DATA516/CSED516 Scalable Data Systems and Algorithms

Lecture 4

Spark, MapReduce, Hive

Intro to Parallel Processing

Announcements

- Project proposals were due Friday
  - If you have not submitted, staff will reach out
- HW2 (Spark) due on Monday 11/13
  - Released later today/early tomorrow
  - Pull upstream for new assignment
- Let us know when grades/late policy don't reflect prior arrangements

Outline

- Spark
- MapReduce and critique
- Fault Tolerance
- Hive (short)

Next lecture: Parallel databases (Start Today)

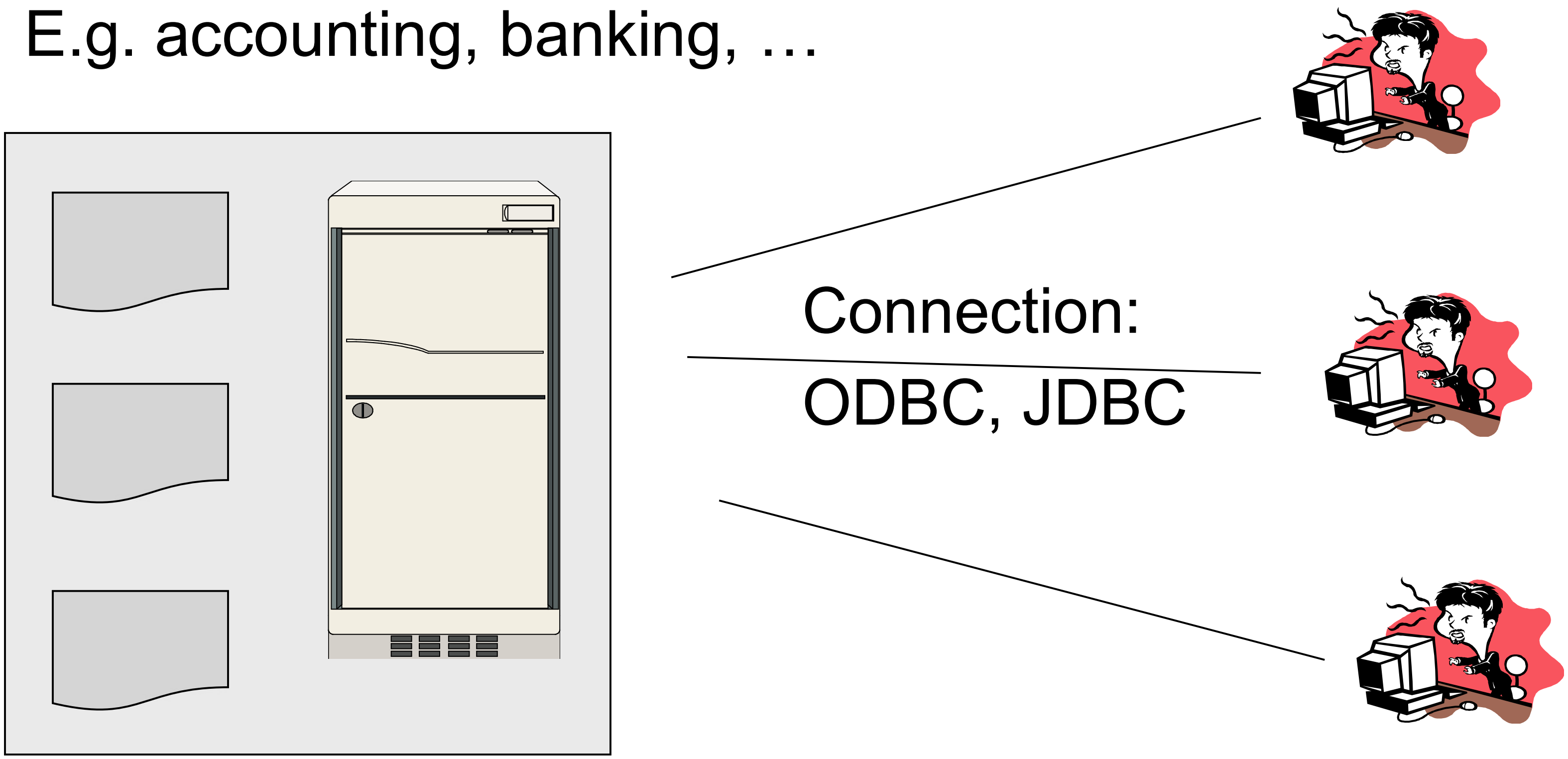
Spark

Review: Single Client

E.g. data analytics

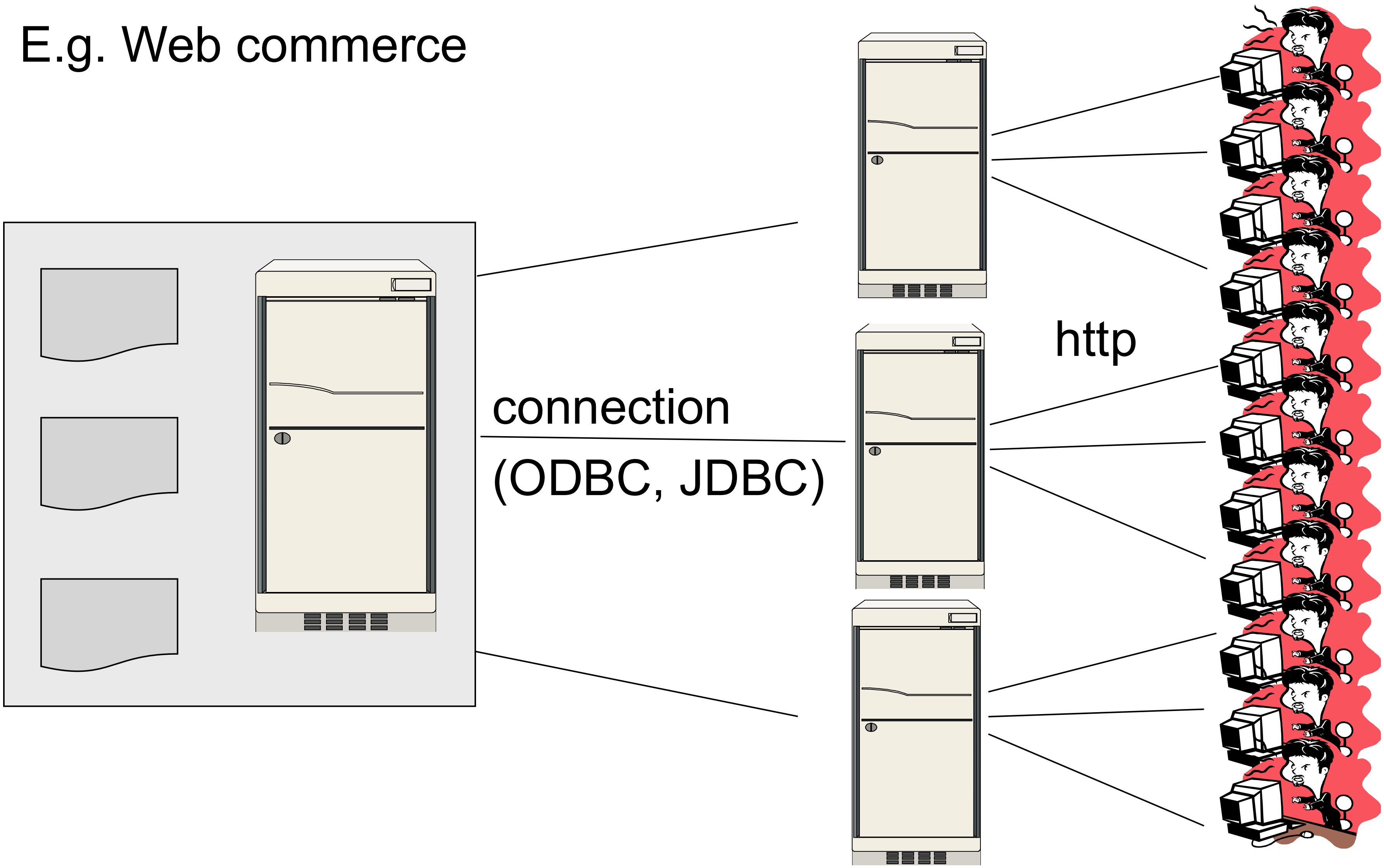
Review: Client-Server

E.g. accounting, banking, …

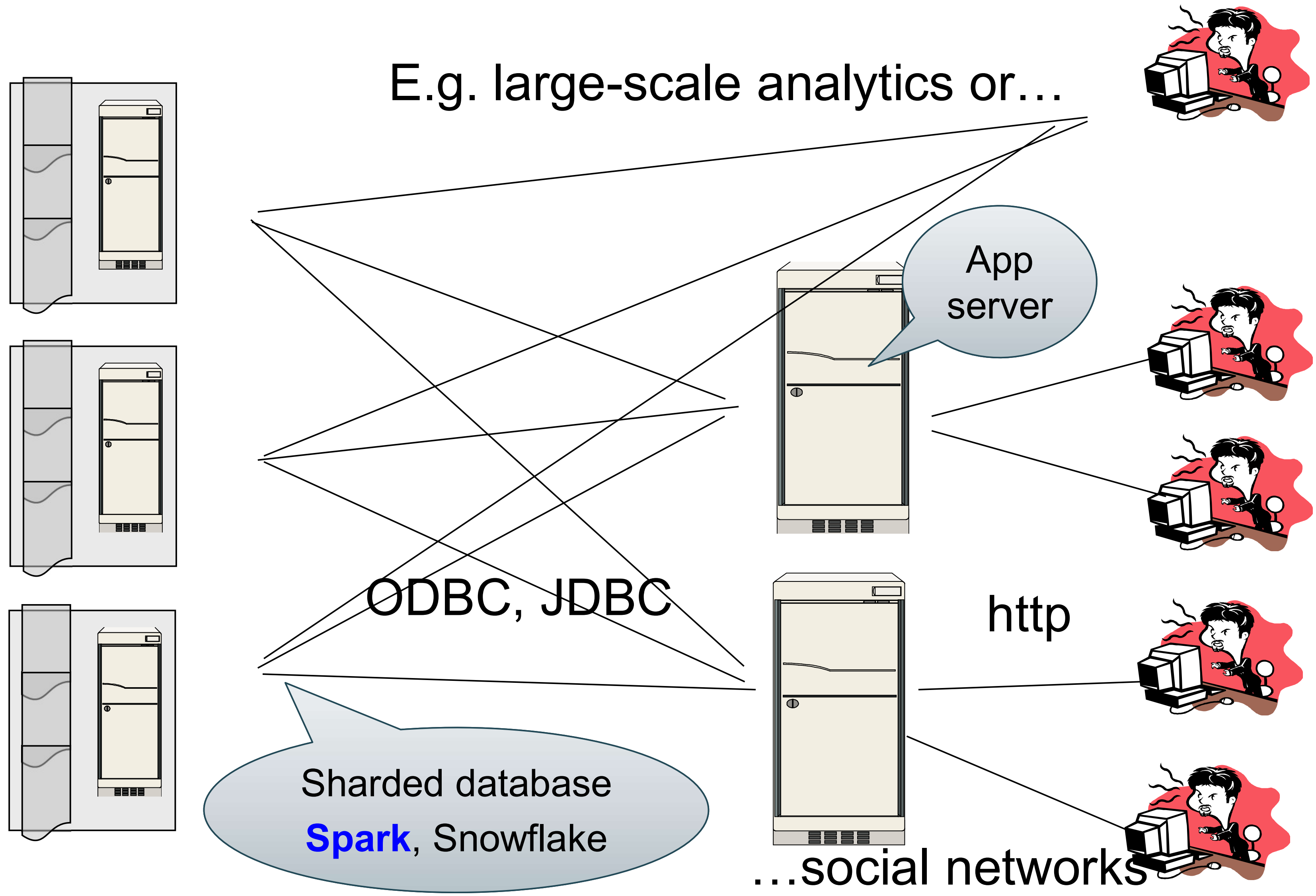


Review: Three-tier

E.g. Web commerce



Review: Distributed Database



Distributed or Parallel Query Processing

- Clusters:
  - More servers → more in main memory
  - More servers → more computing power
  - Clusters are now cheaply available in the cloud
  - *Distributed* query processing

- Multicores:
  - The end of Moore's law
  - *Parallel* query processing

Motivation

- Limitations of relational database systems:
  – Single server (at least traditionally)
  – SQL is a limited language (eg no iteration)
- Spark:
  – Distributed system
  – Functional language (Python/R) good for ML
- Implementation:
  – Extension of MapReduce
  – Distributed physical operators

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

Collections in Spark

RDD<T> = an RDD collection of type T

- Distributed on many servers, not nested
- Operations are done in parallel
- Recoverable via lineage; more later

Seq<T> = a sequence

- Local to one server, may be nested
- Operations are done sequentially

Example from paper, new syntax

Search logs stored in HDFS

```
// First line defines RDD backed by an HDFS file
lines = spark.textFile(“hdfs://…”)

// Now we create a new RDD from the first one
errors = lines.filter(x -> x.startsWith(“Error”))

// Persist the RDD in memory for reuse later
errors.persist()
errors.collect()
errors.filter(x -> x.contains(“MySQL”)).count()
```

Example from paper, new syntax

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Transformation: Not executed yet…

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```

Transformation: Not executed yet…

Action: triggers execution of entire program

Anonymous Functions

A.k.a. lambda expressions, starting in Java 8

```
errors = lines.filter(x -> x.startsWith("Error"))
```

Example

The RDD s:

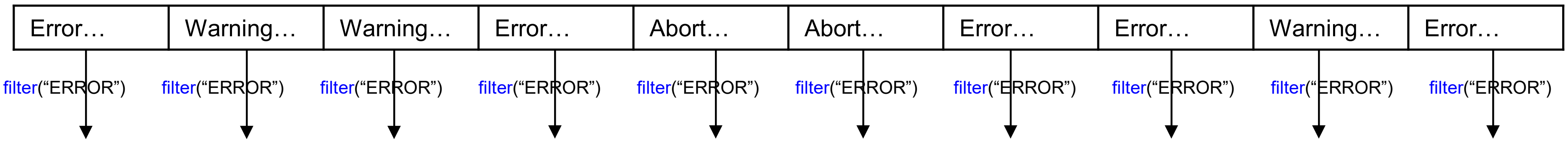
Error…	Warning…	Warning…	Error…	Abort…	Abort…	Error…	Error…	Warning…	Error…

```
sqlerrors = spark.textFile(“hdfs://…”)
            .filter(x -> x.startsWith(“ERROR”))
            .filter(x -> x.contains(“sqlite”))
            .collect();
```

Example

Parallel step 1

The RDD s:

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Example

Parallel step 1

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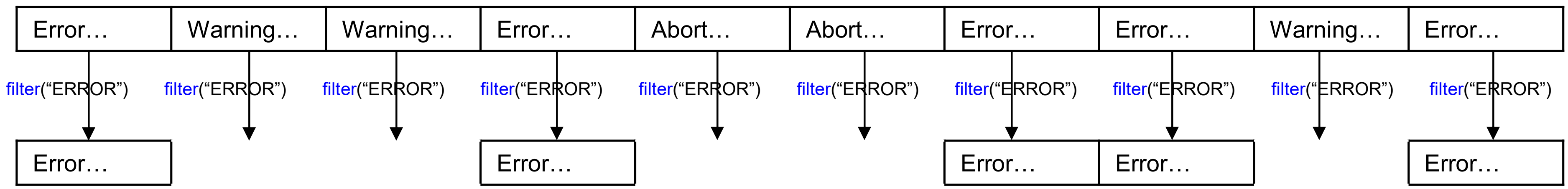


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Example

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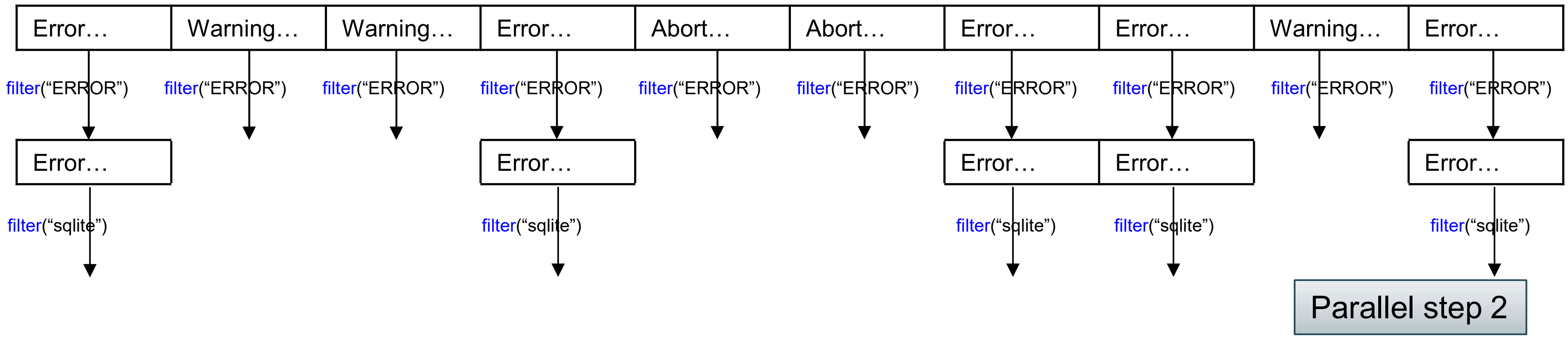
Parallel step 1

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```

More on Programming Interface

Large set of pre-defined transformations:

- Map, filter, flatMap, sample, groupByKey, reduceByKey, union, join, cogroup, crossProduct, …

Small set of pre-defined actions:

- Count, collect, reduce, lookup, and save

Programming interface includes **iterations**

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

What Am I?

```
val points = spark.textFile(...)
                  .map(parsePoint).persist()
var w = // random initial vector
for (i <- 1 to ITERATIONS) {
  val gradient = points.map{ p =>
    p.x * (1/(1+exp(-p.y*(w dot p.x)))-1)*p.y
  }.reduce((a,b) => a+b)
  w -= gradient
}
```

[From Zaharia12]

What Am I?

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val points = spark.textFile(...)
                  .map(parsePoint).persist()
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}
```

Logistic Regression!!

[From Zaharia12]

Spark Ecosystem Growth

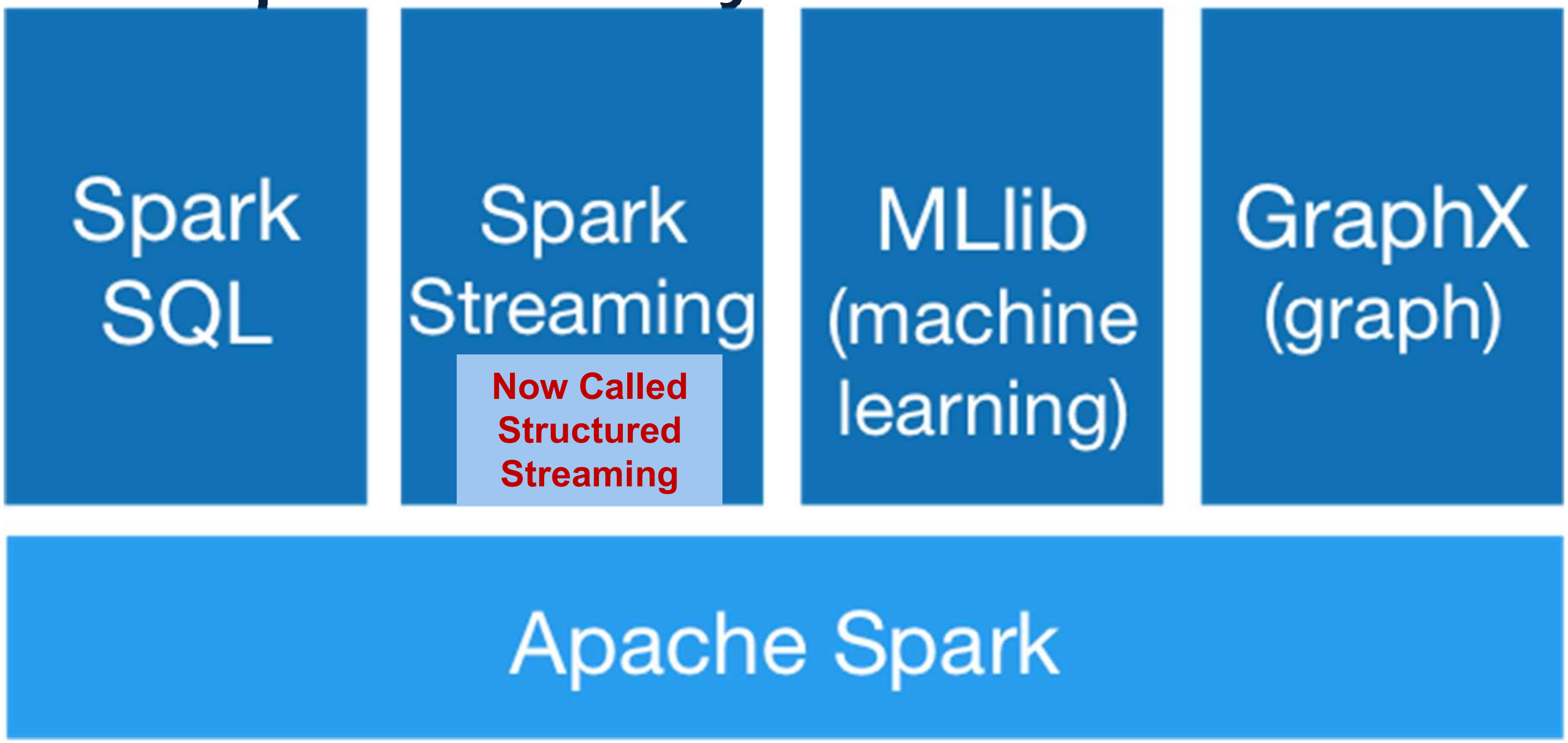

Image from: http://spark.apache.org/

Spark SQL vs Functional Prog. API

- Spark's original functional programming API
  - General
  - But limited opportunities for automatic optimization
- Spark SQL simultaneously
  - Makes Spark accessible to more users
  - Improves opportunities for automatic optimizations

Three Java-Spark APIs

- RDDs: Syntax: JavaRDD<T>
  - T = anything, basically untyped
- Data frames: Dataset<Row>
  - <Row> = a record, dynamically typed
- Datasets: Dataset<Person>
  - <Person> = user defined type
  - Not in Python/R

DataFrames

- Like RDD: immutable distributed collection
- Organized into *named columns*
  - 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

- Like DataFrames, but elements must be typed
- 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)

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?

Outline

- Spark
- MapReduce and critique
- Fault Tolerance
- Hive (short)

MapReduce: References

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

- D. DeWitt and M. Stonebraker. Mapreduce – a major step backward. In Database Column (Blog), 2008.

MapReduce

- Google:
  - Started around 2000
  - Paper published 2004
  - Discontinued September 2019
- Free variant: Hadoop

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

Distributed File System (DFS)

- For very large files: TBs, PBs
- Each file partitioned into *chunks* (64MB)
- Each chunk replicated (≥3 times) – why?
- Implementations:
  - Google's DFS: GFS, proprietary
  - Hadoop's DFS: HDFS, open source

MapReduce

- Describe the **input** and **output** to map reduce
- Describe the **Map** function
- Describe the **Reduce** function

MapReduce

- Describe the **input** and **output** to map reduce
  - Input: a bag of `(inputkey, value)` pairs
  - Output: a bag of `(outputkey, value)` pairs
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- Describe the **Map** function
  – Input: `(input key, value)`
  – Ouput: bag of `(intermediate key, value)`
- Describe the **Reduce** function
  – Input: `(intermediate key, bag of values)`
  – Output: bag of output `(values)`

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 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)

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

Example

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  - The key = document id (did)
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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));
```

Think "Relational"!

Documents: Relation

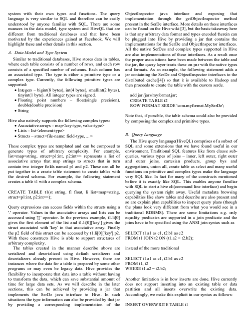
did1


Hive – A Petabyte Scale Data Warehouse Using Hadoop

Ashish Thusoo, Joydeep Sen Sarma, Namit Jain, Zheng Shao, Prasad Chakka, Ning Zhang, Suresh Antony, Hao Liu and Raghotham Murthy

Facebook Data Infrastructure Team

did2



. . .

Think “Relational”!

Documents:

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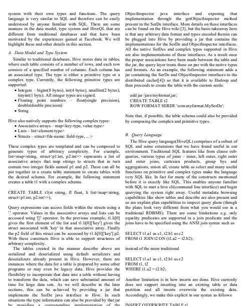

. . .

Relation

Did	Word
did1	Scalable
did1	analysis
did1	on
did1	large
did1	…
did2	system
did2	with
…	

Think “Relational”!

```
select      word, count(*)
from        Data
group by    word
```

Relation

Did	Word
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Think “Relational”!

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select      word, count(*)
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map = group by

reduce = count(…) (or sum(…) or…)

Relation

Did	**Word**
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Think “Relational”!

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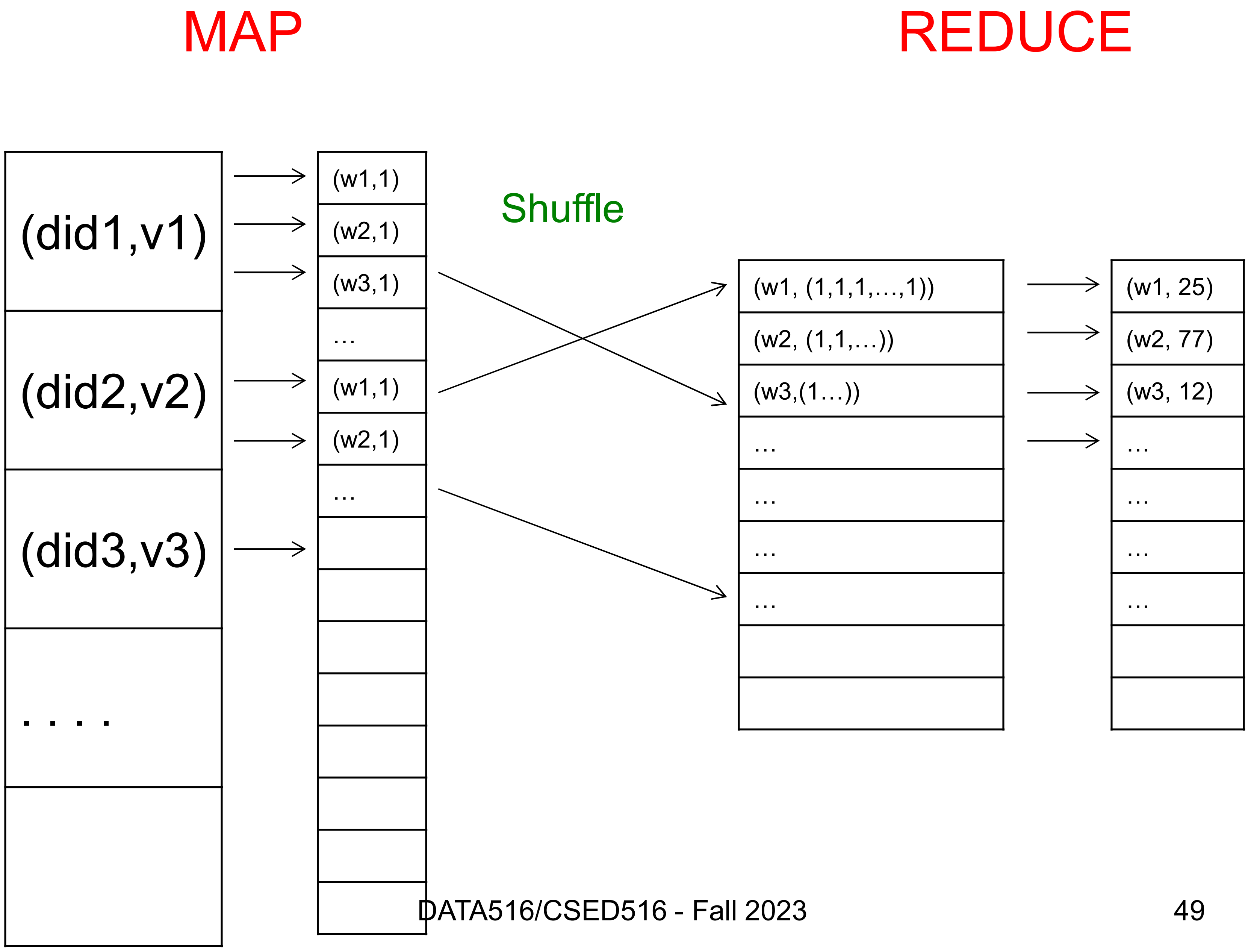
map = group by

reduce = count(…) (or sum(…) or…)

MapReduce = Group-by-aggregate


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)
…
…
…
…

Examples from the paper

Discuss in class how to implement in MR

- Distributed grep
- Count URL access frequency: (URL, count)
- Reverse web-link graph: (URL, (list of URLs))
- Inverted index: (word, (list of URLs))

Jobs v.s. Tasks

- A MapReduce Job
  - One simple “query”, e.g. count words in docs
  - Complex queries may require many jobs
- A Map Task, or a Reduce Task
  - A group of instantiations of the map-, or reduce-function, to be scheduled on a single worker

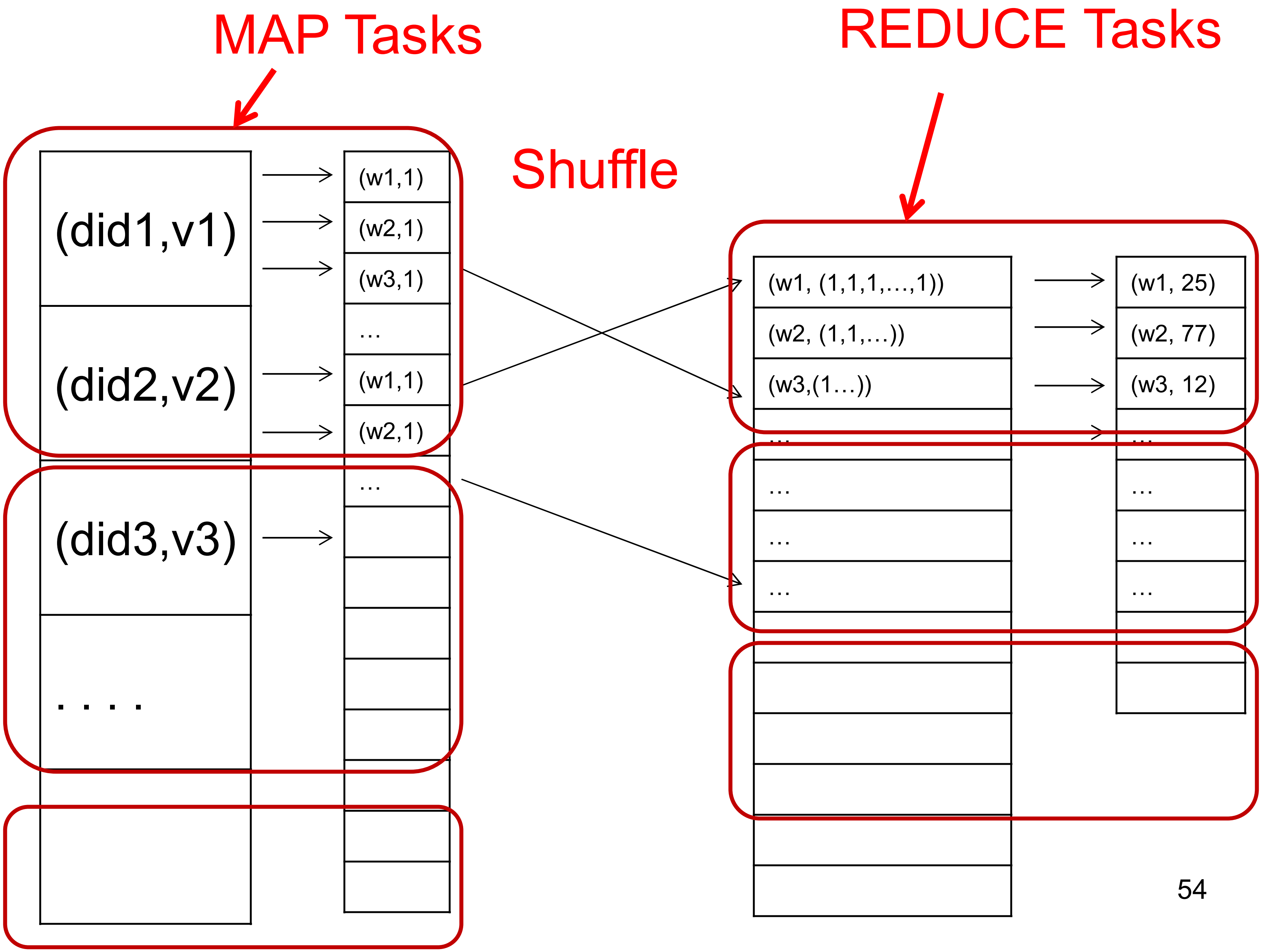
Workers

- 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

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 disk
  – Reducers read the files (=reshuffling); if the server fails, the reduce task is restarted on another server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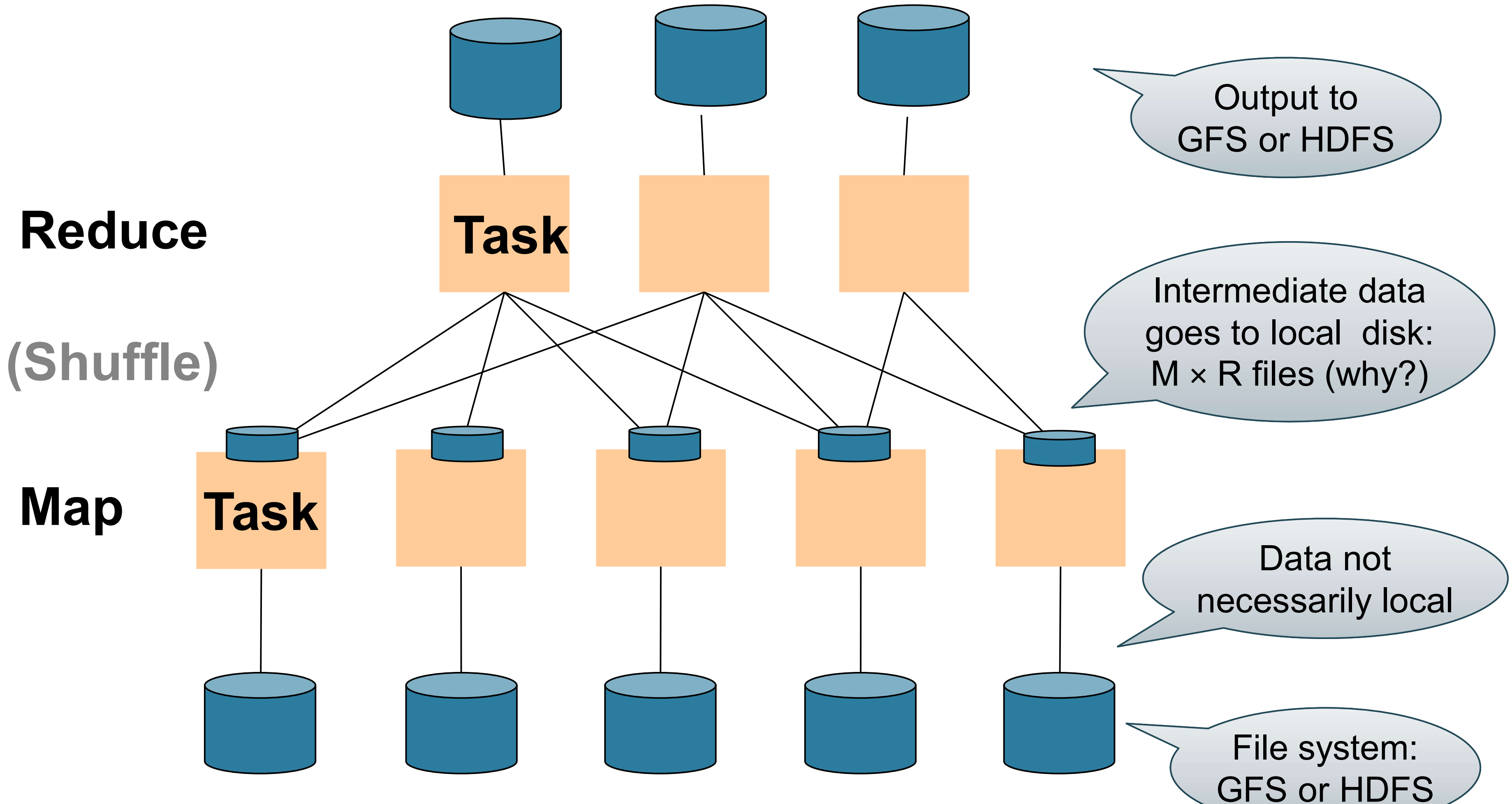
…
…

Choosing Parameters in MR

- Number of map tasks (M):
  - Default: one map task per chunk
  - E.g. data = 64TB, chunk = 64MB ➔ M = 10^6
- Number of reduce tasks (R):
  - No good default; set manually R << M
  - E.g. R = 500 or 5000

- In general, MapReduce had very many parameters that required expertise to tune

MapReduce Execution Details



Discussion

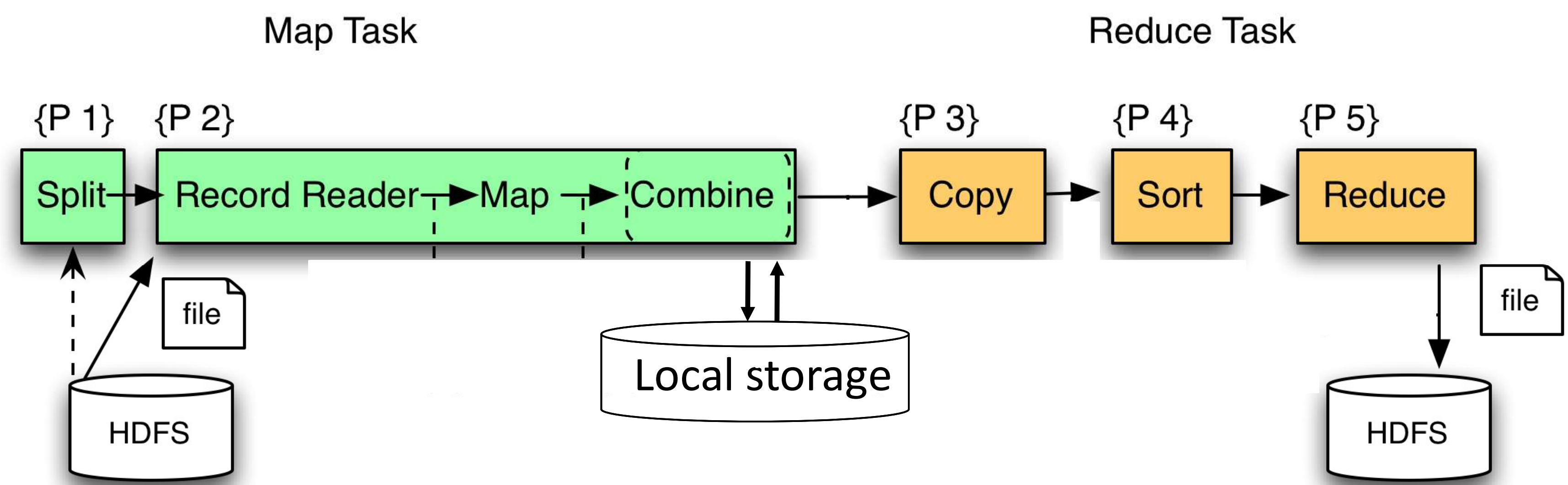
Why doesn't MR determine the number of reduce tasks R dynamically, after all map tasks finish?

Discussion

Why doesn’t MR determine the number of reduce tasks R dynamically, after all map tasks finish?

Because each map tasks needs to write its output into R file; so R must be known before the map tasks start

MapReduce Phases



Riddle

- The combiner function performs an optimization that you already know
- Which one?

Riddle

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- Which one?

- Pushing aggregates down

Riddle

- The combiner function performs an optimization that you already know
- Which one?

```
Temp=
  select server, word, count(*) as c
  from Data
  group by server, word
```

- Pushing aggregates down:
  – Each mapper groups by word

Riddle

- The combiner function performs an optimization that you already know
- Which one?

```
Temp=
  select server, word, count(*) as c
  from Data
  group by server, word
```

- Pushing aggregates down:
  – Each mapper groups by word
  – Reducers perform final group-by

```
Output =
  select word, sum(c)
  from Temp
  group by word
```

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

MapReduce v.s. Databases

Blog by DeWitt and Stonebraker

MapReduce v.s. Databases

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- “Schemas are good”

MapReduce v.s. Databases

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- The M * R problem – what is it?

MapReduce v.s. Databases

Blog by DeWitt and Stonebraker

- “Schemas are good”
- “Indexes”
- “Skew” (MR mitigates it somewhat, how?)
- The M * R problem – what is it?
- “Parallel databases uses push (to sockets) instead of pull” – what’s the point?

Outline

- Spark
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- Fault Tolerance
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Fault Tolerance

Fault Tolerance

- Traditional RDBMs:
  - Major concern: recover after failure
- Massively distributed systems:
  - Probability of failure increases w/ no. of workers and length of job

Fault Tolerance

Example:

- if a server fails once/year…
- … a job with 10000 servers fails once/hour

Fault Tolerance

How is fault tolerance handled in each system?

- **MapReduce**: if a worker fails then

- **Spark**:

Fault Tolerance

How is fault tolerance handled in each system?

- **MapReduce**: if a worker fails then
  - All its completed map tasks need re-executed
  - Its in-progress reduce task needs re-executed
- **Spark**:

Fault Tolerance

How is fault tolerance handled in each system?

- **MapReduce**: if a worker fails then
  - All its completed map tasks need re-executed
  - Its in-progress reduce task needs re-executed

- **Spark**: will discuss next

Approach

New abstraction: Resilient Distributed Datasets

RDD properties

- Parallel data structure
- Can be persisted in memory
- Fault-tolerant
- Users can manipulate RDDs with rich set of operators

Resilient Distributed Datasets

- RDD = Resilient Distributed Dataset
  - Distributed, immutable.
  - Records 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

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

Parses each line into an object

persisting
in memory
or on disk

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

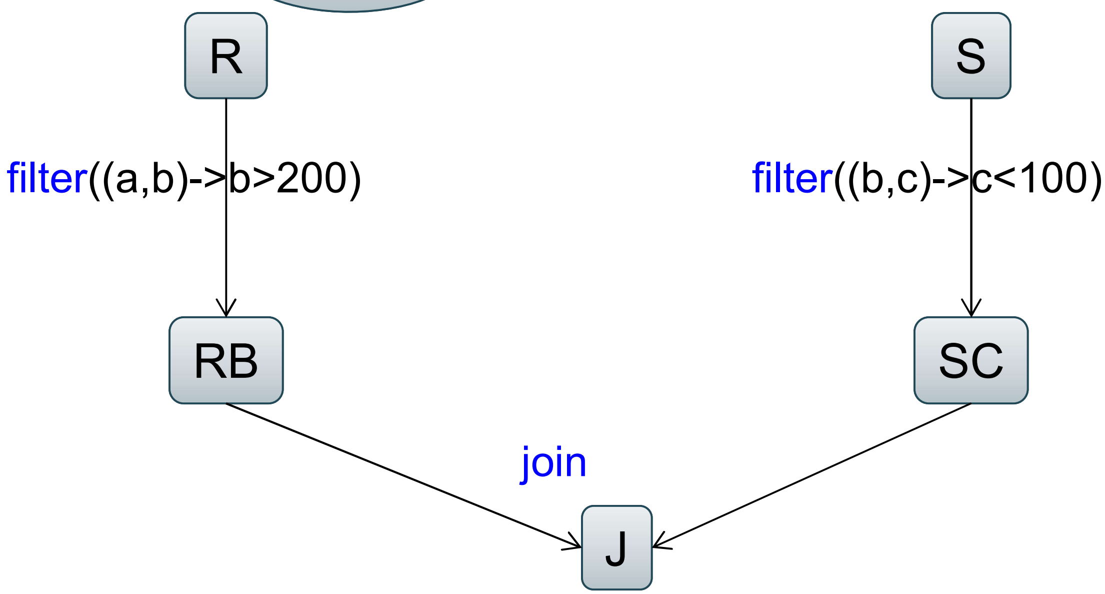
```
SELECT count(*)  FROM R, S
WHERE R.B > 200 and S.C < 100  and R.A = S.A
```

Example

```
R = strm.read().textFile("R.csv").map(parseRecord).persist();
S = strm.read().textFile("S.csv").map(parseRecord).persist();
RB = R.filter(t -> t.b > 200);
SC = S.filter(t -> t.c < 100);
J = RB.join(SC);
J.count();
```

transformations

action



RDD Details

- An RDD is a partitioned collection of records
  - RDD’s are typed: RDD[Int] is an RDD of integers
  - Records are Java/Python objects
- An RDD is read only
  - This means no updates to individual records
  - This is to contrast with in-memory key-value stores
- To create an RDD
  - Execute a deterministic operation on another RDD
  - Or on data in stable storage
  - Example operations: map, filter, and join

RDD Materialization

- Users control persistence and partitioning
- Persistence
  - Materialize this RDD in memory
- Partitioning
  - Users can specify key for partitioning an RDD

Outline

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Hive

- Facebook's implementation of SQL over MR
- Supports subset of SQL
- Uses MapReduce runtime (pros/cons?)
  - Note: this is similar to Google's FlumeJava

Hive

- Facebook's implementation of SQL over MR
- Supports subset of SQL
- Uses MapReduce runtime (pros/cons?)
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- Optimizations:

Hive

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  - Column pruning
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  - Partition pruning
  - Map-side join = ”broadcast join” (discuss in class)

Hive

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- Supports subset of SQL
- Uses MapReduce runtime (pros/cons?)
  - Note: this is similar to Google's FlumeJava
- Optimizations:
  - Column pruning
  - Predicate push-down
  - Partition pruning
  - Map-side join = ”broadcast join” (discuss in class)
  - Join reordering

Discussion

- Parallel database systems: since the 80s
- MapReduce: around 2000
- Hive: built on MapReuce
- Spark: “better” MapReduce around 2010
- Snowflake, Aurora: cloud, parallel databases; around 2015

Quick comparison (next slides)

MapReduce v.s. Spark

MapReduce	Spark
• Job = Map+Reduce	• Job = any query
• Language = Java	• Language ≈ RA
• Data = untyped	• Data = has schema
• Optimization = no	• Optimization = yes but limited: missing stats on base data

Spark v.s. RDBMS

- Query language = its own proprietary
- Optimizer = limited
- Runtime = its own proprietary
- External functions = yes; very useful in ML

- Query language = SQL
- Optimizer = full scale
- Runtime = efficient SQL query engine
- External functions = no

Outline

- Spark Review
- MapReduce and critique
- Fault Tolerance
- Hive (short)

Next lecture: $\boxed{\text{Parallel databases (Start Today)}}$

Parallel Databases

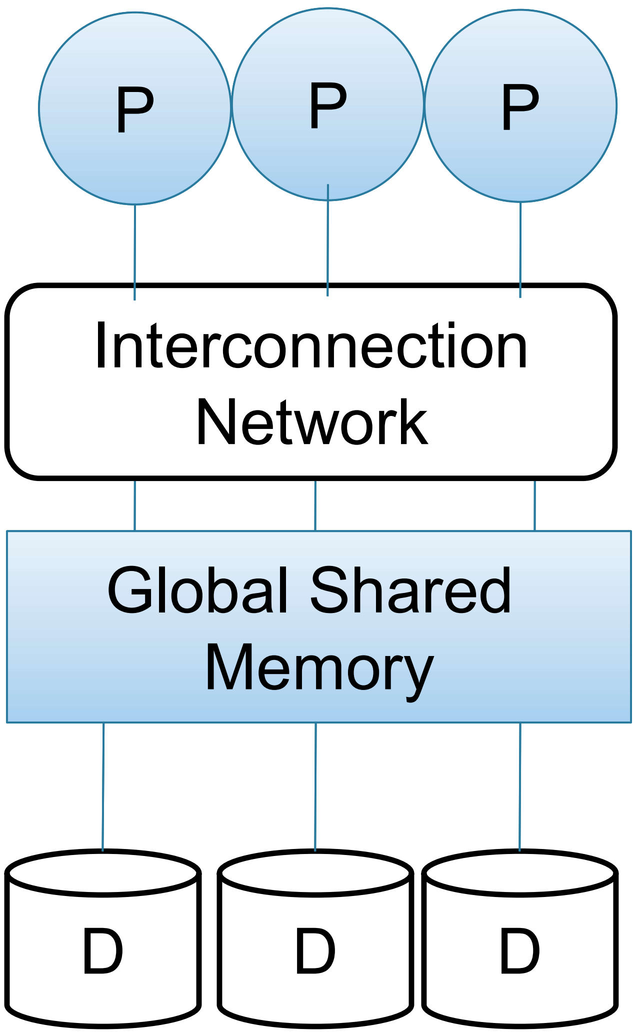
Outline

- $\boxed{\text{Basic notions}}$
- Distributed query processing algorithms (Start)
- Skew (will continue next lecture)

Architectures for Parallel Databases

- Shared memory
- Shared disk
- Shared nothing

Shared Memory

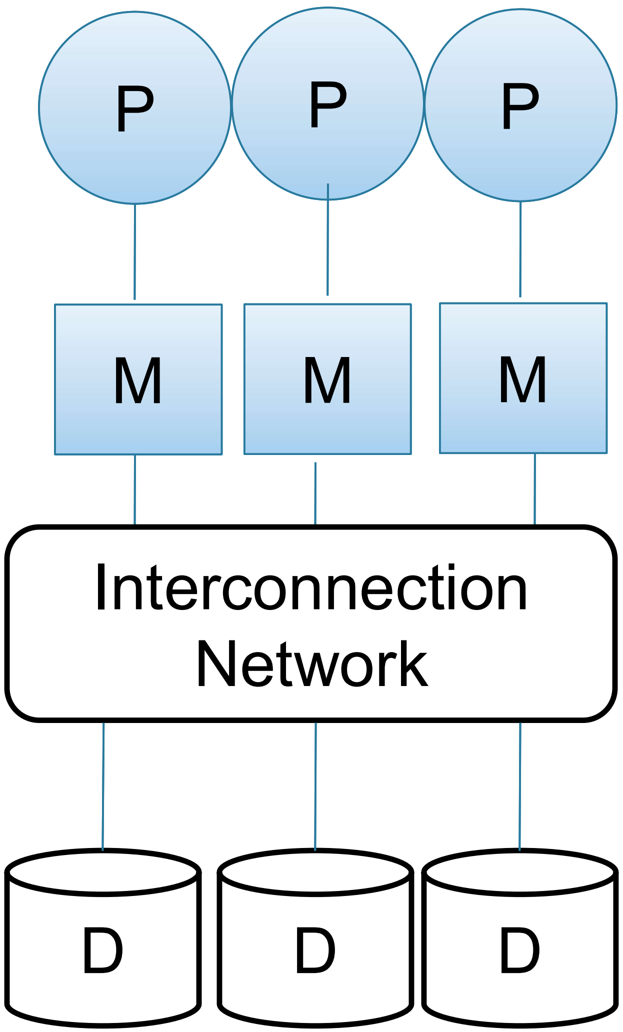


- SMP = symmetric multiprocessor
- Nodes share RAM and disk
- 10x … 100x processors

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

- Easy to use and program
- Expensive to scale

Shared Disk



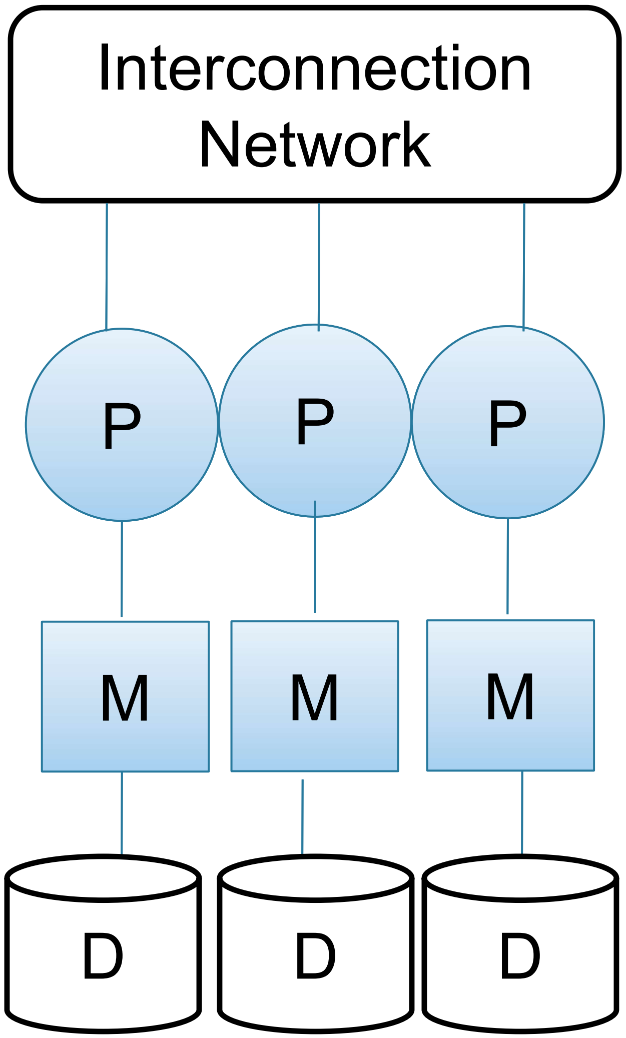
- All nodes access same disks
- 10x processors

- Example: Oracle

- No more memory contention

- Harder to program
- Still hard to scale

Shared Nothing



- Cluster of commodity machines
- Called "clusters" or "blade servers”
- Each machine: own memory & disk
- Up to x1000-x10000 nodes
- Example: redshift, spark, snowflake

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.

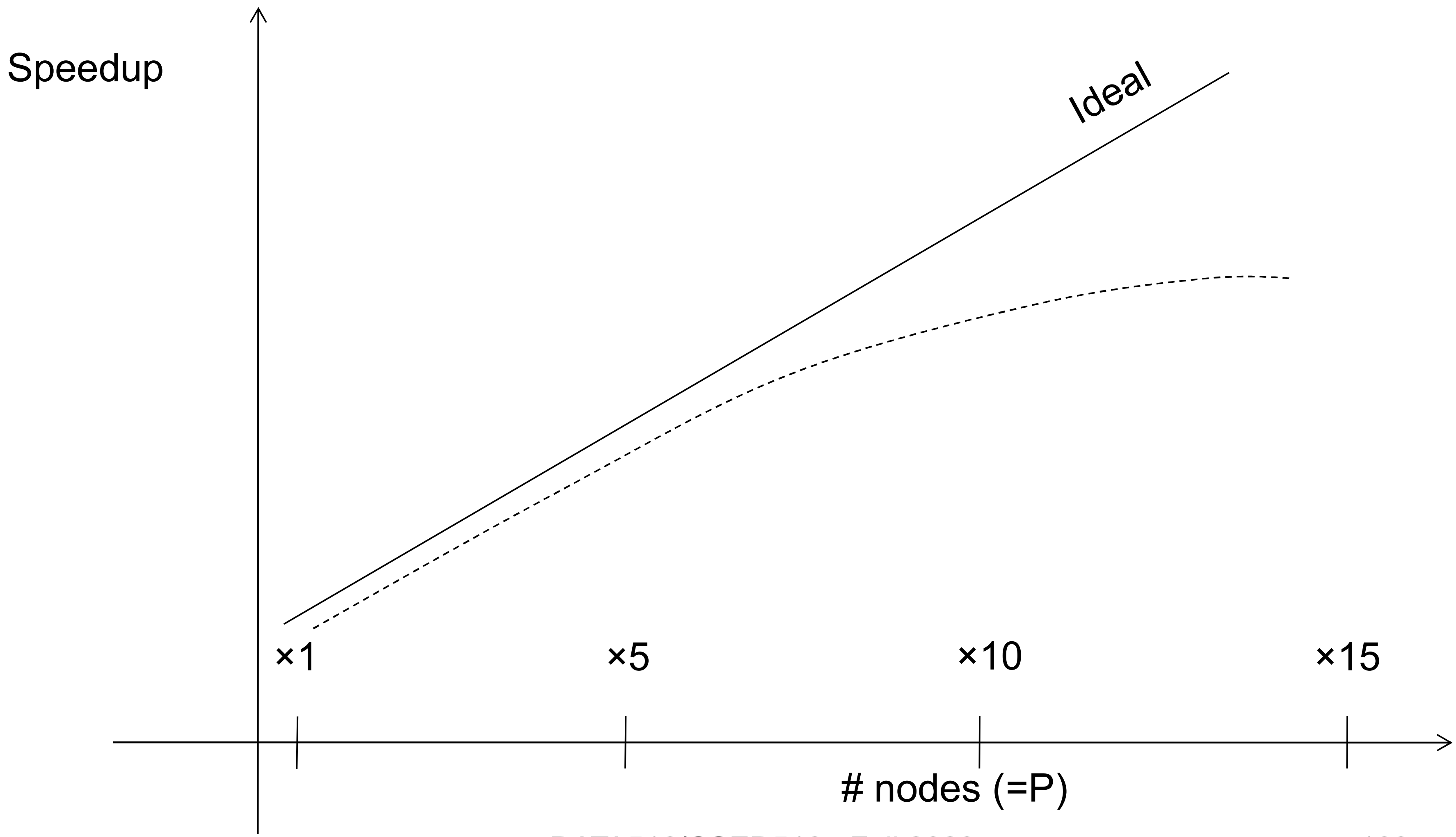
Performance Metrics

Nodes = processors = computers

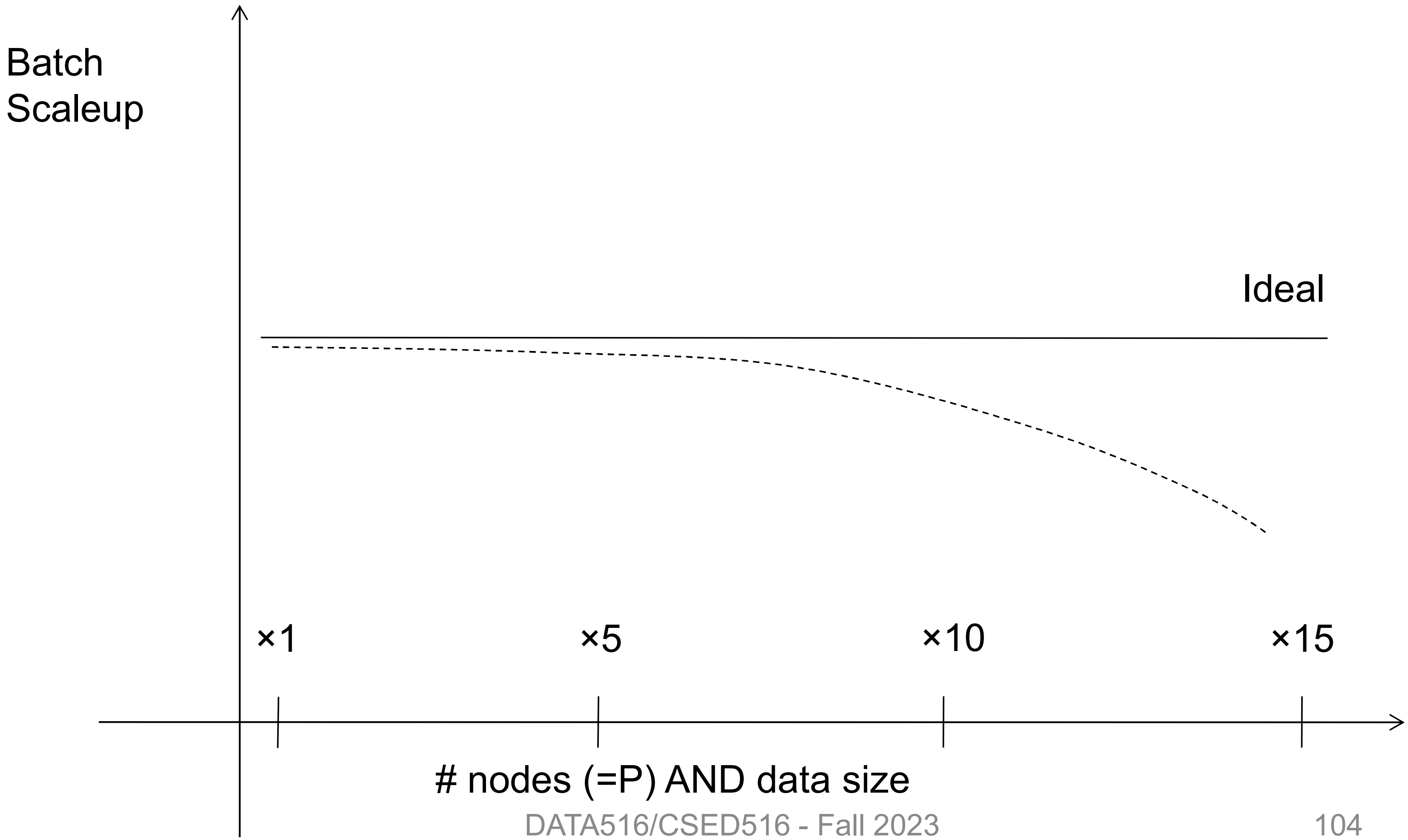
- Speed Up:
  - More nodes, same data ➔ higher speed
- Scale Up:
  - More nodes, more data ➔ same speed

Disclaimer: *Scale Up* is often mis-used as *Speed Up*

Linear v.s. Non-linear Speedup



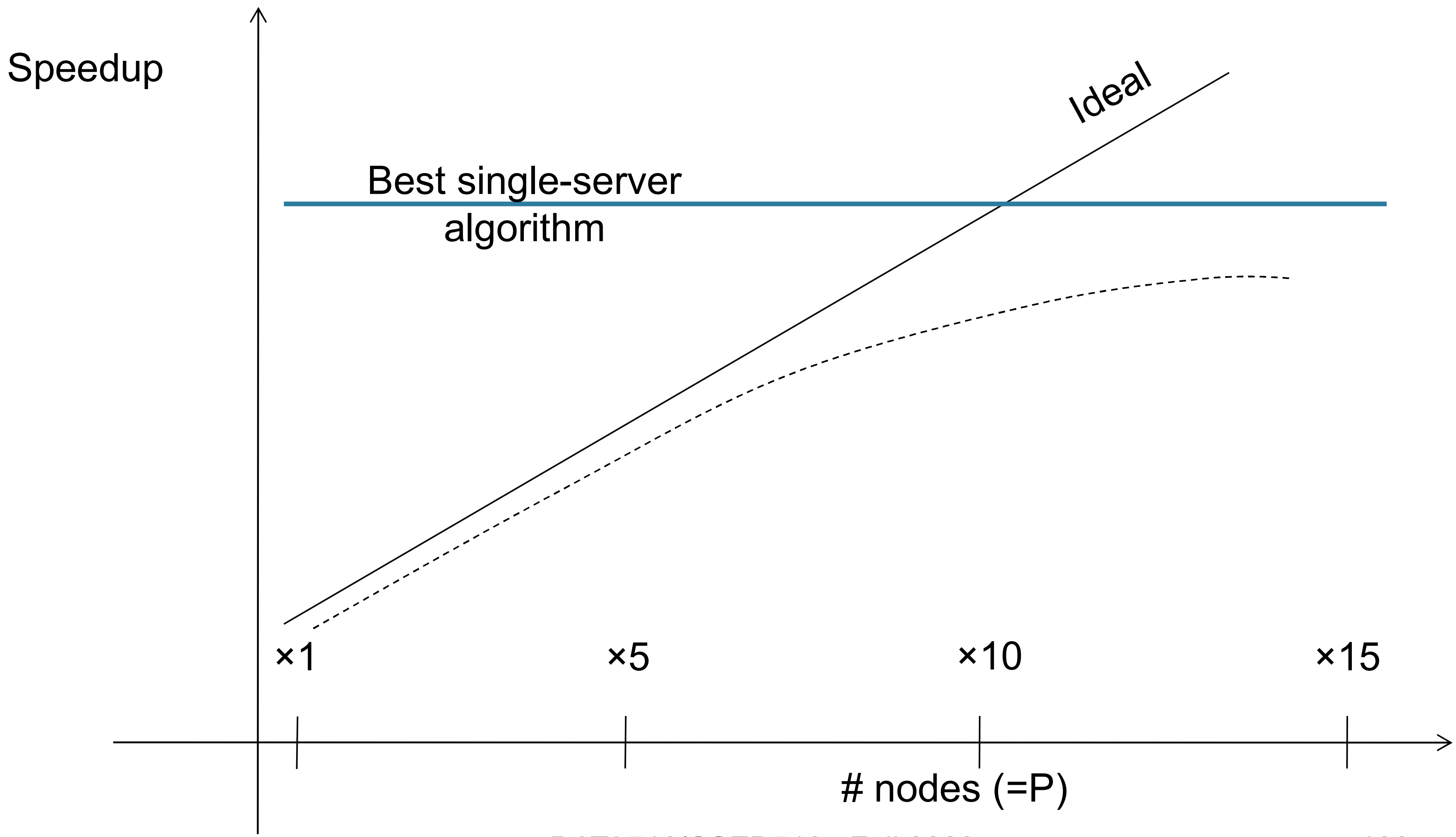
Linear v.s. Non-linear Scaleup



Why Sub-linear?

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

“Scalability but at what cost?”



Discussion

Parallel/distributed data processing:

- Scales up* to more data:
  - More servers can hold more data
- Speedup w/ number of nodes:
  - Harder to achieve
  - But can get there in with more nodes/future research

* “Scale up” is often used informally, like here

Outline

- Basic notions
- Distributed query processing algorithms
- Skew (will continue next lecture)

Distributed Query Processing Algorithms

Horizontal Data Partitioning

Table

R

sid	name	…	…

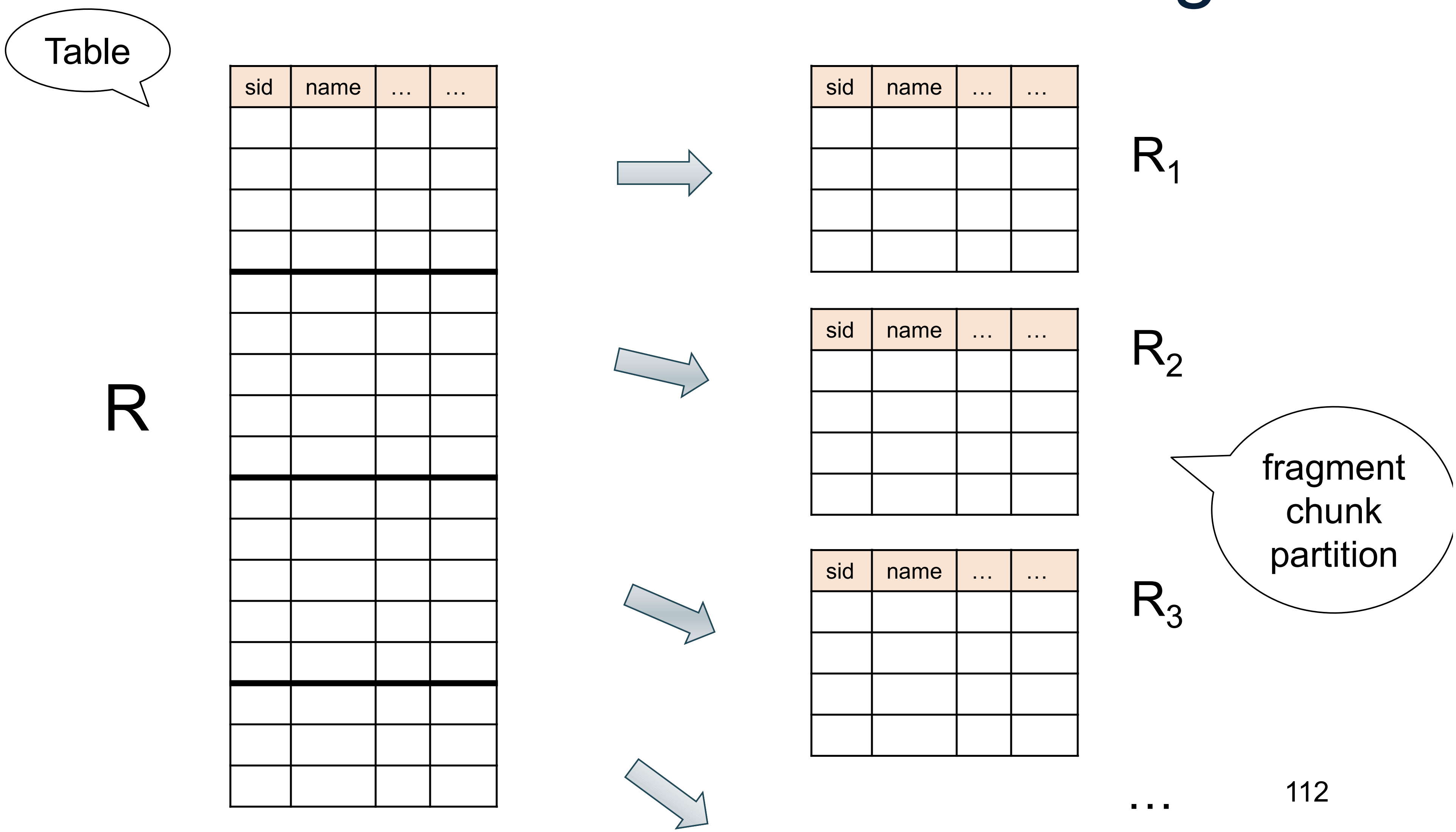
Horizontal Data Partitioning

Table

R

sid	name	…	…

Horizontal Data Partitioning



Horizontal Data Partitioning

- Block Partition, a.k.a. Round Robin:
  - 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 $v_{i-1} < t.A < v_i$

Notations

p = number of servers (nodes) that hold the chunks

When a relation R is distributed to p servers,
we draw the picture like this:

R_1 R_2 R_P

Here R_1 is the fragment of R stored on server 1, etc

$$R = R_1 \cup R_2 \cup \cdots \cup R_P$$

Uniform Load and Skew

- $|R| = N$ tuples, then $|R_1| + |R_2| + \ldots + |R_p| = N$
- We say the load is uniform when:

  $$|R_1| \approx |R_2| \approx \ldots \approx |R_p| \approx N/p$$

- Skew means that some load is much larger:

  $$\max_i |R_i| >> N/p$$

We design algorithms for uniform load, discuss skew later

Parallel Algorithm

- Selection σ
- Join ⋈
- Group by γ

Parallel Selection

Data: $R(\underline{K}, A, B, C)$
Query: $\sigma_{A=v}(R)$, or $\sigma_{v1<A<v2}(R)$

- Block partitioned:
- Hash partitioned:
- Range partitioned:

Parallel Selection

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

Query: $\sigma_{A=v}(R)$, or $\sigma_{v1<A<v2}(R)$

- Block partitioned:
  - All servers need to scan
- Hash partitioned:
- Range partitioned:

Parallel Selection

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Query: $\sigma_{A=v}(R)$, or $\sigma_{v1<A<v2}(R)$

- Block partitioned:
  - All servers need to scan
- Hash partitioned:
  - Point query: only one server needs to scan
  - Range query: all servers need to scan
- Range partitioned:

Parallel Selection

Data: R(<u>K</u>, A, B, C)

Query: $\sigma_{A=v}(R)$, or $\sigma_{v1<A<v2}(R)$

- Block partitioned:
  - All servers need to scan
- Hash partitioned:
  - Point query: only one server needs to scan
  - Range query: all servers need to scan
- Range partitioned:
  - Only some servers need to scan

Parallel GroupBy

Data: R(<u>K</u>, 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 or hash-partitioned on K

Parallel GroupBy

Data: R(<u>K</u>, A, B, C)

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

Discuss in class how to compute in each case:

- R is hash-partitioned on A
  - Each server i computes locally $\gamma_{A,sum(C)}(R_i)$
- R is block-partitioned or hash-partitioned on K

Parallel GroupBy

Data: R(<u>K</u>, A, B, C)

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

Discuss in class how to compute in each case:

- R is hash-partitioned on A
  - Each server i computes locally $\gamma_{A,sum(C)}(R_i)$
- R is block-partitioned or hash-partitioned on K
  - Need to reshuffle data on A first (next slide)
  - Then compute locally $\gamma_{A,sum(C)}(R_i)$

Basic Parallel GroupBy

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

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

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

R_1 R_2 . . . R_P

Basic Parallel GroupBy

Data: R(<u>K</u>, A, B, C)

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

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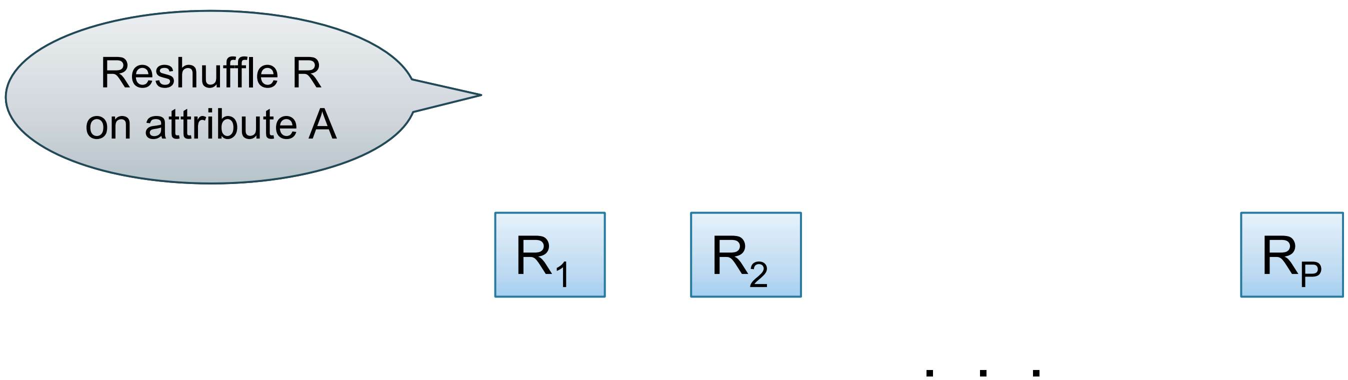

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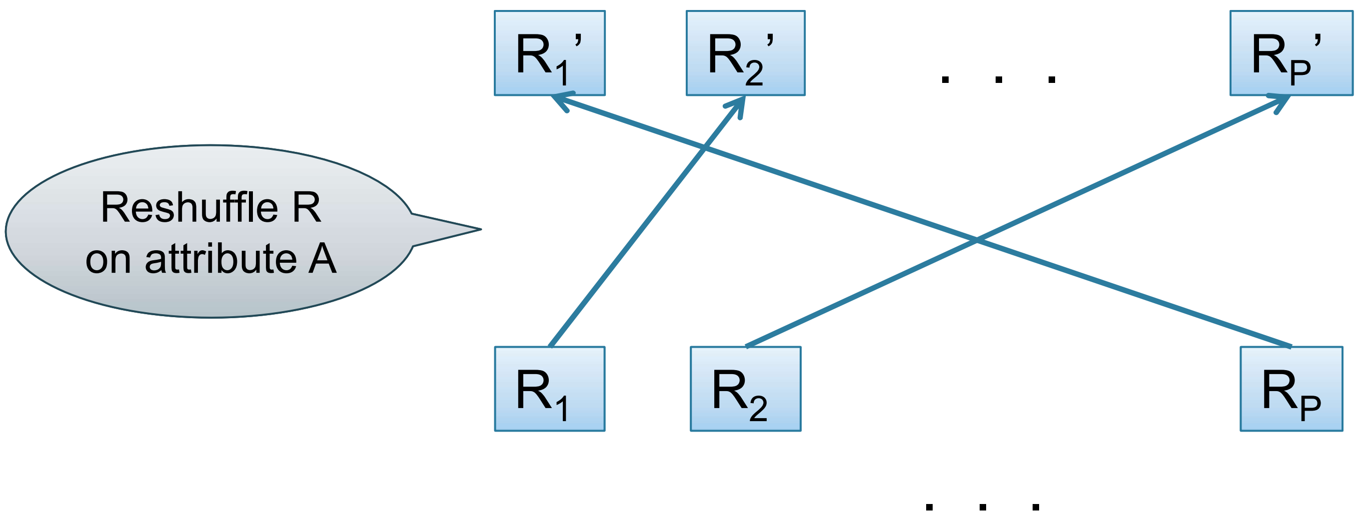

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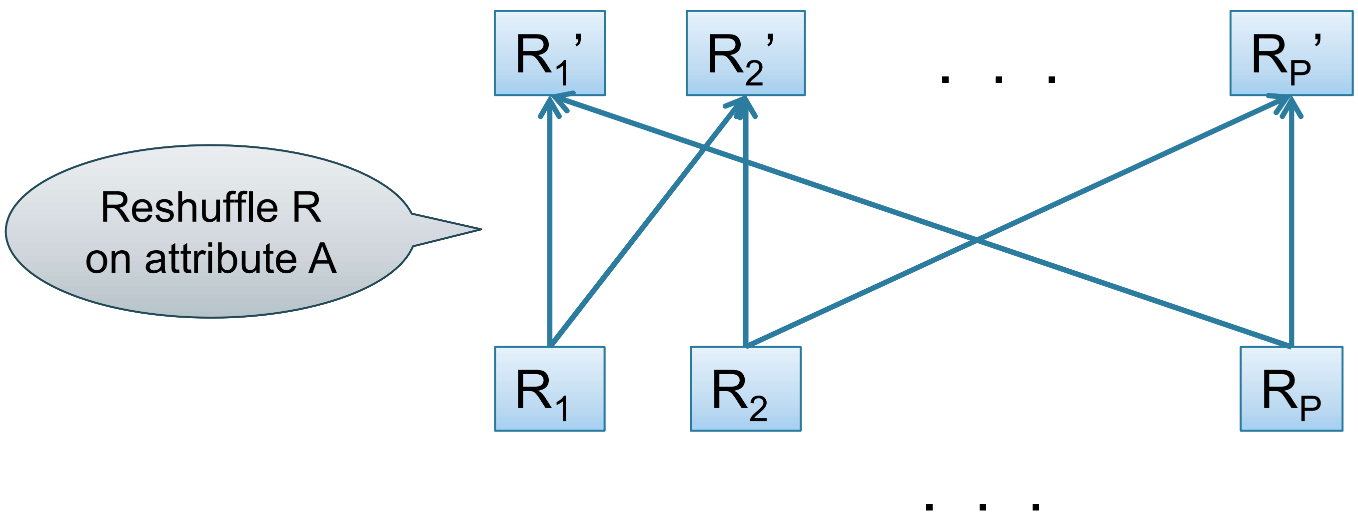

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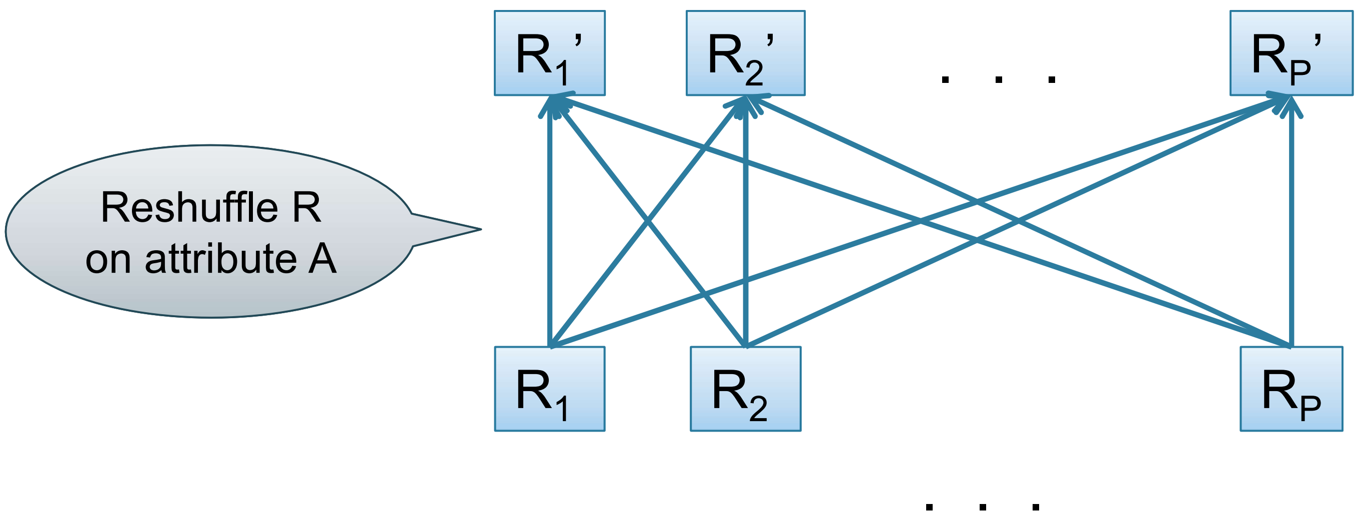

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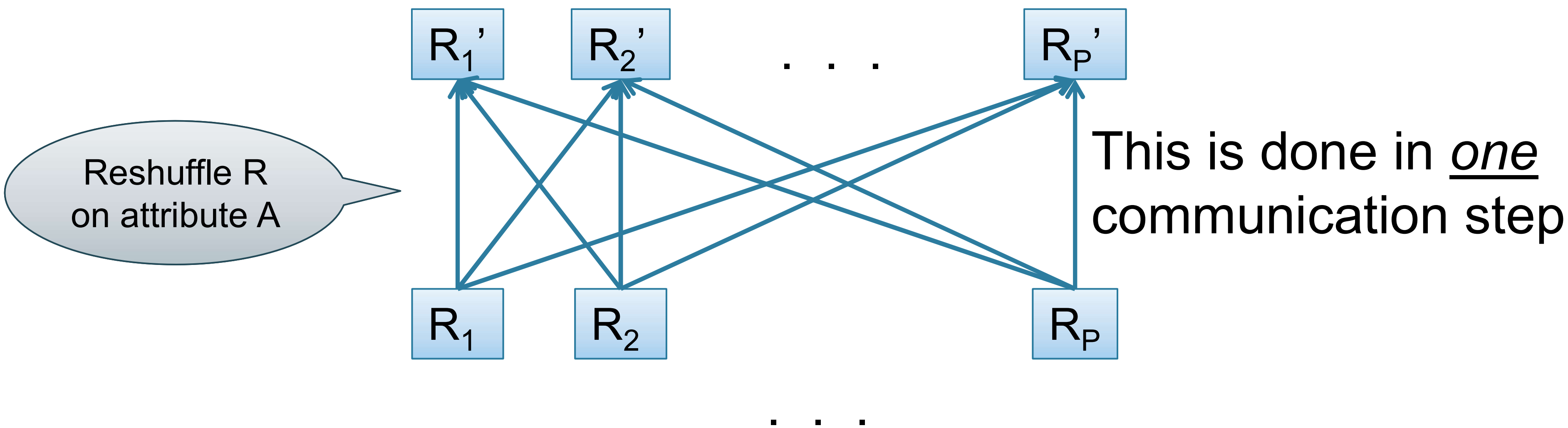

Reshuffling

- Nodes send data over the network
- Many-many communications possible
- Throughput:
  – Better than disk
  – Worse than main memory

Basic Parallel GroupBy

Data: R(<u>K</u>, A, B, C)

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

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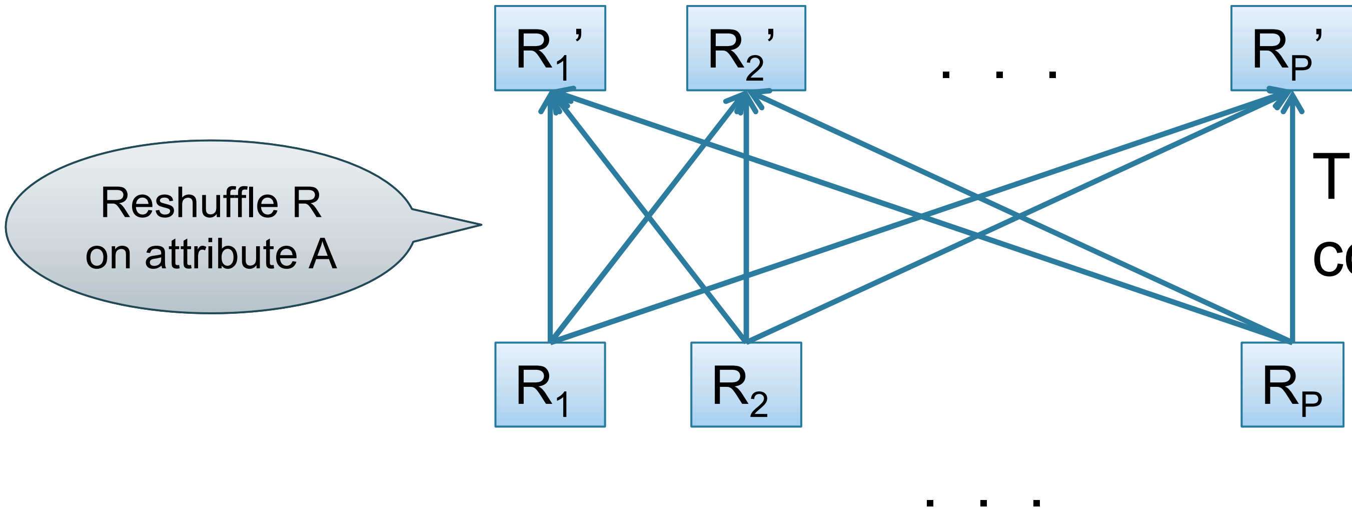

This is done in *one* communication step

Can you think of an optimization?

GroupBy/Union Commutativity

	city	…	qant
	Seattle		10
	LA		20
	Seattle		30
	NY		40

	city	…	qant
	LA		22
	NY		33
	LA		44
	Austin		55

	city	…	qant
	Seattle		66
	LA		77
	NY		88
	LA		99

```
SELECT city, sum(quant)
FROM R
GROUP BY city
```

GroupBy/Union Commutativity

	city	…	qant
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Q: What is sum for Seattle?

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GroupBy/Union Commutativity

	city	…	qant
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	LA		20
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Q: What is sum for Seattle?
A: 106

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GroupBy/Union Commutativity

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	LA		20
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	NY		40

Sum here = 40

Q: What is sum for Seattle?
A: 106

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```
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	city	…	qant
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	NY		88
	LA		99

Sum here = 66

GroupBy/Union Commutativity

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	Seattle		**30**
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$$\gamma_{city,sum(q)}(R_1 \cup R_2 \cup R_3) =$$

GroupBy/Union Commutativity

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Sum here = 66

$$\gamma_{city,sum(q)}(R_1 \cup R_2 \cup R_3) =$$

$$= \gamma_{city,sum(q)}\left(\gamma_{city,sum(q)}(R_1) \cup \gamma_{city,sum(q)}(R_2) \cup \gamma_{city,sum(q)}(R_3)\right)$$

Basic Parallel GroupBy

Data: R(<u>K</u>, A, B, C)
Query: $\gamma_{A,sum(C)}(R)$

Basic Parallel GroupBy

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Step 0: [Optimization] each server i computes local group-by:
$$T_i = \gamma_{A,sum(C)}(R_i)$$

Basic Parallel GroupBy

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Step 0: [Optimization] each server i computes local group-by:
$$T_i = \gamma_{A,sum(C)}(R_i)$$

Step 1: partitions tuples in T_i using hash function h(A):
$$T_{i,1}, T_{i,2}, \ldots, T_{i,p}$$
then send fragment $T_{i,j}$ to server j

Basic Parallel GroupBy

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

Step 0: [Optimization] each server i computes local group-by:

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Step 1: partitions tuples in T_i using hash function h(A):

$$T_{i,1}, T_{i,2}, \ldots, T_{i,p}$$

then send fragment $T_{i,j}$ to server j

Step 2: receive fragments, union them, then group-by

$$R_j' = T_{1,j} \cup \ldots \cup T_{p,j}$$

$$Answer_j = \gamma_{A,\ sum(C)}\ (R_j')$$

Pushing Aggregates Past Union

Which other rules can we push past union?

- Sum?
- Count?
- Avg?
- Max?
- Median?

Pushing Aggregates Past Union

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- Sum?
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Distributive	Algebraic	Holistic
$\text{sum}(a_1+a_2+\ldots+a_9)=$ $\text{sum}(\text{sum}(a_1+a_2+a_3)+$ $\text{sum}(a_4+a_5+a_6)+$ $\text{sum}(a_7+a_8+a_9))$	avg(B) = sum(B)/count(B)	median(B)

Example Query with Group By

```
SELECT a, sum(b) as sb
FROM R WHERE c > 0
GROUP BY a
```

Example Query with Group By

```
SELECT a, sum(b) as sb
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```

$$\gamma_{a,\ sum(b) \rightarrow sb}$$

$$\sigma_{c>0}$$

$$R$$

Example Query with Group By

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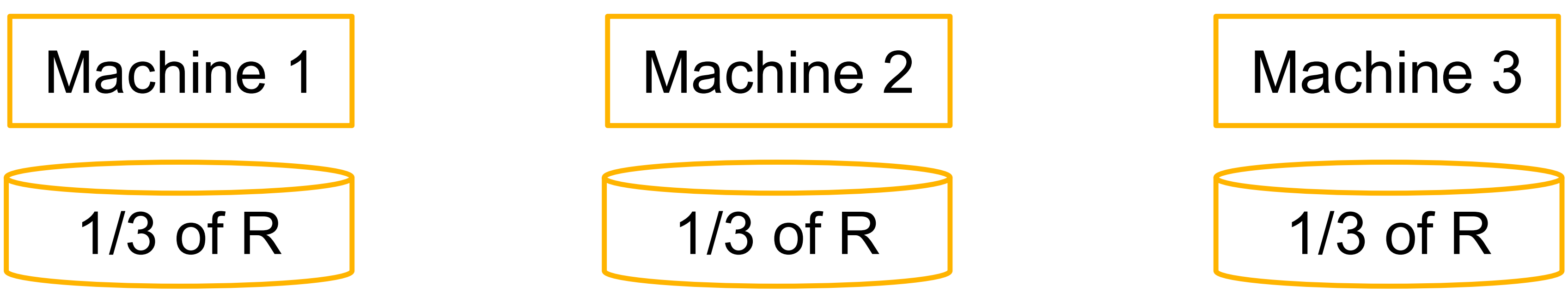
$\gamma_{\text{a, sum(b)}\rightarrow\text{sb}}$

$\sigma_{c>0}$

R



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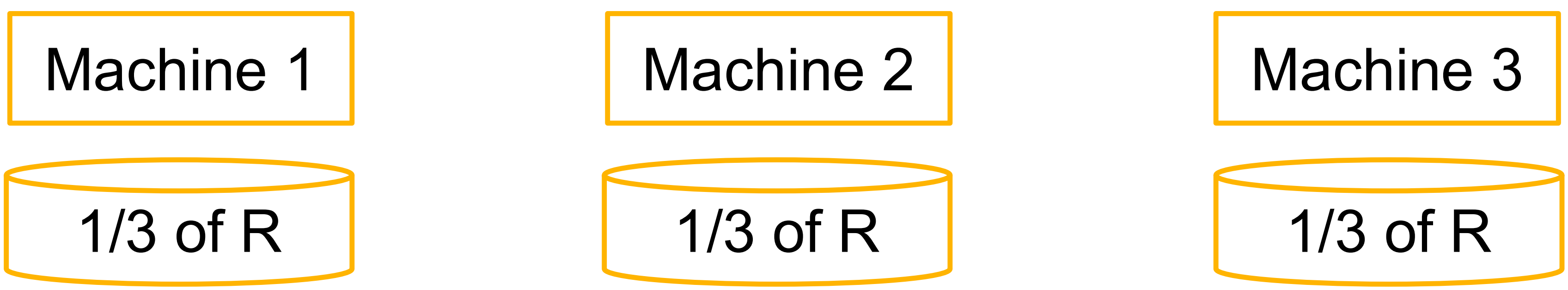

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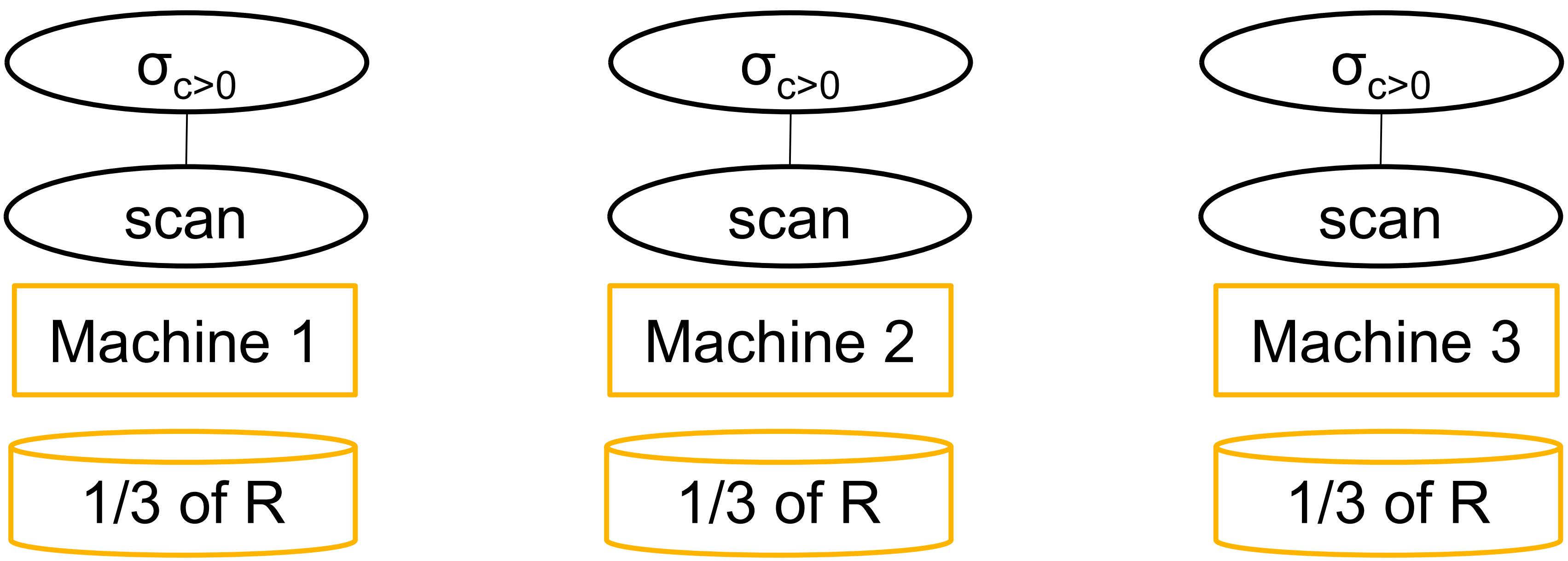

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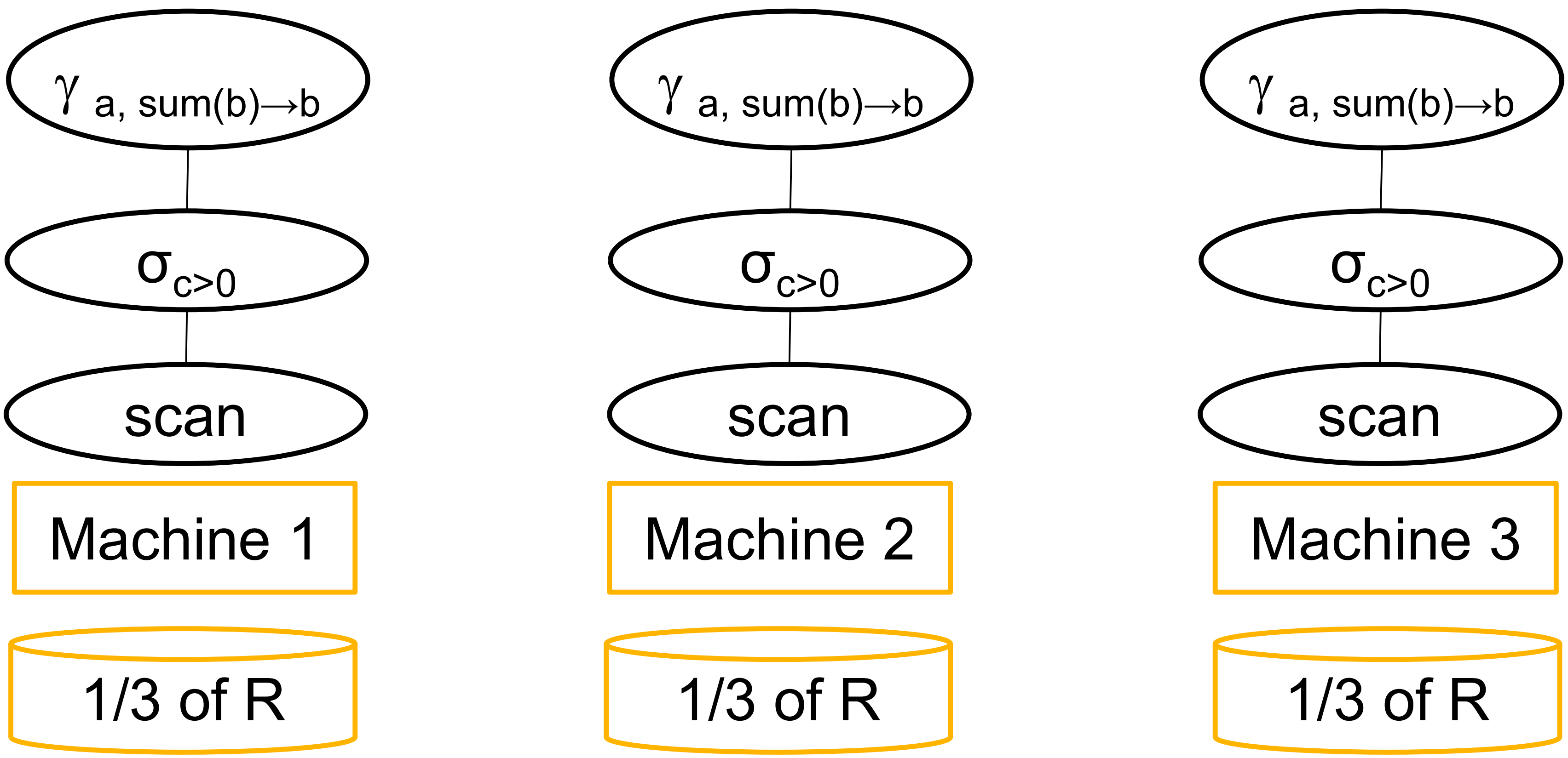

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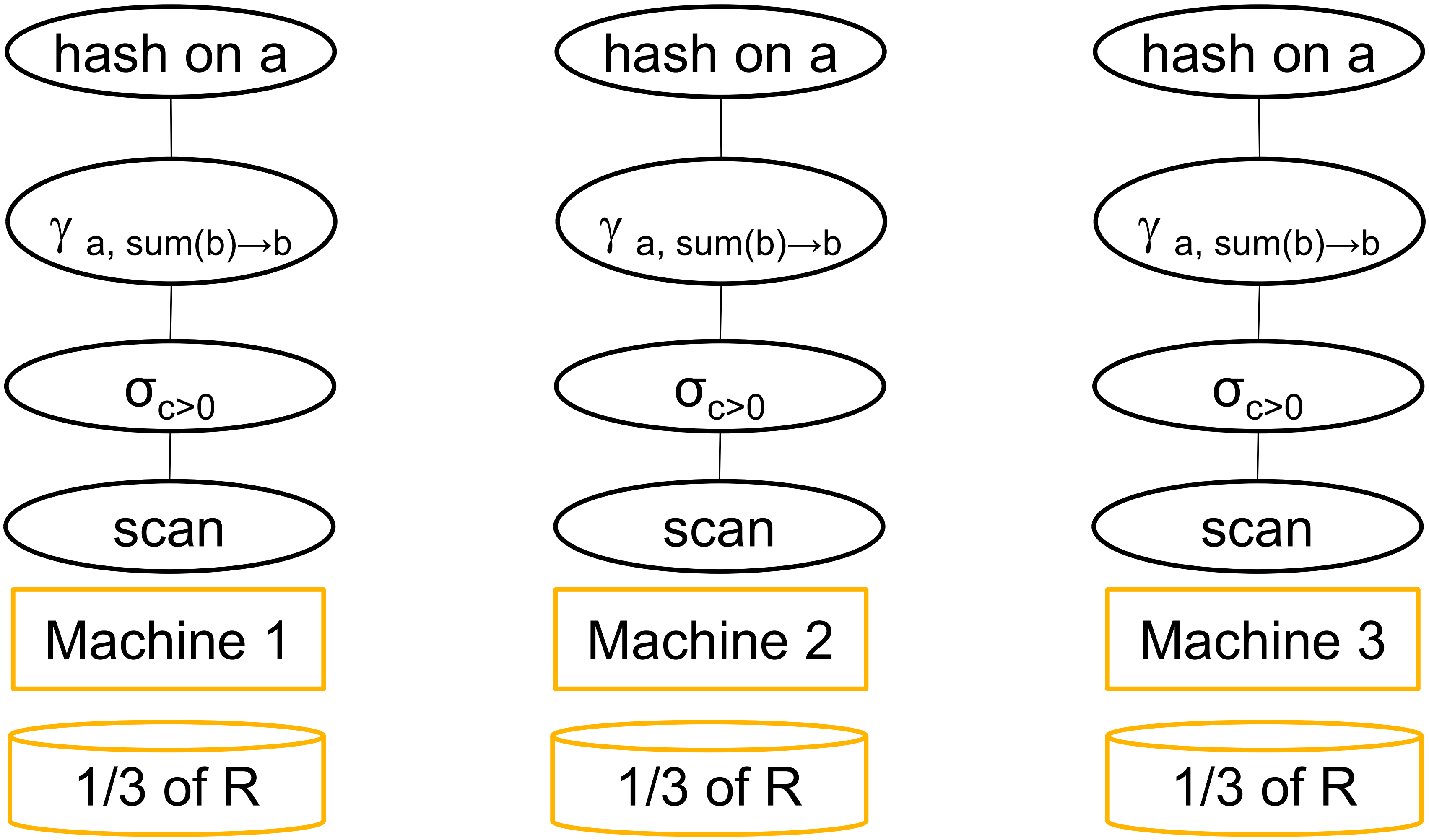
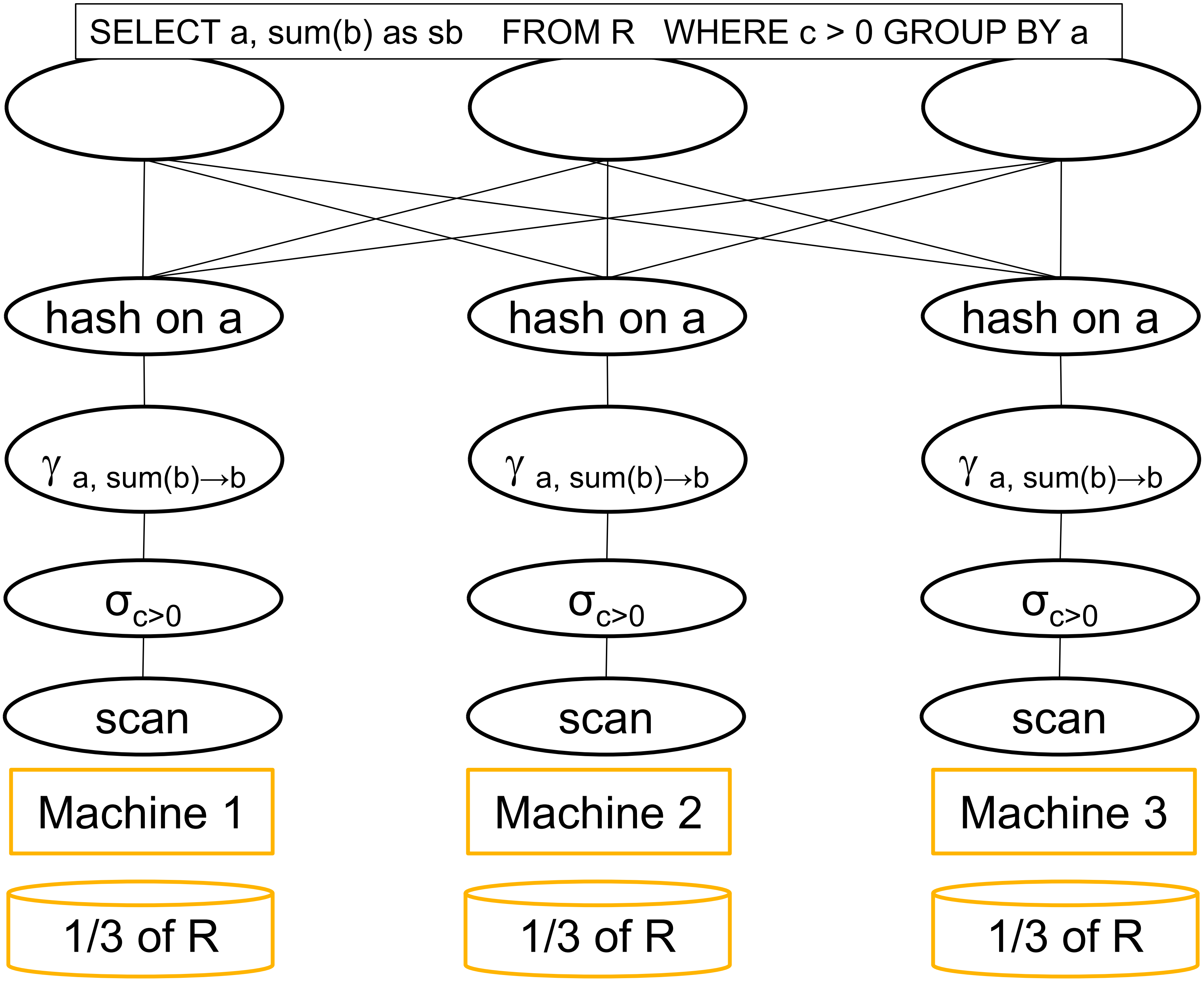
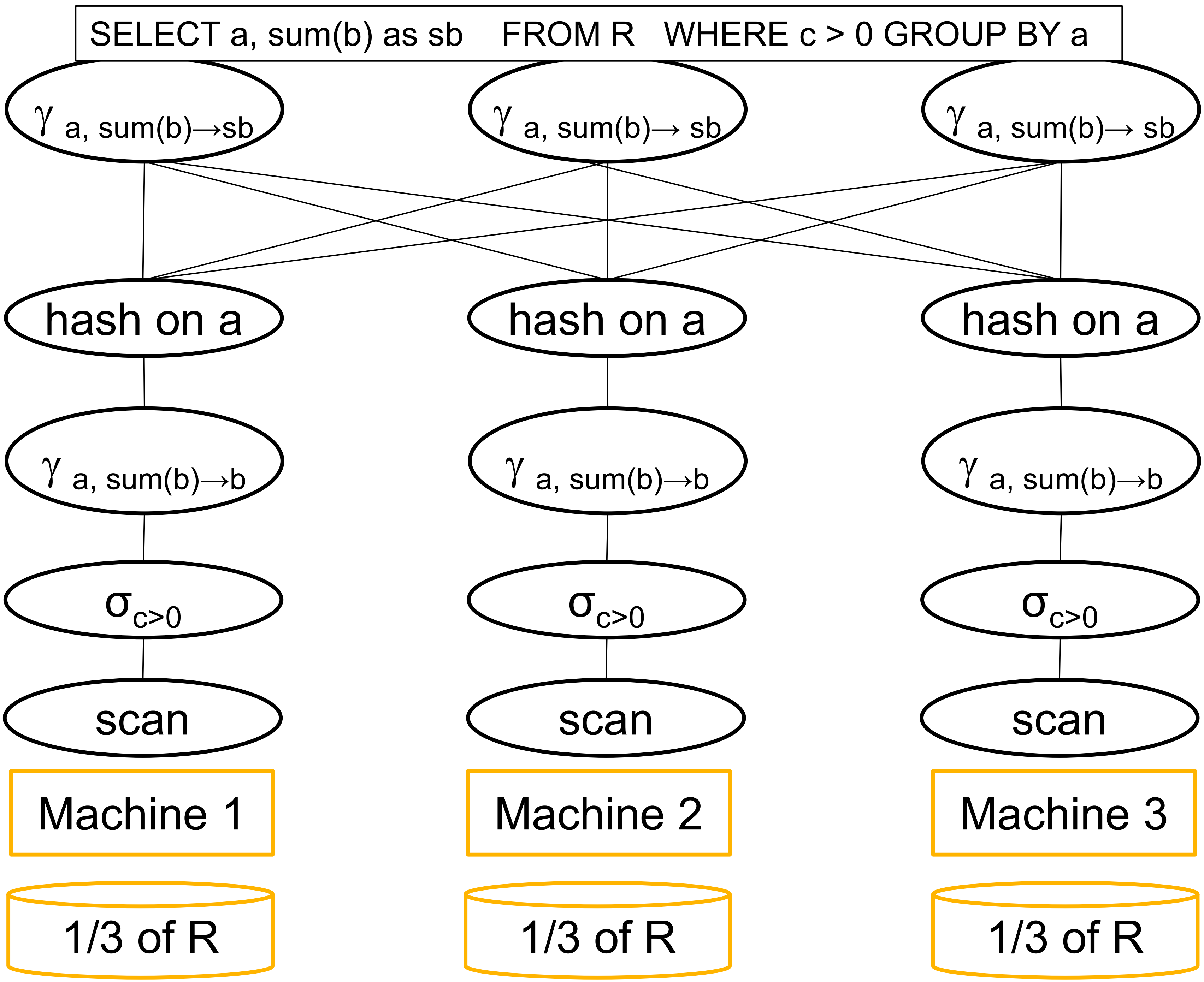




SELECT a, sum(b) as sb FROM R WHERE c > 0 GROUP BY a
hash on a
hash on a
hash on a
$\gamma_{a, sum(b) \to b}$
$\gamma_{a, sum(b) \to b}$
$\gamma_{a, sum(b) \to b}$
$\sigma_{c>0}$
$\sigma_{c>0}$
$\sigma_{c>0}$
scan
scan
scan
Machine 1
Machine 2
Machine 3
1/3 of R
1/3 of R
1/3 of R



SELECT a, sum(b) as sb FROM R WHERE c > 0 GROUP BY a
γ a, sum(b)→sb
γ a, sum(b)→ sb
γ a, sum(b)→ sb
hash on a
hash on a
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γ a, sum(b)→b
σc>0
σc>0
σc>0
scan
scan
scan
Machine 1
Machine 2
Machine 3
1/3 of R
1/3 of R
1/3 of R

Speedup and Scaleup

Consider the query $\gamma_{A,sum(C)}(R)$
Assume the local runtime for group-by is linear O(|R|)

If we double number of nodes P, what is the runtime?

If we double both P and size of R, what is the runtime?

Speedup and Scaleup

Consider the query $\gamma_{A,sum(C)}(R)$
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- Half (chunk sizes become ½)

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- Same (chunk sizes remain the same)

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- Same (chunk sizes remain the same)

But only if the data is without skew!