Introduction to Database Systems CSE 414

Lecture 28

Parallel Databases Wrap-up

Announcements

- Homework 8 (last) due on Friday night
  - Help each other out with configuration funnies
- Final exam Monday, 2:30
  - Review Sunday afternoon, 2:00

A Challenge

- Have P servers (say P=27 or P=1000)
- How do we compute this query?
  $Q(x,y,z) = R(x,y) \bowtie S(y,z) \bowtie T(z,x)$

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- This computes all "triangles".
- E.g. let Follows(x,y) be all pairs of Twitter users s.t. x follows y. Let R=S=T=Follows. Then Q computes all triples of people that follow each other.

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- Step 1:
  - Each server sends R(x,y) to server h(y) mod P
  - Each server sends S(y,z) to server h(y) mod P

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- Step 2:
  - Each server computes $R \bowtie S$ locally
  - Each server sends $[R(x,y) \bowtie S(y,z)]$ to h(x) mod P
  - Each server sends T(z,x) to h(x) mod P

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  - Each server sends $[R(x,y) \bowtie S(y,z)]$ to h(x) mod P
  - Each server sends T(z,x) to h(x) mod P
- Final output:
  - Each server computes locally and outputs $R \bowtie S \bowtie T$

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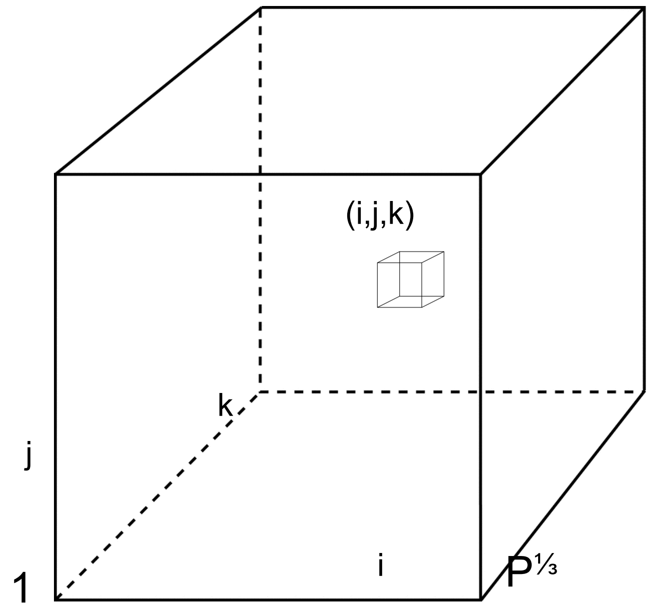
- How do we compute this query in one step?
  $Q(x,y,z) = R(x,y) \bowtie S(y,z) \bowtie T(z,x)$
- Organize the P servers into a cube with side $P^{1/3}$
  – Thus, each server is uniquely identified by (i,j,k), $i,j,k \leq P^{1/3}$



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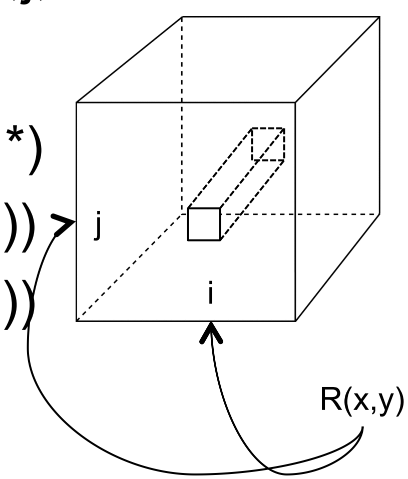

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- How do we compute this query in one step?
  $Q(x,y,z) = R(x,y) \bowtie S(y,z) \bowtie T(z,x)$
- Organize the P servers into a cube with side $P^{⅓}$
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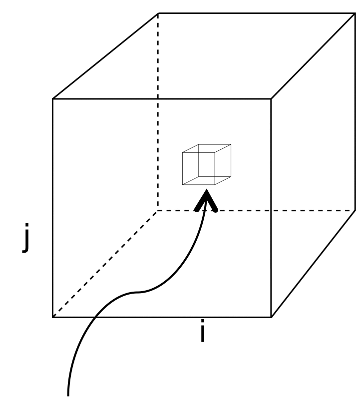

- Final output:
  - Each server (i,j,k) computes the query R(x,y),S(y,z),T(z,x) locally

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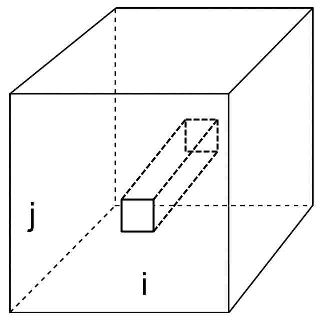

- Final output:
  – Each server (i,j,k) computes the query R(x,y),S(y,z),T(z,x) locally
- Analysis: each tuple R(x,y) is replicated at most $P^{1/3}$ times

Parallel DBs v.s. MapReduce

Parallel DB

- Plusses
  - Efficient binary format
  - Indexes, physical tuning
  - Cost-based optimization
- Minuses
  - Difficult to import data
  - Lots of baggage: logging, transactions

MapReduce

- Minuses
  - Lots of time spent parsing!
  - Text files
  - "Optimizers is between your eyes and your keyboard"
- Plusses
  - Any data
  - Lightweight, easy to speedup
  - Arguably more scalable

Example: Parallel DBMS vs. MR

1a. Parallel DBMS

R(a,b) is horizontally partitioned across N = 3 machines.

Each machine locally stores approximately 1/N of the tuples in R.

The tuples are randomly organized across machines (i.e., R is **block partitioned** across machines).

Show a RA plan for this query and how it will be executed across the N = 3 machines.
Pick an efficient plan that leverages the parallelism as much as possible.

SELECT a, max(b) as topb
FROM R
WHERE a > 0
GROUP BY a

R(a, b)

```
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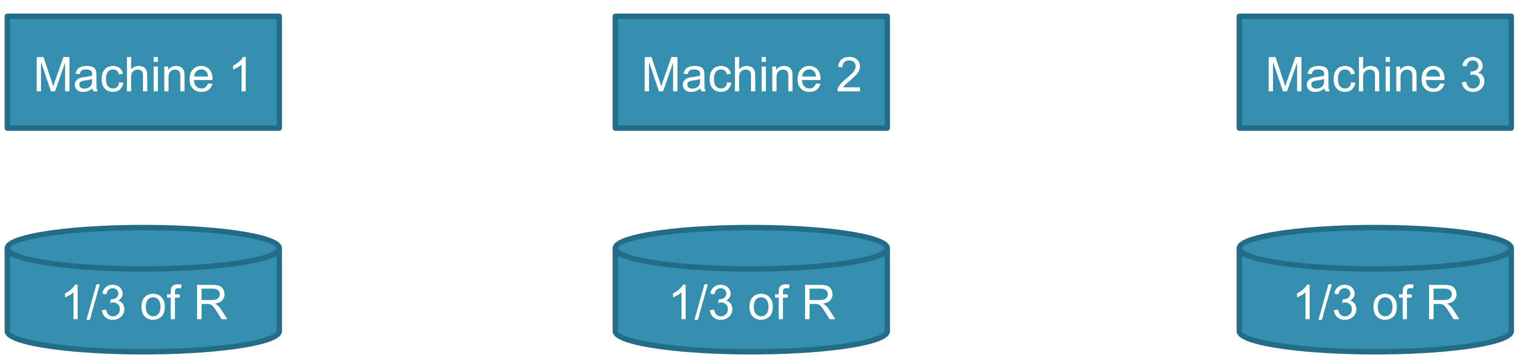

R(a, b)

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```
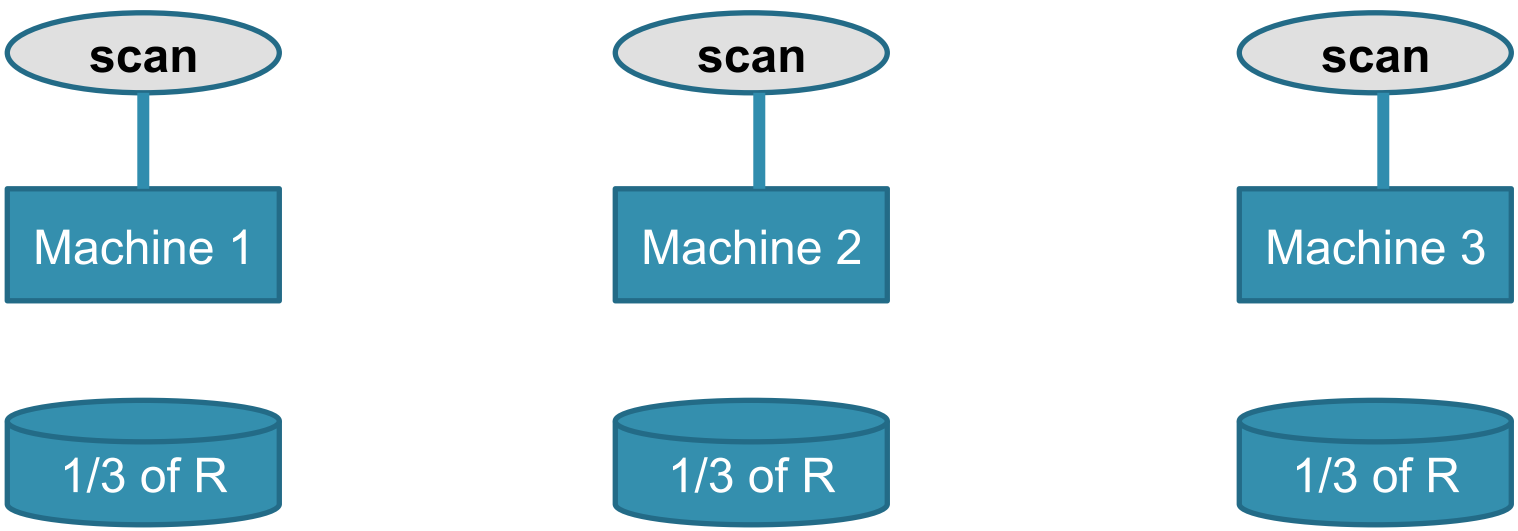

If more than one relation on a machine, then “scan S”, “scan R” etc



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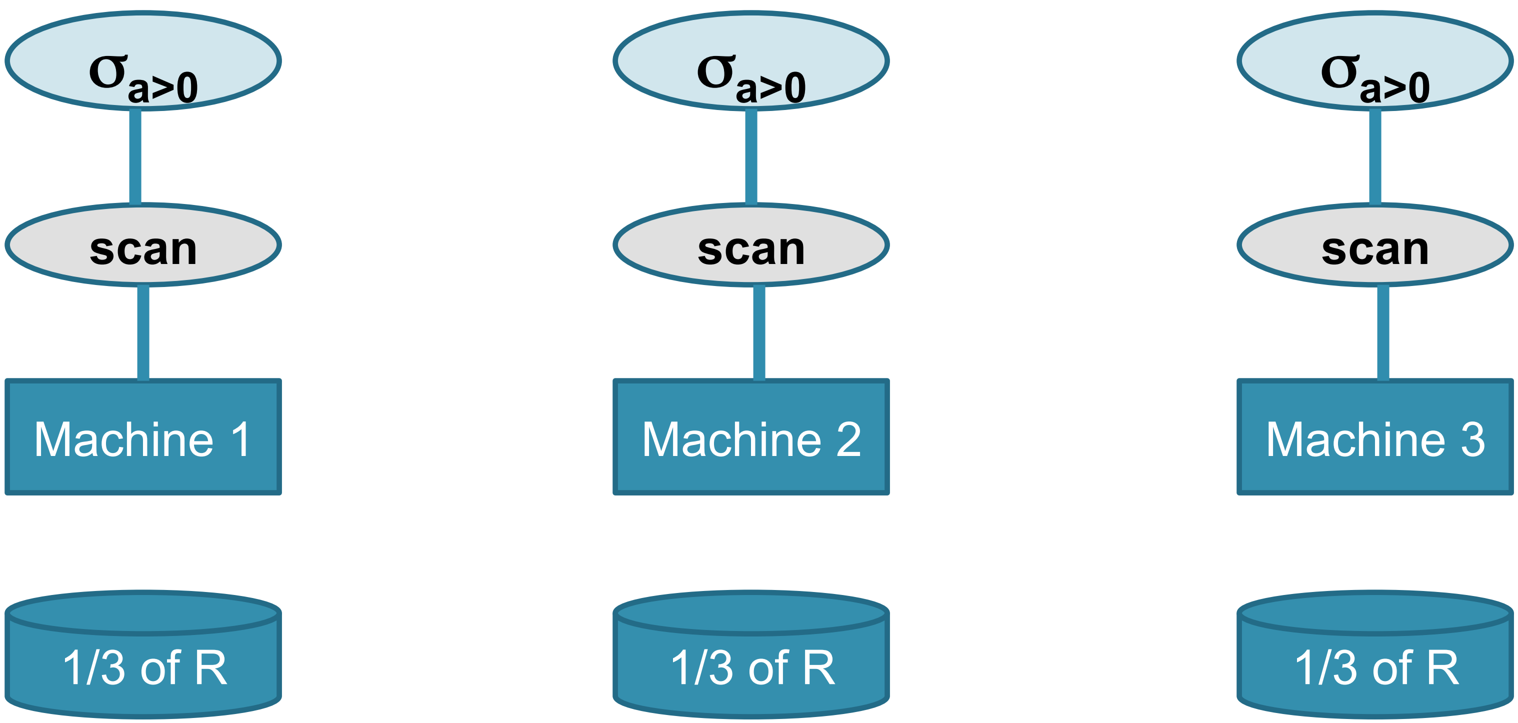

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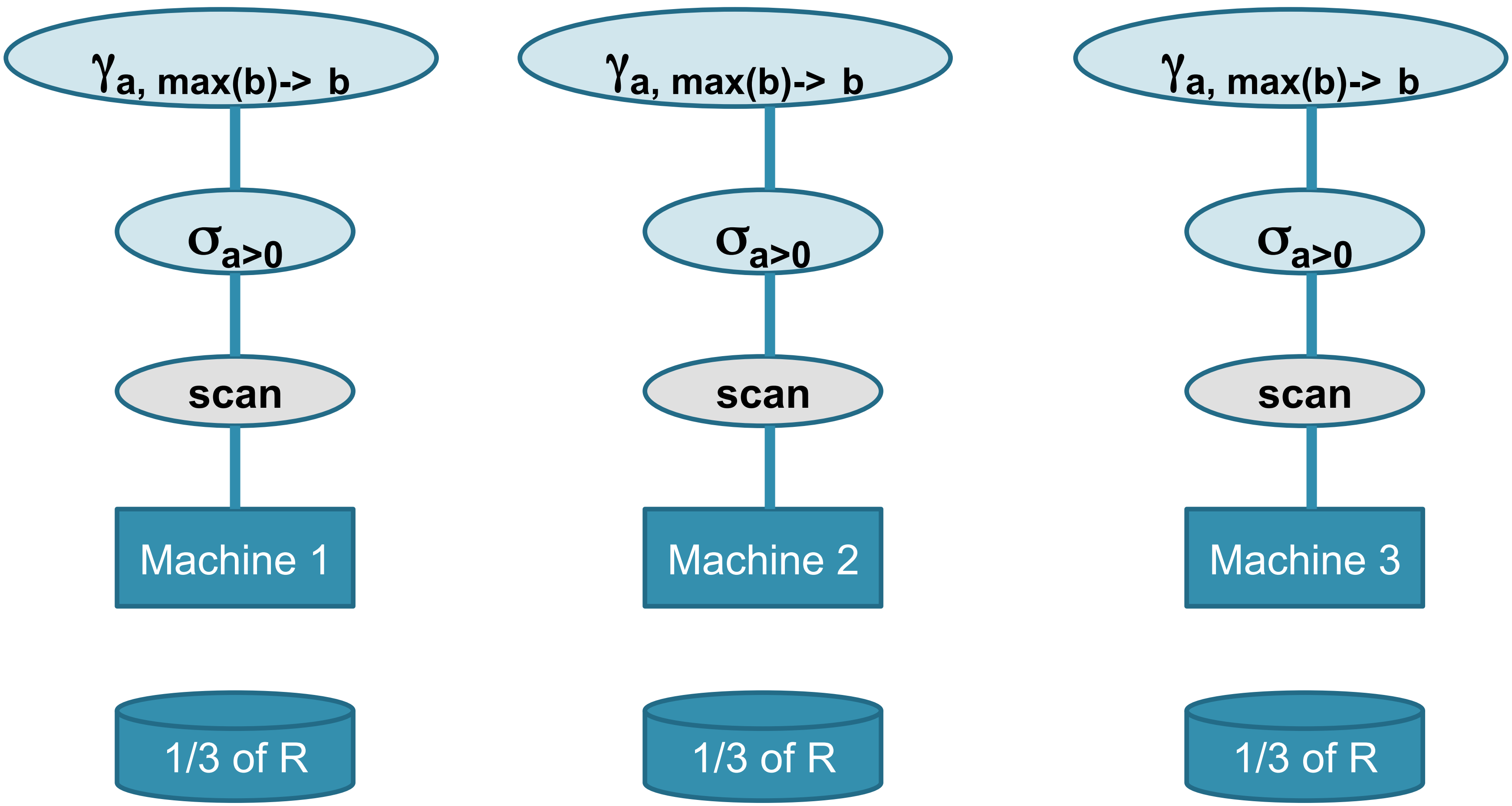

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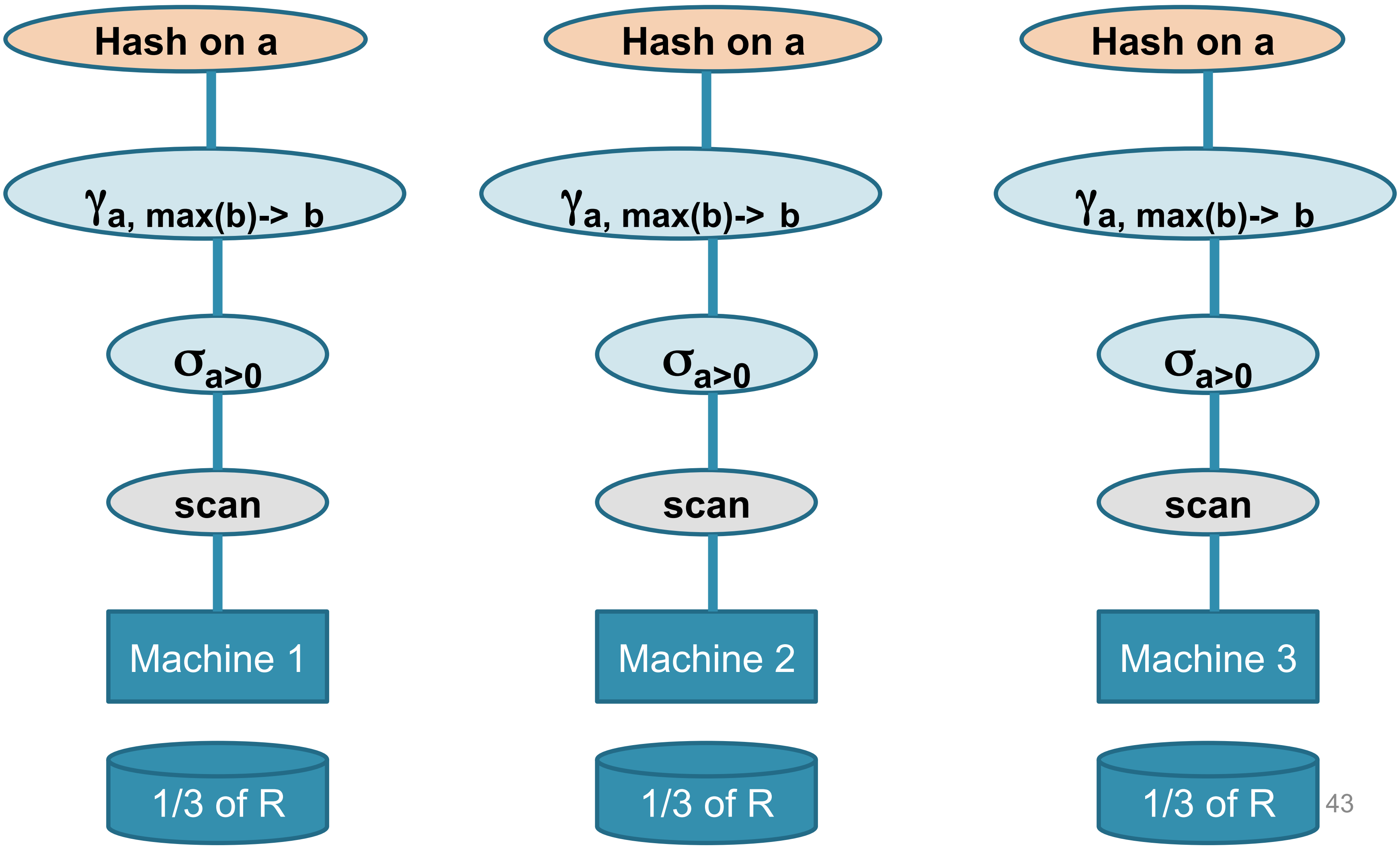

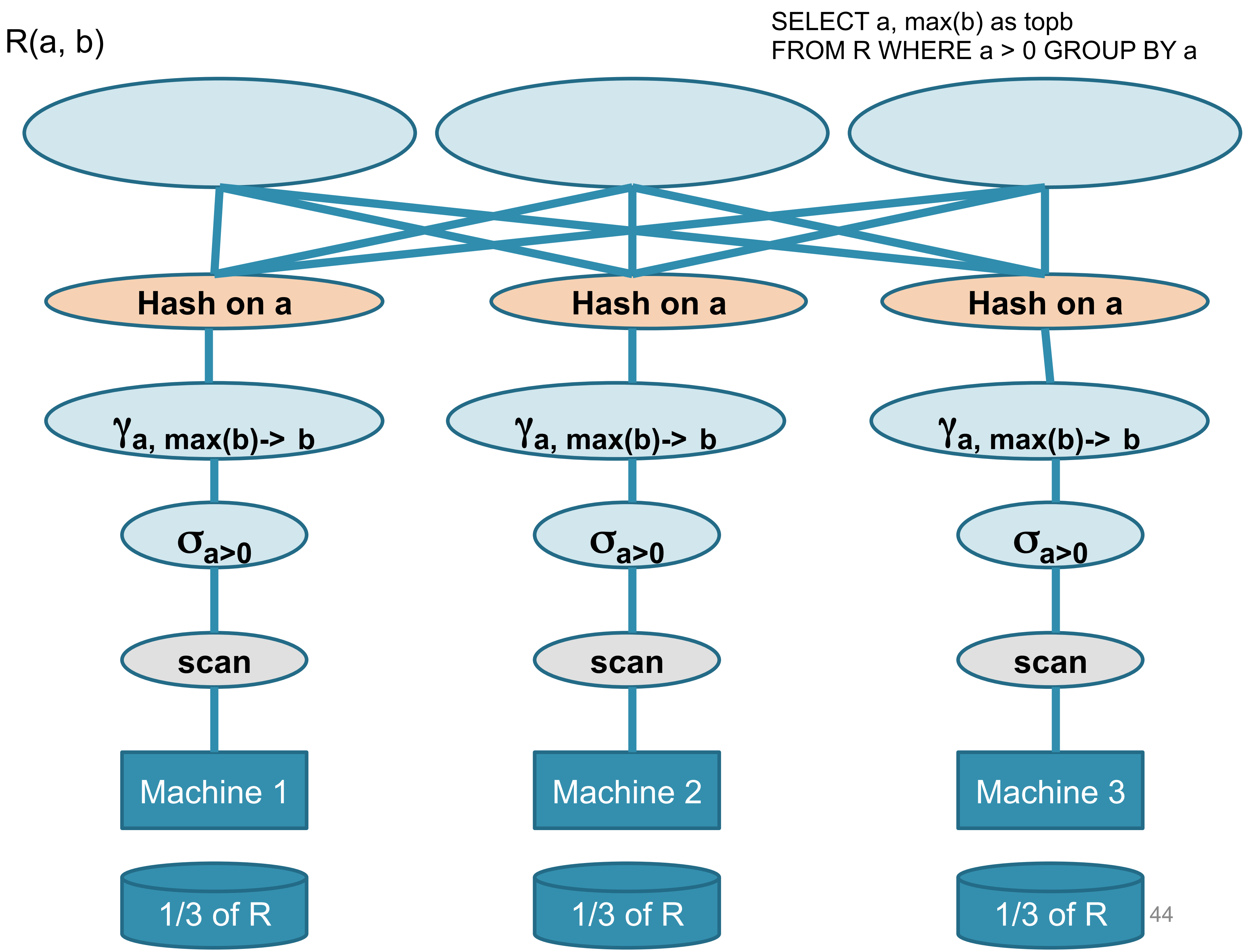
R(a, b)
SELECT a, max(b) as topb
FROM R WHERE a > 0 GROUP BY a
Hash on a
Hash on a
Hash on a
γa, max(b)-> b
γa, max(b)-> b
γa, max(b)-> b
σa>0
σa>0
σa>0
scan
scan
scan
Machine 1
Machine 2
Machine 3
1/3 of R
1/3 of R
1/3 of R

R(a, b)

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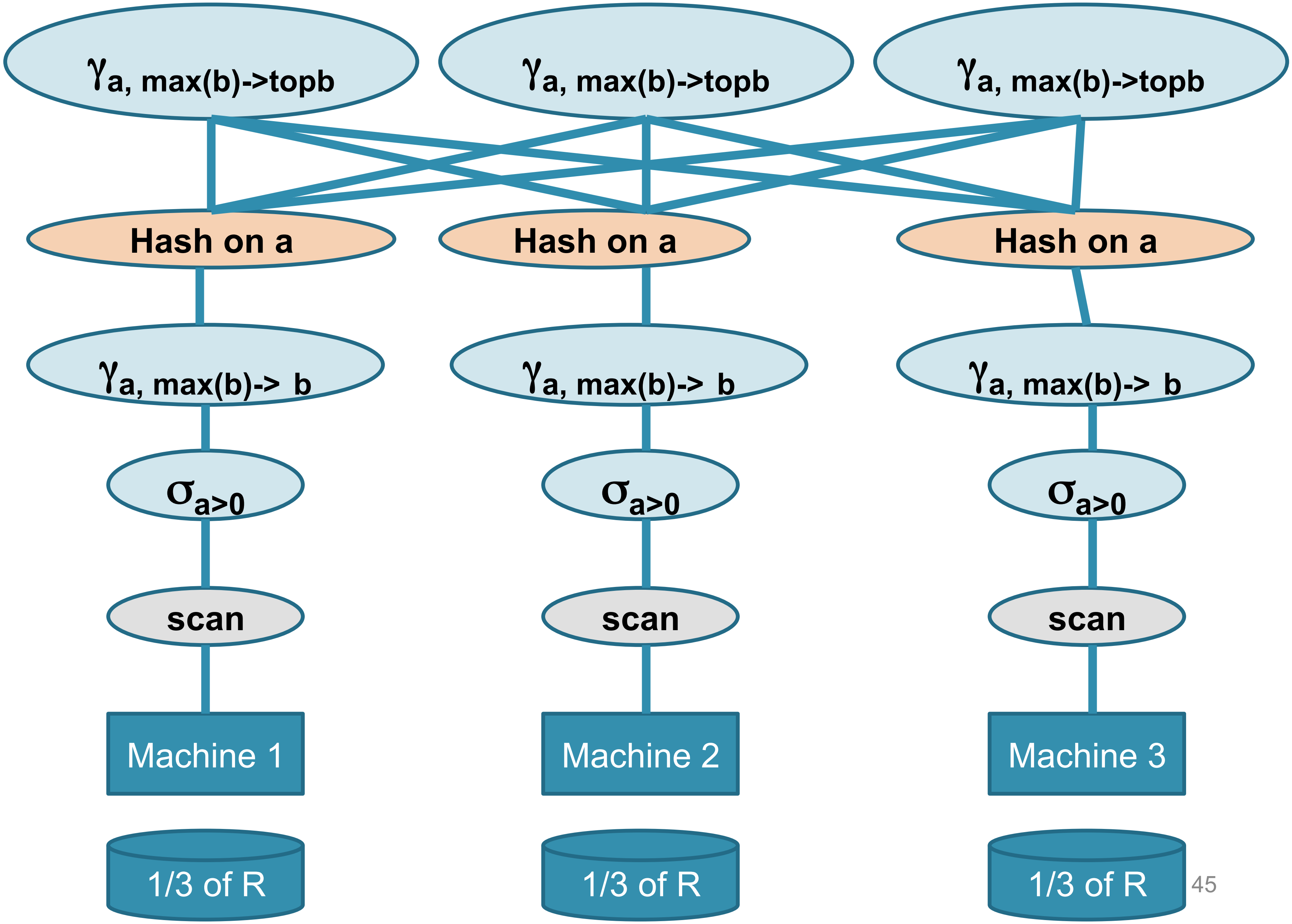


1b. Map Reduce

Explain how the query will be executed in MapReduce (not PIG)

SELECT a, max(b) as topb
FROM R
WHERE a > 0
GROUP BY a

Specify the computation performed in the map and the reduce functions

Map

```
SELECT a, max(b) as topb
FROM R
WHERE a > 0
GROUP BY a
```

- Each map task
  - Scans a block of R
  - Calls the map function for each tuple
  - The map function applies the selection predicate to the tuple
  - For each tuple satisfying the selection, it outputs a **record with key = a and value = b**

•When each map task scans multiple relations, it needs to output something like
key = a and value = (‘R’, b)
which has the relation name ‘R’

Shuffle

SELECT a, max(b) as topb
FROM R
WHERE a > 0
GROUP BY a

- The MapReduce engine reshuffles the output of the map phase and groups it on the intermediate key, i.e. the attribute a

Reduce

SELECT a, max(b) as topb
FROM R
WHERE a > 0
GROUP BY a

- Each reduce task
  - computes the aggregate value **max(b) = topb** for each group (i.e. ***a***) assigned to it (by calling the reduce function)
  - outputs the final results: **(a, topb)**

• A local combiner can be used to compute local max before data gets reshuffled (in the map tasks)

• Multiple aggregates can be output by the reduce phase like **key = a and value = (sum(b), min(b))** etc.

• Sometimes a second (third etc) level of Map-Reduce phase might be needed

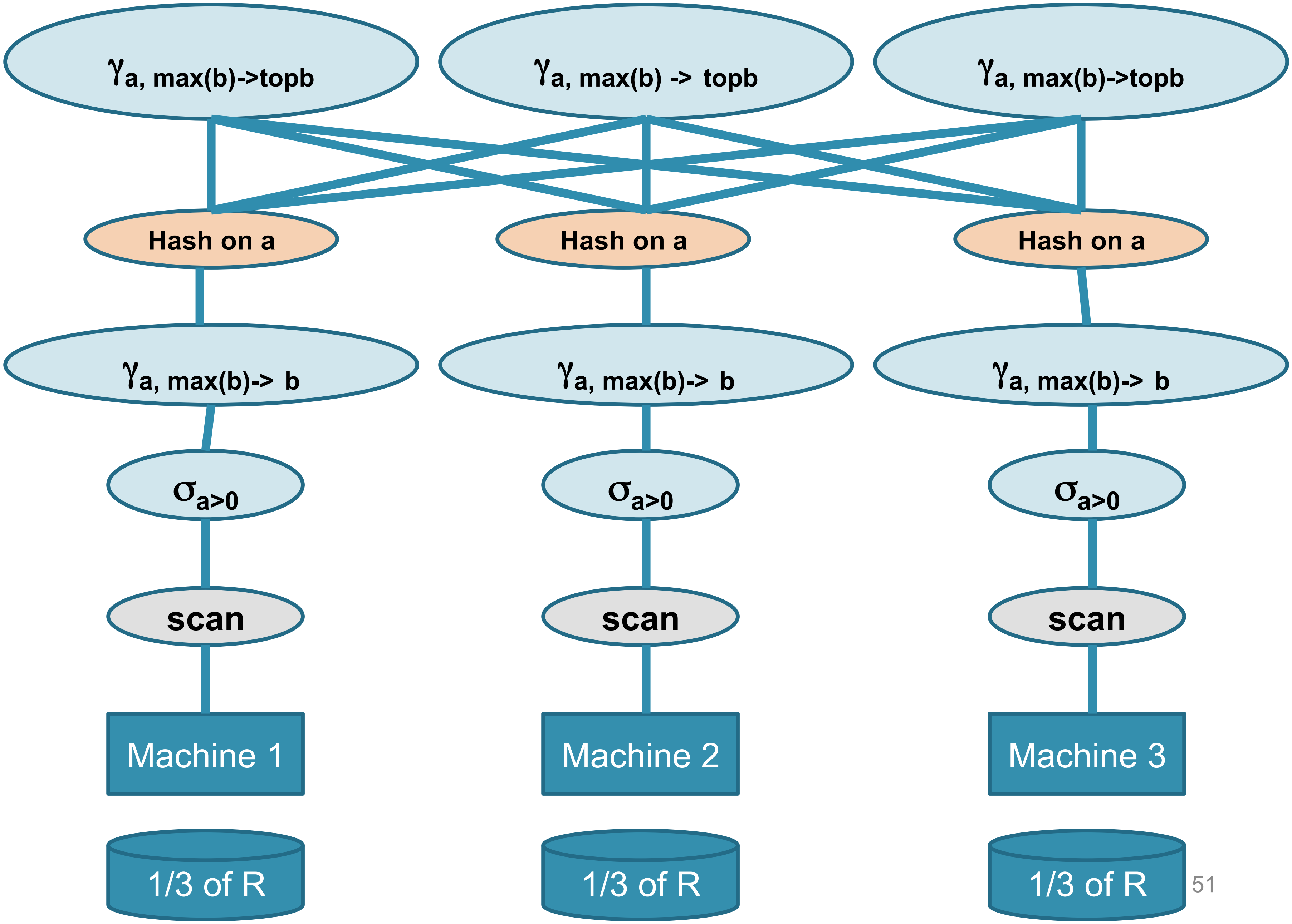
```
SELECT a, max(b) as topb
FROM R WHERE a > 0 GROUP BY a
```

1c. Benefit of hash-partitioning

- What would change if we hash-partitioned R on R.a before executing this query
  - For parallel DBMS
  - For MapReduce

Block partition

SELECT a, max(b) as topb
FROM R WHERE a > 0 GROUP BY a



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1c. Benefit of hash-partitioning

- **For parallel DBMS**
  - It would avoid the data re-shuffling phase
  - It would compute the aggregates locally

Hash-partition on a for R(a, b)

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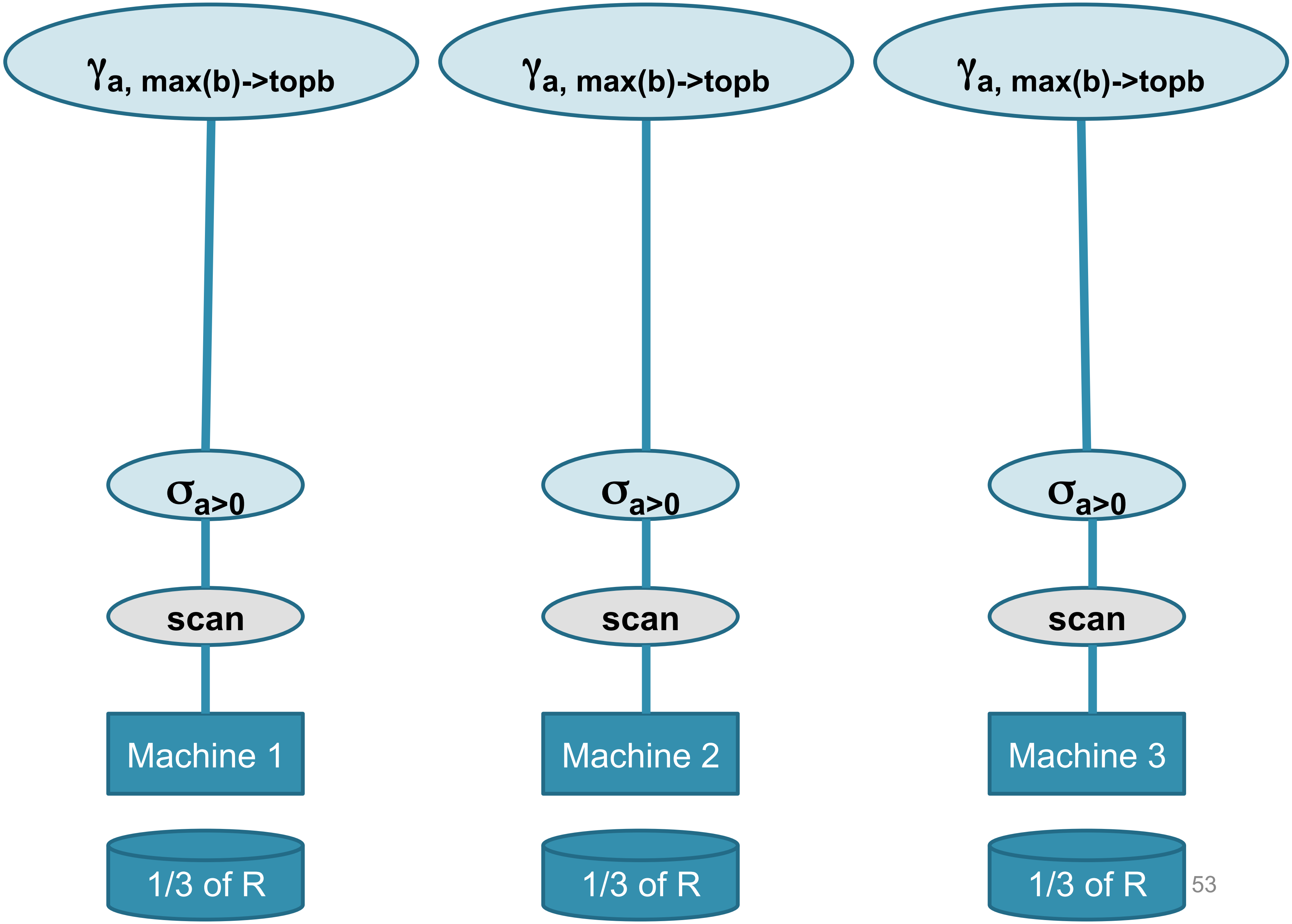

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1c. Benefit of hash-partitioning

- **For MapReduce**
  - Logically, MR won't know that the data is hash-partitioned
  - MR treats map and reduce functions as black-boxes and does not perform any optimizations on them

- But, if a local combiner is used
  - Saves communication cost:
    - fewer tuples will be emitted by the map tasks
  - Saves computation cost in the reducers:
    - the reducers would not have to do anything (if one map task/node) or less computation (multiple map tasks/node)