Introduction to Database Systems
CSE 414

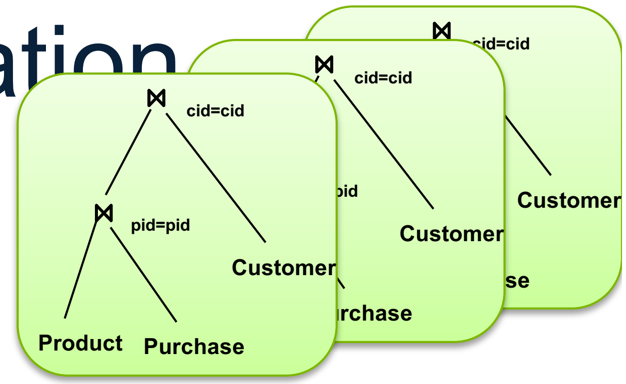
Lecture 17: MapReduce and Spark

Announcements

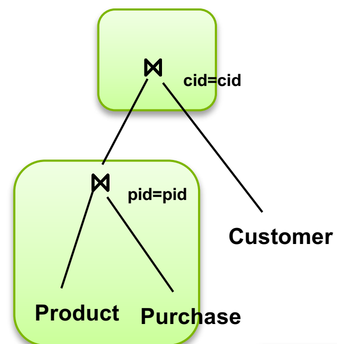
- Midterm this Friday in class!
  - Review session tonight
  - See course website for OHs
  - Includes everything up to Monday’s lecture
- HW6 released
  - Not due until next Friday 5/11
  - No WQ6 (Yay!)

Approaches to Parallel Query Evaluation

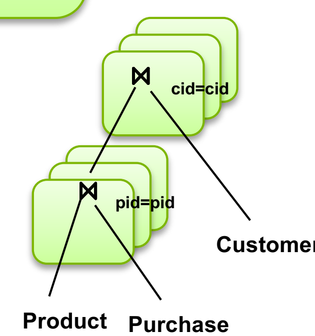
- Inter-query parallelism
  - One query per node
  - Good for transactional (OLTP) workloads



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



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

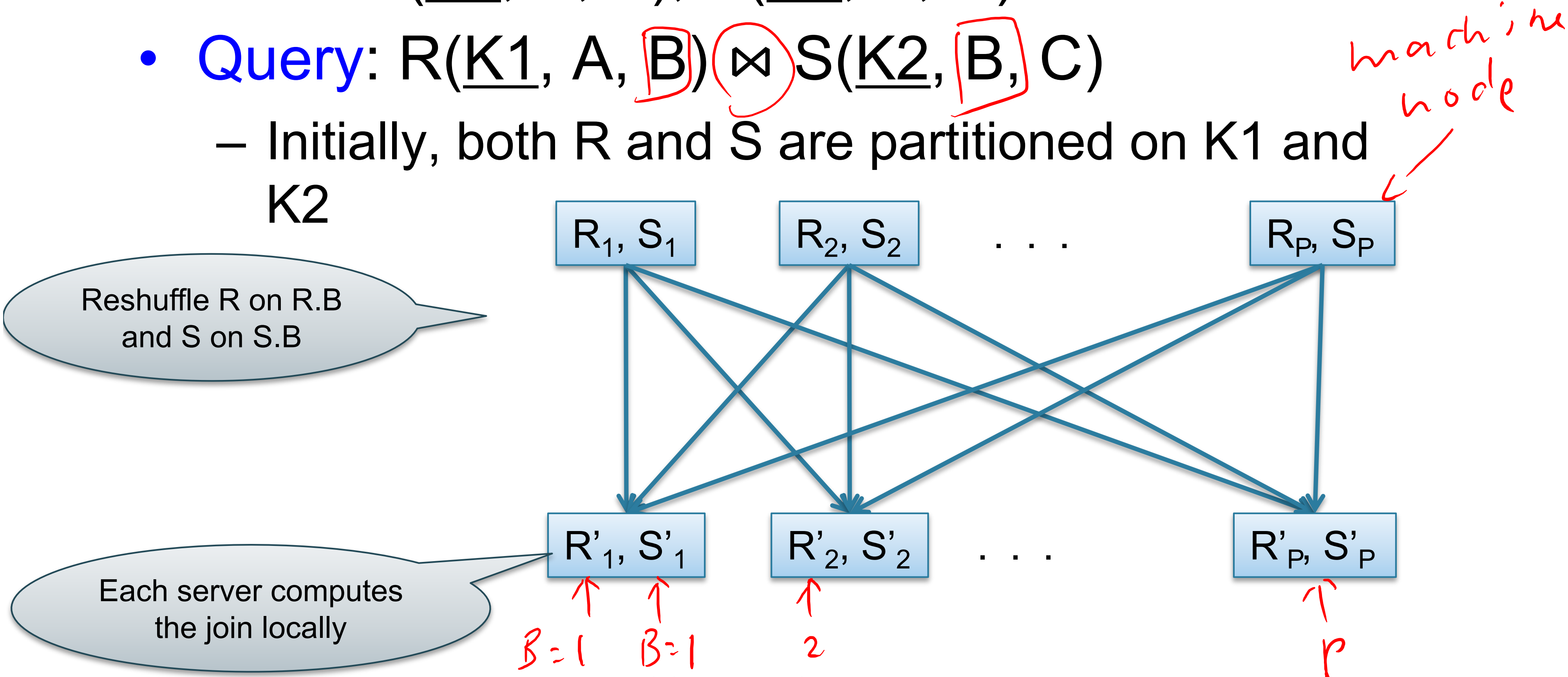


We study only intra-operator parallelism: most scalable

Parallel Data Processing in the 20th Century

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



Parallel Join Illustration

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

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

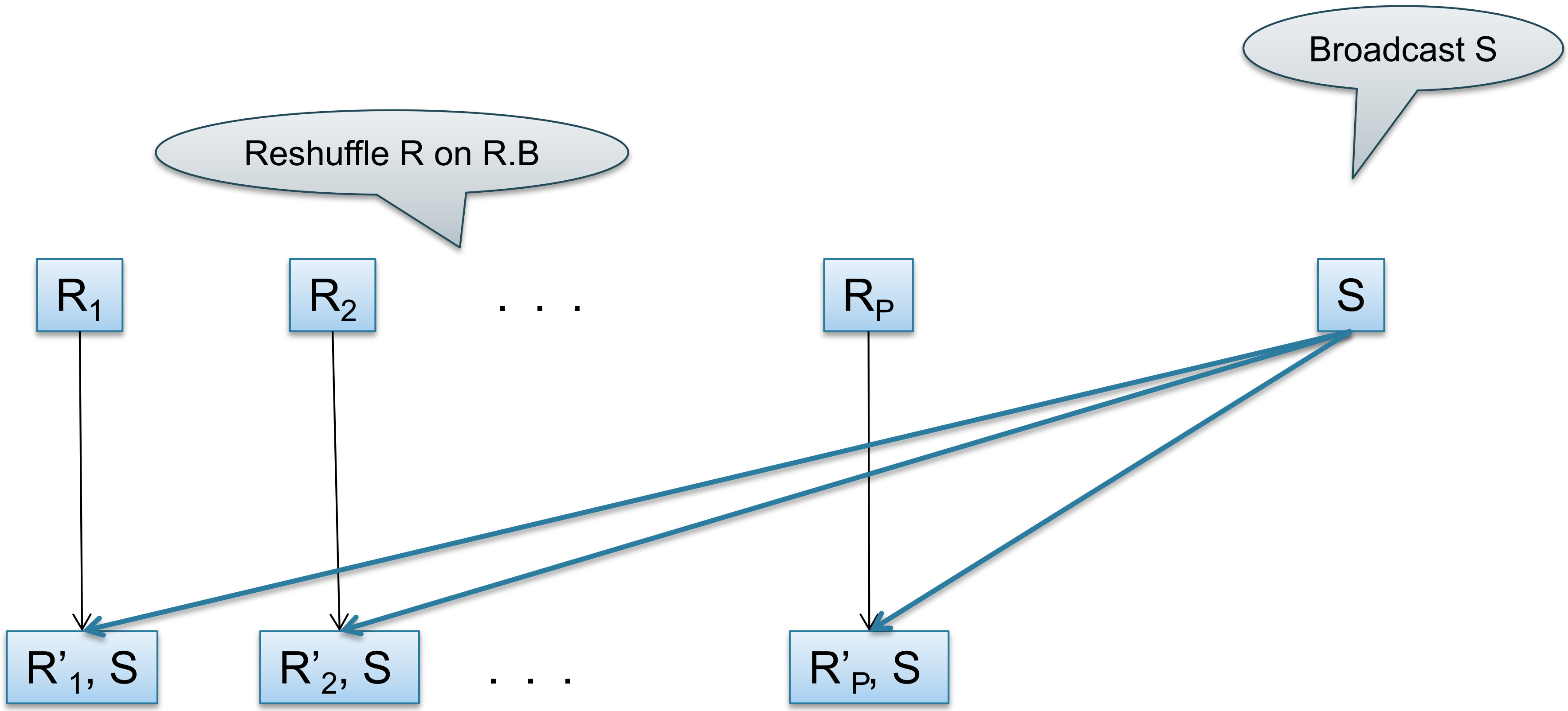
⋈

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?

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

Sounds familiar after HW5?

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)`

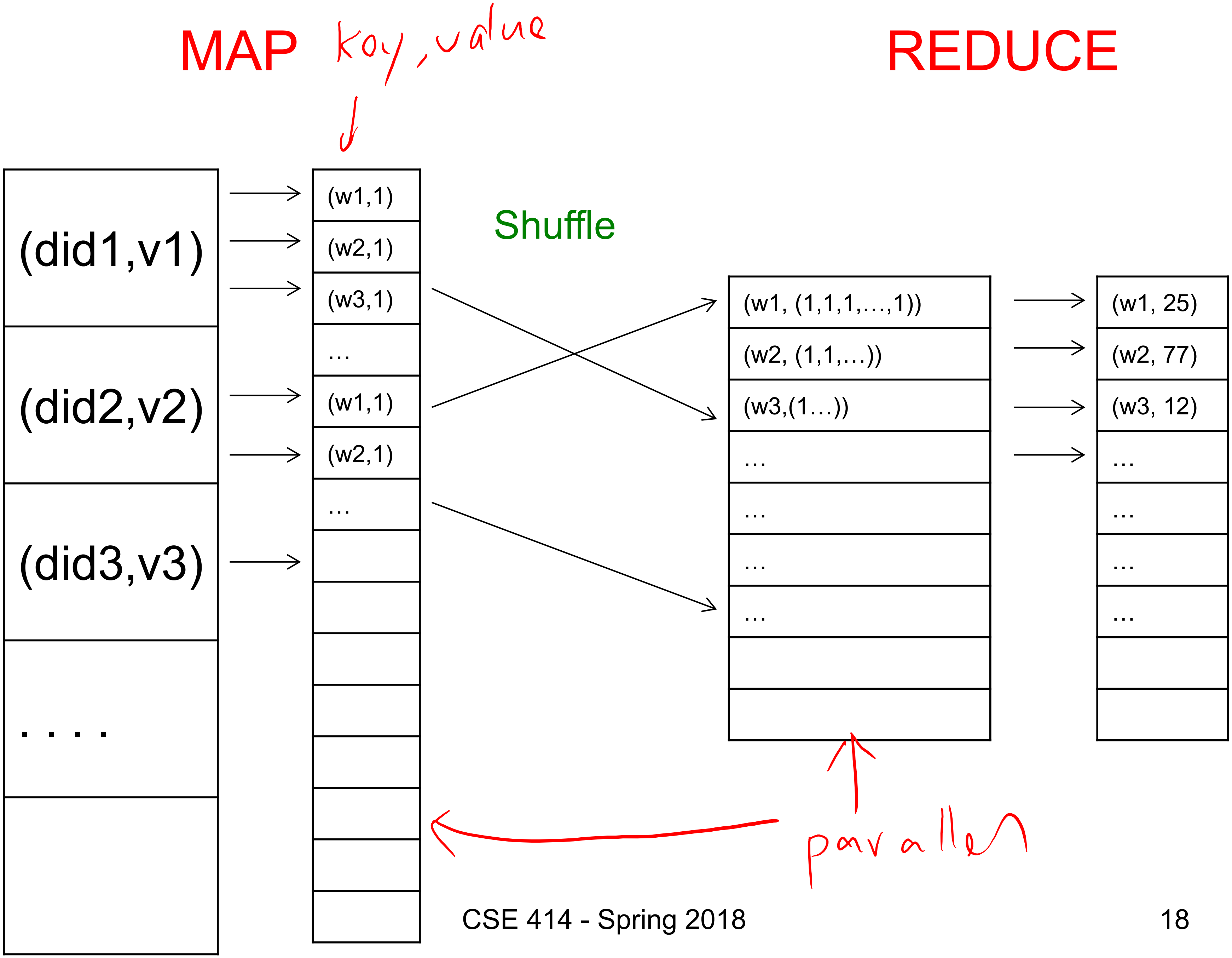
System groups all pairs with the same intermediate key, and passes the bag of values to the REDUCE function

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)

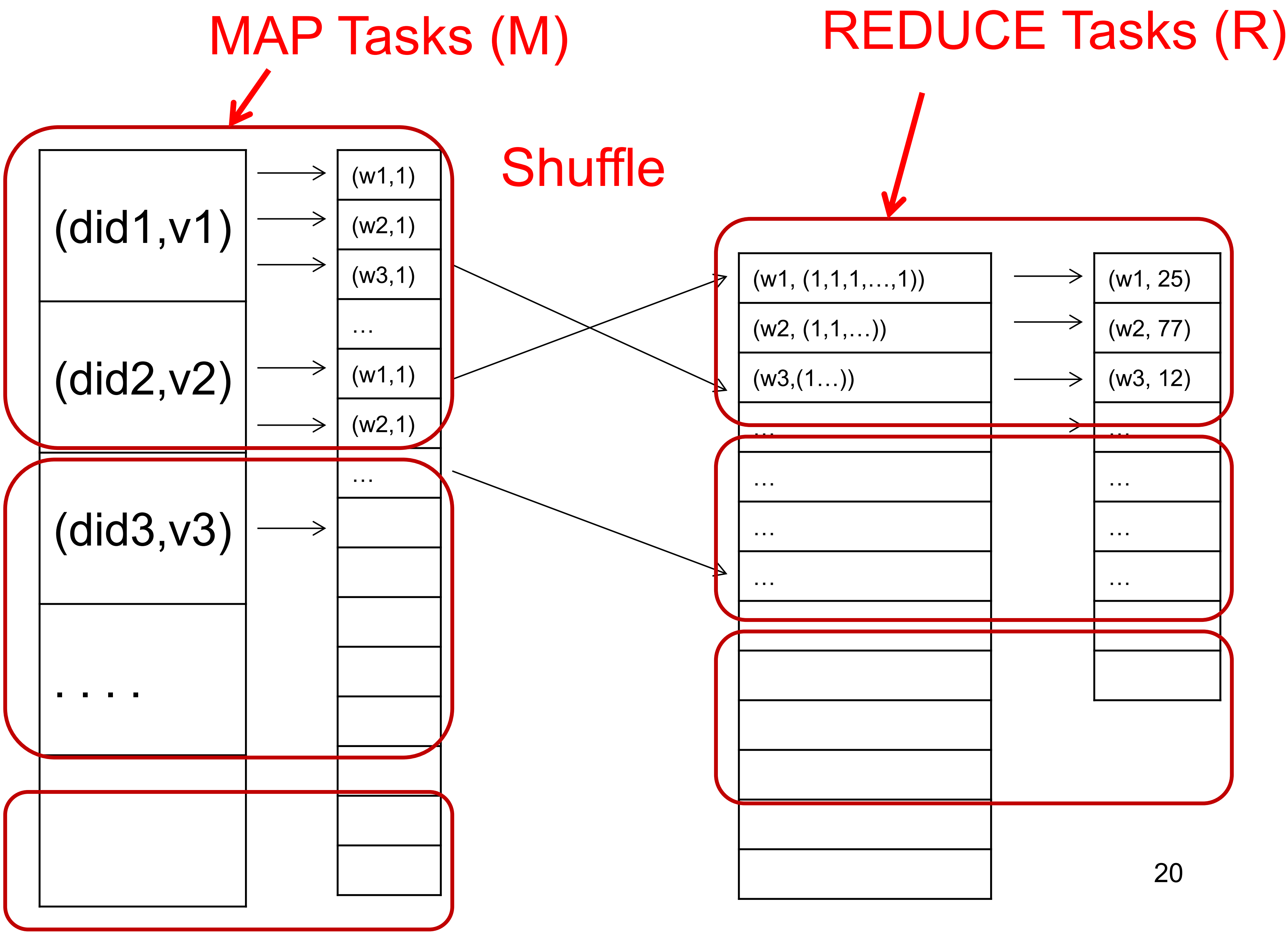
```
map(String key, String value):
   // key: document name
   // value: document contents
   for each word w in value:
        emitIntermediate(w, “1”);
```

```
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
key, value
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)
…
…
…
…
parallel

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

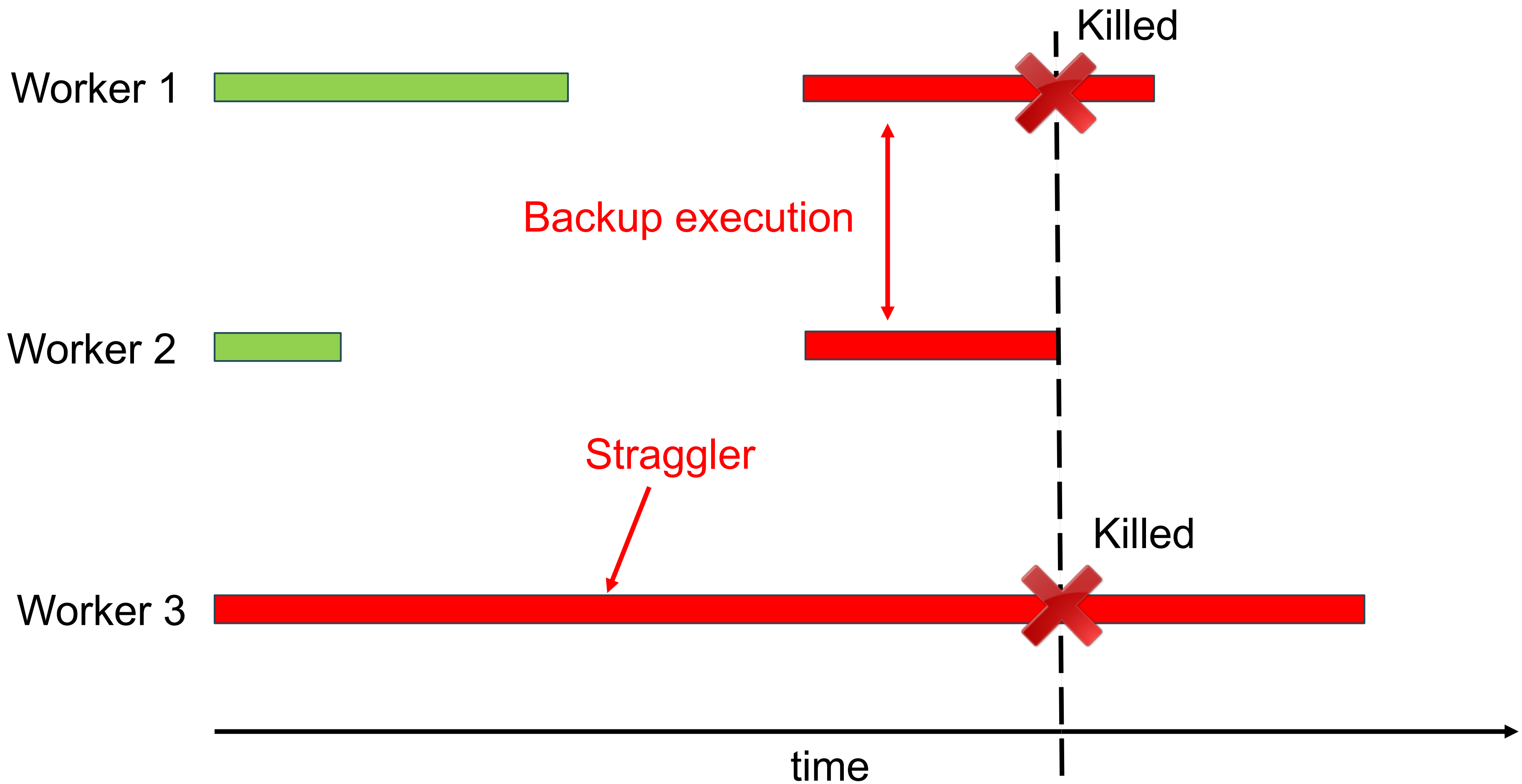
- There is one master node
- Master partitions input file into *M splits*, by key
- Master assigns *workers* (=servers) to the *M map tasks*, keeps track of their progress
- Workers write their output to local disk, partition into *R regions*
- Master assigns workers to the *R reduce tasks*
- Reduce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

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

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

	A
t_1	23
t_2	123
t_3	123
t_4	42

→ $(123, [\ t_2, t_3\ ])$

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

→ $(\ t_2, t_3\ )$

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

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

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

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

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

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

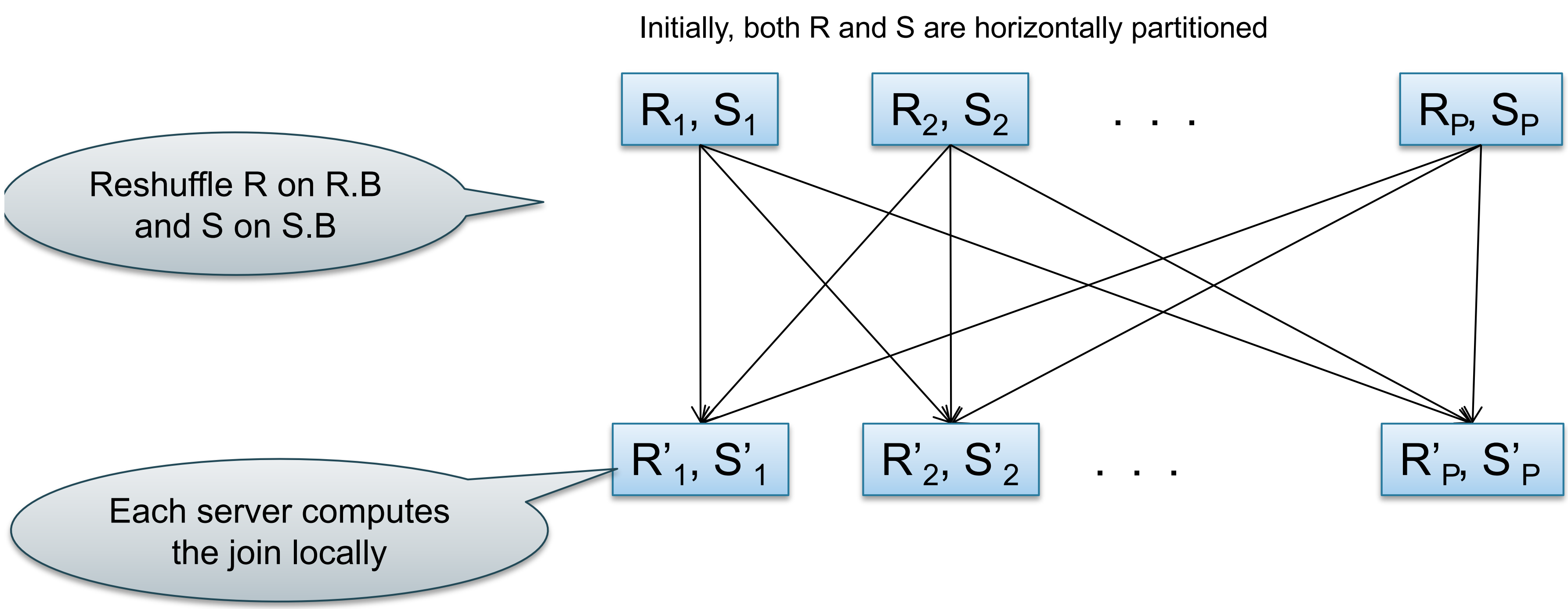
Join

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



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

Partitioned Hash-Join

key — type — actual tuple

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

→ 5, {('R', t_1), (R, t_3), (S, t_4)}
6, {(R, t_2), (S, t_5)}

R

	B	C
t_1	5	10
t_2	6	20
t_3	5	20

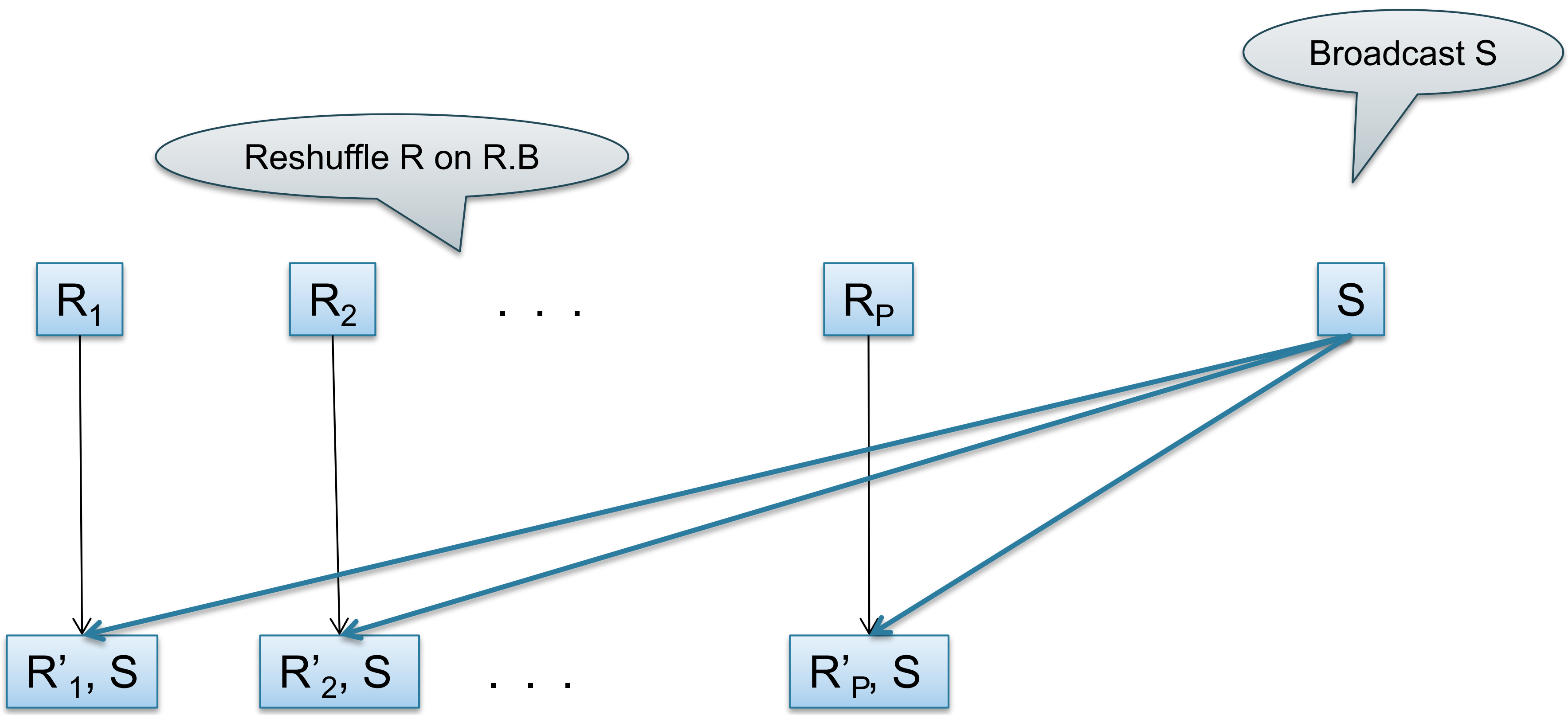
S

C	D	
5	2	t_4
6	10	t_5

```
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

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

```
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);
```

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?