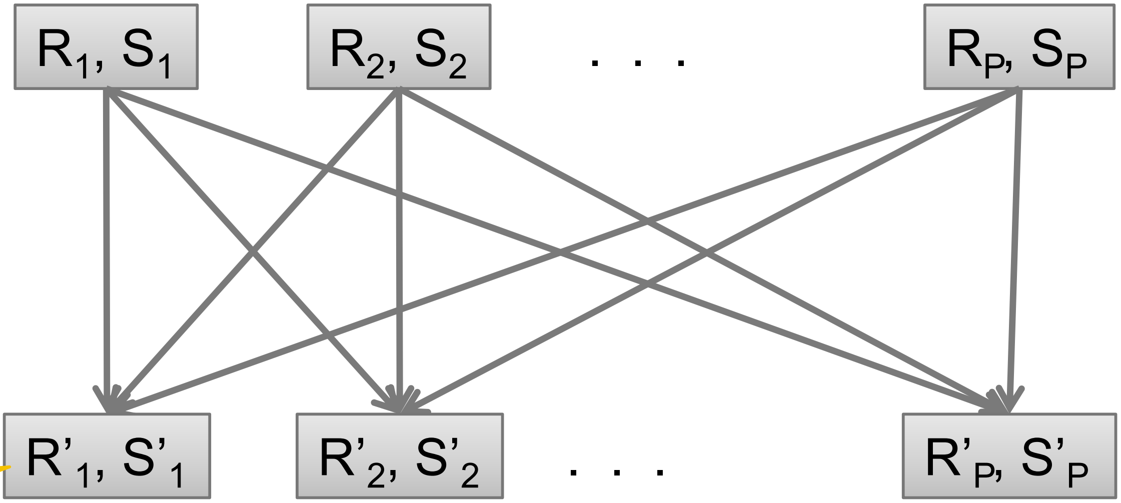
Run grouping on reshuffled partitions

PARALLEL EXECUTION OF RA OPERATORS: PARTITIONED HASH-JOIN

Data: R(<u>K1</u>, A, B), S(<u>K2</u>, B, C)

Query: R(<u>K1</u>, A, B) ⋈ S(<u>K2</u>, B, C)

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



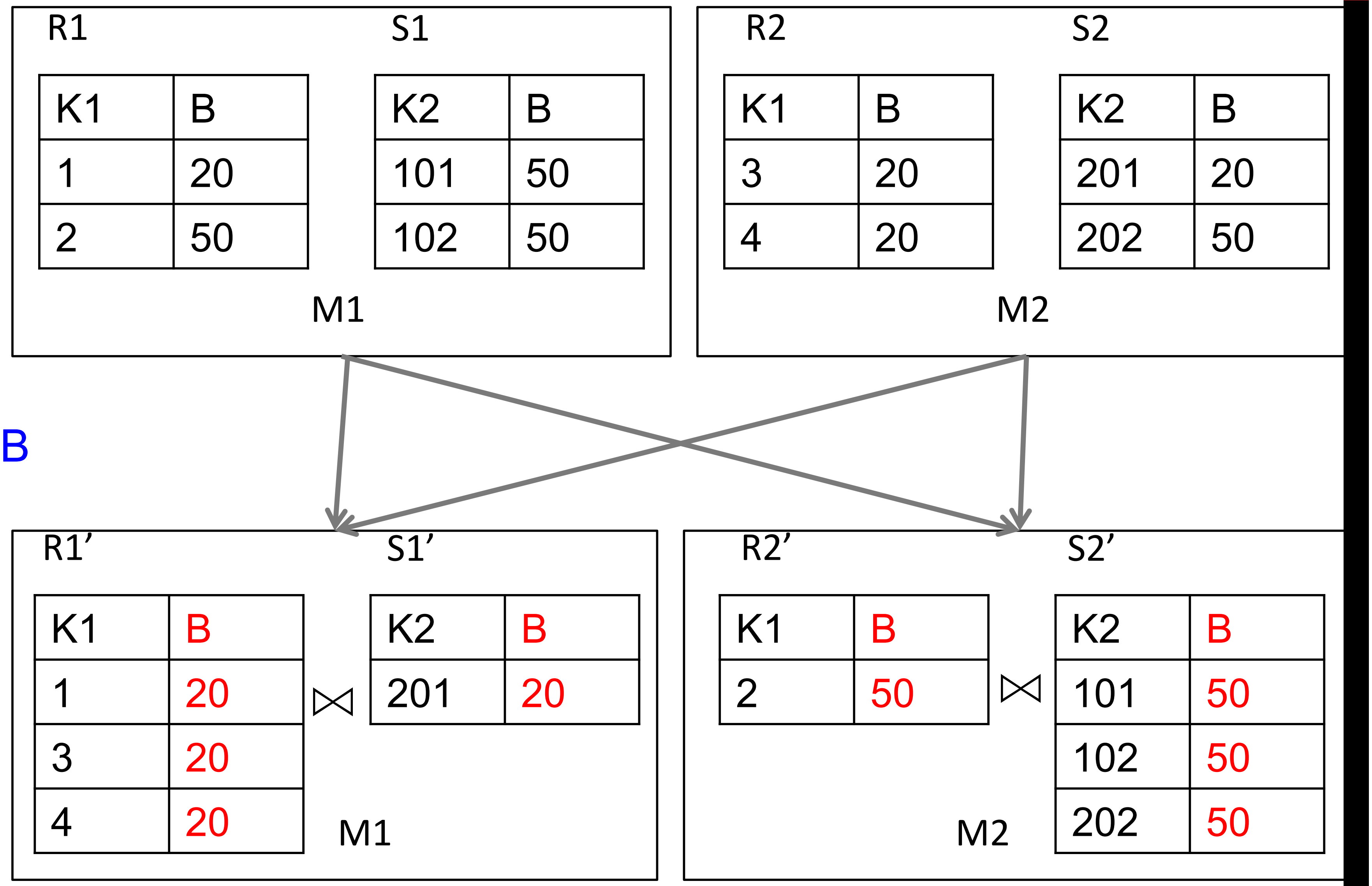
Reshuffle R on R.B and S on S.B

Each server computes the join locally

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

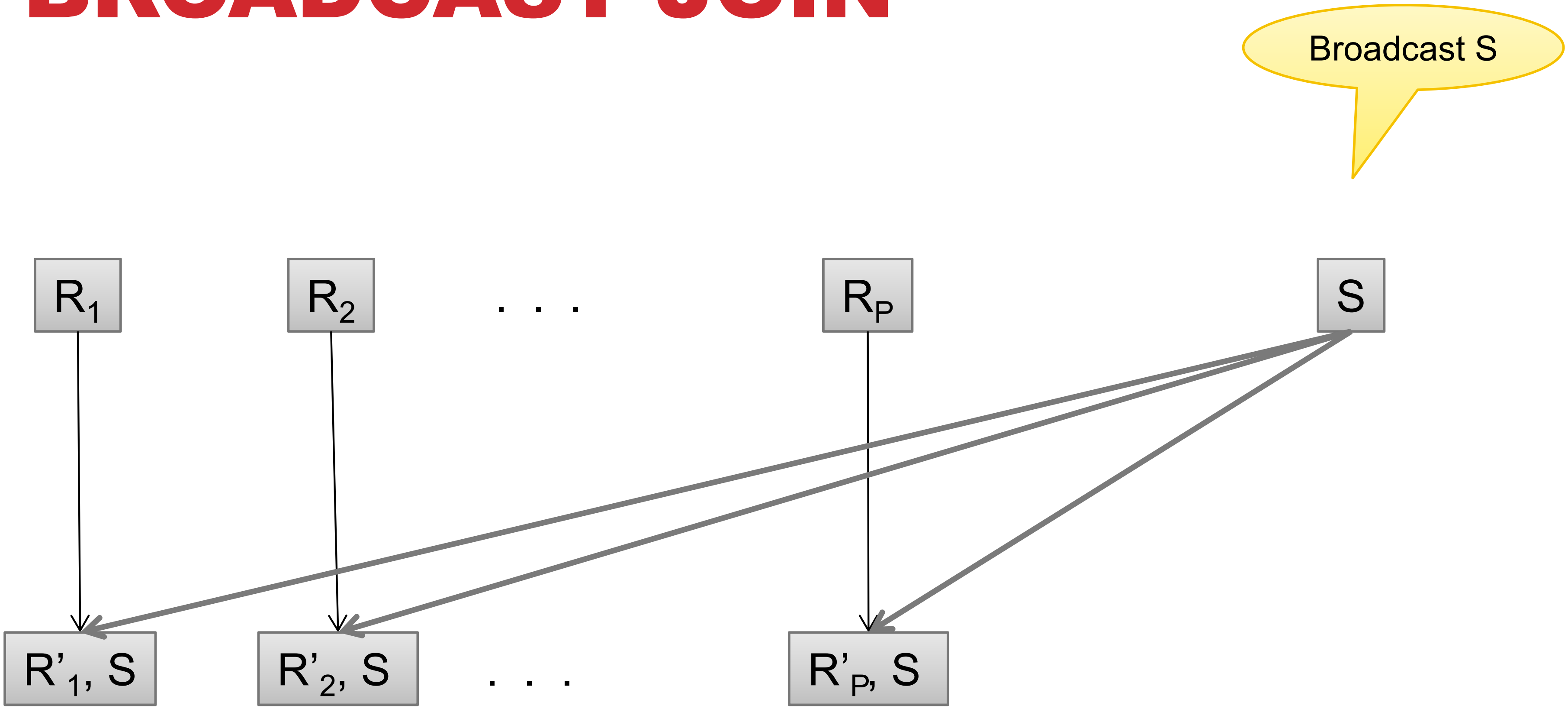
⋈

S2’

K2	B
101	50
102	50
202	50

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

BROADCAST JOIN



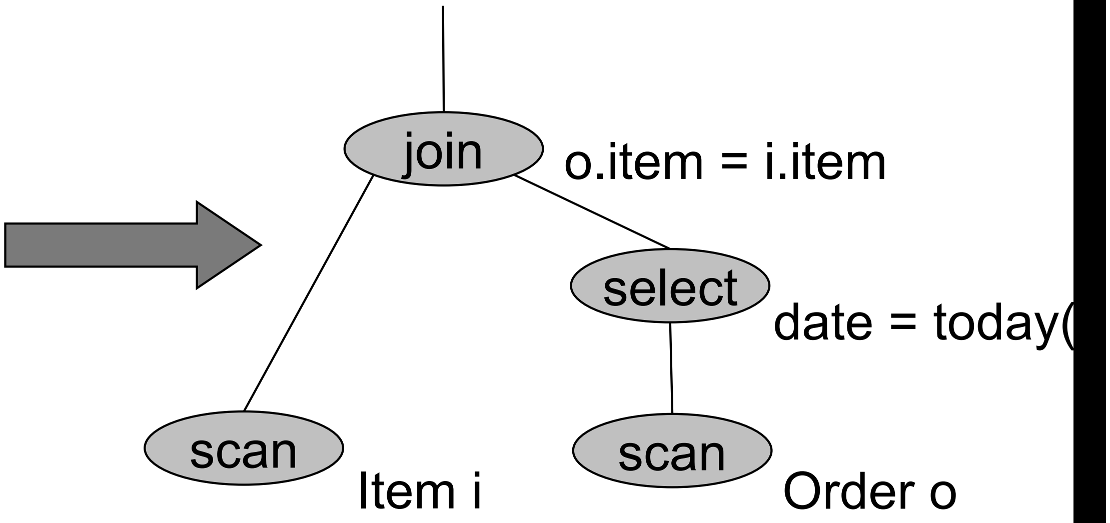
Why would you want to do this?

Order(oid, item, date), Line(item, …)

EXAMPLE PARALLEL QUERY PLAN

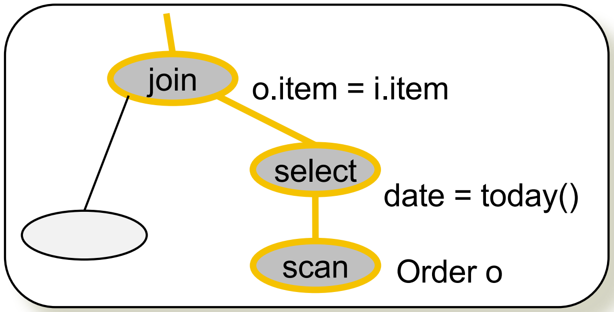
Find all orders from today, along with the items ordered

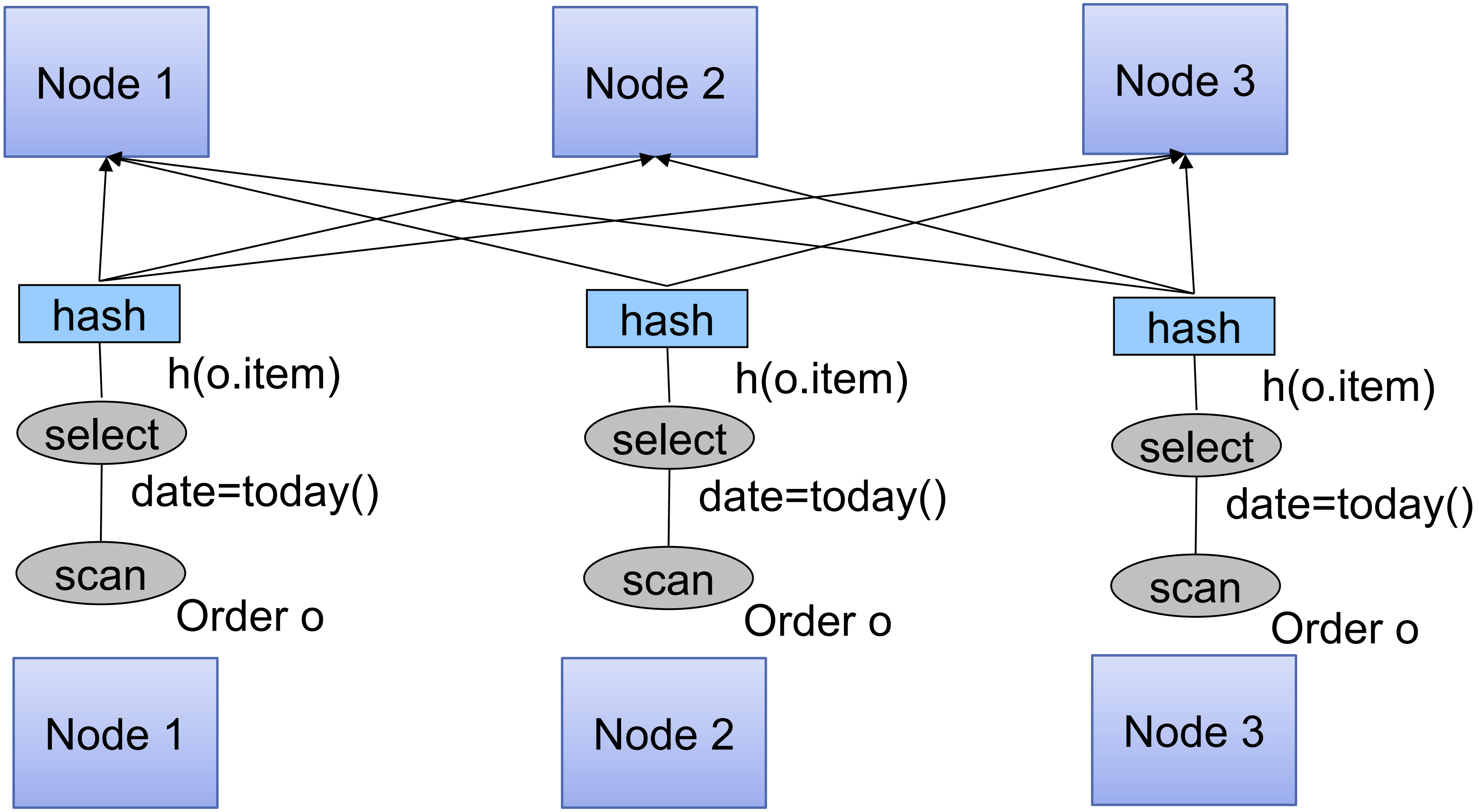
```
SELECT *
  FROM Order o, Line i
 WHERE o.item = i.item
   AND o.date = today()
```



Order(oid, item, date), Line(item, …)

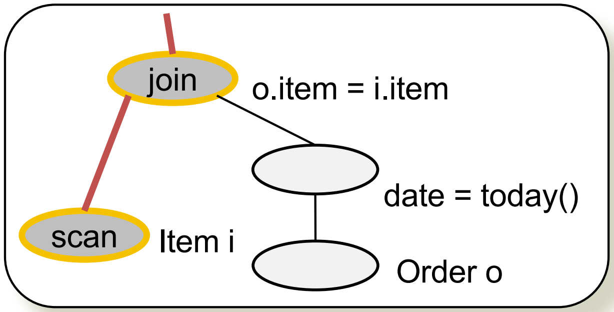
PARALLEL QUERY PLAN

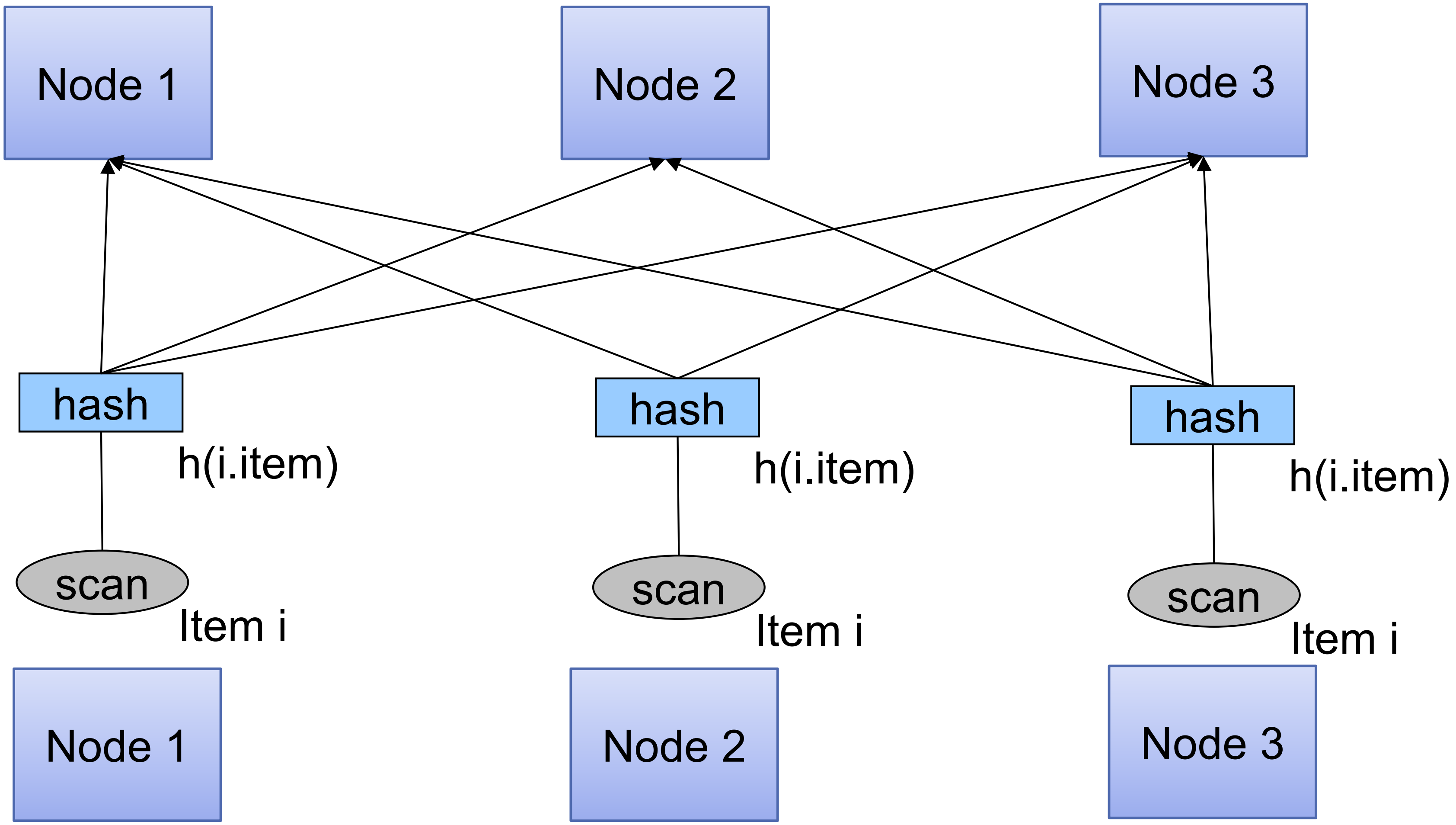




Order(<u>oid</u>, item, date), Line(item, …)

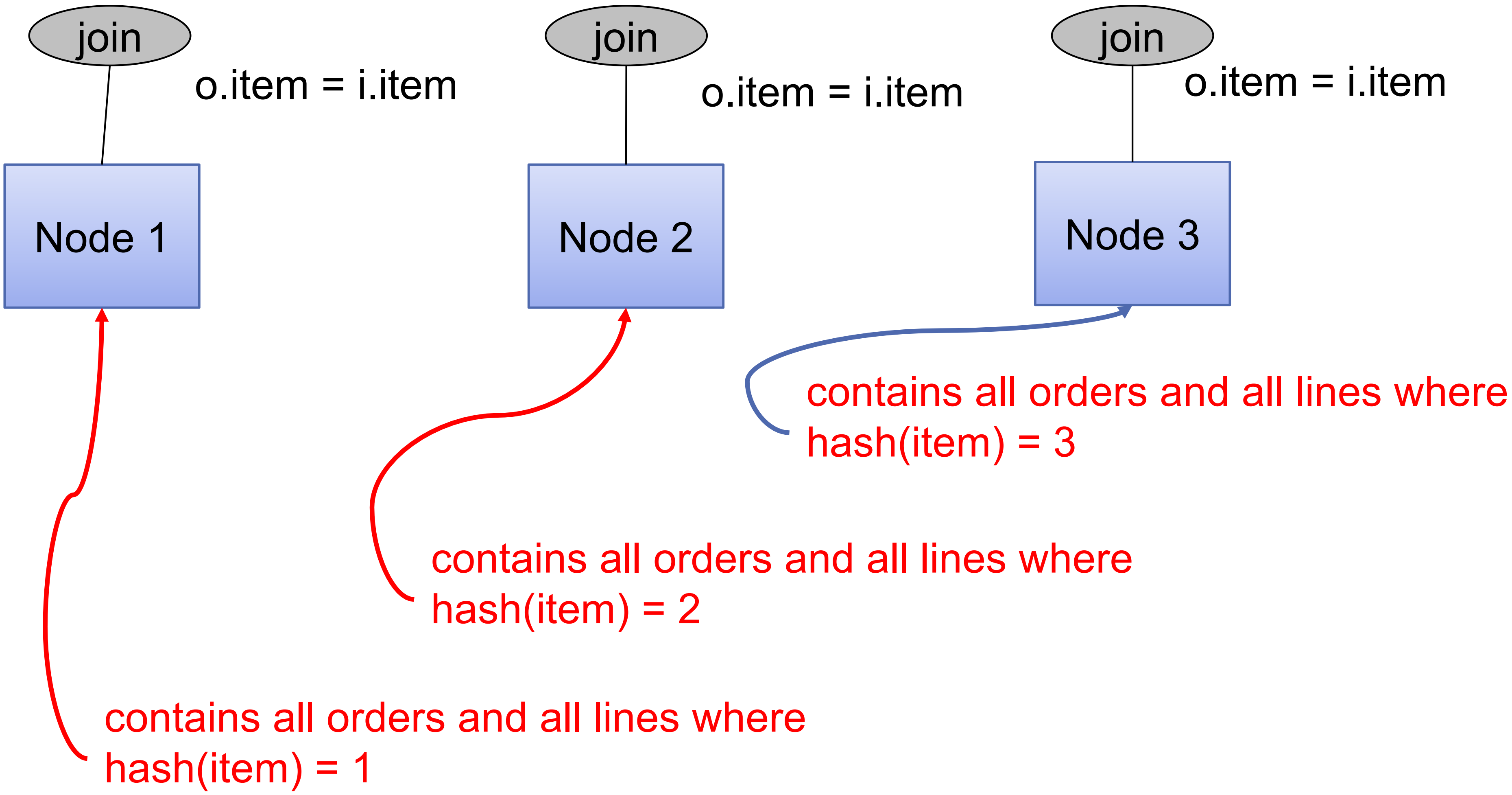
PARALLEL QUERY PLAN





Order(oid, item, date), Line(item, …)

EXAMPLE PARALLEL QUERY PLAN



contains all orders and all lines where hash(item) = 3

contains all orders and all lines where hash(item) = 2

contains all orders and all lines where hash(item) = 1

MOTIVATION

In principle, we covered how to parallelize relational database systems

In practice, it is useful to hide some of the lower level details of these computations

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

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)`

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

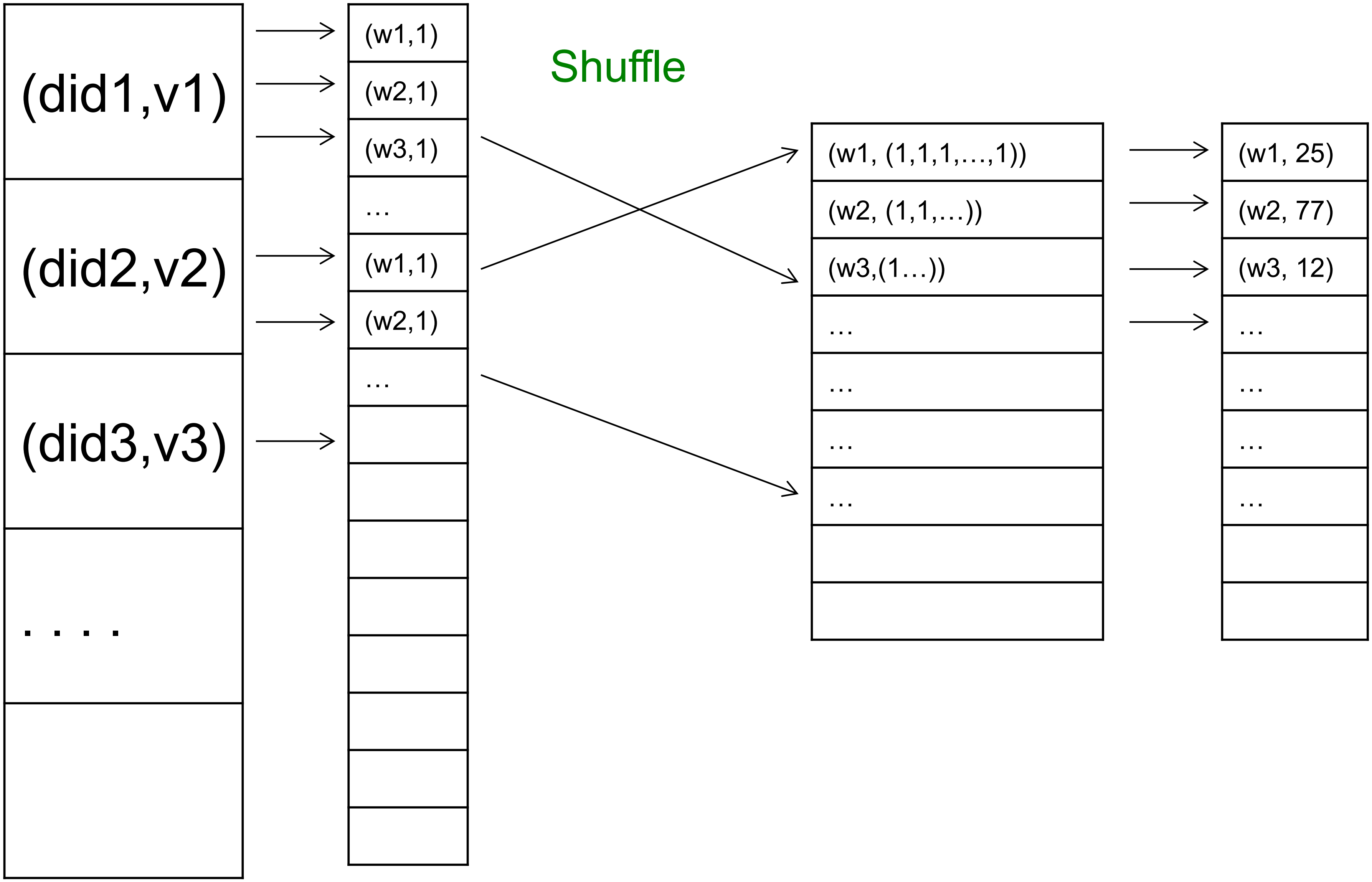
- The key = document id (did)
- The value = set of words (word)

```
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



(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 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 machine

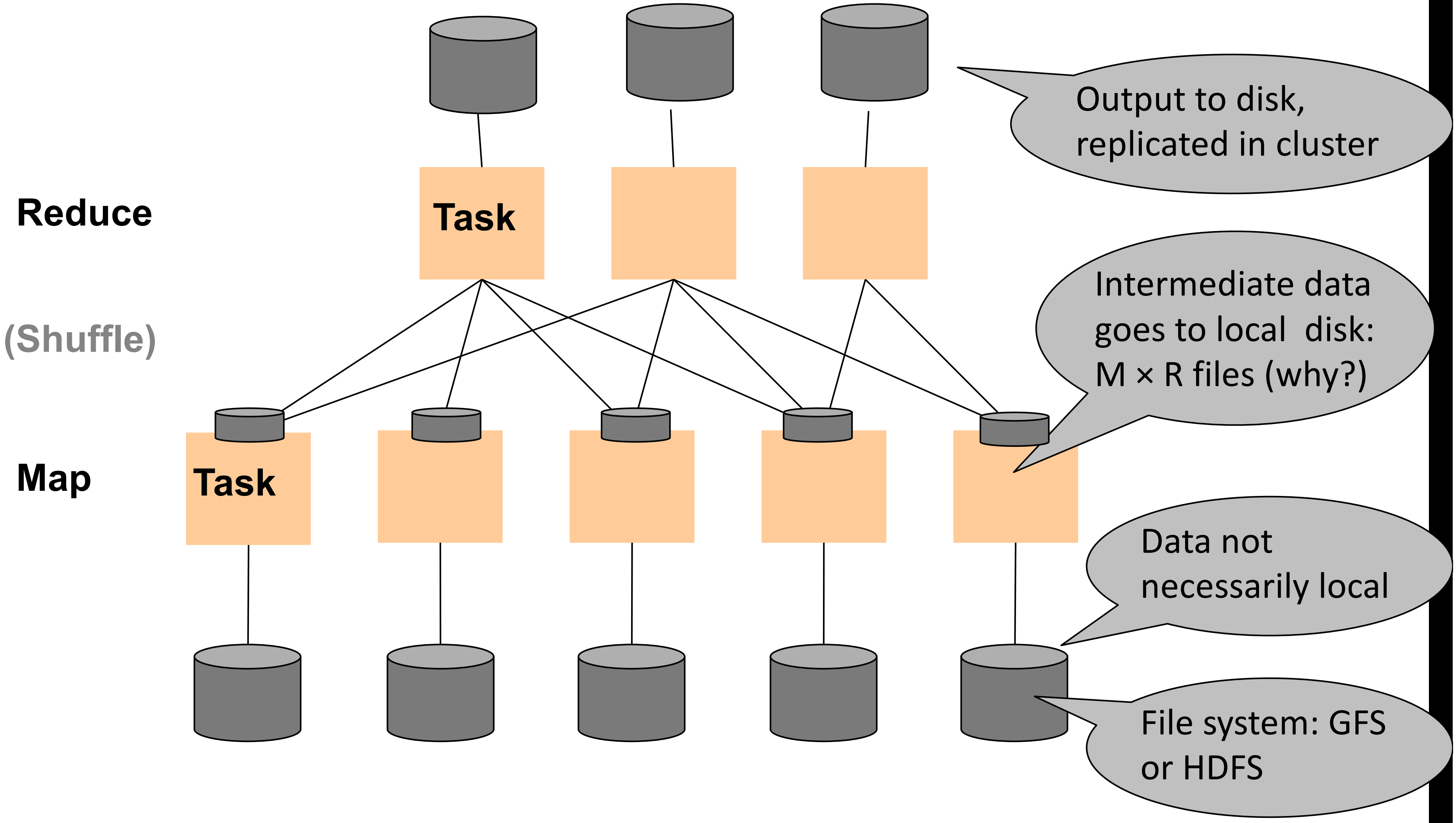
FAULT TOLERANCE

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

MAPREDUCE EXECUTION DETAILS



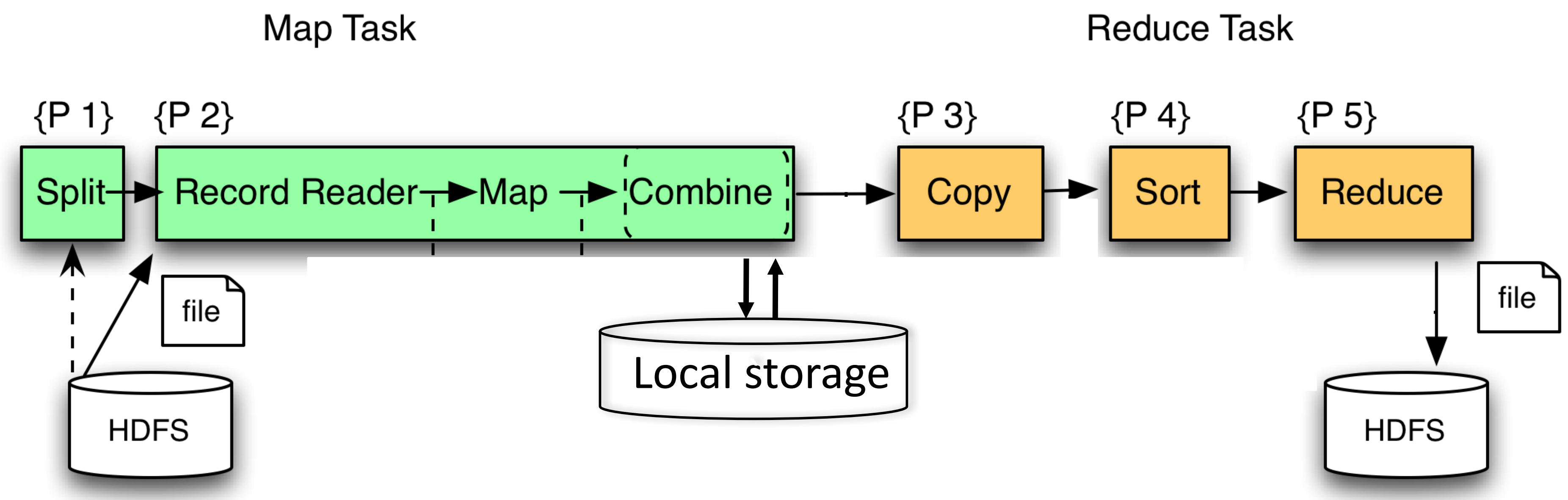
Output to disk, replicated in cluster

Intermediate data goes to local disk: M × R files (why?)

Data not necessarily local

File system: GFS or HDFS

MAPREDUCE PHASES



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:

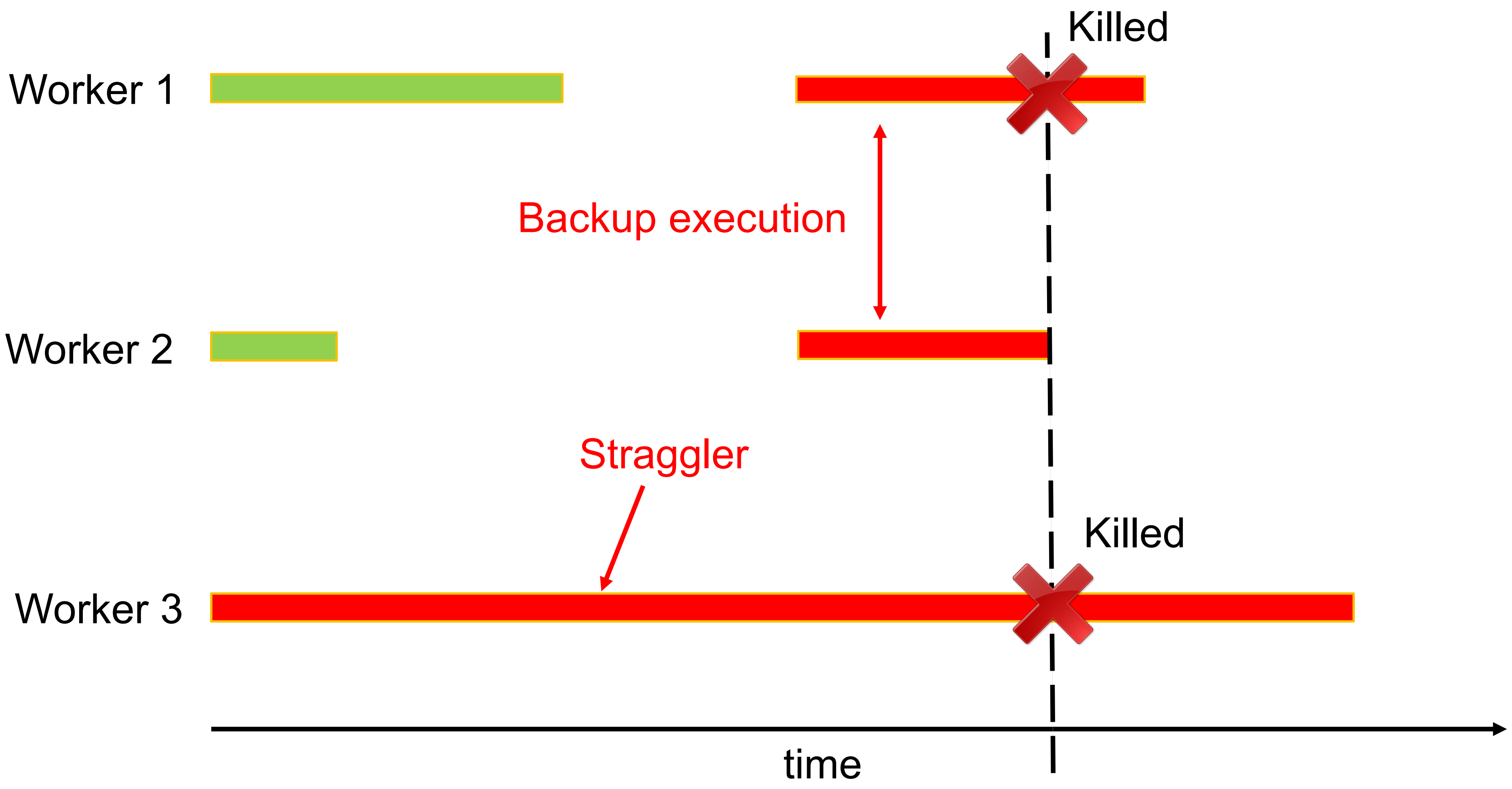
Straggler **= a machine that takes unusually long time to complete one of the last tasks. E.g.:**

- 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



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: $R \bowtie S$

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

```
map(String value):
    if  value.A = 123:
     EmitIntermediate(value.key, value);
```

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

SELECTION $\Sigma_{A=123}$(R)

```
map(String value):
    if  value.A = 123:
     EmitIntermediate(value.key, value);
```

```
reduce(String k, 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(String value):
    EmitIntermediate(value.A, value.B);
```

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

JOIN

Two simple parallel join algorithms:

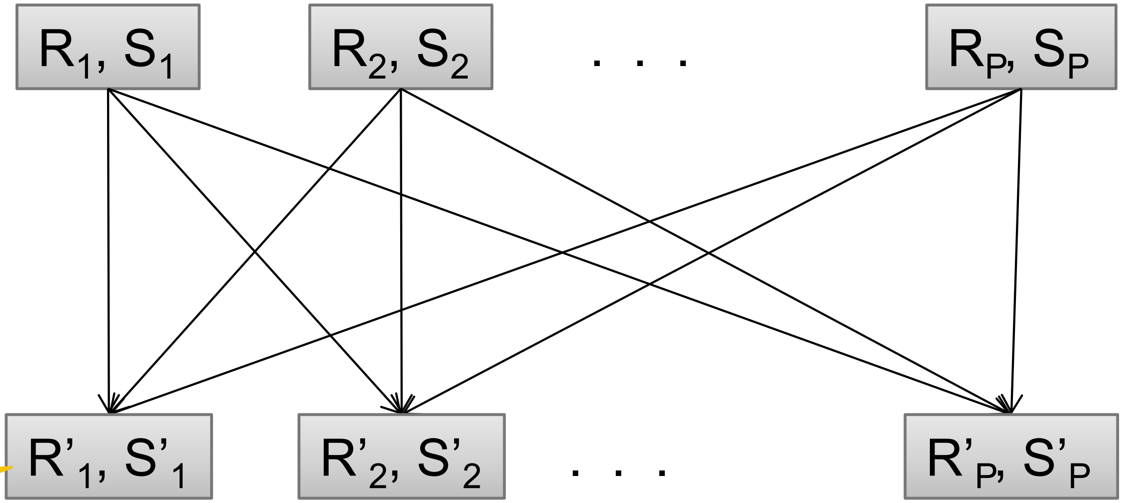
Partitioned hash-join (we saw it, will recap)

Broadcast join

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

PARTITIONED HASH-JOIN

Initially, both R and S are horizontally partitioned



R_1, S_1 R_2, S_2 . . . R_P, S_P

R'_1, S'_1 R'_2, S'_2 . . . R'_P, S'_P

Reshuffle R on R.B and S on S.B

Each server computes the join locally

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

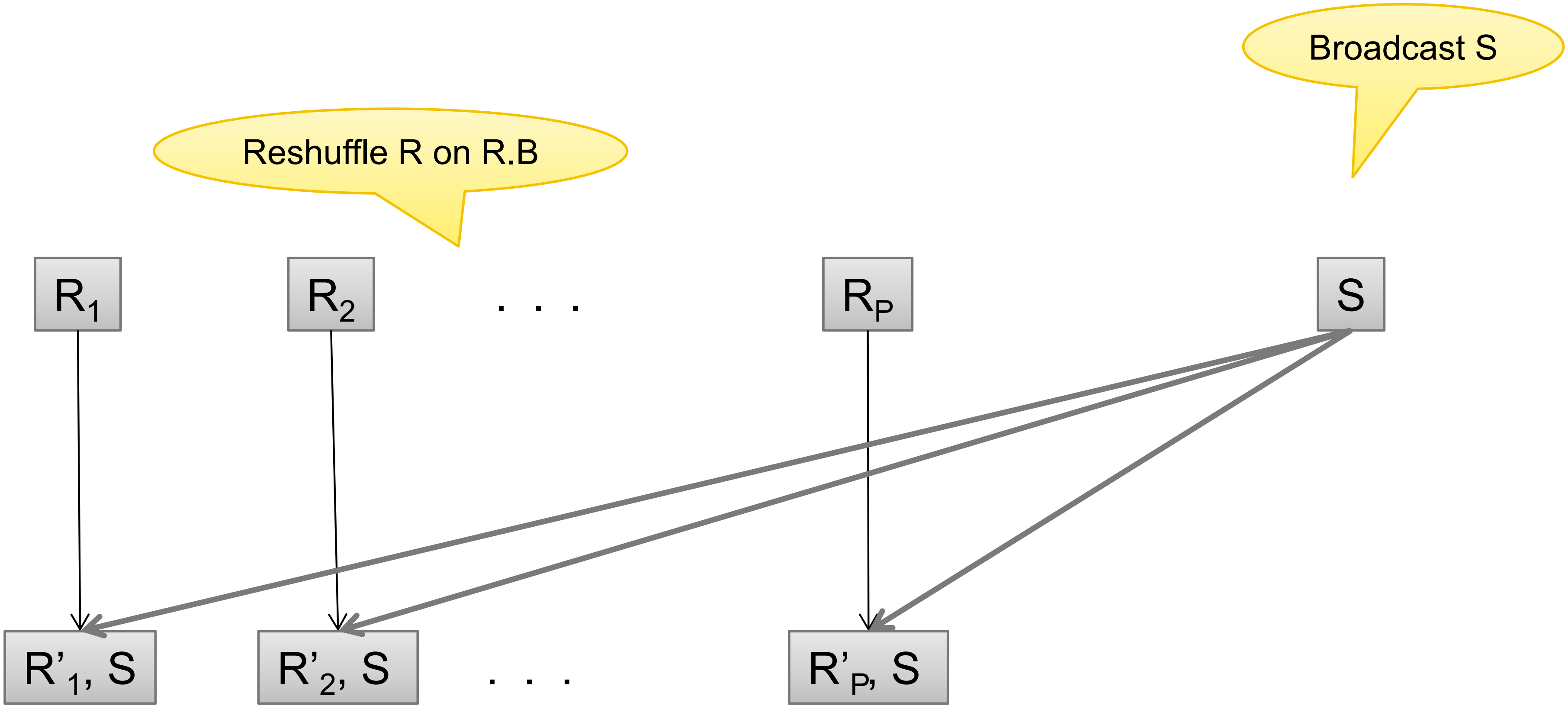
PARTITIONED HASH-JOIN

```
map(Row value):
    case value.relationName of
     'R': EmitIntermediate(value.B, ('R', value));
     'S': EmitIntermediate(value.C, ('S', value));
```

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

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

BROADCAST JOIN



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

BROADCAST JOIN

```
init():
    open(S); /* over the network */
    hashTbl = new()
    for each w in S:
     hashTbl.insert(w.C, w)
    close(S);

map(Row v):
     for each w in hashTbl.find(v.B)
          Emit(v,w);
```

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

Read entire table S, build a Hash Table

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

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?

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