DATA516/CSED516 Scalable Data Systems and Algorithms

Lecture 5

Parallel Query Execution

Announcements

- Project proposals were due on Friday
- Small review assignment was due today
- HW3 is posted, due on Nov. 15

Outline

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

Distributed/Parallel Query Processing

Parallel DBs since the 80s

Usually limited to small number of servers

Why?

New trend: cloud databases.
E.g. Snowflake

Distributed/Parallel Query Processing

Parallel DBs since the 80s

Usually limited to small number of servers

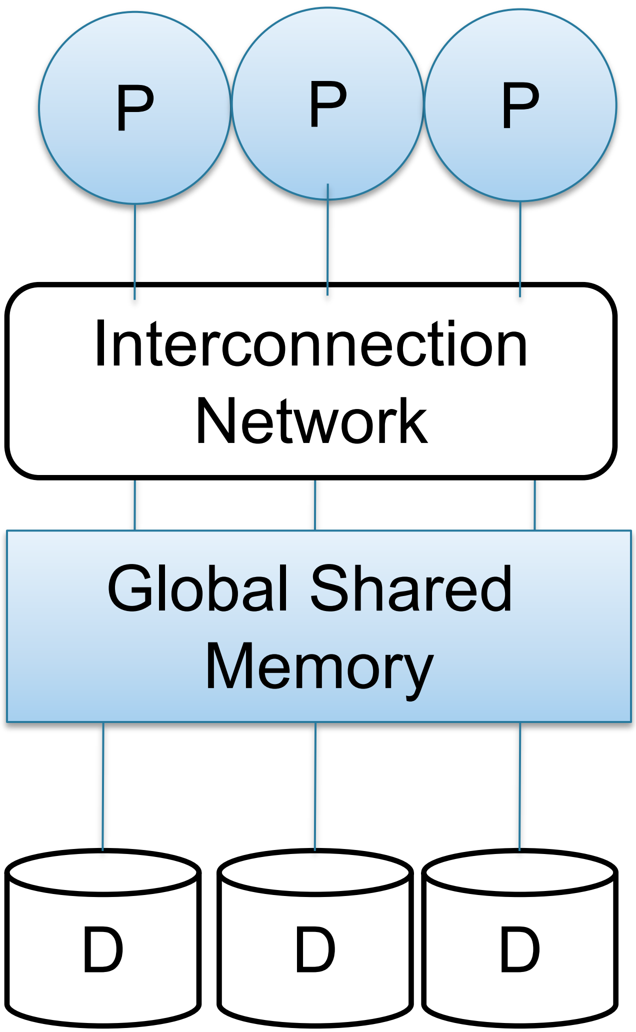
Why? Transactions!

New trend: cloud databases.
E.g. Snowflake

Architectures for Parallel Databases

- Shared memory
- Shared disk
- Shared nothing

Shared Memory

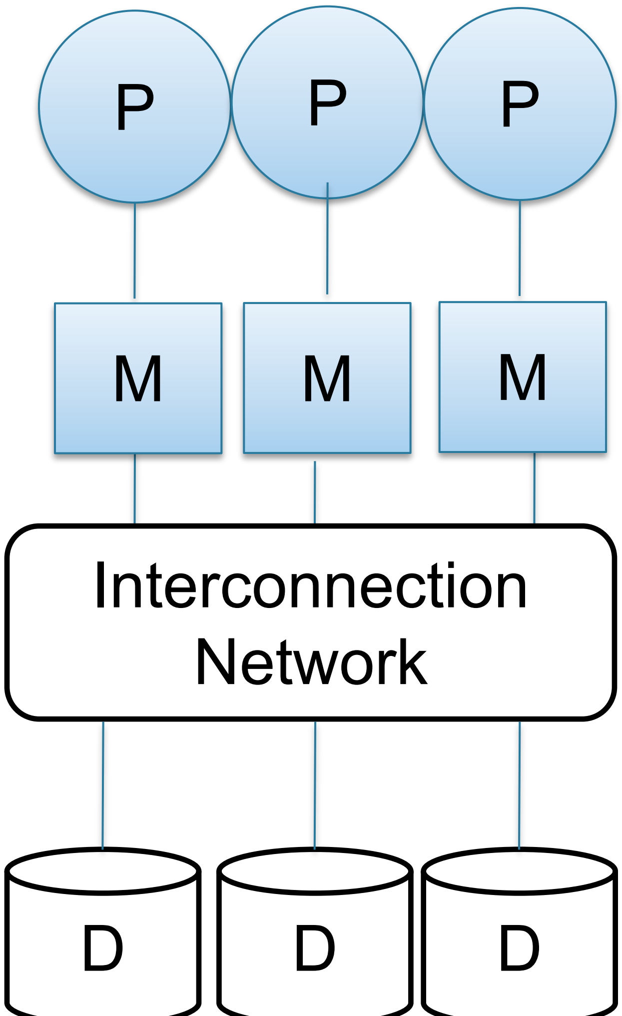


- SMP = symmetric multiprocessor
- Nodes share RAM and disk
- 10x … 100x processors

- 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



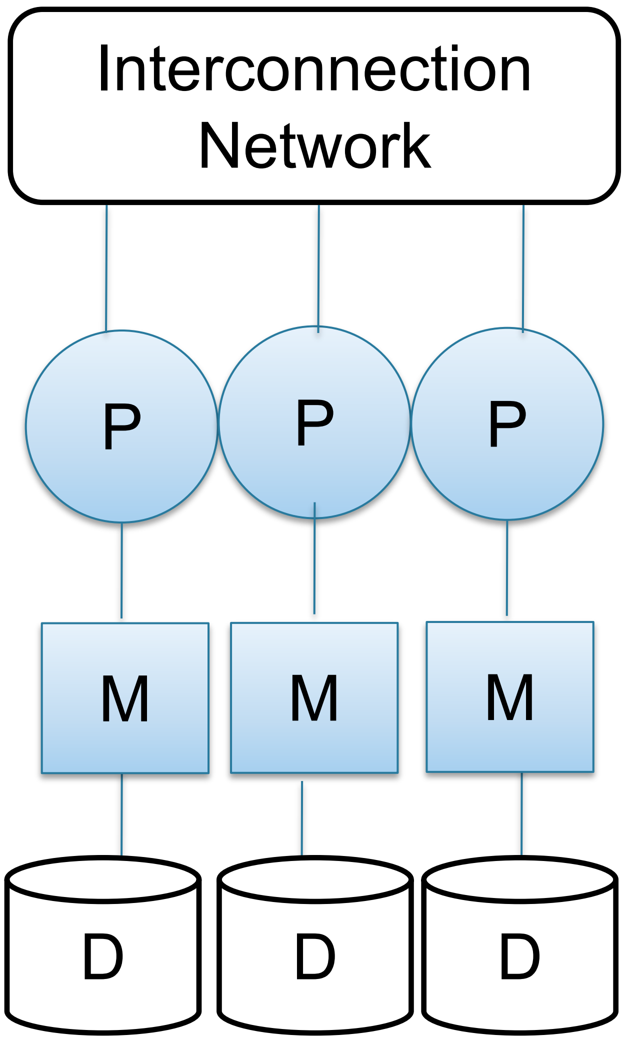
- All nodes access same disks
- 10x processors

- 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.

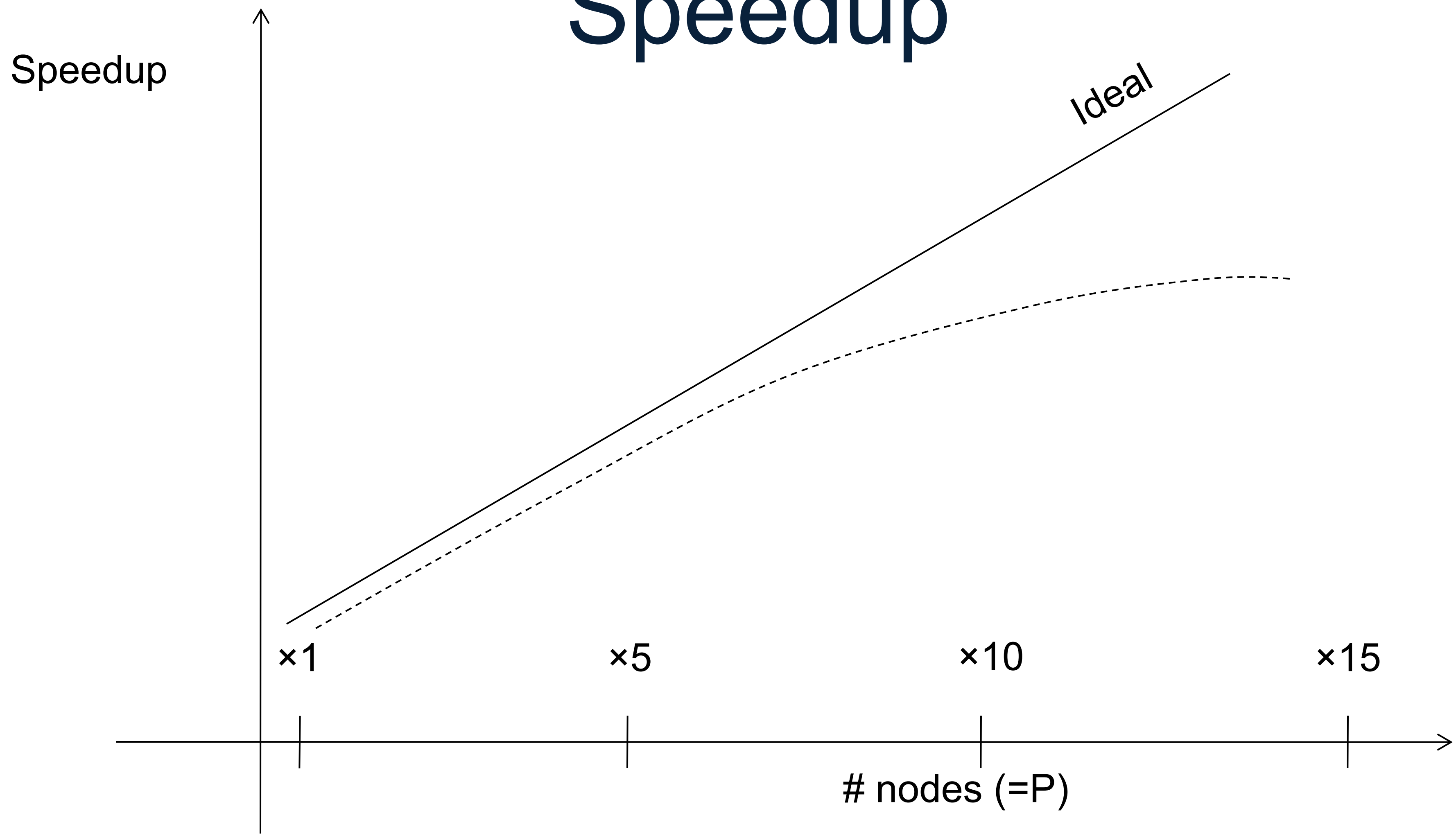
Performance Metrics

Nodes = processors = computers

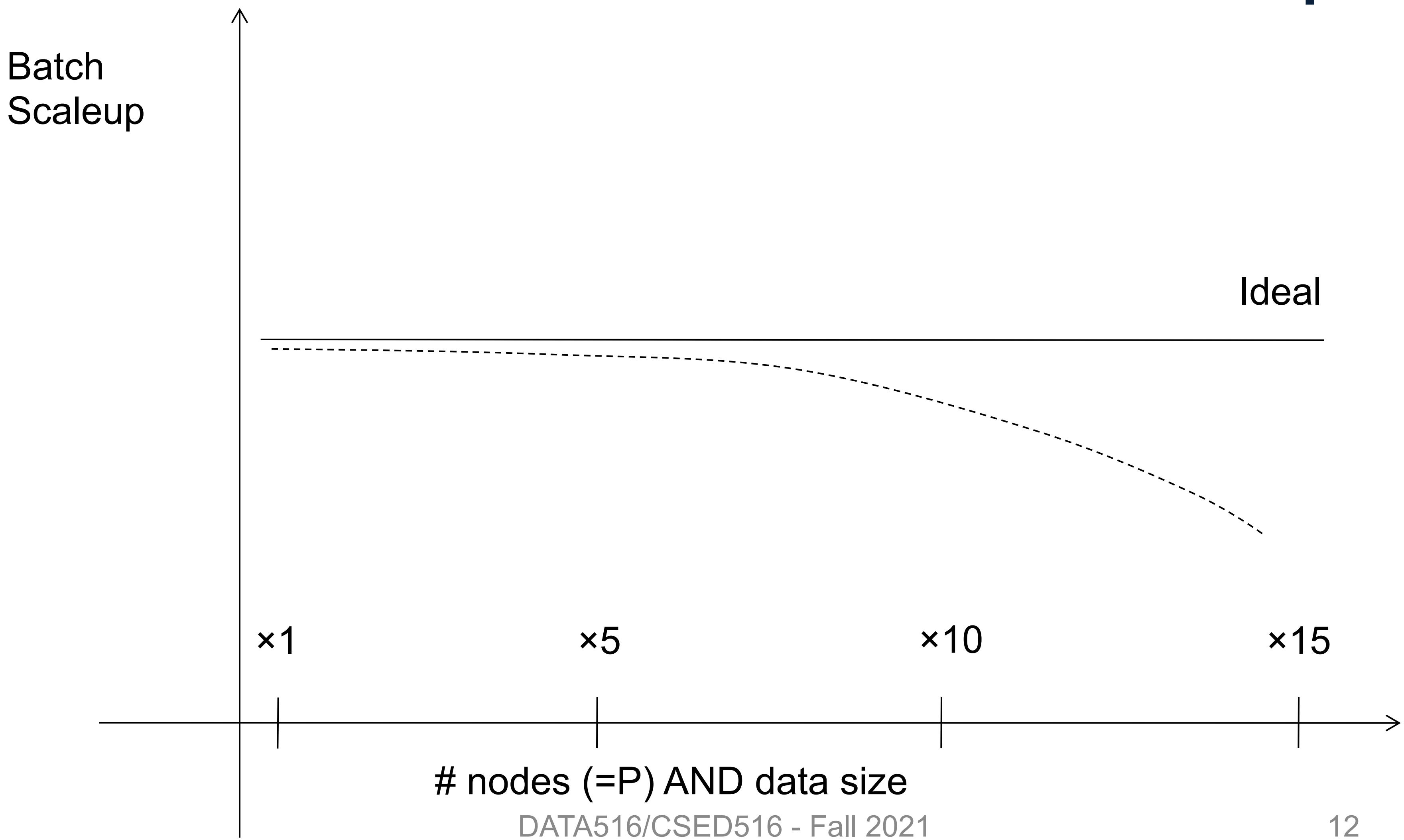
- Speedup:
  - More nodes, same data ➔ higher speed
- Scaleup:
  - More nodes, more data ➔ same speed

Warning: sometimes *Scaleup* is used to mean *Speedup*

Linear v.s. Non-linear Speedup



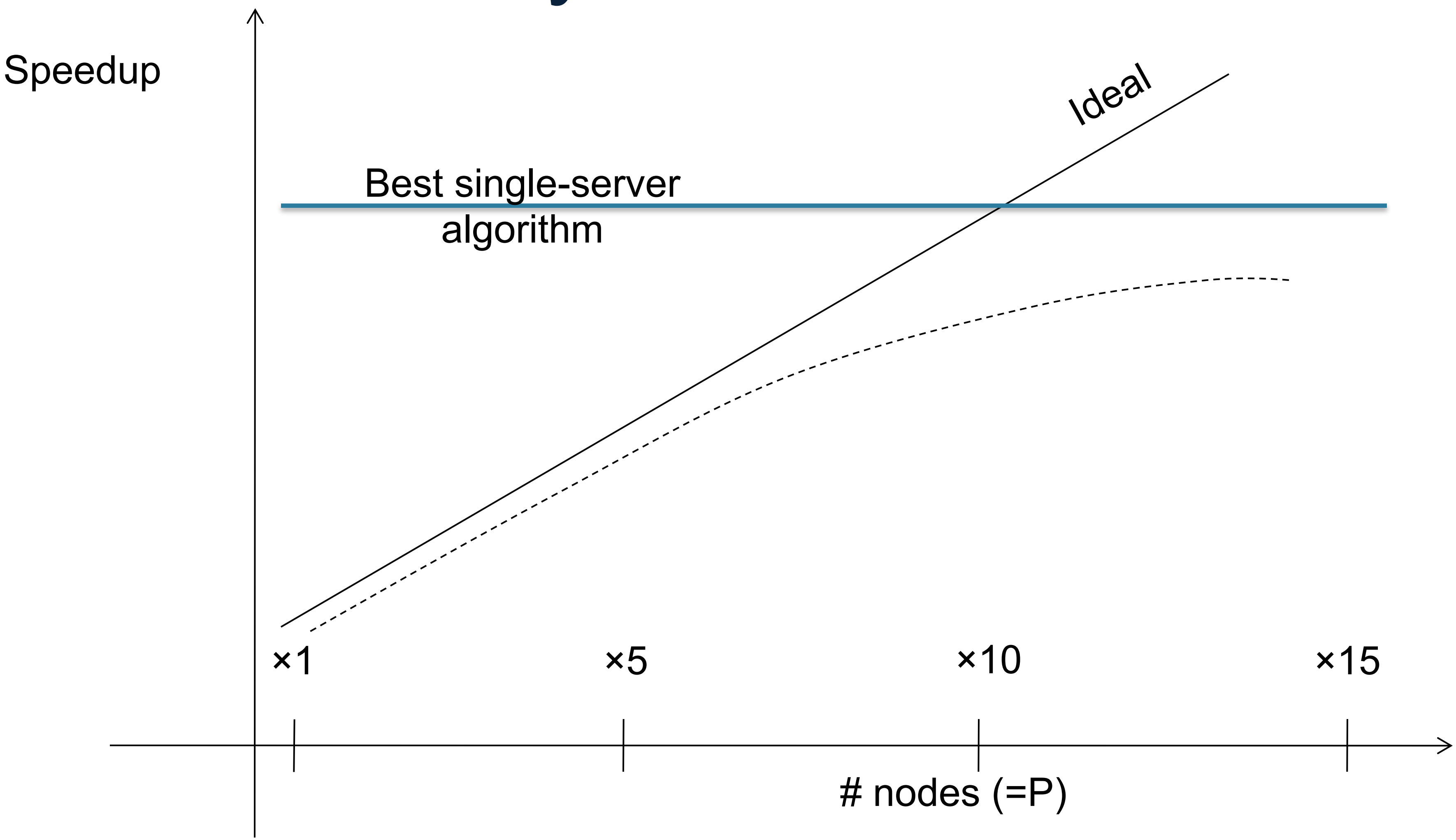
Linear v.s. Non-linear Scaleup



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 with very large p

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

More Discussion

New terminology:

- Scale-up = speedup w/ shared memory
- Scale-out = more data w/ more nodes

Acknowledges that speed comes from shared memory, capacity for large data comes from shared nothing

Outline

- Basic notions
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Distributed Query Processing Algorithms

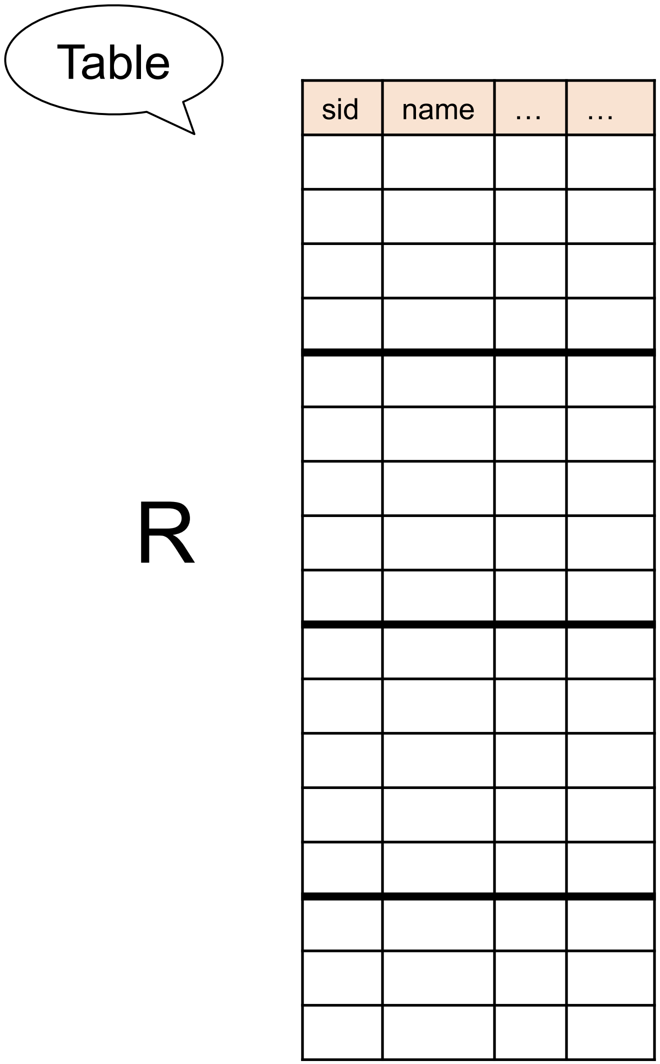
Horizontal Data Partitioning

Table

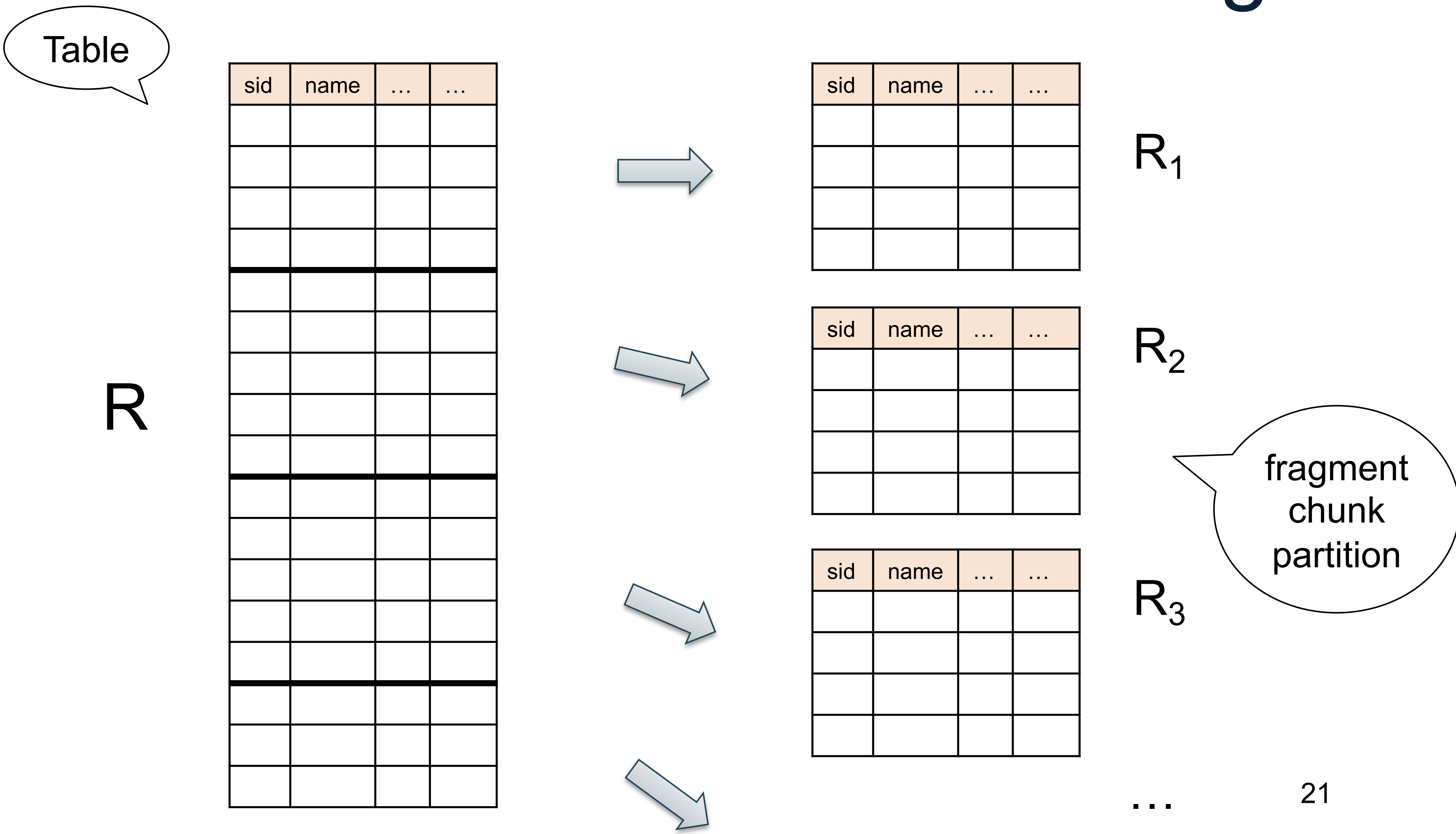
R

sid	name	…	…

Horizontal Data Partitioning



Horizontal Data Partitioning



Horizontal Data Partitioning

- Block Partition, a.k.a. Round Robin:
  - 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
- 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:

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

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

- Range partitioned:

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  - 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

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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:
  - 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

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  - 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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Reshuffle R
on attribute A

R_1 R_2 . . . R_P

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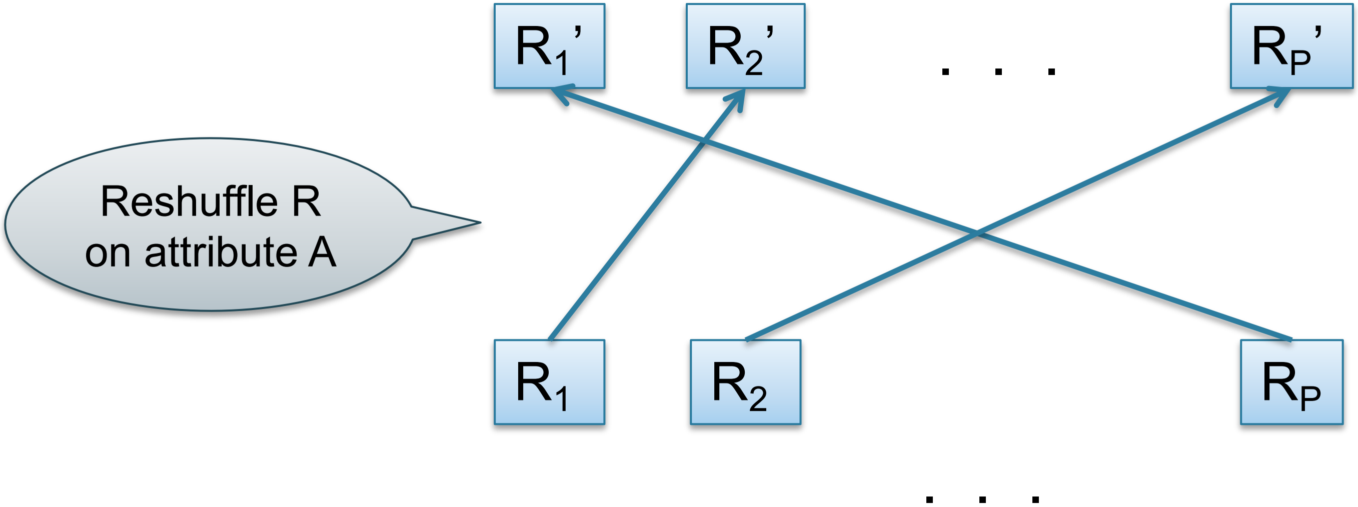

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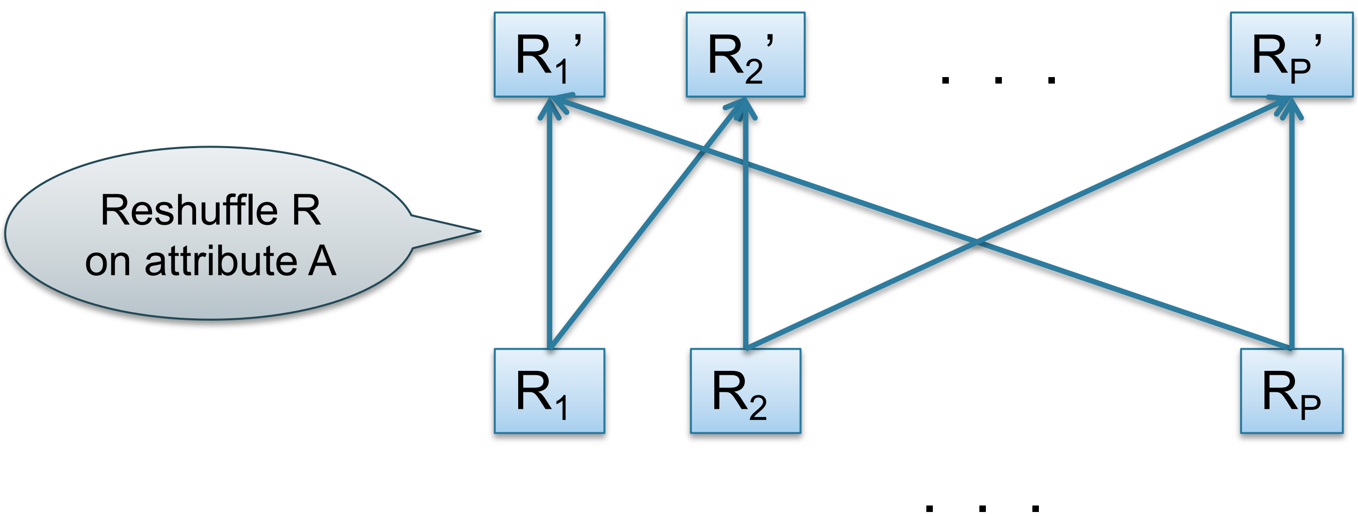

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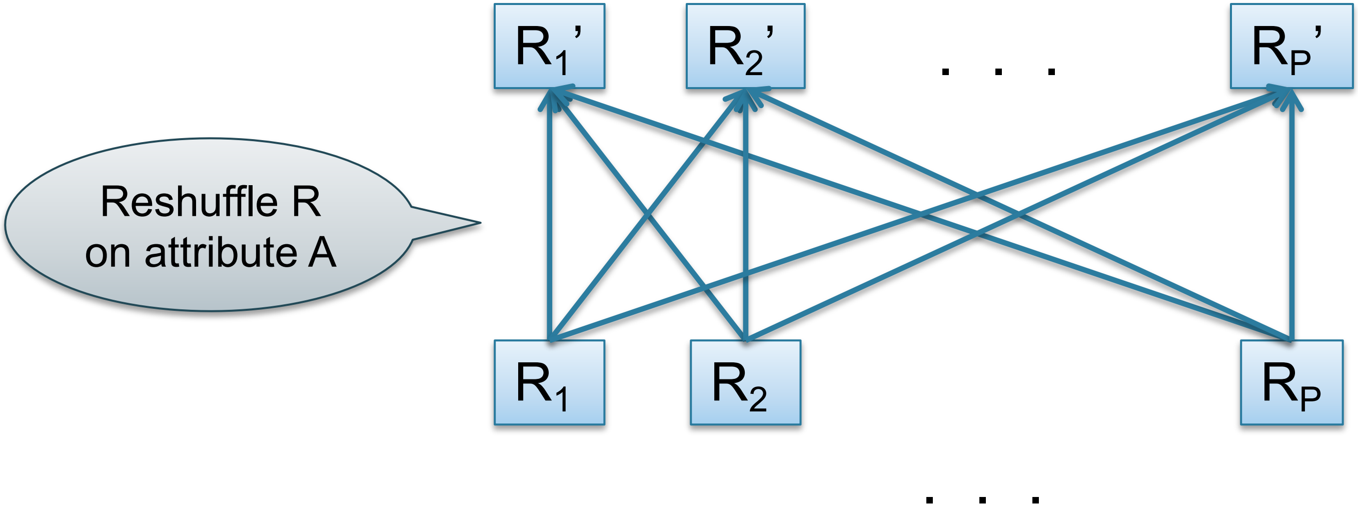

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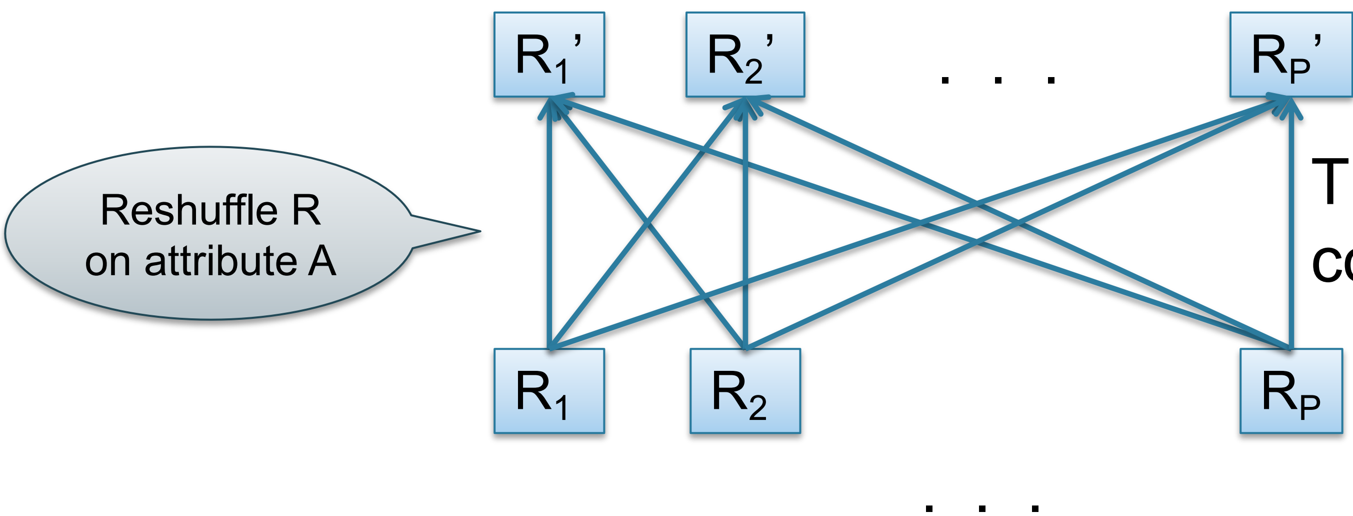

This is done in *one* communication step

Basic Parallel GroupBy

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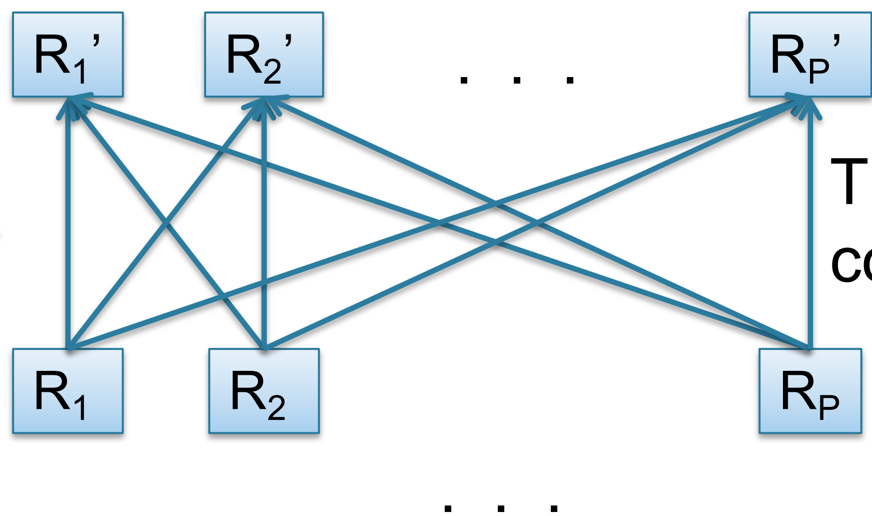
Reshuffle R on attribute A



This is done in *one* communication step

Describe the push v.s. pull method

Reshuffling

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

Basic Parallel GroupBy

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

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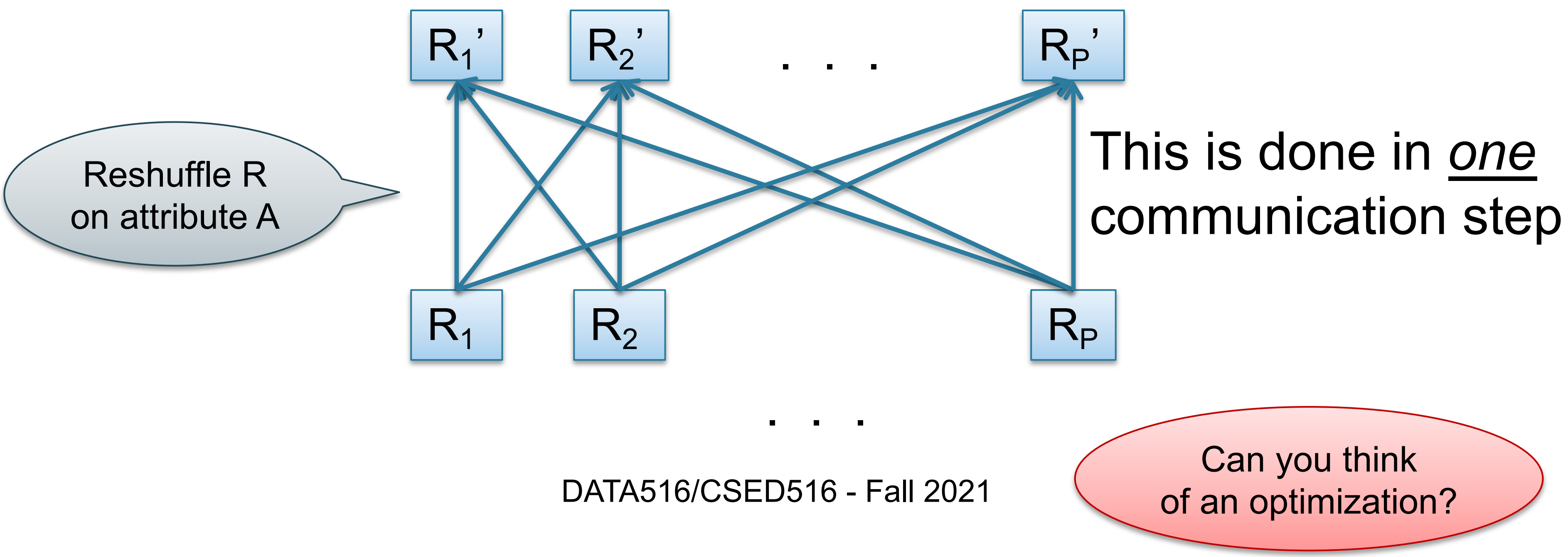

GroupBy/Union Commutativity

	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
```

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Q: What is sum for Seattle?

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Q: What is sum for Seattle?
A: 106

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GroupBy/Union Commutativity

	city	…	qant
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Sum here = 40

Q: What is sum for Seattle?
A: 106

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Sum here = 66

GroupBy/Union Commutativity

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Sum here = 66

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

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)
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$T_{i,1}, T_{i,2}, \ldots, T_{i,p}$
then send fragment $T_{i,j}$ to server j

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$T_{i,1}, T_{i,2}, \ldots, T_{i,p}$
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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Distributive	Algebraic	Holistic
$sum(a_1+a_2+\ldots+a_9) = sum(sum(a_1+a_2+a_3) + sum(a_4+a_5+a_6) + sum(a_7+a_8+a_9))$	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
```

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

$$|$$

$$\sigma_{c>0}$$

$$|$$

$$R$$

Example Query with Group By

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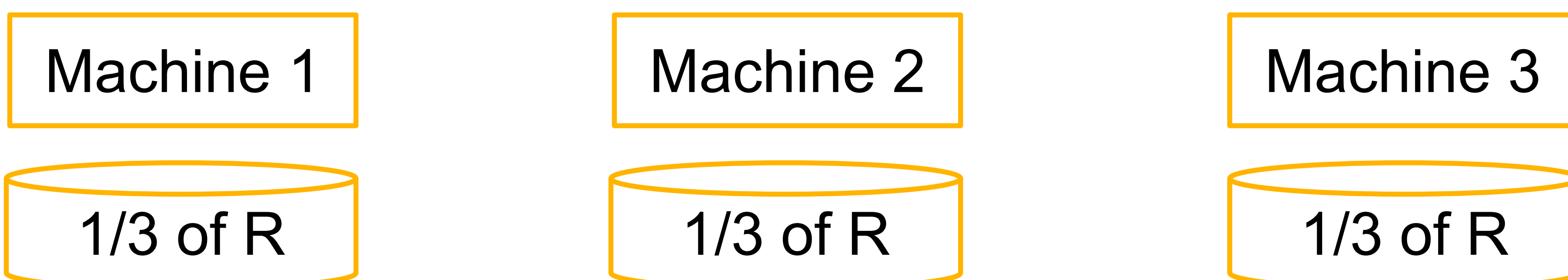

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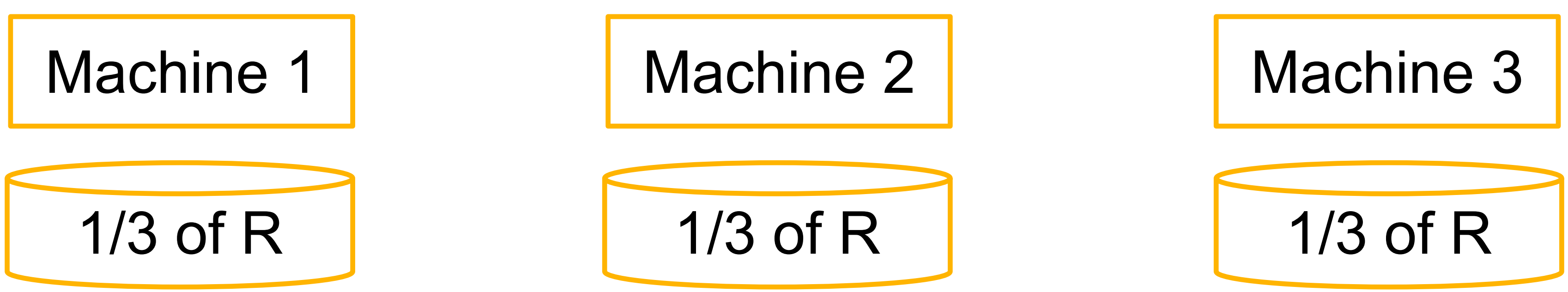

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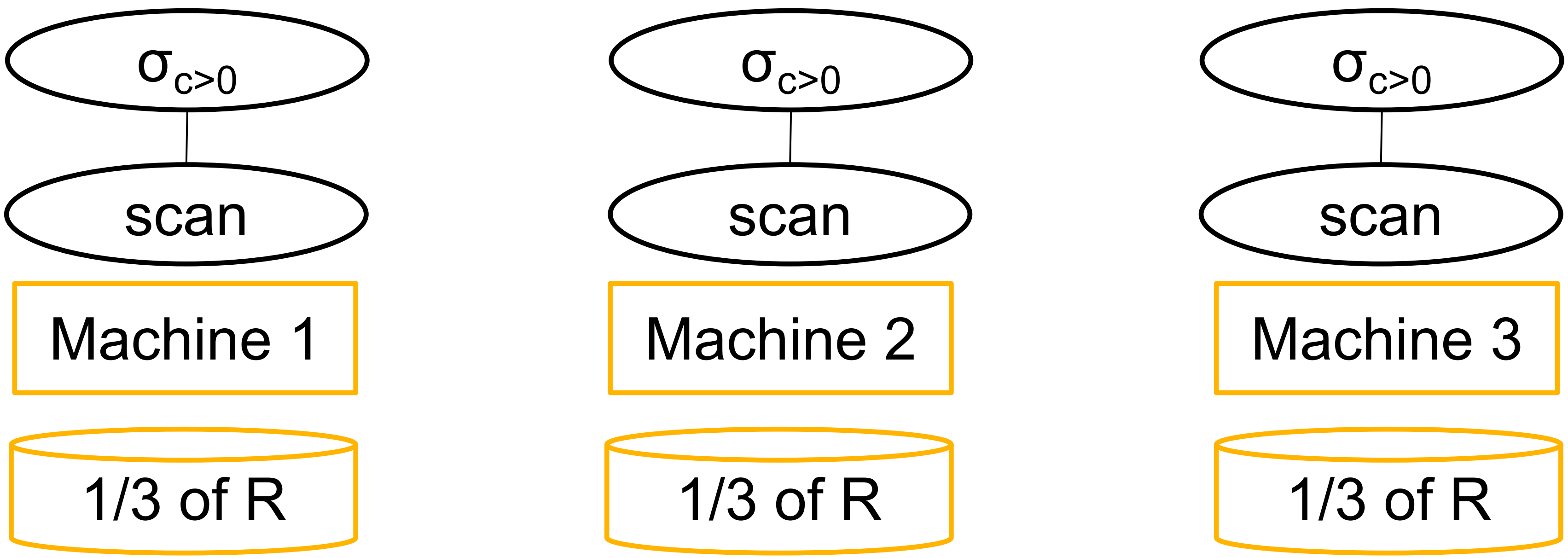

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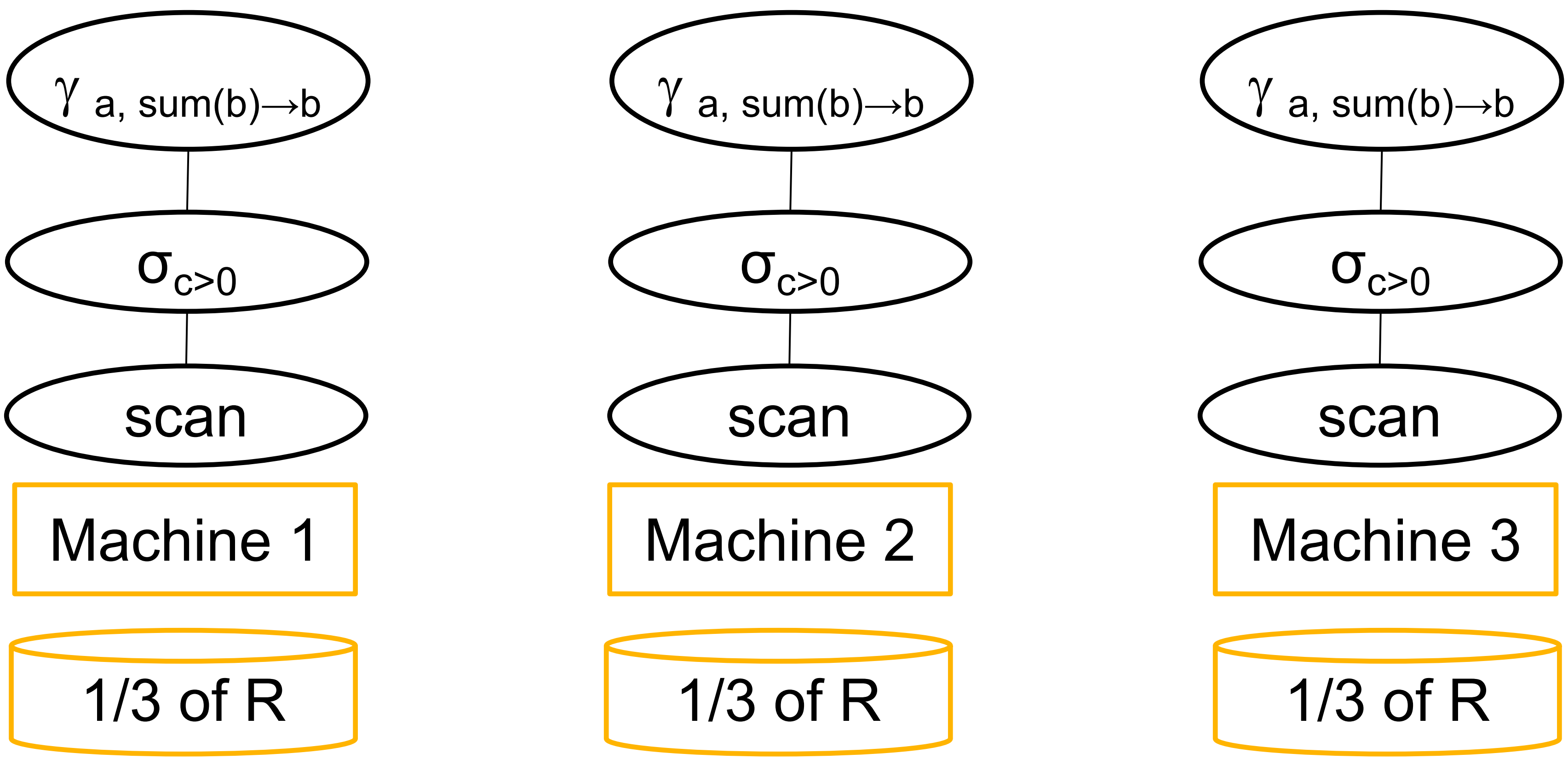

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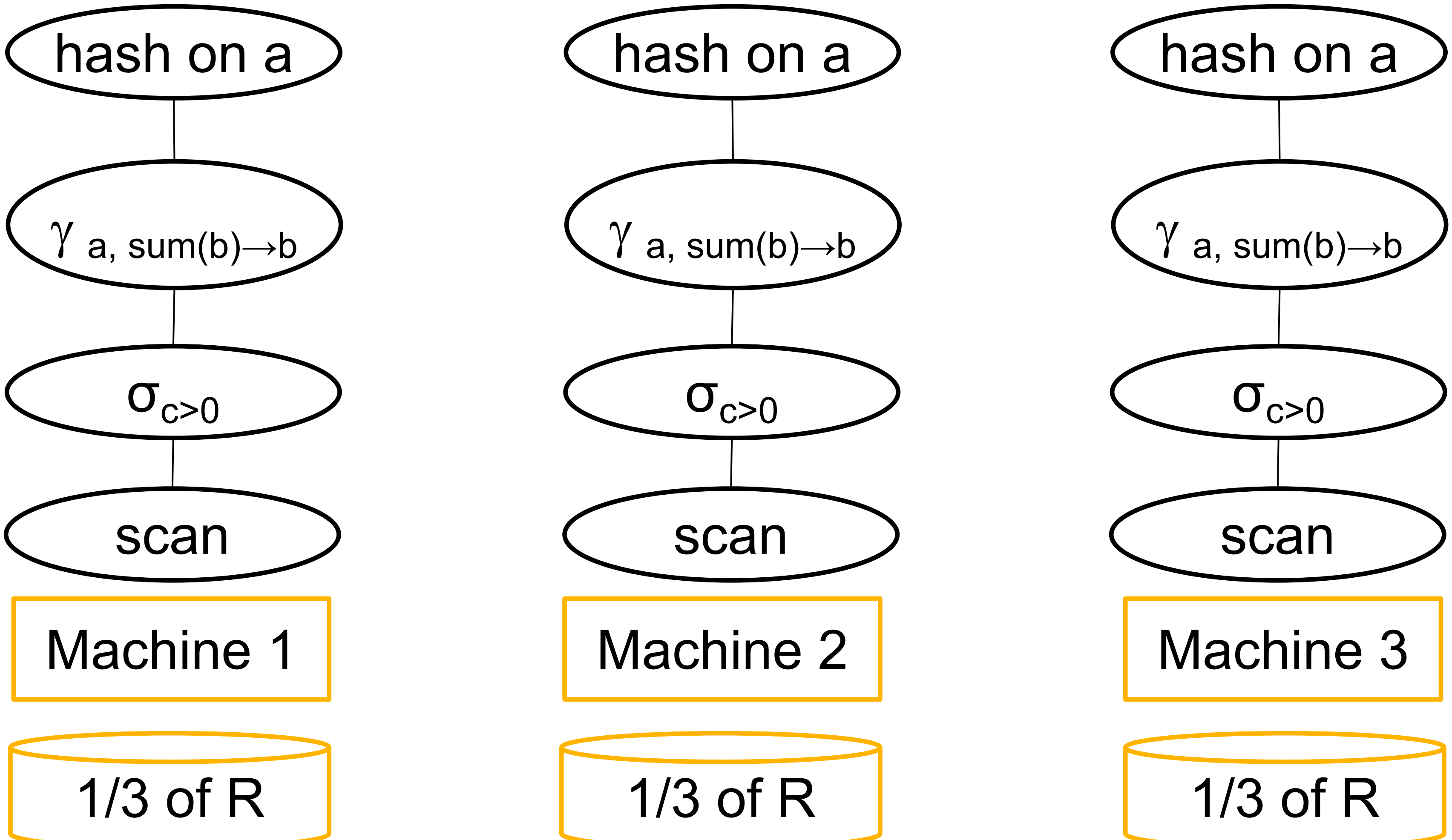

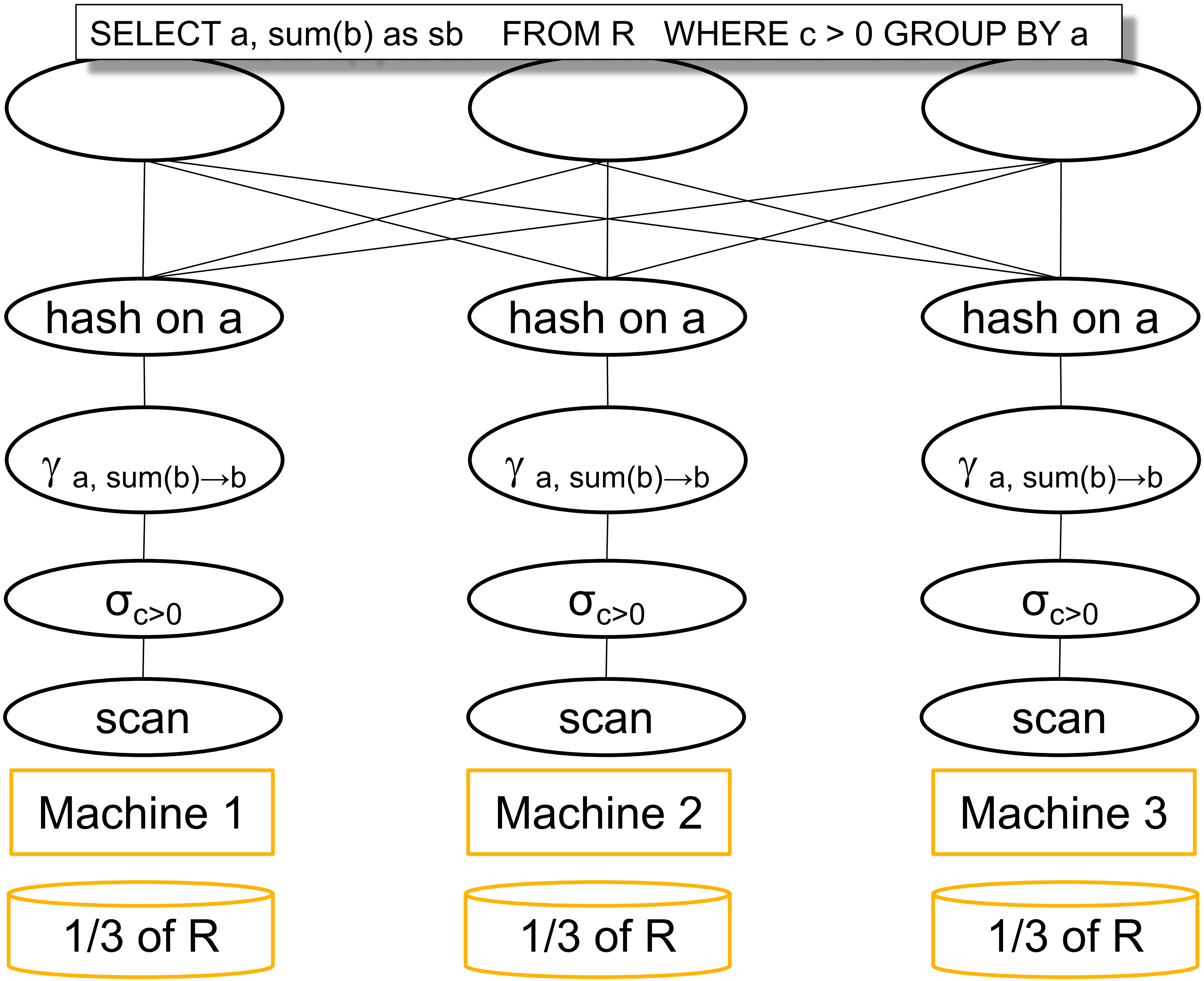

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hash on a
hash on a
hash on a
γ a, sum(b)→b
γ a, sum(b)→b
γ a, sum(b)→b
σc>0
σc>0
σc>0
scan
scan
scan
Machine 1
Machine 2
Machine 3
1/3 of R
1/3 of R
1/3 of R

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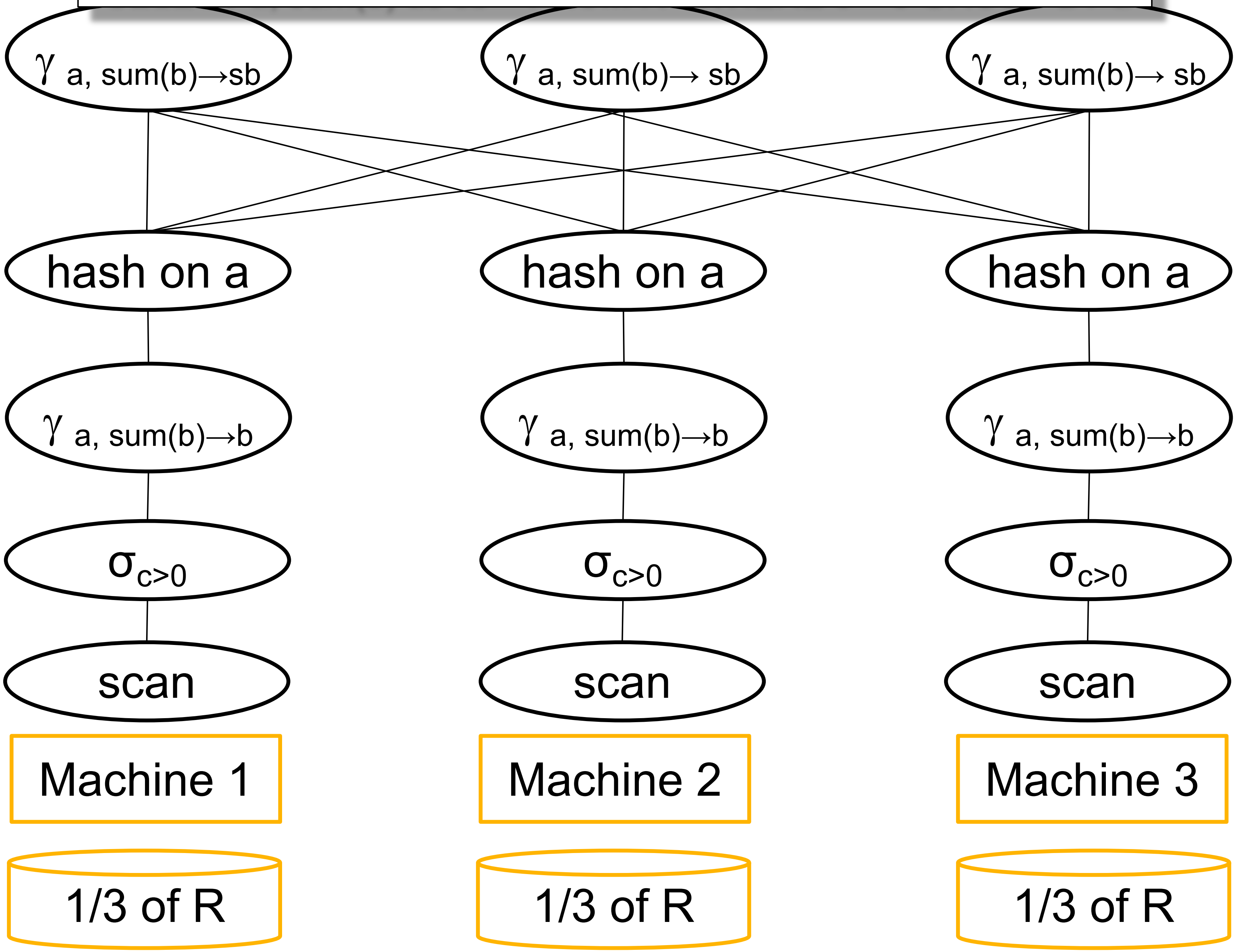

Speedup and Scaleup

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?

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But only if the data is without skew!

Parallel/Distributed Join

Three “algorithms”:

- Hash-partitioned
- Broadcast
- Combined: “skew-join” or other names

Distributed Hash-Join

Hash Join: $R \bowtie_{A=B} S$

Data: $R(A, C), S(B, D)$

Query: $R \bowtie_{A=B} S$

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

Initially, R and S are block partitioned.
Notice: they may be stored in DFS (recall MapReduce)

Some servers hold R-chunks, some hold S-chunks, some hold both

Hash Join: $R \bowtie_{A=B} S$

Data: $R(A, C), S(B, D)$

Query: $R \bowtie_{A=B} S$

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

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

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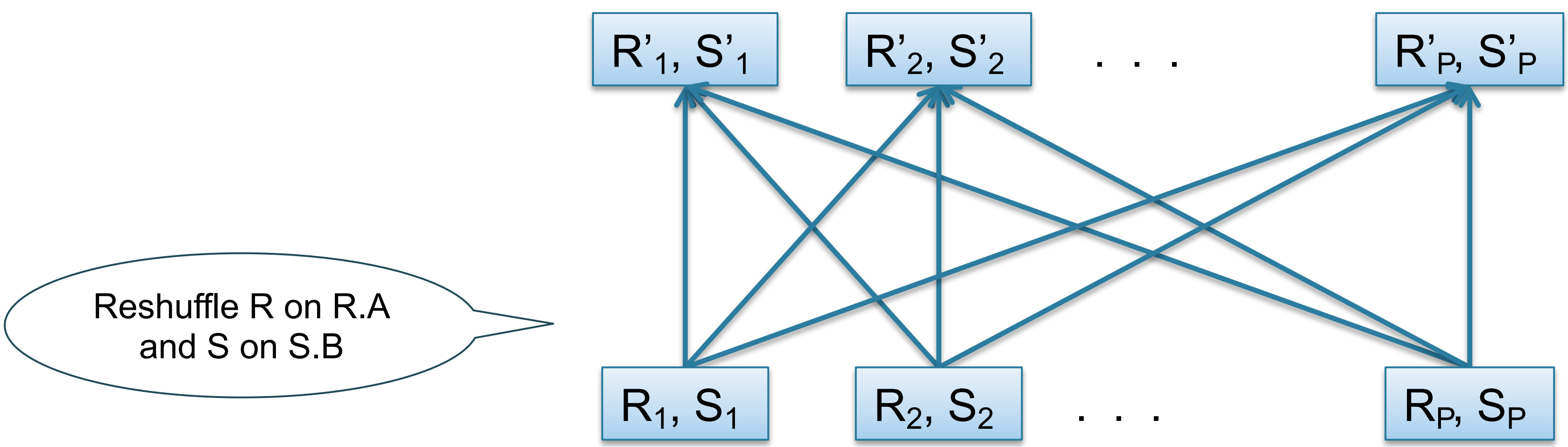

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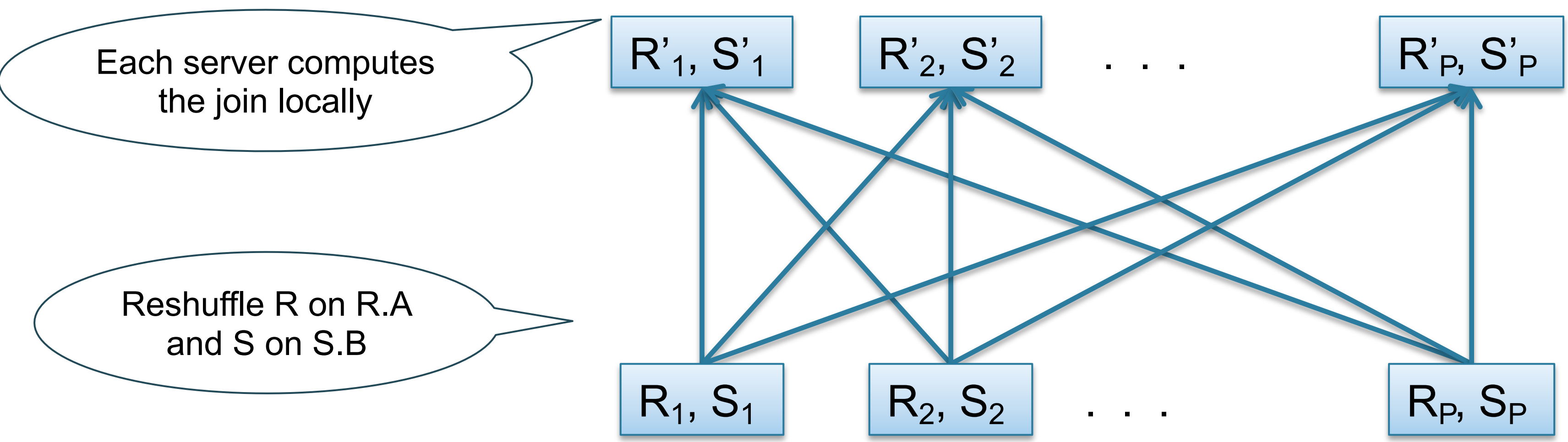

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Hash Join: R $\bowtie_{A=B}$ S

- Step 1
  - Every server holding any chunk of R partitions its chunk using a hash function h(t.A)
  - Every server holding any chunk of S partitions its chunk using a hash function h(t.B)
- Step 2:
  - Each server computes the join of its local fragment of R with its local fragment of S

Broadcast Join
A.k.a. “Small Join”

Broadcast Join

- When joining R and S
- If |R| >> |S|
  - Leave R where it is
  - Replicate entire S relation across R-nodes

- Called a small join or a broadcast join

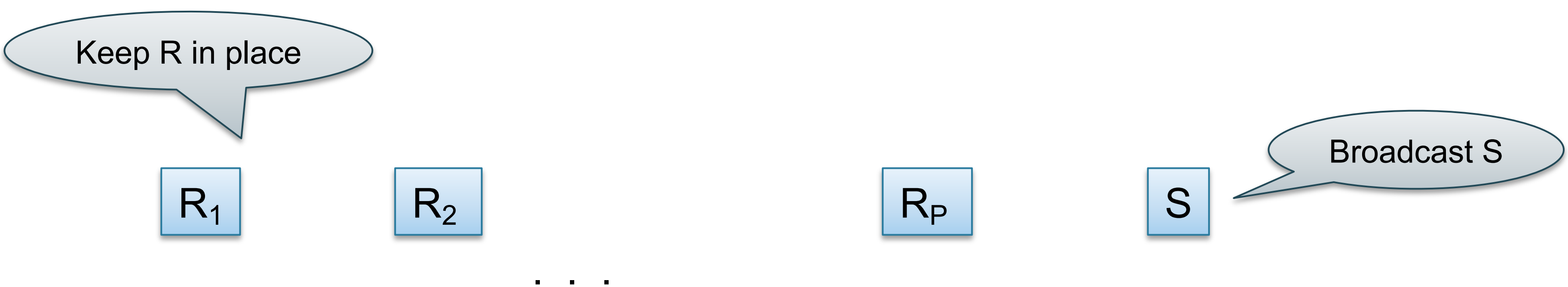
Query: $R \bowtie S$

Broadcast Join

R_1 R_2 . . . R_P S

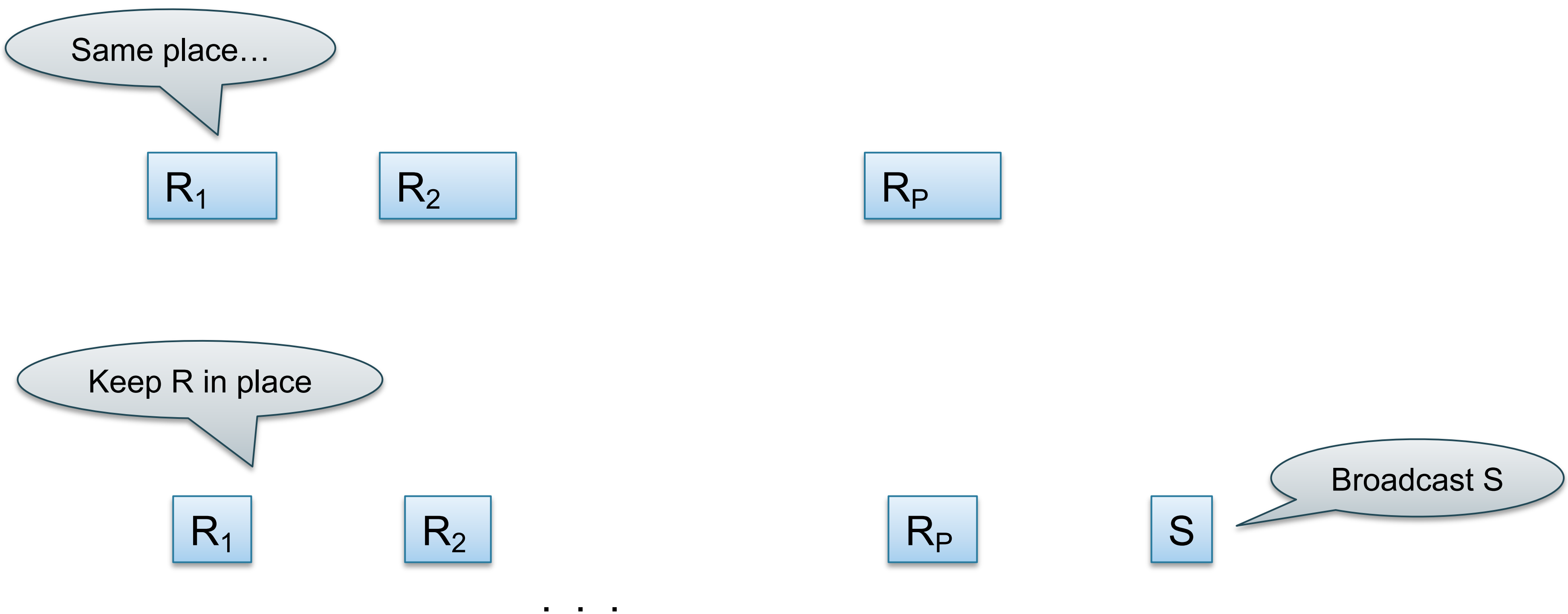
Query: $R \bowtie S$

Broadcast Join



Query: $R \bowtie S$

Broadcast Join



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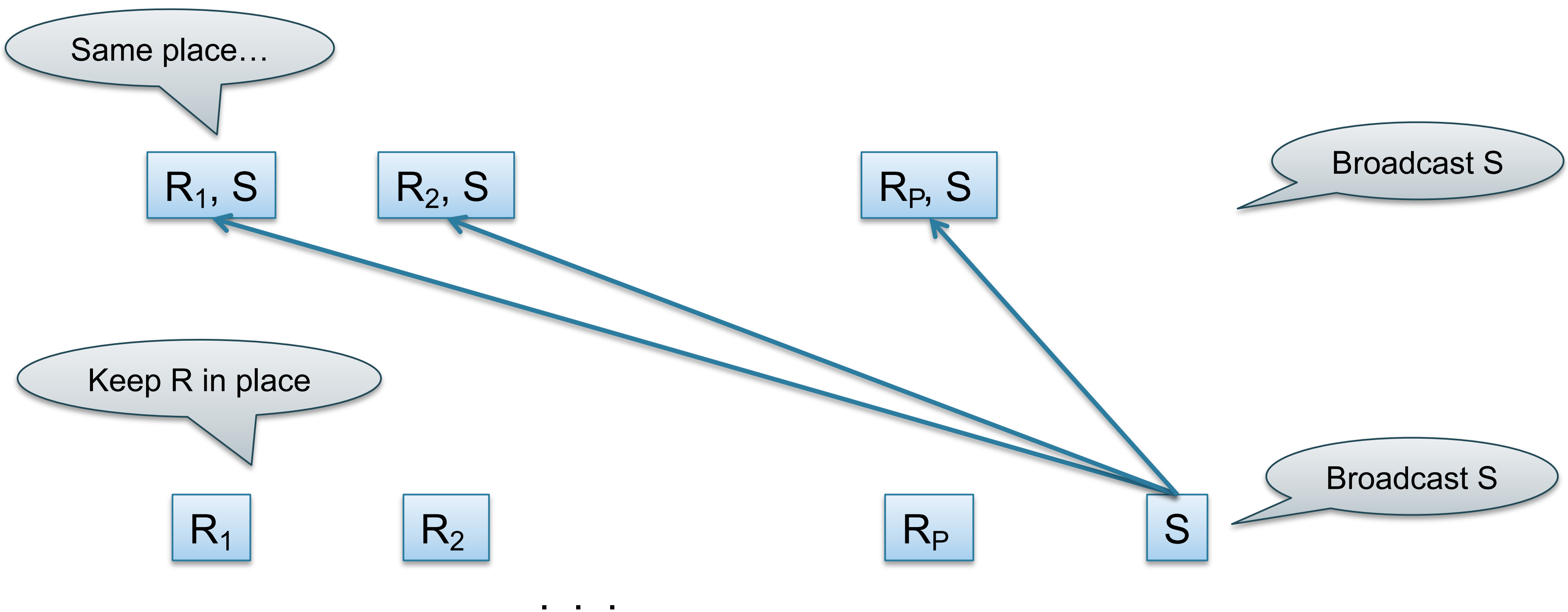
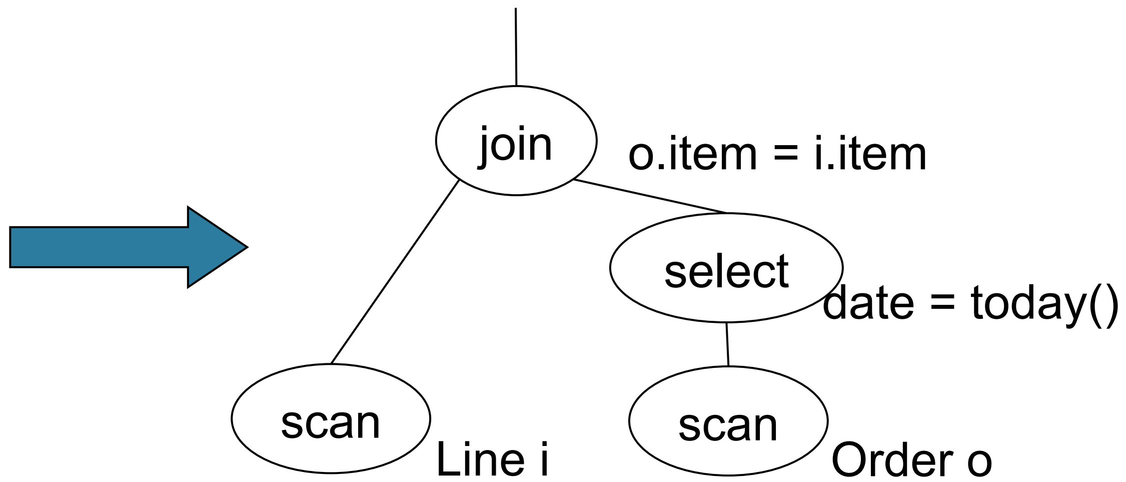


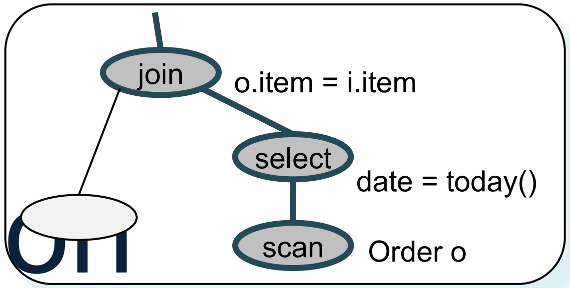
Example Query Execution

Find all orders from today, along with the items ordered

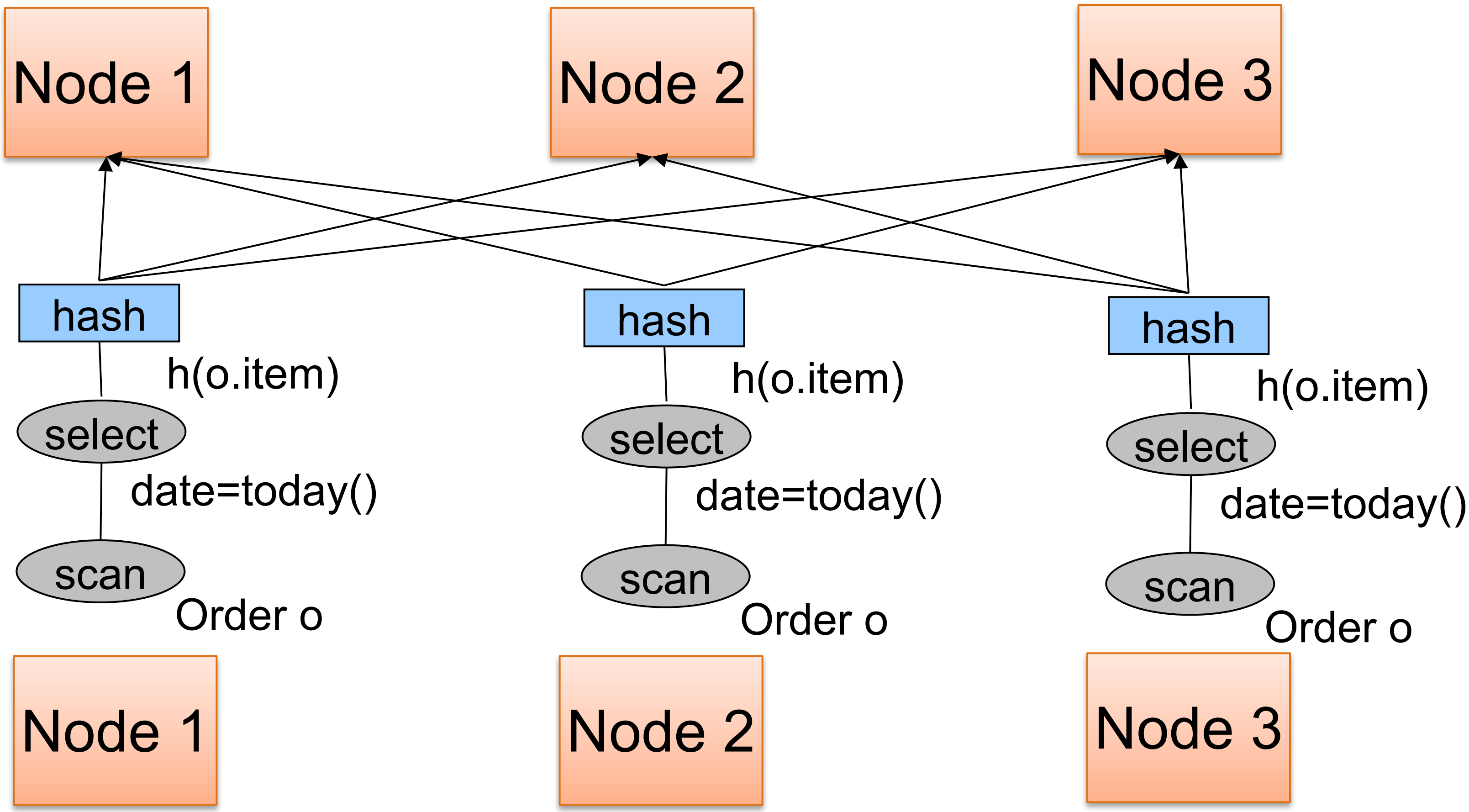
```
SELECT *
FROM Order o, Line i
WHERE o.item = i.item
    AND o.date = today()
```



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

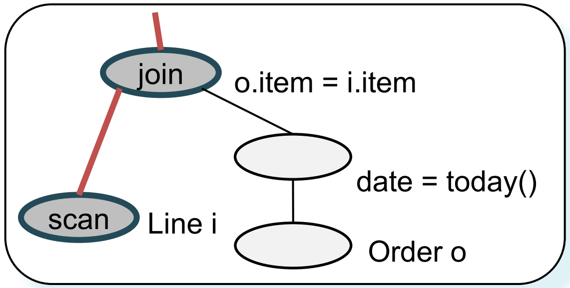


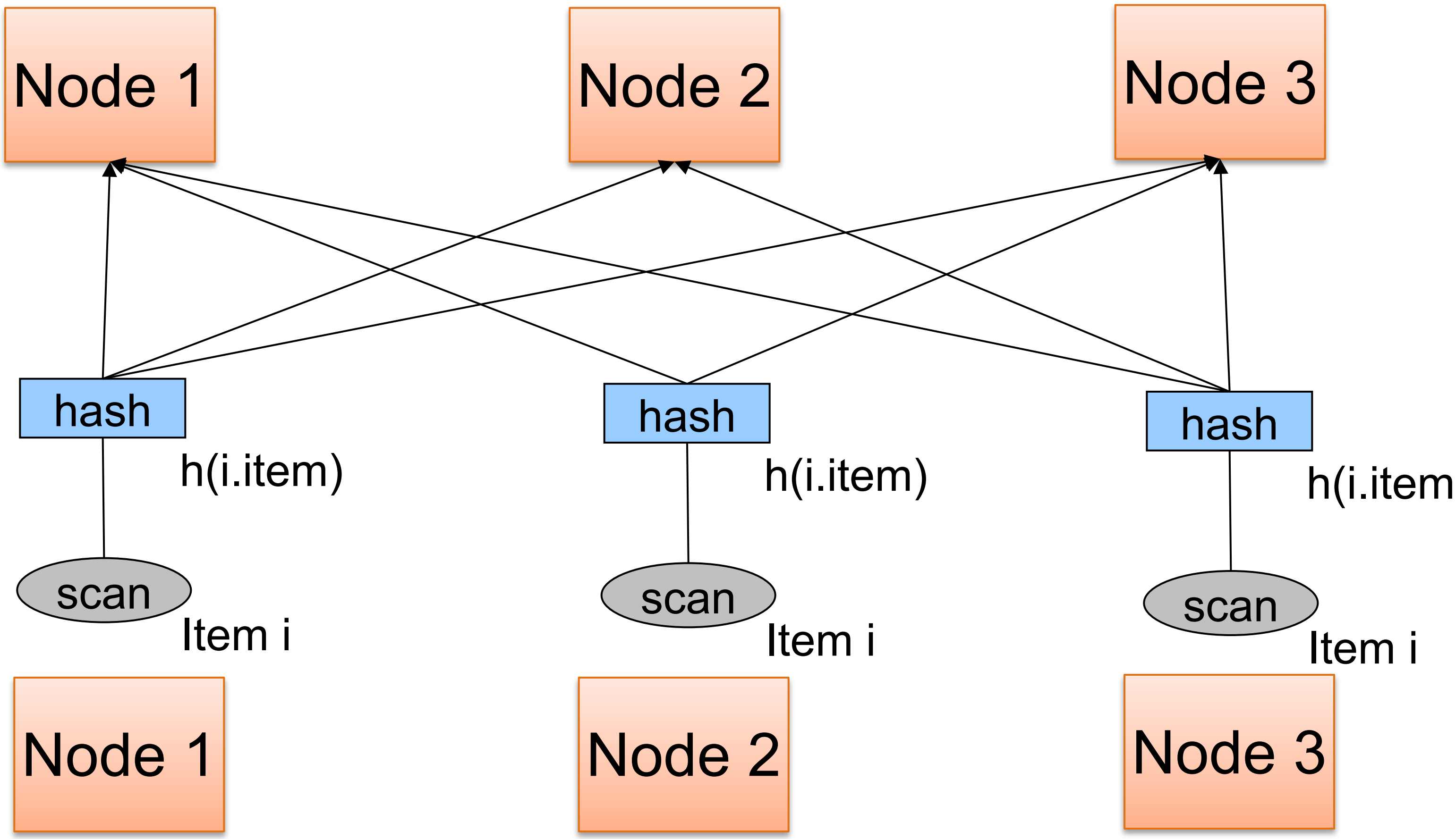
Query Execution



Order(oid, item, date), Line(item, …)

Query Executi





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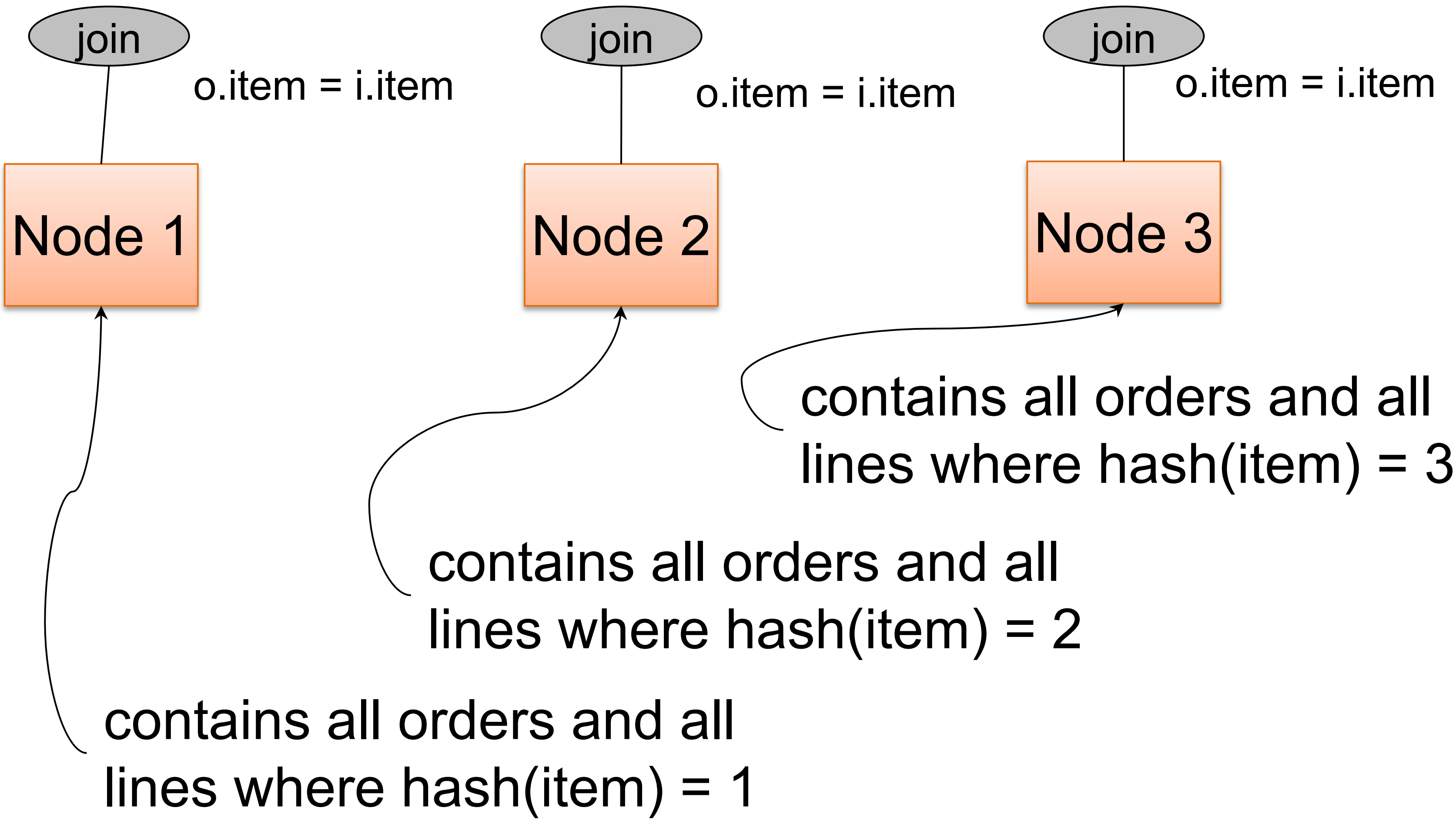
Query Execution

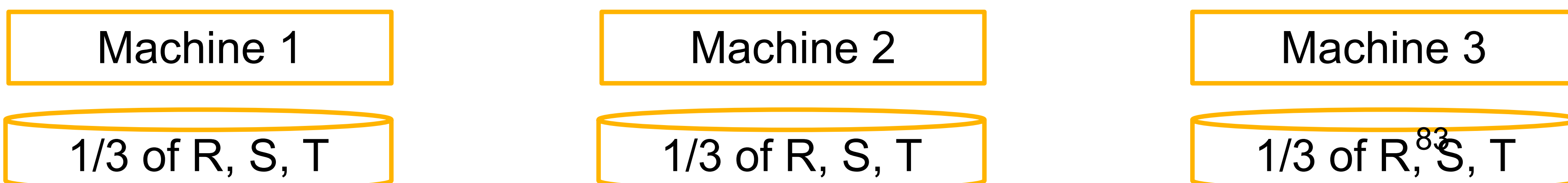


Example 2

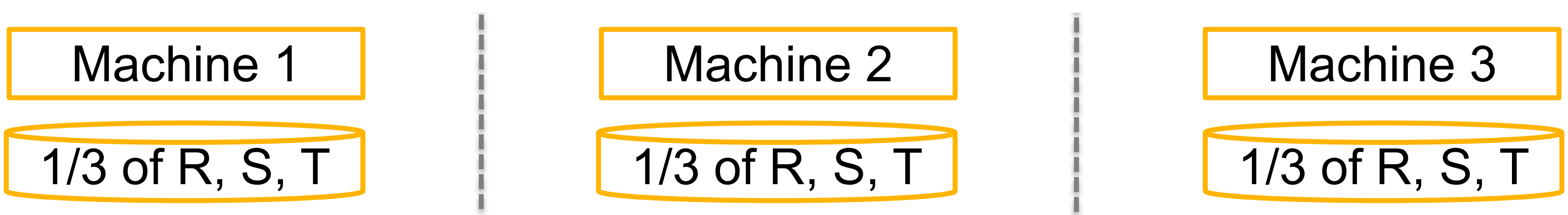
SELECT *

FROM R, S, T

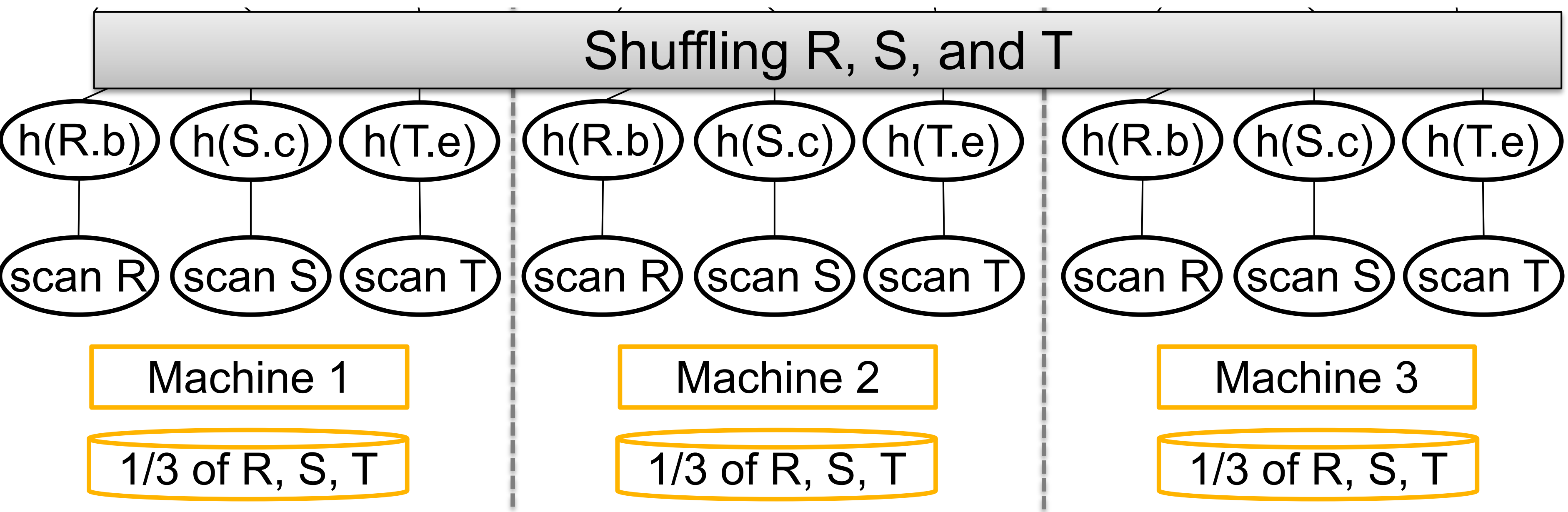
WHERE R.b = S.c AND S.d = T.e AND (R.a - T.f) > 100



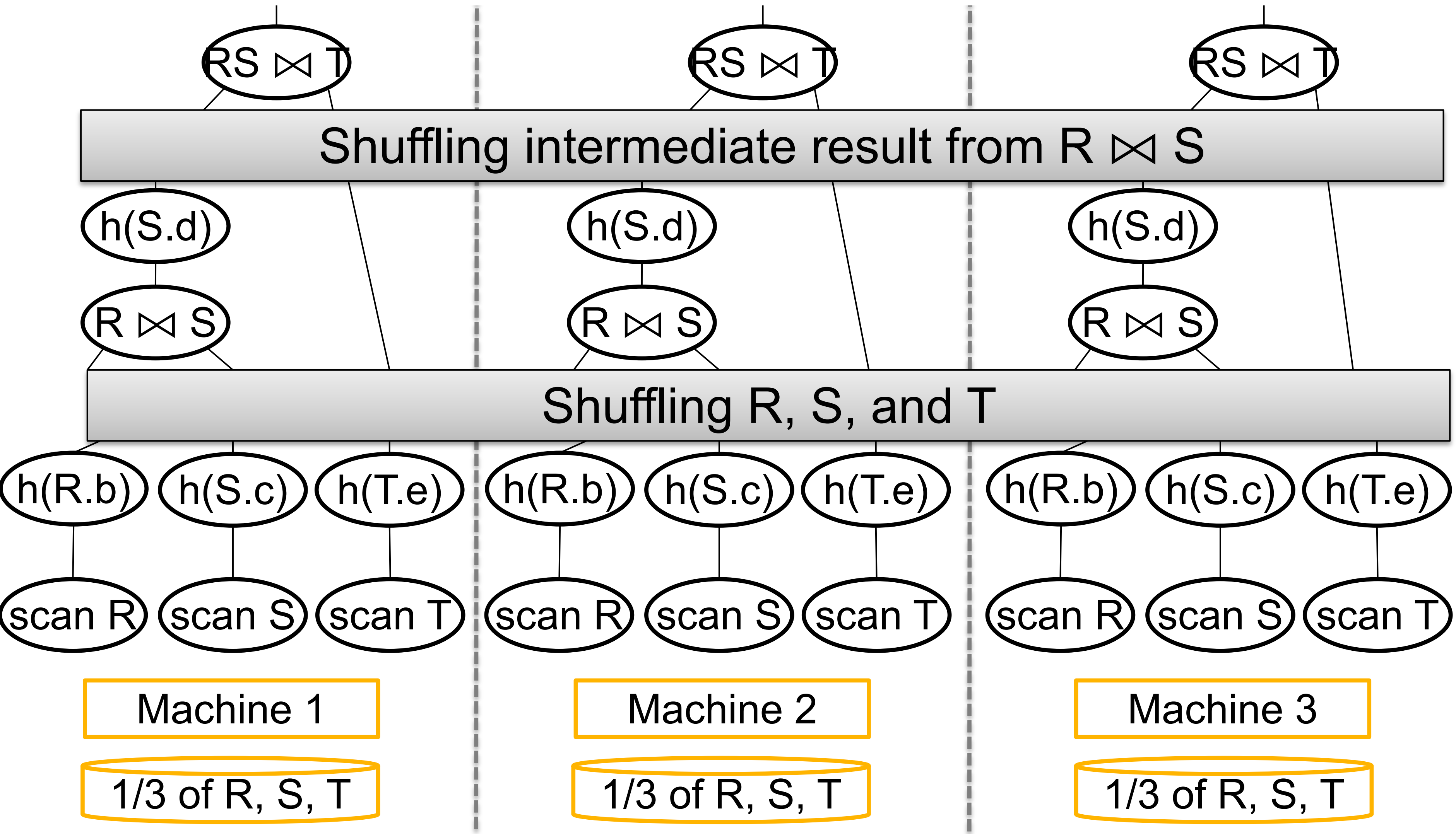
… WHERE R.b = S.c AND S.d = T.e AND (R.a - T.f) > 100



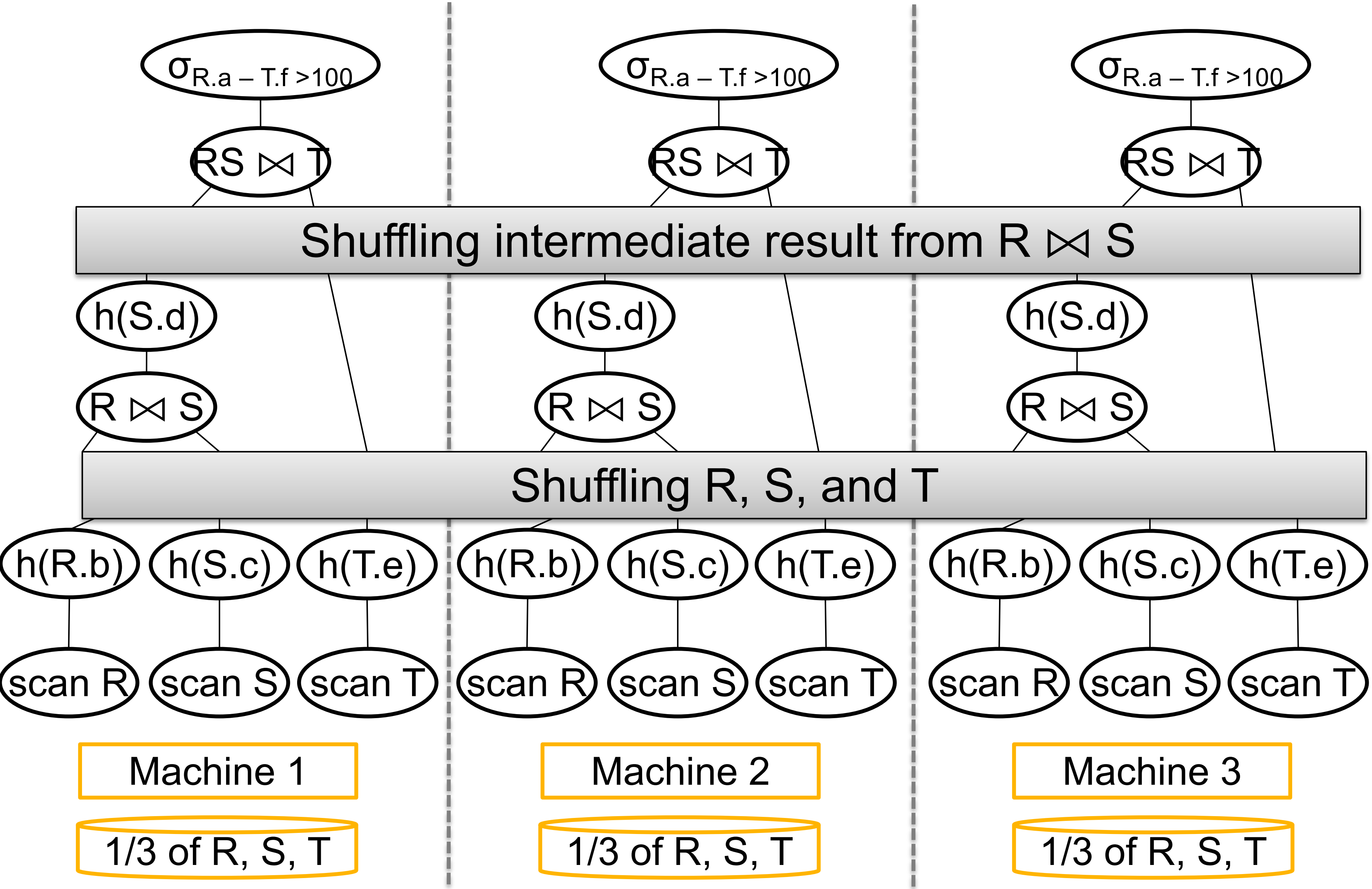
… WHERE R.b = S.c AND S.d = T.e AND (R.a - T.f) > 100



… WHERE R.b = S.c AND S.d = T.e AND (R.a - T.f) > 100



… WHERE R.b = S.c AND S.d = T.e AND (R.a - T.f) > 100



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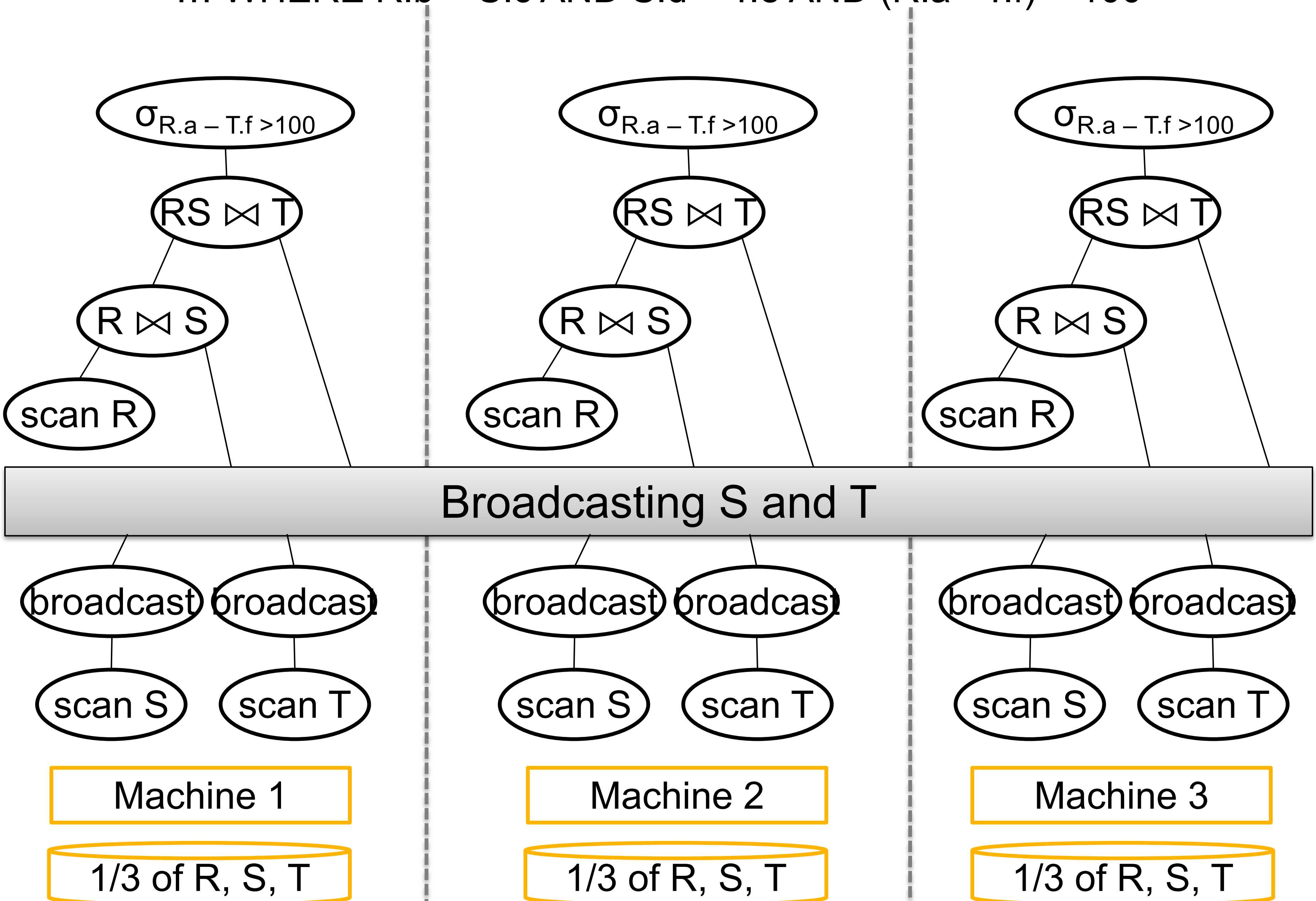

Discussion

- Hash-join:
  - Both relations are partitioned (good)
  - May have skew (bad)

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Discussion

- Hash-join:
  - Both relations are partitioned (good)
  - May have skew (bad)
- Broadcast join
  - One relation must be broadcast (bad)
  - No worry about skew (good)
- Skew join (has other names):
  - Combine both: in class

Outline

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

Skew

Skew

- Skew means that one server runs much longer than the other servers

- Reasons:
  - Computation skew
  - Data skew

Computation Skew

- All workers receive the same amount of input data, but some need to run much longer than others
- E.g. perform some image processing whose runtimes depends on the image
- Solution: use virtual servers

Virtual Servers

Main idea:

- If we send the data uniformly to the P servers, and one of them is stuck with the complicated image, then we have skew
- Solution: pretend we have many "virtual" servers. (Next slide.)

Virtual Servers

Large number P_v of "virtual servers"

- Design algorithm for P_v virtual servers
- Scale down to $P << P_v$ physical servers, by simulating them round-robin

E.g. MapReduce: P=workers, P_v=map tasks

Data Skew

- We fail to distribute the data uniformly to the servers
- Question: why can this happen?

Data Skew

- We fail to distribute the data uniformly to the servers
- Question: why can this happen?
- Answer:
  - Range partition may have many more tuples in one bucket than another
  - Hash partition may suffer from heavy hitters

Next Lecture

- Analyze skew: notice hw3 question

- New topic: scalable graph processing