Announcements

- HW 6 releases tonight
  - Due Nov. 20th
  - Waiting for AWS credit can take up to *two days*
  - Sign up early:
  - https://aws.amazon.com/education/awseducate/apply/
  - https://piazza.com/class/jmftm54e88t2kk?cid=452
- Extended office hours Friday to help with first parts of HW 6: 11:30 to 5:00pm in CSE 023
- Extra office hours 5:30pm today on 2nd Floor Breakout

Introduction to Database Systems
CSE 414

Lecture 19: Parallel DBMS

Class Overview

- Unit 1: Intro
- Unit 2: Relational Data Models and Query Languages
- Unit 3: Non-relational data
- Unit 4: RDMBS internals and query optimization
- Unit 5: Parallel query processing
  - Spark and Hadoop
- Unit 6: DBMS usability, conceptual design
- Unit 7: Transactions
- Unit 8: Advanced topics (time permitting)

Why compute in parallel?

- Multi-cores:
  - Most processors have multiple cores
  - This trend will likely increase in the future
- Big data: too large to fit in main memory
  - Distributed query processing on 100x-1000x servers
  - Widely available now using cloud services
  - Recall HW3

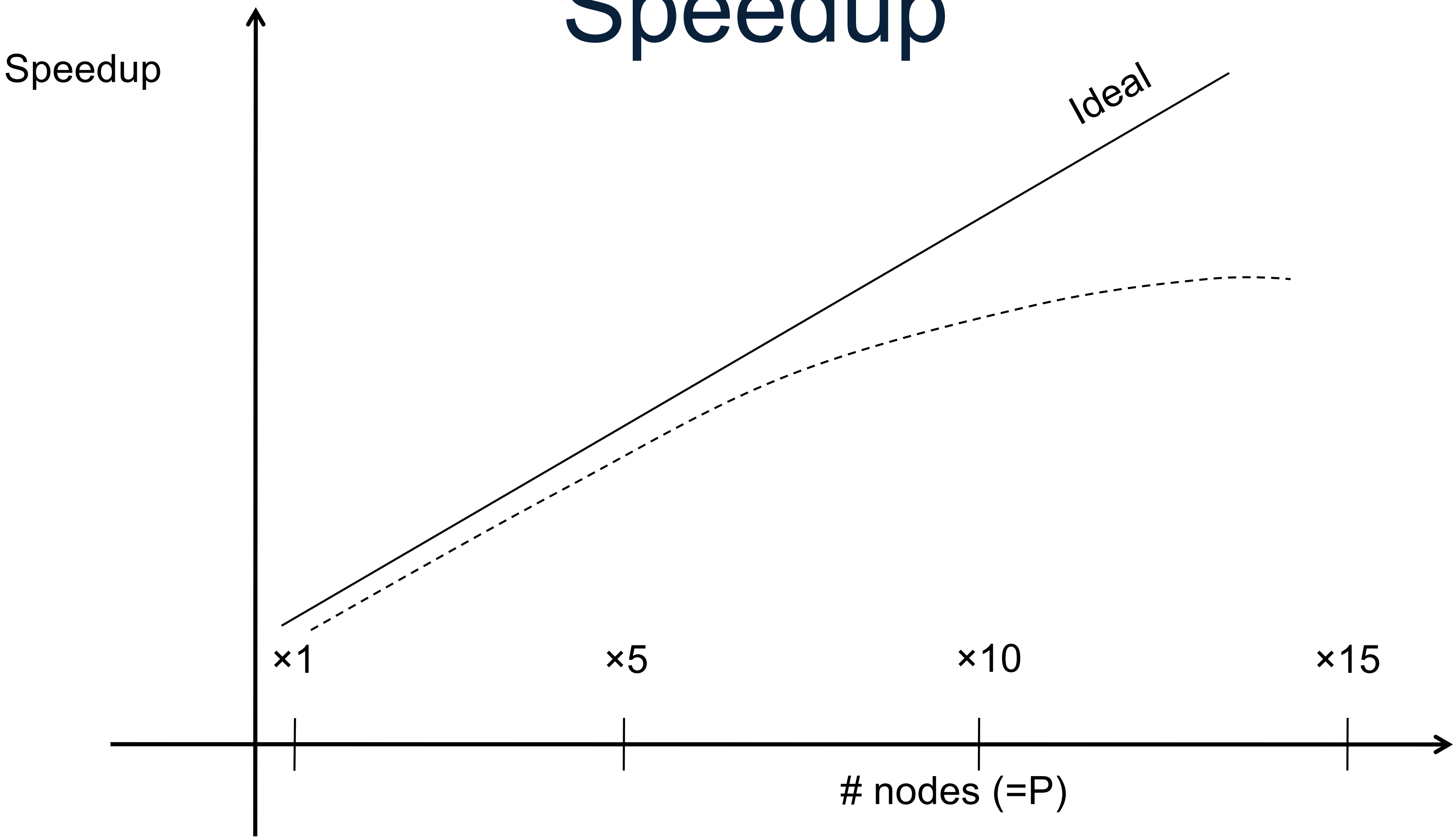
Performance Metrics for Parallel DBMSs

Nodes = processors, computers

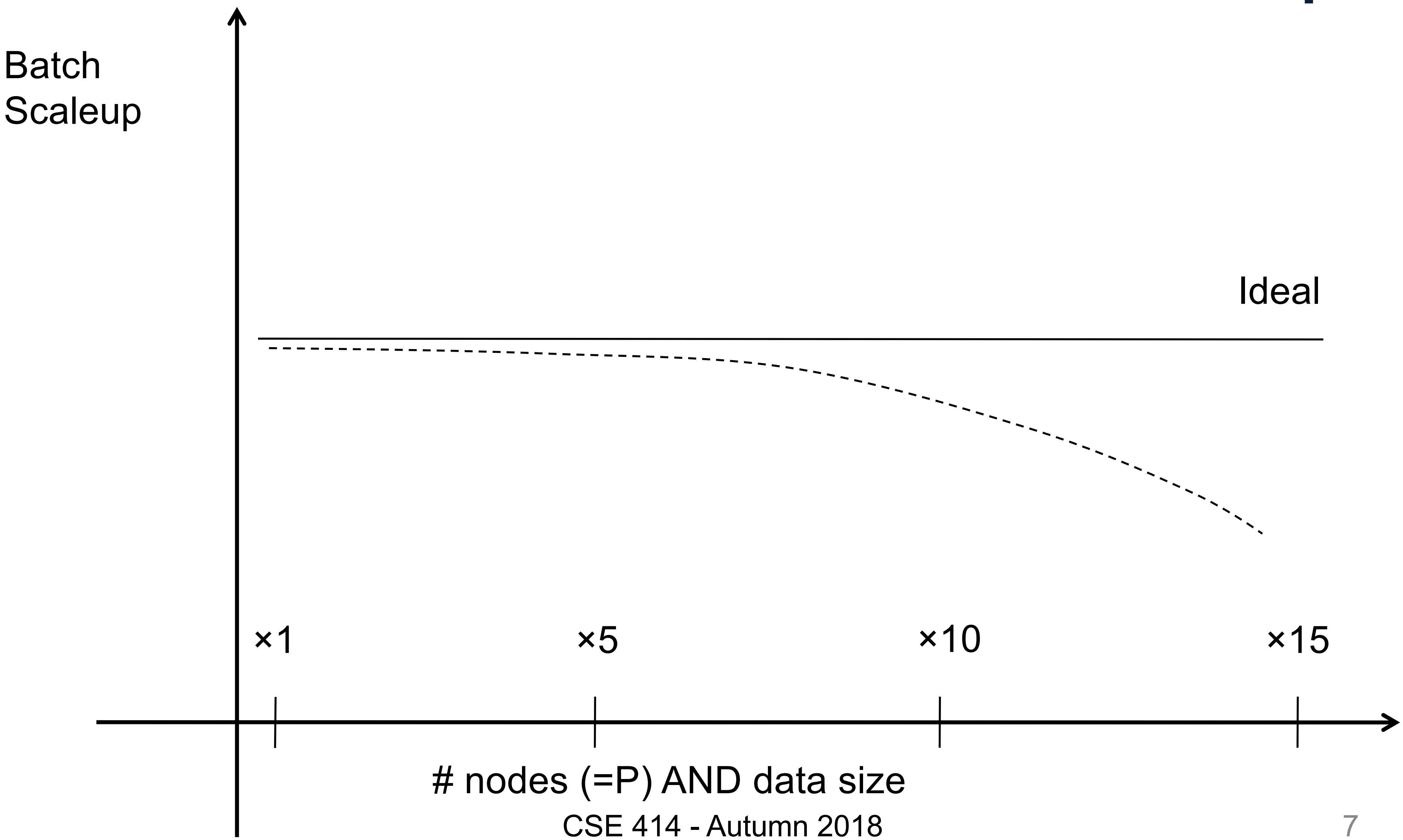
- Speedup:
  – More nodes, same data → higher speed

- Scaleup:
  – More nodes, more data → same speed

Linear v.s. Non-linear Speedup



Linear v.s. Non-linear Scaleup



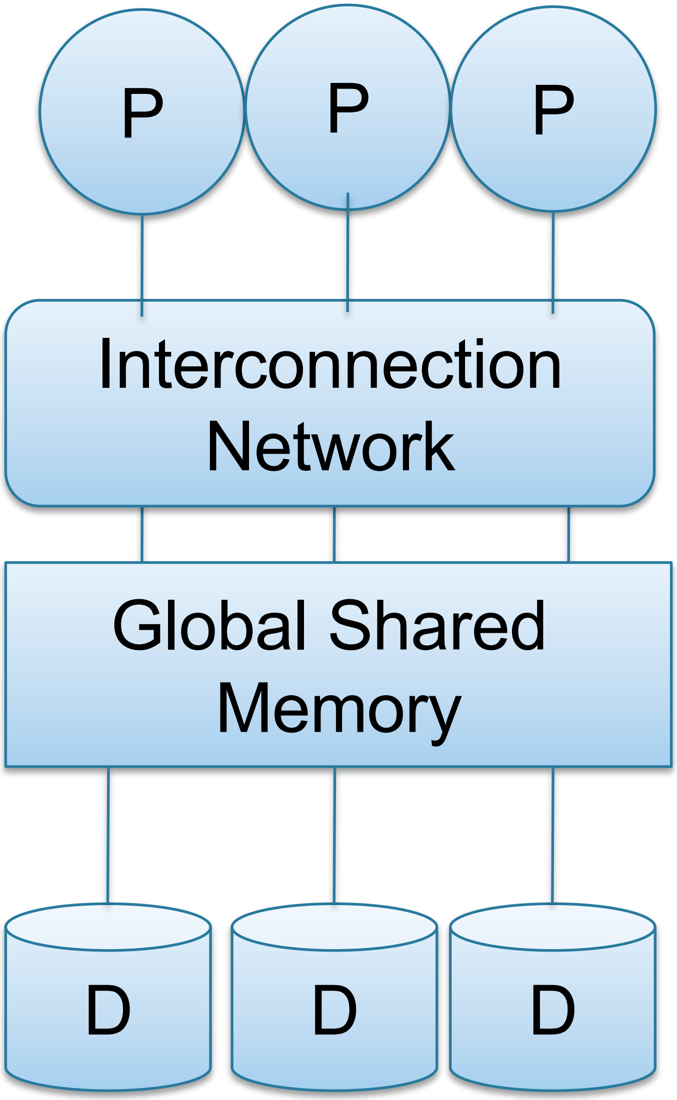
Why Sub-linear Speedup and Scaleup?

- Startup cost
  - Cost of starting an operation on many nodes
- Interference
  - Contention for resources between nodes
- Skew
  - Slowest node becomes the bottleneck

Architectures for Parallel Databases

- Shared memory
- Shared disk
- Shared nothing

Shared Memory



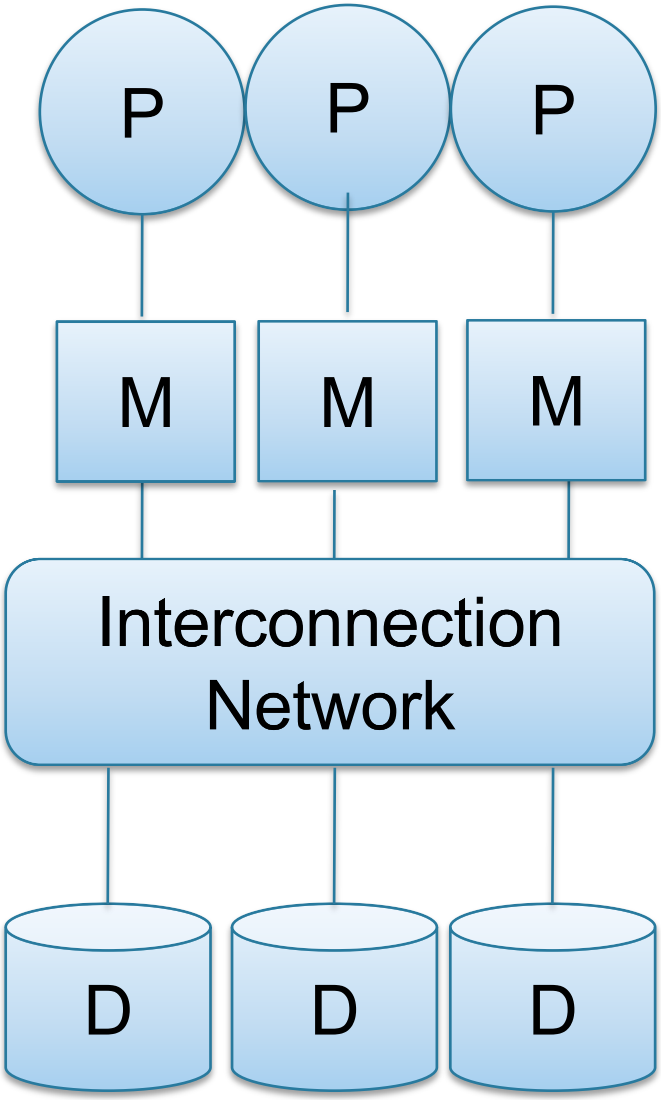
- Nodes share both RAM and disk
- Dozens to hundreds of processors

Example: SQL Server runs on a single machine and can leverage many threads to speed up a query

- check your HW3 query plans

- Easy to use and program
- Expensive to scale
  - last remaining cash cows in the hardware industry

Shared Disk



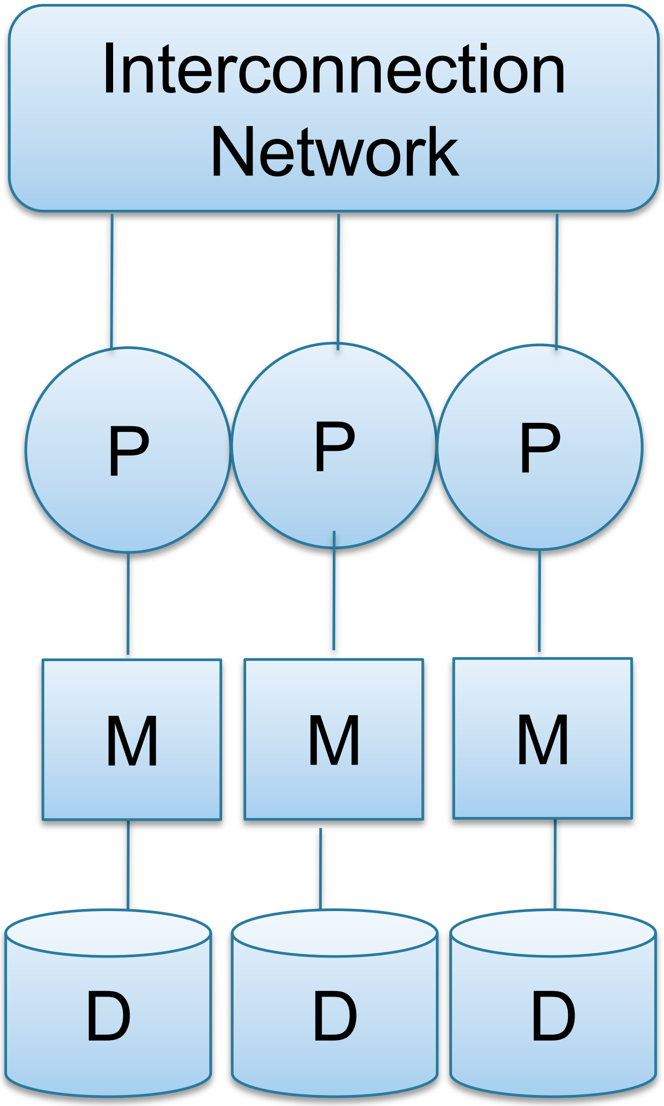
- All nodes access the same disks
- Found in the largest "single-box" (non-cluster) multiprocessors

Example: Oracle

- No need to worry about shared memory

- Hard to scale: existing deployments typically have fewer than 10 machines

Shared Nothing



- Cluster of commodity machines on high-speed network
- Called "clusters" or "blade servers”
- Each machine has its own memory and disk: lowest contention.

Example: Google Mapreduce

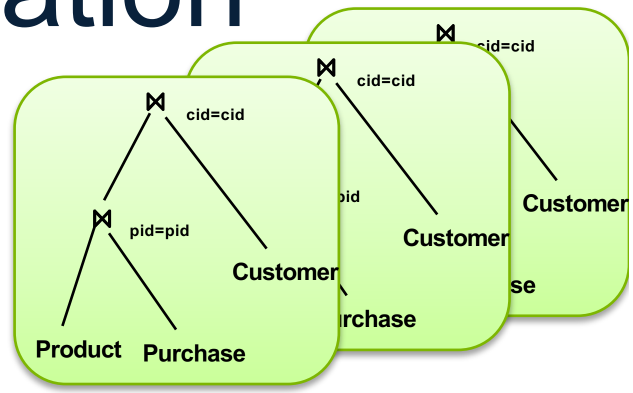
Because all machines today have many cores and many disks, shared-nothing systems typically run many "nodes” on a single physical machine.

- Easy to maintain and scale
- Most difficult to administer and tune.

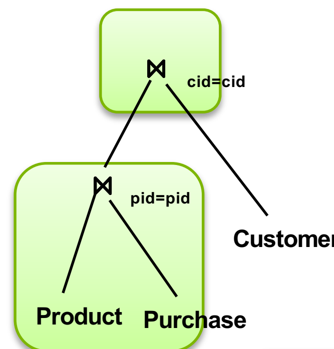
We discuss only Shared Nothing in class

Approaches to Parallel Query Evaluation

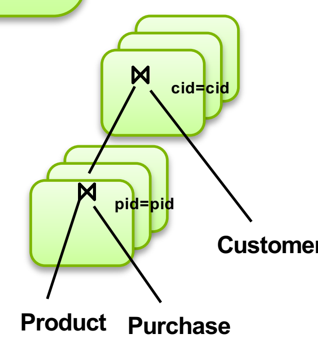
- Inter-query parallelism
  - Transaction per node
  - Good for transactional workloads



- Inter-operator parallelism
  - Operator per node
  - Good for analytical workloads



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



We study only intra-operator parallelism: most scalable

Single Node Query Processing (Review)

Given relations R(A,B) and S(B, C), no indexes:

- 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 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 B as key
  - Scan file R, probe the hash table using B

Distributed Query Processing

- Data is “horizontally partitioned” on many servers
- Operators may require data reshuffling
- First let’s discuss how to distribute data across multiple nodes / servers

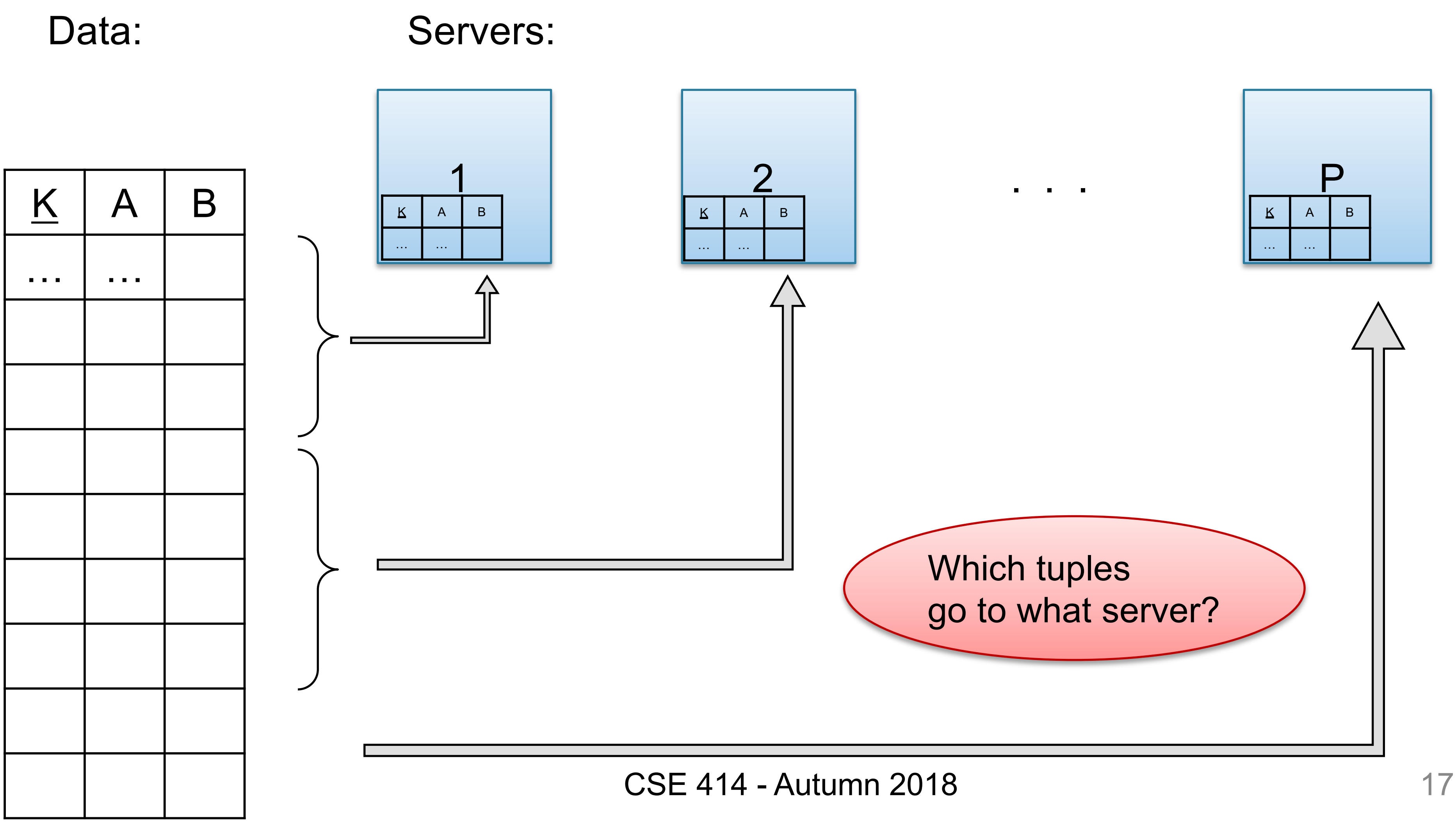
Horizontal Data Partitioning

Data:

K	A	B
…	…	

Servers:

Horizontal Data Partitioning



Horizontal Data Partitioning

- Block Partition:
  - Partition tuples arbitrarily s.t. $\text{size}(R_1) \approx \ldots \approx \text{size}(R_P)$
- 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 compared to disk read time
- 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 $v_{i-1} < t.A < v_i$

Uniform Data v.s. Skewed Data

- Let R(K,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

Uniform

Assuming good hash function

May be skewed

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

Keep this in mind in the next few slides

Parallel Execution of RA Operators: Grouping

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

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

How to compute group by if:

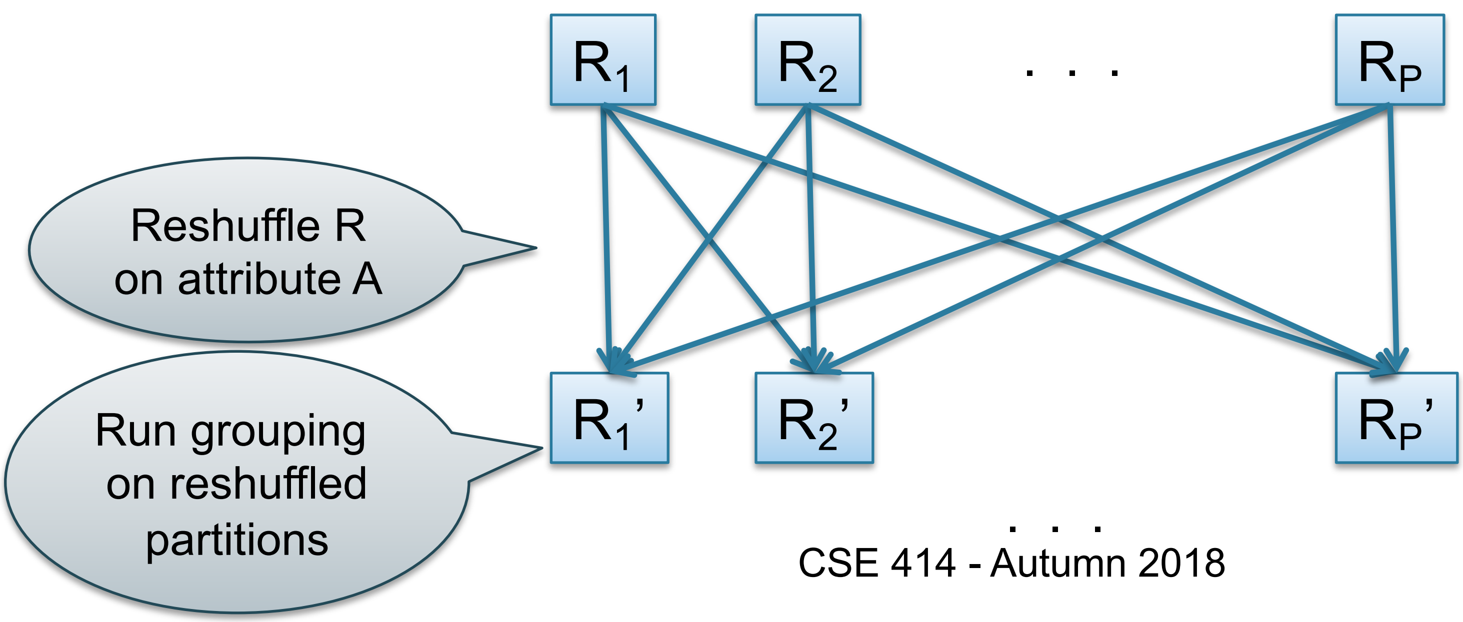
- R is hash-partitioned on A ?
- R is block-partitioned ?
- R is hash-partitioned on K ?

Parallel Execution of RA Operators: Grouping

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

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

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



Speedup and Scaleup

- Consider:
  - Query: $\gamma_{A,sum(C)}(R)$
  - Runtime: only consider I/O costs
- 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)

But only if the data is without skew!

Skewed Data

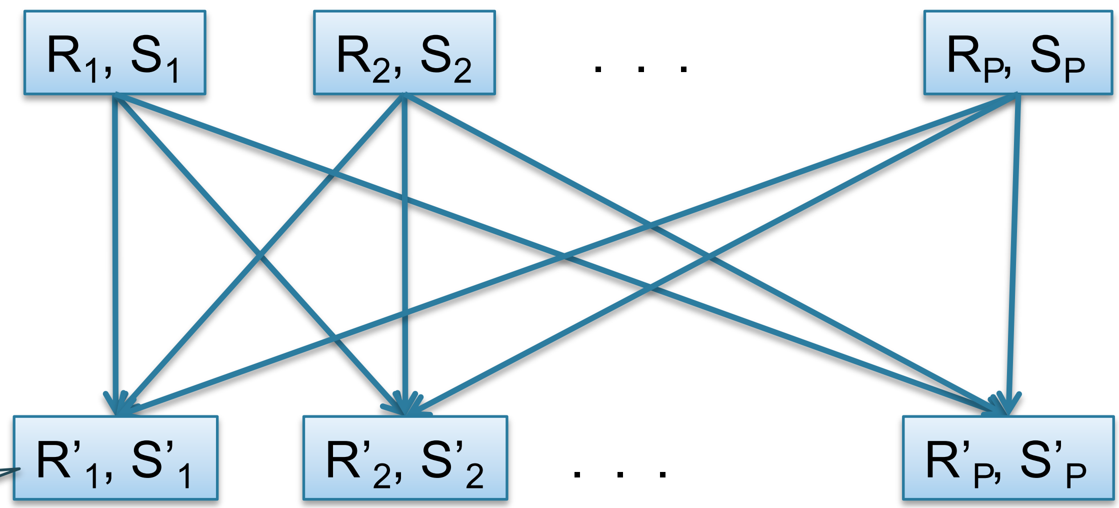
- R(<u>K</u>,A,B,C)
- Informally: we say that the data is skewed if one server holds much more data that the average
- E.g. we hash-partition on A, and some value of A occurs very many times (“Justin Bieber”)
- Then the server holding that value will be skewed

Parallel Data Processing in the 20th Century

Parallel Execution of RA Operators: Partitioned Hash-Join

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

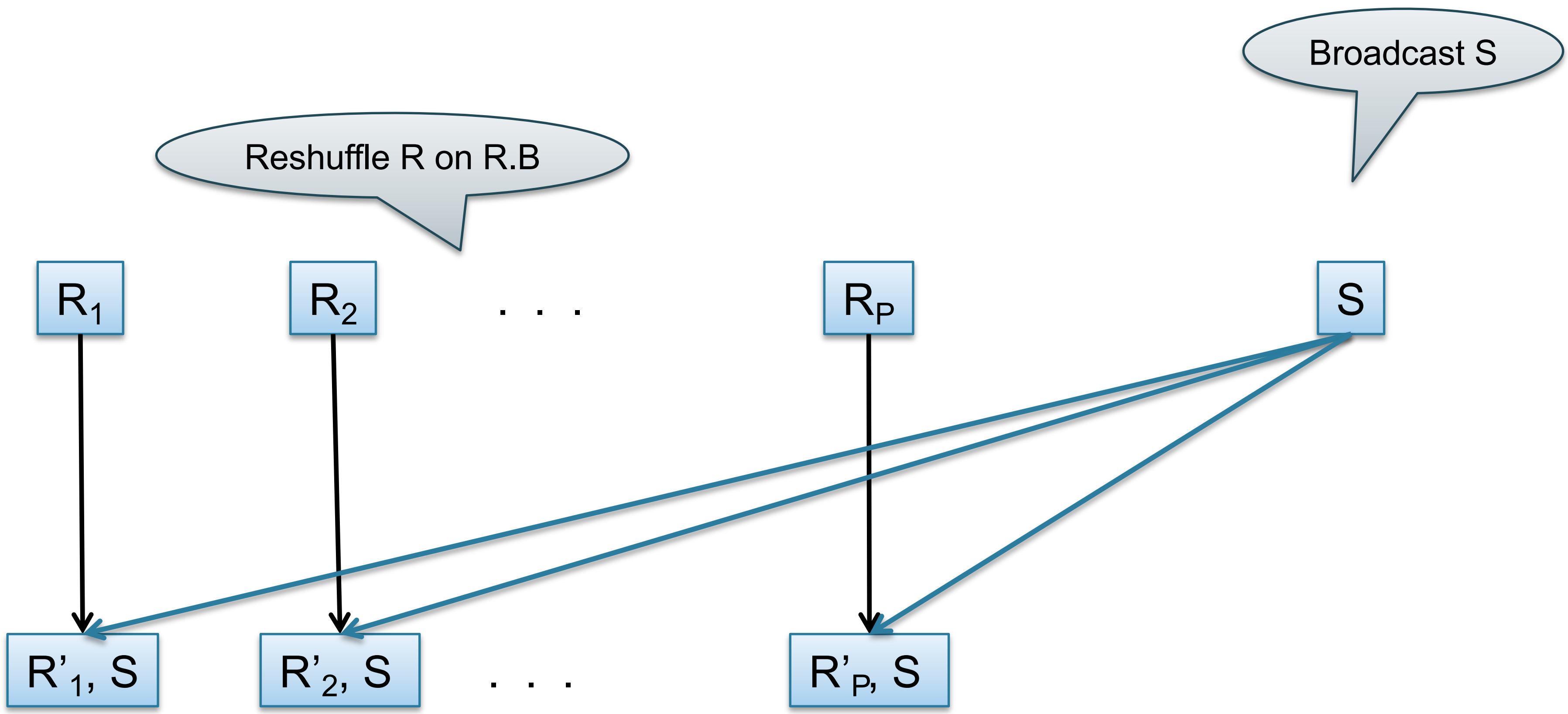
⋈

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?

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

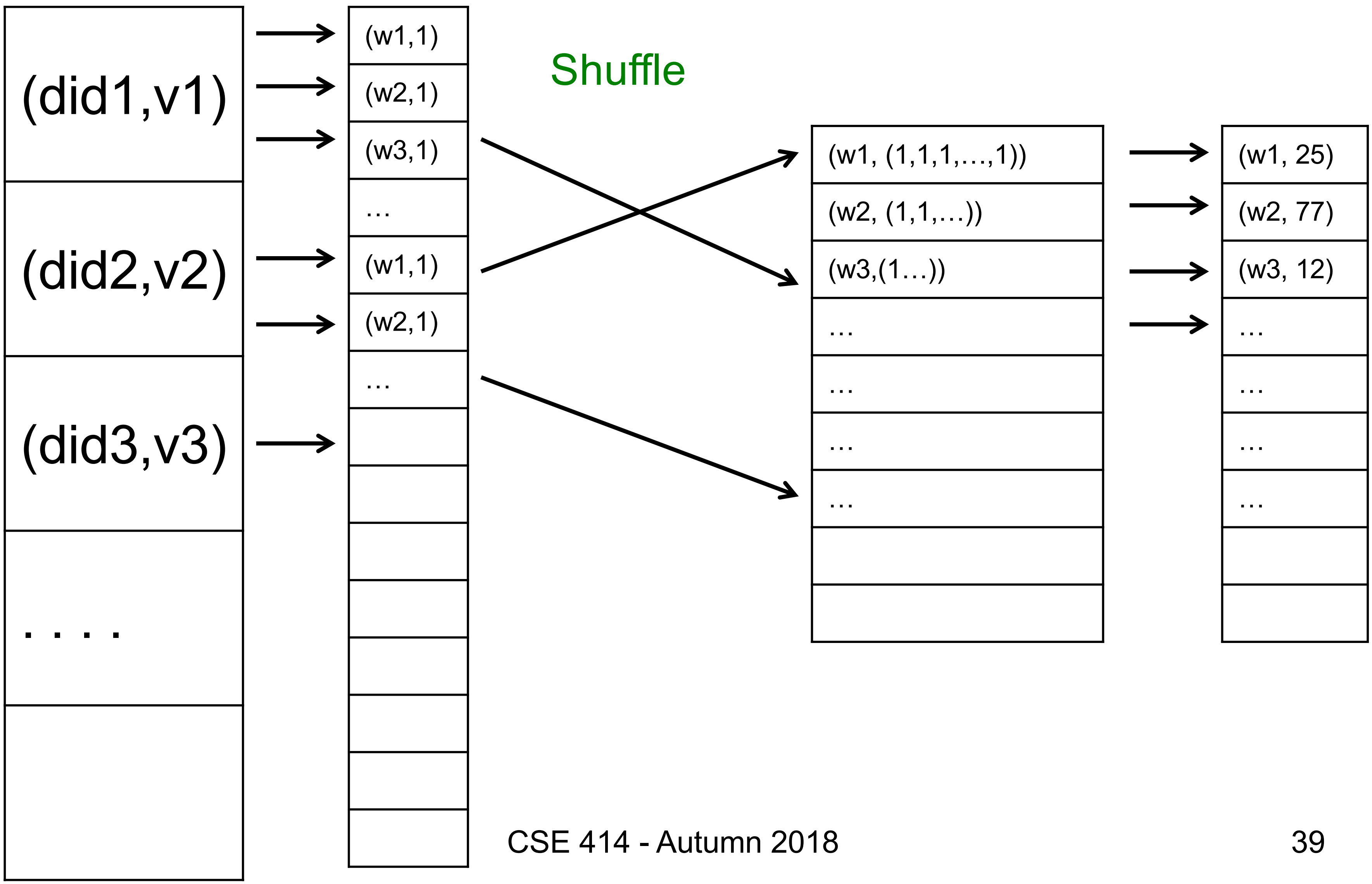
Example

- 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”);
```

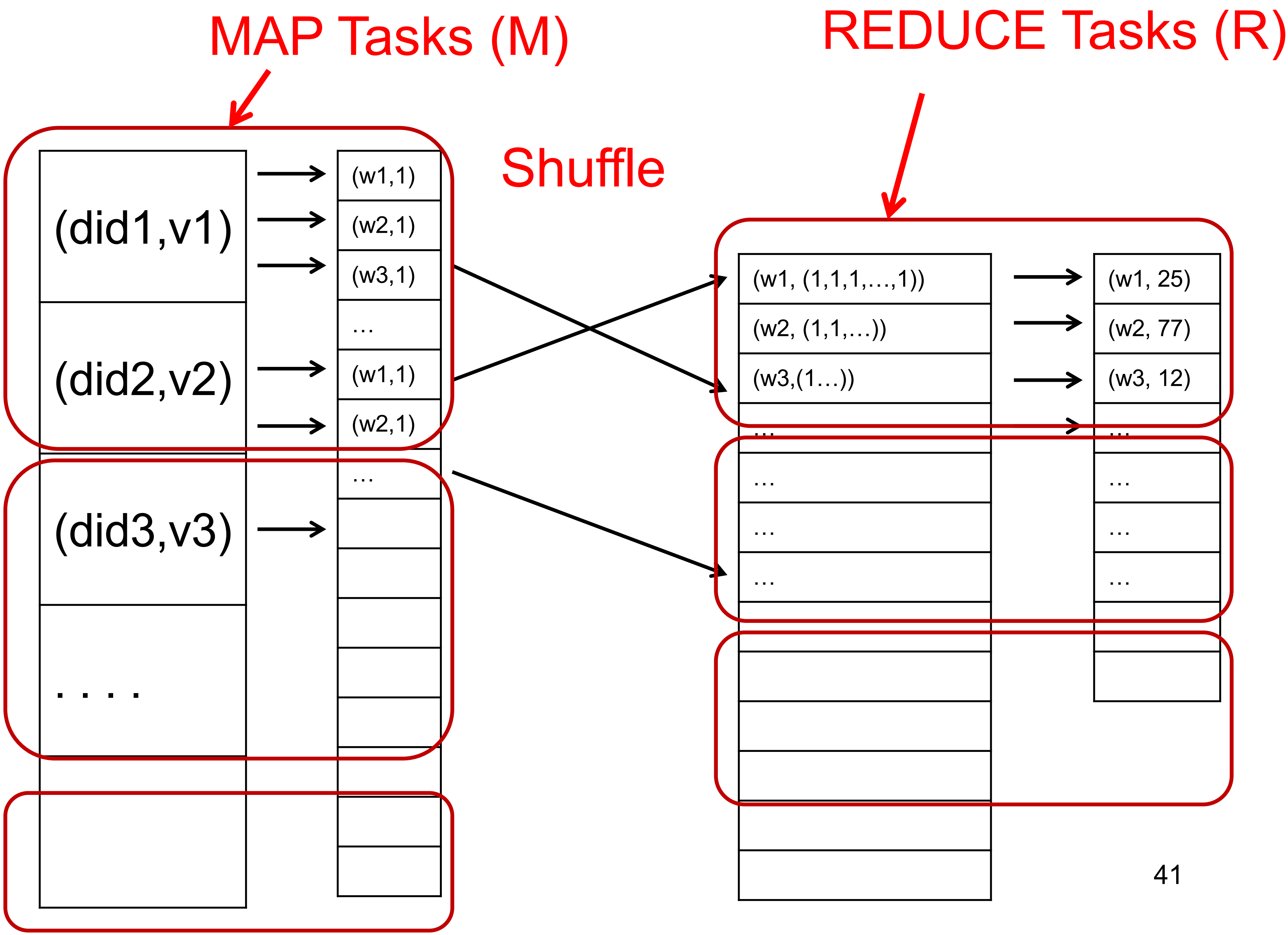
```
reduce(String key, Iterator values):
  // key: a word
  // values: a list of counts
  int result = 0;
    for each v in values:
      result += ParseInt(v);
  emit(AsString(result));
```

MAP 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)
…
…
…
…

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

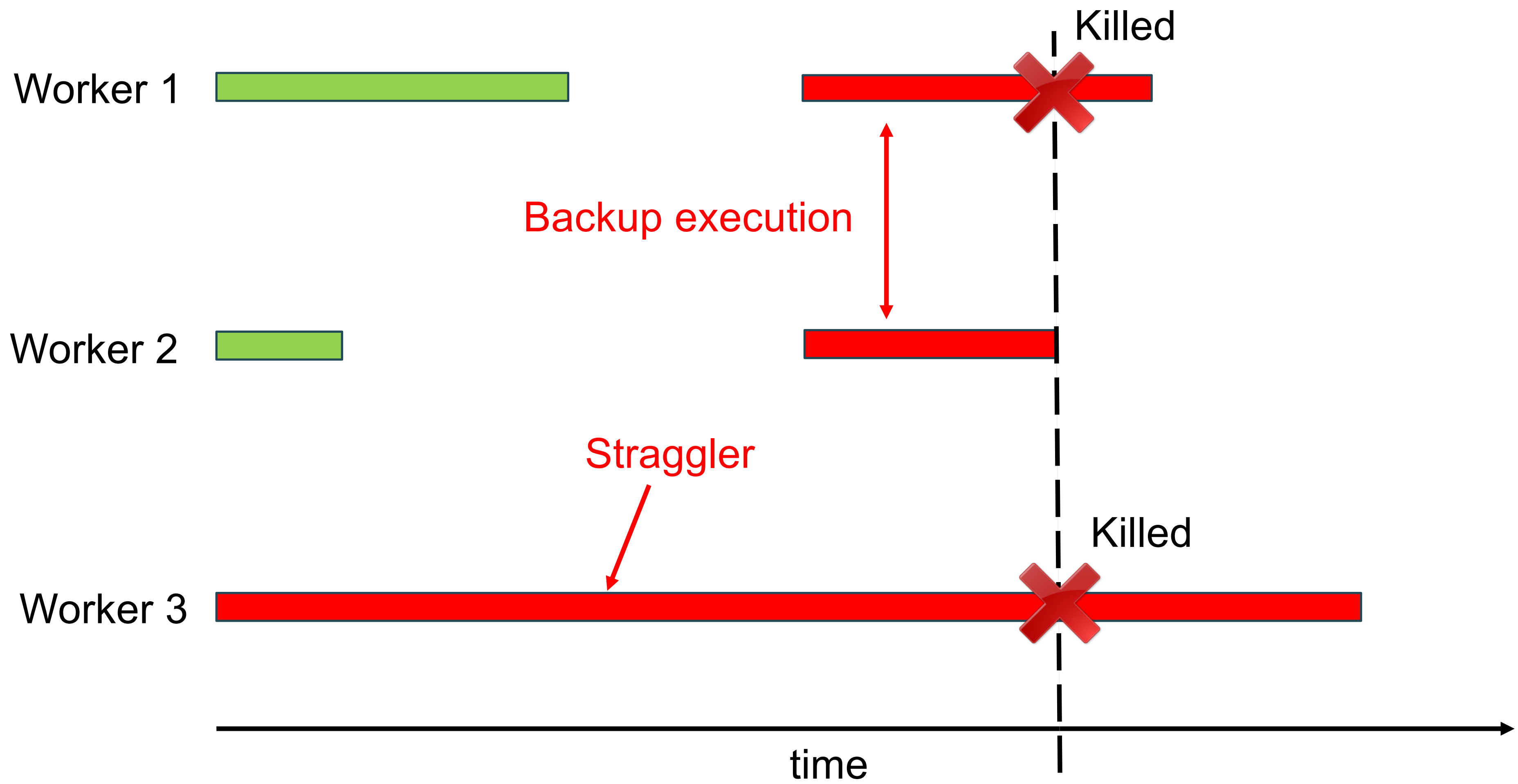
- There is one master node
- Master partitions input file into *M splits*, by key
- Master assigns *workers* (=servers) to the *M map tasks*, keeps track of their progress
- Workers write their output to local disk, partition into *R regions*
- Master assigns workers to the *R reduce tasks*
- Reduce 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);
```

$(123, [\ t_2, t_3\ ]\ )$

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

	A
t_1	23
t_2	123
t_3	123
t_4	42

$(\ t_2, t_3\ )$

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)

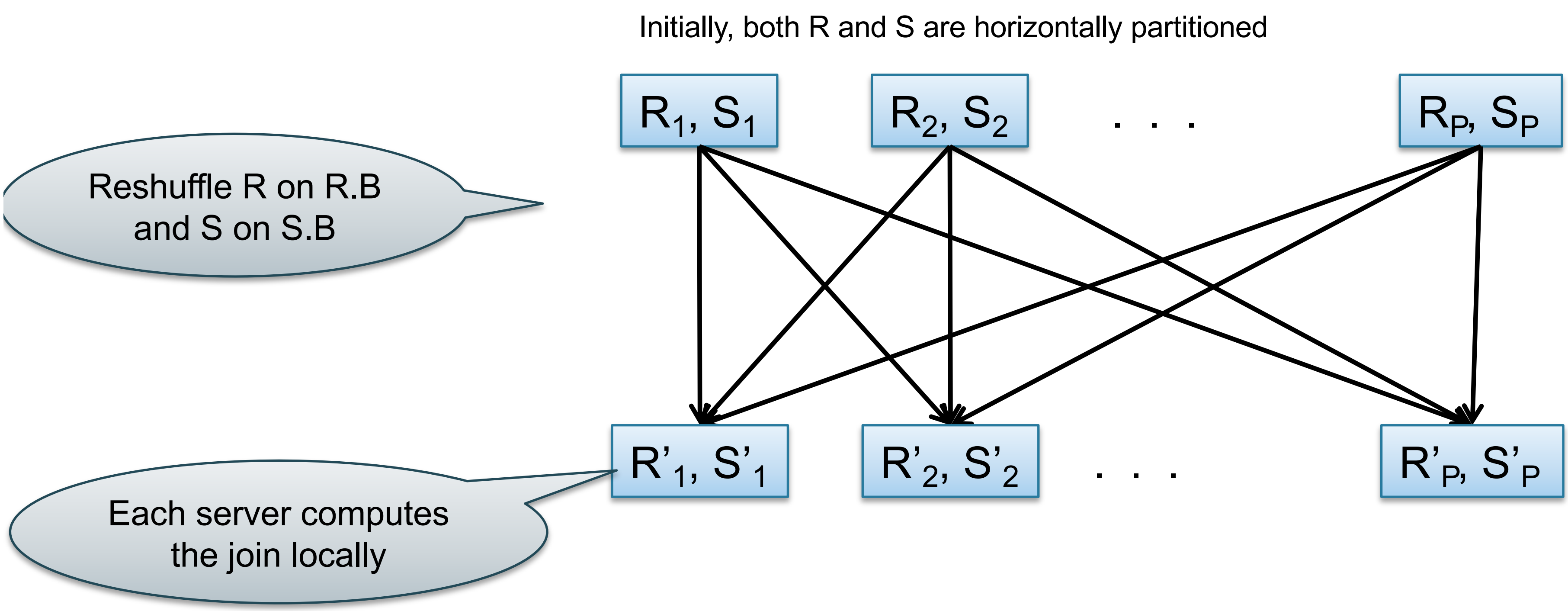
Join

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

type

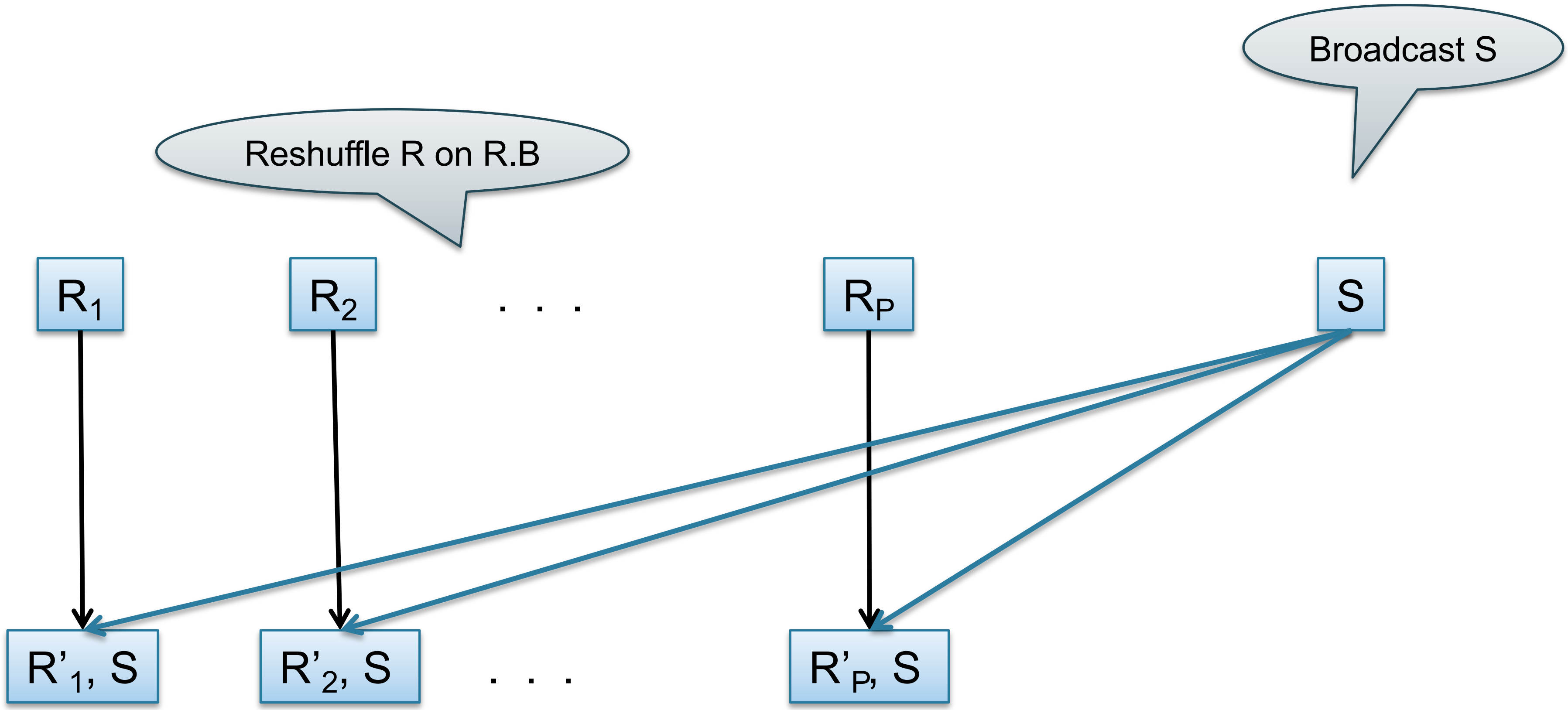
actual tuple

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

```
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?

Spark

A Case Study of the MapReduce Programming Paradigm

Parallel Data Processing @ 2010

Issues with MapReduce

- Difficult to write more complex queries
- Need multiple MapReduce jobs: dramatically slows down because it writes all results to disk

Spark

- Open source system from UC Berkeley
- Distributed processing over HDFS
- Differences from MapReduce:
  - Multiple steps, including iterations
  - Stores intermediate results in main memory
  - Closer to relational algebra (familiar to you)
- Details: http://spark.apache.org/examples.html

Spark

- Spark supports interfaces in Java, Scala, and Python
  – Scala: extension of Java with functions/closures
- We will illustrate use the Spark Java interface in this class
- Spark also supports a SQL interface (SparkSQL), and compiles SQL to its native Java interface

Resilient Distributed Datasets

- RDD = Resilient Distributed Datasets
  - A distributed, immutable relation, together with its *lineage*
  - Lineage = expression that says how that relation was computed = a relational algebra plan
- Spark stores intermediate results as RDD
- If a server crashes, its RDD in main memory is lost. However, the driver (=master node) knows the lineage, and will simply recompute the lost partition of the RDD

Programming in Spark

- A Spark program consists of:
  - Transformations (map, reduce, join…). Lazy
  - Actions (count, reduce, save...). Eager

- Eager: operators are executed immediately

- Lazy: operators are not executed immediately
  - A *operator tree* is constructed in memory instead
  - Similar to a relational algebra tree

What are the benefits of lazy execution?

The RDD Interface

Collections in Spark

- RDD<T> = an RDD collection of type T
  - Partitioned, recoverable (through lineage), not nested
- Seq<T> = a sequence
  - Local to a server, may be nested

Example

Given a large log file hdfs://logfile.log retrieve all 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();
```

Example

Given a large log file hdfs://logfile.log
retrieve all lines that:

- Start with “ERROR”
- Contain the string “sqlite”

`lines, errors, sqlerrors` have type `JavaRDD<String>`

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sqlerrors = errors.filter(l                           e”));

sqlerrors.collect();
```

Transformation:
Not executed yet…

Action:
triggers execution
of entire program

Example

Recall: anonymous functions
(lambda expressions) starting in Java 8

```
errors = lines.filter(l -> l.startsWith("ERROR"));
```

is the same as:

```
class FilterFn implements Function<Row, Boolean>{
  Boolean call (Row r)
  { return l.startsWith("ERROR"); }
}

errors = lines.filter(new FilterFn());
```

Example

Given a large log file hdfs://logfile.log retrieve all lines that:

- Start with “ERROR”
- Contain the string “sqlite”

```
s = SparkSession.builder()...getOrCreate();

sqlerrors = s.read().textFile(“hdfs://logfile.log”)
              .filter(l -> l.startsWith(“ERROR”))
              .filter(l -> l.contains(“sqlite”))
              .collect();
```

“Call chaining” style

MapReduce Again…

Steps in Spark resemble MapReduce:

- `col.filter(p)` applies in parallel the predicate p to all elements x of the partitioned collection, and returns collection with those x where `p(x) = true`
- `col.map(f)` applies in parallel the function f to all elements x of the partitioned collection, and returns a new partitioned collection

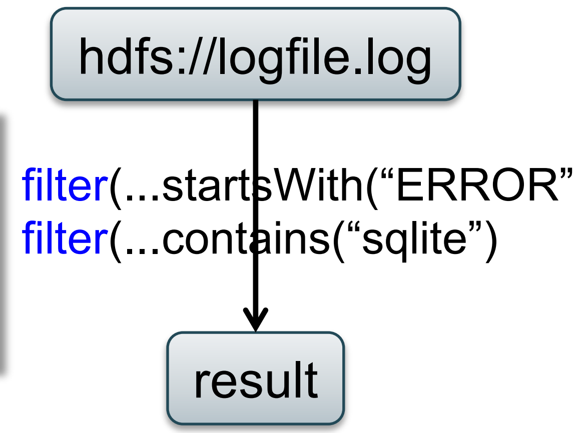
Persistence

```
lines = s.read().textFile("hdfs://logfile.log");
errors = lines.filter(l->l.startsWith("ERROR"));
sqlerrors = errors.filter(l->l.contains("sqlite"));
sqlerrors.collect();
```

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

Persistence

RDD:

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errors = lines.filter(l->l.startsWith("ERROR"));
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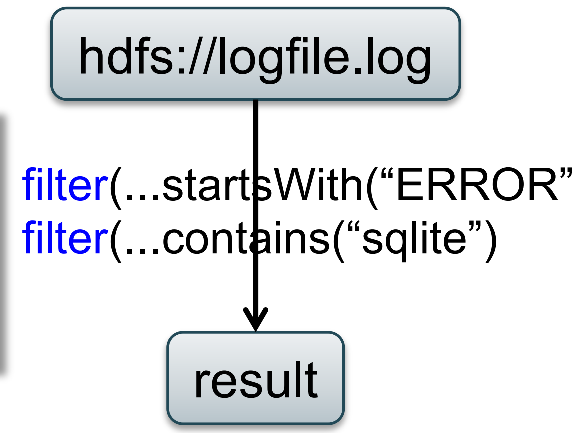
```

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

Persistence

RDD:




```
lines = s.read().textFile("hdfs://logfile.log");
errors = lines.filter(l->l.startsWith("ERROR"));
sqlerrors = errors.filter(l->l.contains("sqlite"));
sqlerrors.collect();
```

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

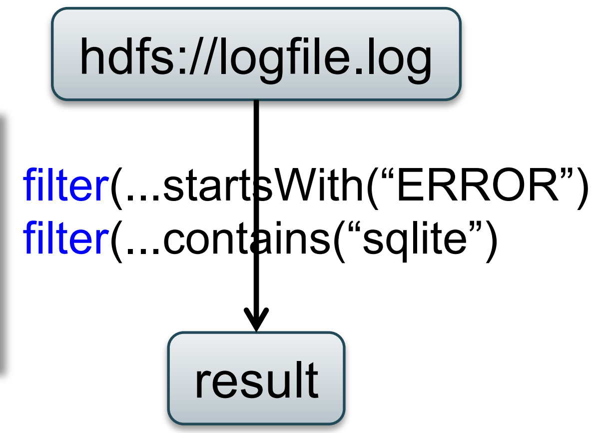
```
lines = s.read().textFile("hdfs://logfile.log");
errors = lines.filter(l->l.startsWith("ERROR"));
errors.persist();
sqlerrors = errors.filter(l->l.contains("sqlite"));
sqlerrors.collect()
```

New RDD

Spark can recompute the result from errors

Persistence

RDD:

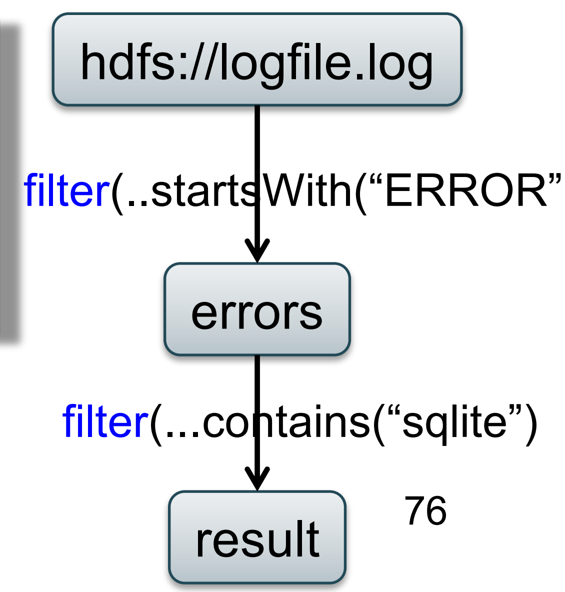



```
lines = s.read().textFile(“hdfs://logfile.log”);
errors = lines.filter(l->l.startsWith(“ERROR”));
sqlerrors = errors.filter(l->l.contains(“sqlite”));
sqlerrors.collect();
```

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

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

Parses each line into an object

persisting on disk

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

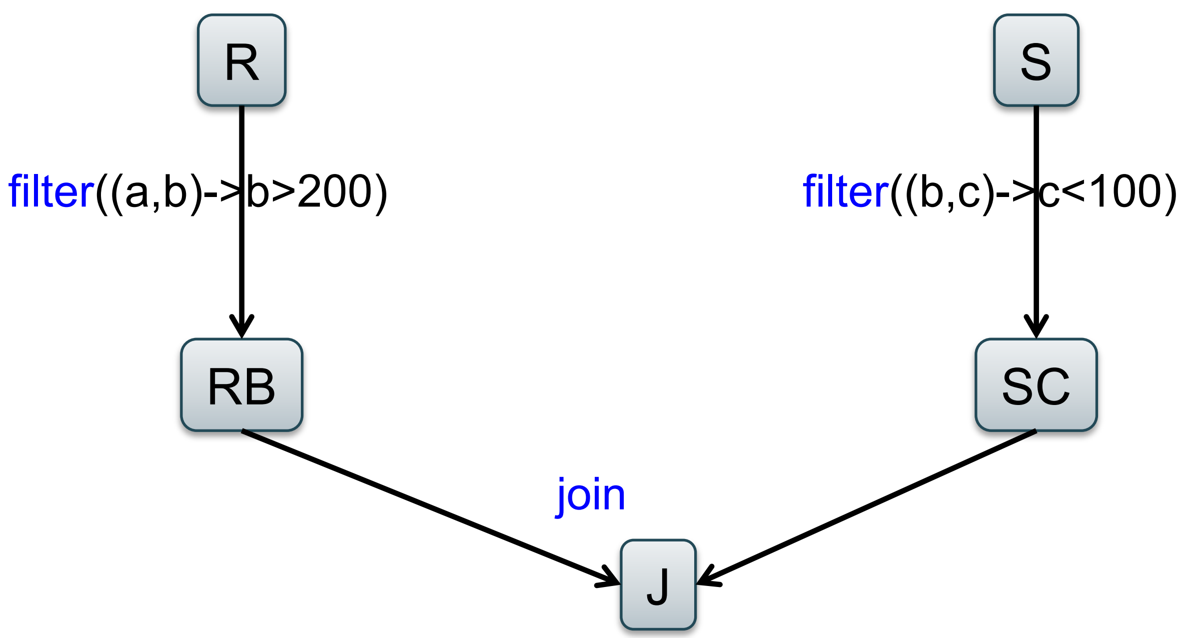
SELECT count(*) FROM R, S
WHERE R.B > 200 and S.C < 100 and R.A = S.A

Example

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



Recap: Programming in Spark

- A Spark/Scala program consists of:
  - Transformations (map, reduce, join…). Lazy
  - Actions (count, reduce, save...). Eager

- RDD<T> = an RDD collection of type T
  - Partitioned, recoverable (through lineage), not nested
- Seq<T> = a sequence
  - Local to a server, may be nested

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

The DataFrame and Dataset Interfaces

DataFrames

- Like RDD, also an immutable distributed collection of data
- Organized into *named columns* rather than individual objects
  - Just like a relation
  - Elements are untyped objects called `Row`'s
- Similar API as RDDs with additional methods
  - ```
    people = spark.read().textFile(…);
    ageCol = people.col("age");
    ageCol.plus(10); // creates a new DataFrame
    ```
    ```

Datasets

- Similar to DataFrames, except that elements must be typed objects
- E.g.: `Dataset<People>` rather than `Dataset<Row>`
- Can detect errors during compilation time
- DataFrames are aliased as `Dataset<Row>` (as of Spark 2.0)
- You will use both Datasets and RDD APIs in HW6

Datasets API: Sample Methods

- Functional API
  - `agg(Column expr, Column... exprs)`
    Aggregates on the entire Dataset without groups.
  - `groupBy(String col1, String... cols)`
    Groups the Dataset using the specified columns, so that we can run aggregation on them.
  - `join(Dataset<?> right)`
    Join with another DataFrame.
  - `orderBy(Column... sortExprs)`
    Returns a new Dataset sorted by the given expressions.
  - `select(Column... cols)`
    Selects a set of column based expressions.
- "SQL" API
  - `SparkSession.sql("select * from R");`
- Look familiar?

Conclusions

- Parallel databases
  - Predefined relational operators
  - Optimization
  - Transactions
- MapReduce
  - User-defined map and reduce functions
  - Must implement/optimize manually relational ops
  - No updates/transactions
- Spark
  - Predefined relational operators
  - Must optimize manually
  - No updates/transactions