

Introduction to Data Management Introducing Parallel DBMSs

Paul G. Allen School of Computer Science and Engineering
University of Washington, Seattle

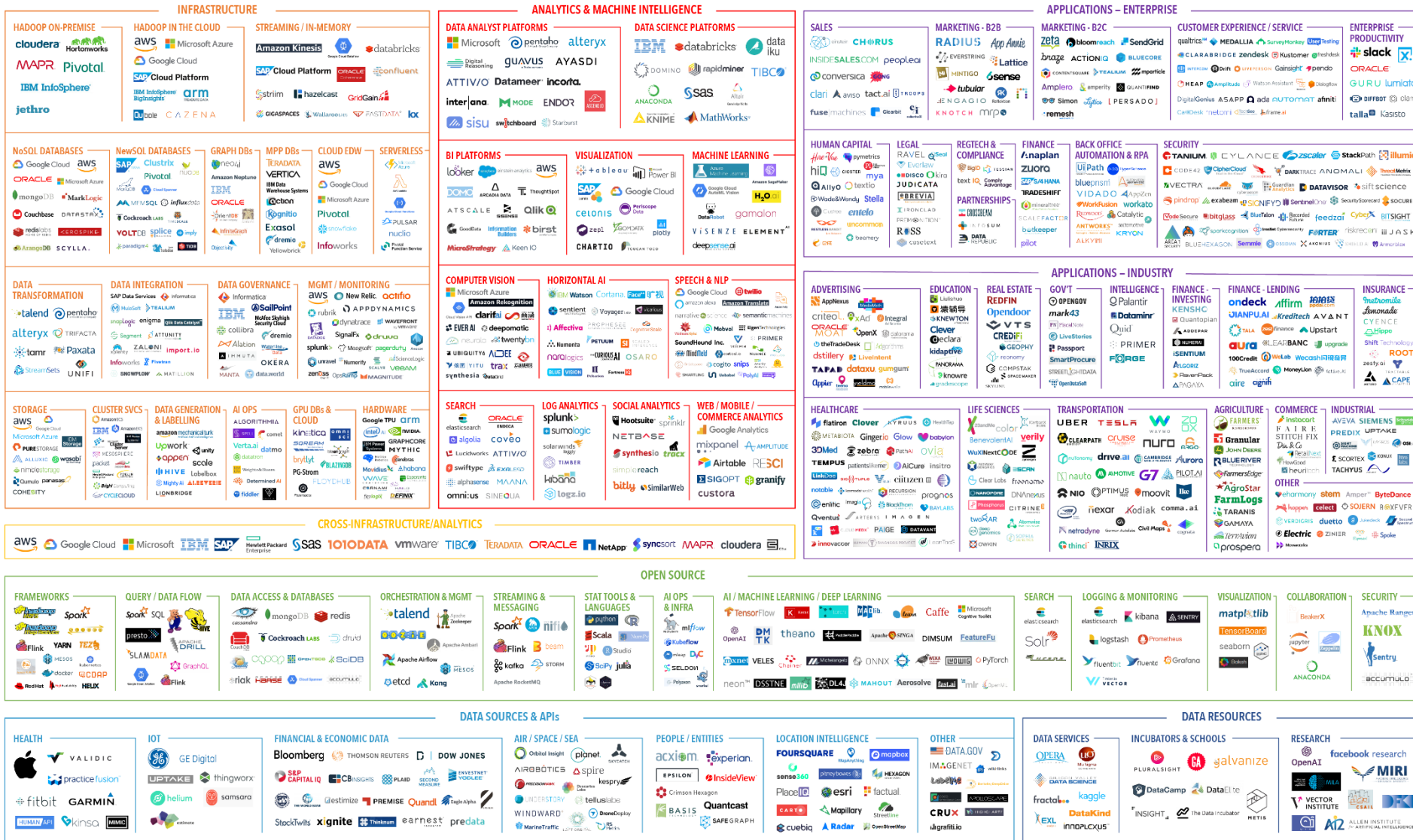
Announcements

- Midterm quiz released
 - Due Tuesday night (no late days)

Where We Are Headed Next

- Scaling the execution of a query
 - Parallel DBMS
 - MapReduce
 - Spark

DATA & AI LANDSCAPE 2019



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© Matt Turck (@mattturck), Lisa Xu (@lisaxu92), & FirstMark (@firstmarkcap) mattturck.com/data2019

FIRSTMARK
EARLY STAGE VENTURE CAPITAL

How to Scale the DBMS?

- Can easily replicate the web servers and the application servers
- We cannot so easily replicate the database servers, because the database is unique
- We need to design ways to **scale up the DBMS**

Building Our Parallel DBMS

Data model?

Relational
(familiar!)

Building Our Parallel DBMS

Data model?

Relational
(familiar!)

Scaleup goal?

Scaling Transactions Per Second

- OLTP: Transactions per second
“Online Transaction Processing”
- Amazon
- Facebook
- Twitter
- ... your favorite Internet application...
- Goal is to increase transaction throughput

Scaling Single Query Response Time

- OLAP: Query response time
“Online Analytical Processing”
- Entire parallel system answers one query
- Goal is to improve query runtime
- Use case is analysis of massive datasets

Big Data

Volume alone is not an issue

- Relational databases *do* parallelize easily; techniques available from the 80's
 - Data partitioning
 - Parallel query processing
- SQL is *embarrassingly parallel*
 - We will learn how to do this!

Big Data

New **workloads** are an issue

- Big volumes, small analytics
 - OLAP queries: join + group-by + aggregate
 - Can be handled by today's RDBMSs
- Big volumes, big analytics
 - More complex Machine Learning, e.g. click prediction, topic modeling, SVM, k-means
 - Requires innovation – Active research area

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Relational

Scaleup goal?

OLAP

Building Our Parallel DBMS

Data model?

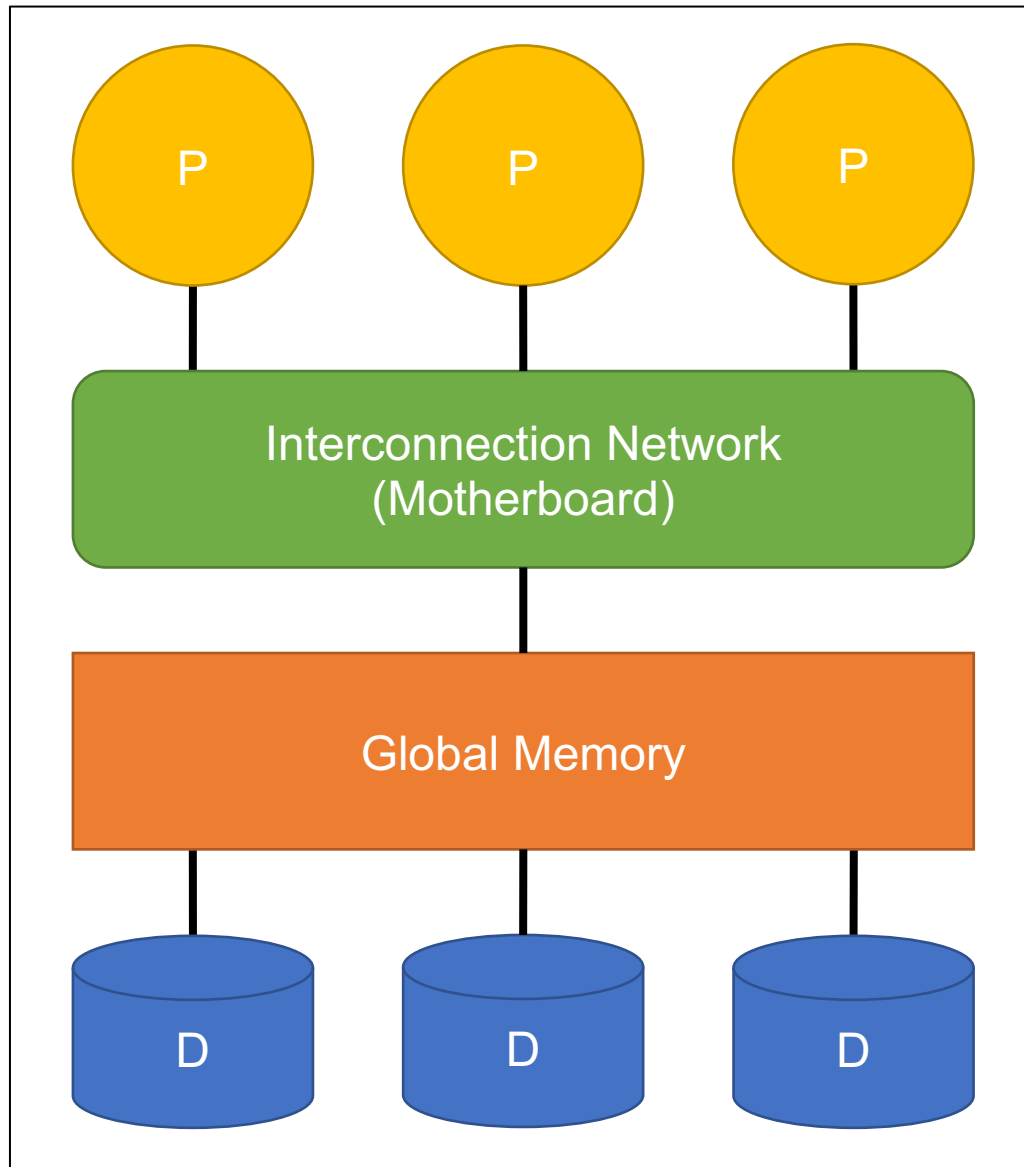
Relational

Scaleup goal?

OLAP

Architecture?

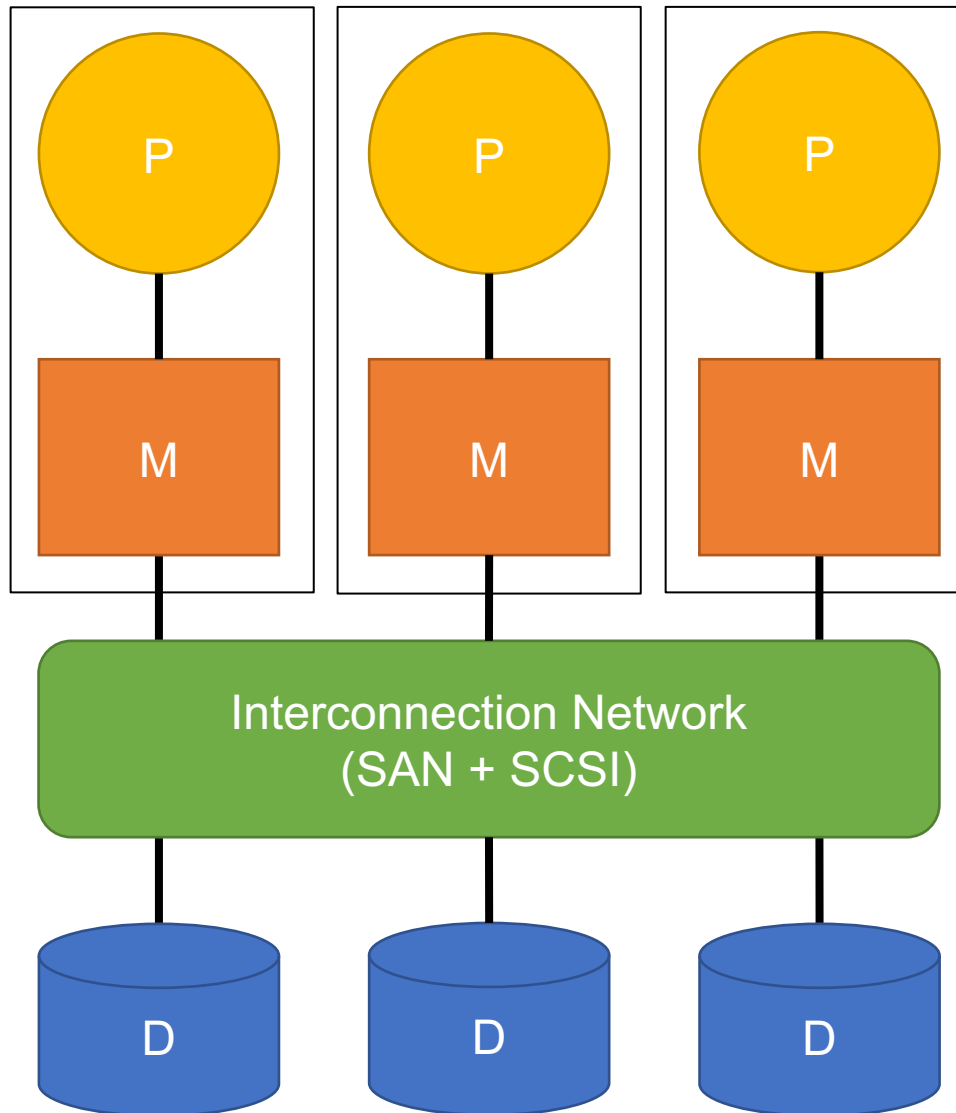
Shared-Memory Architecture



- Shared main memory and disks
- Your laptop or desktop uses this architecture
- **Expensive to scale**
- **Easiest to implement on**



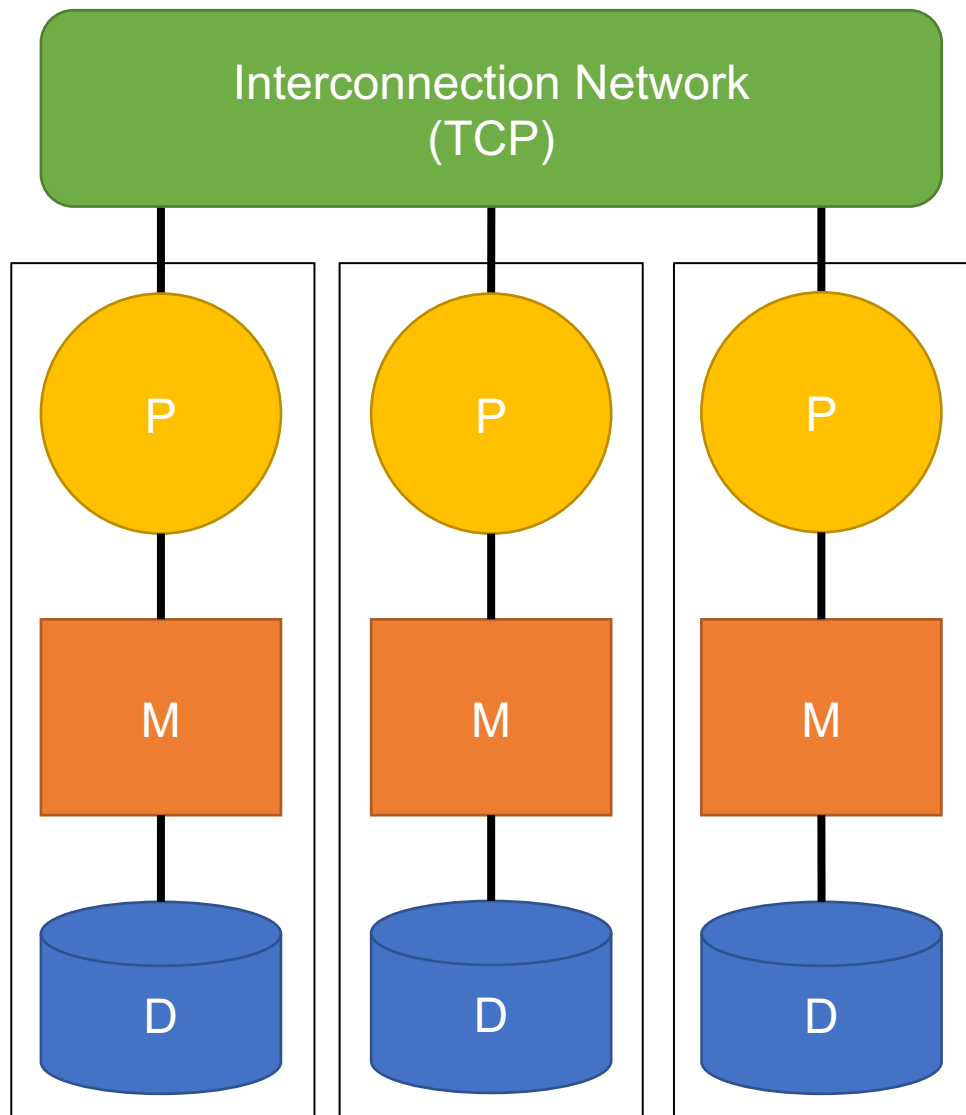
Shared-Disk Architecture



- Only shared disks
- No contention for memory and high availability
- Typically 1-10 machines

ORACLE[®]
D A T A B A S E

Shared-Nothing Architecture



- Uses cheap, commodity hardware
- No contention for memory and high availability
- Theoretically can **scale infinitely**
- Hardest to implement on

teradata.

APACHE
Spark[™]

MySQL[™] Cluster

Building Our Parallel DBMS

Data model?

Relational

Scaleup goal?

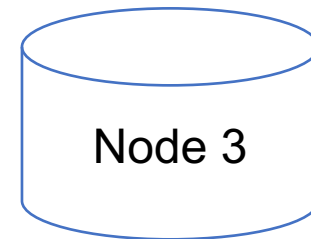
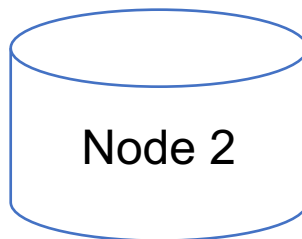
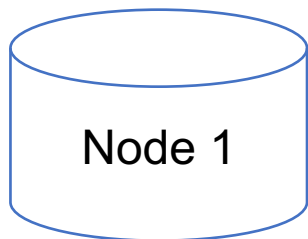
OLAP

Architecture?

Shared-Nothing

Shared-Nothing Execution Basics

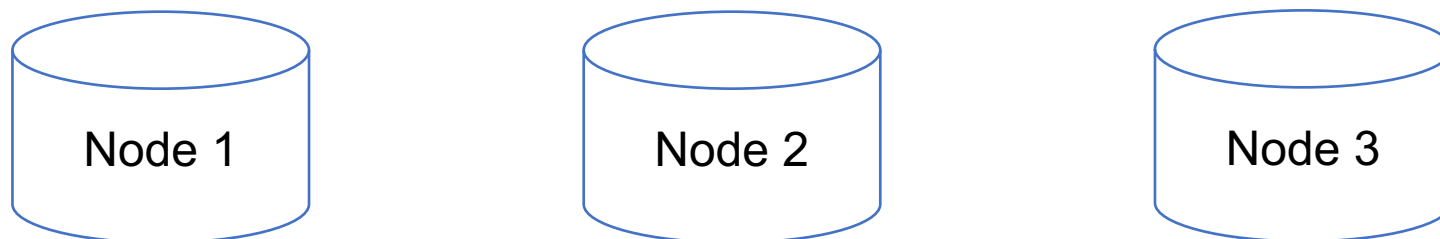
- Multiple DBMS instances (= processes) also called “nodes” execute on machines in a cluster
 - One node plays role of the coordinator
 - Other nodes play role of workers
- Workers execute queries
 - Typically **all workers execute the same plan**
 - Workers can execute multiple queries at the same time



Shared-Nothing Database

We will assume a system that consists of multiple commodity machines on a common network

New problem: **Where does the data go?**

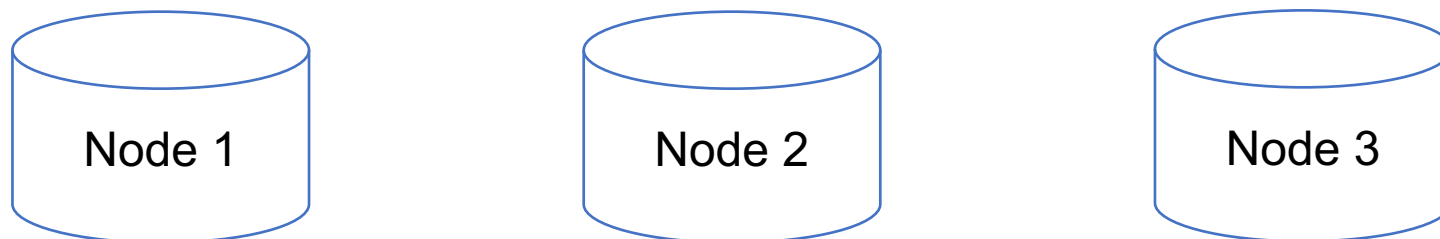


Shared-Nothing Database

We will assume a system that consists of multiple commodity machines on a common network

New problem: **Where does the data go?**

The answer will influence our execution techniques

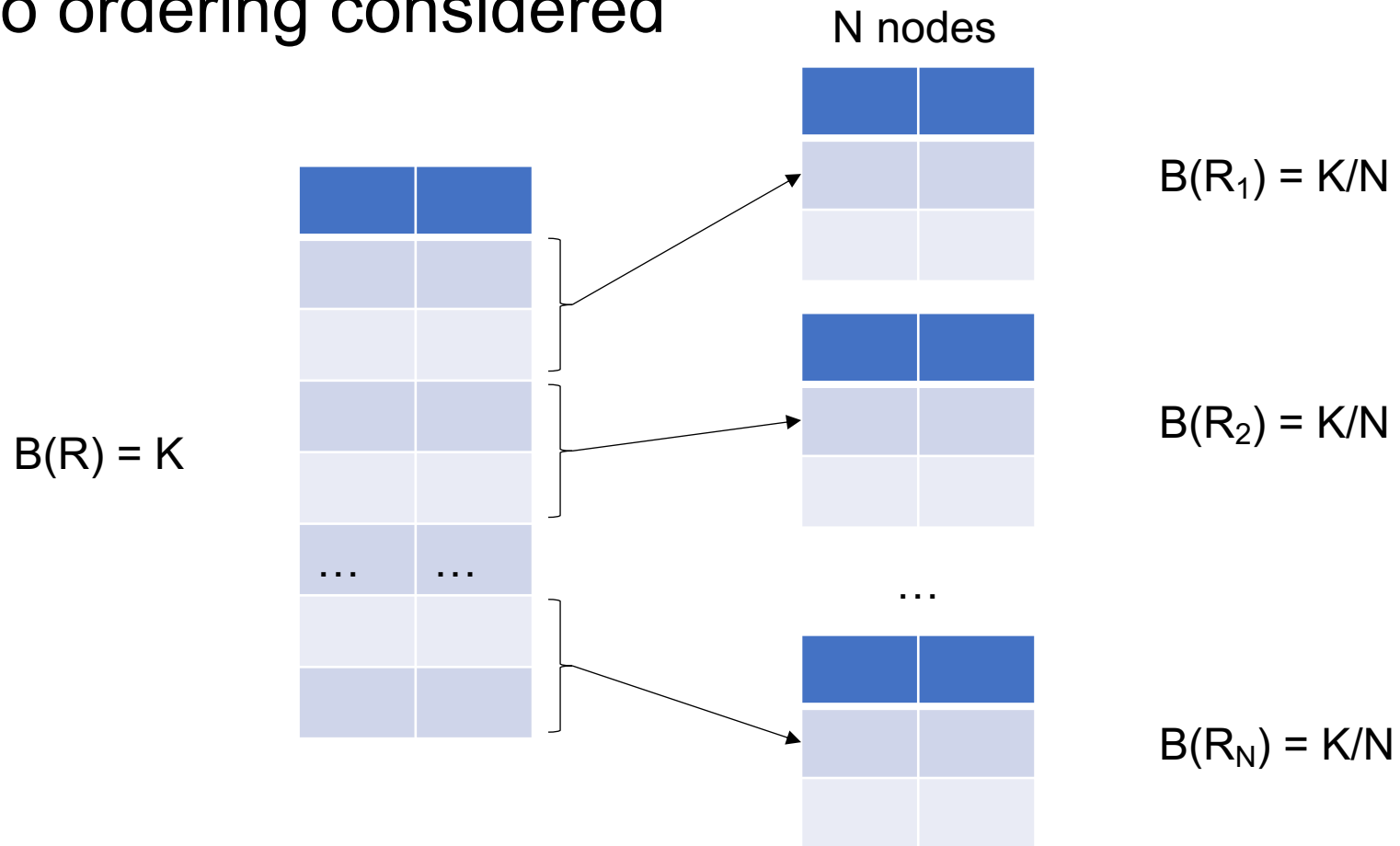


Option 1: Unpartitioned Table

- Entire table on just one node in the system
- Will bottleneck any query we need to run in parallel
- We choose partitioning scheme to divide rows among machines

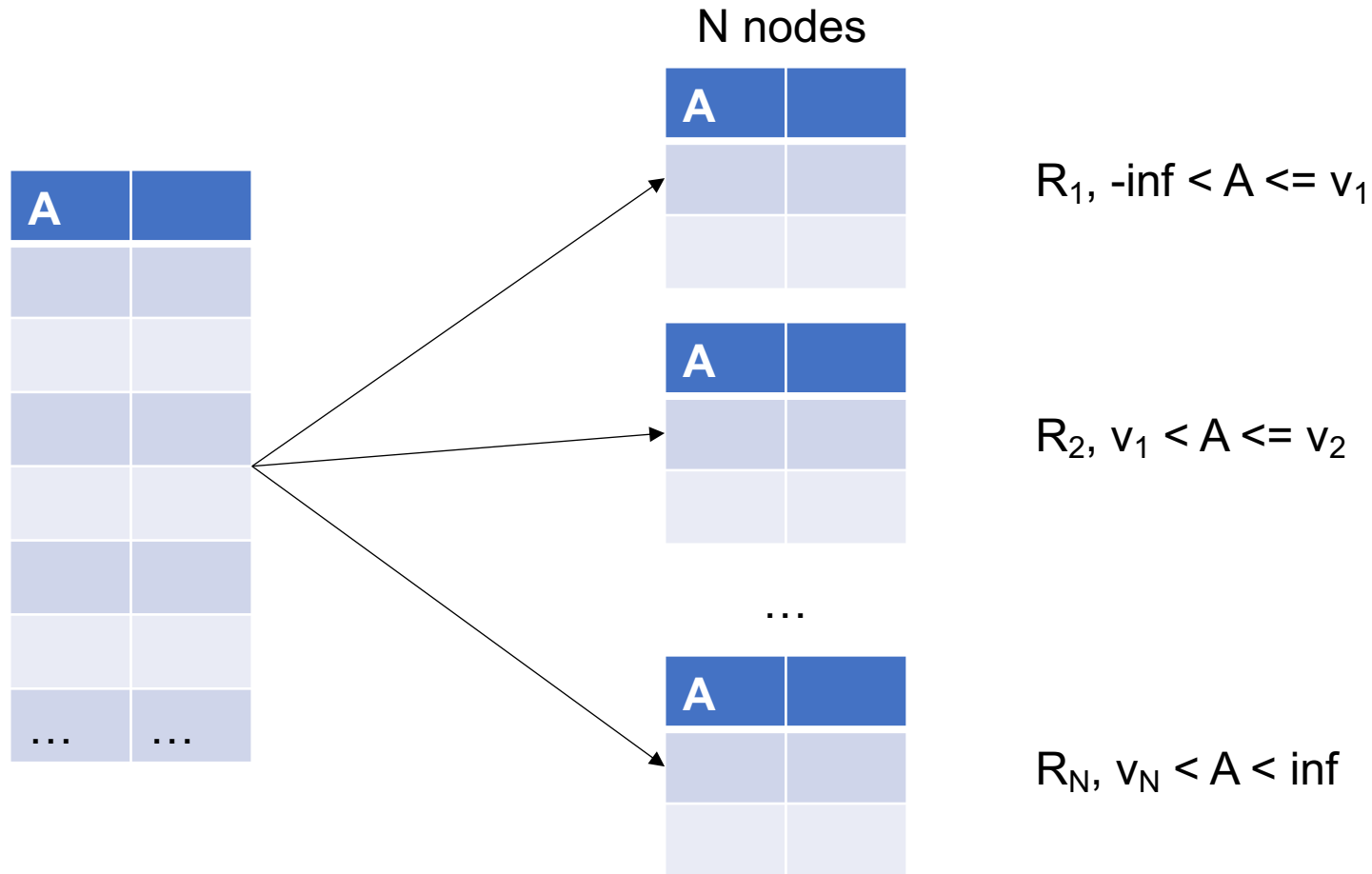
Option 2: Block Partitioning

Tuples are horizontally (row) partitioned by raw size with no ordering considered



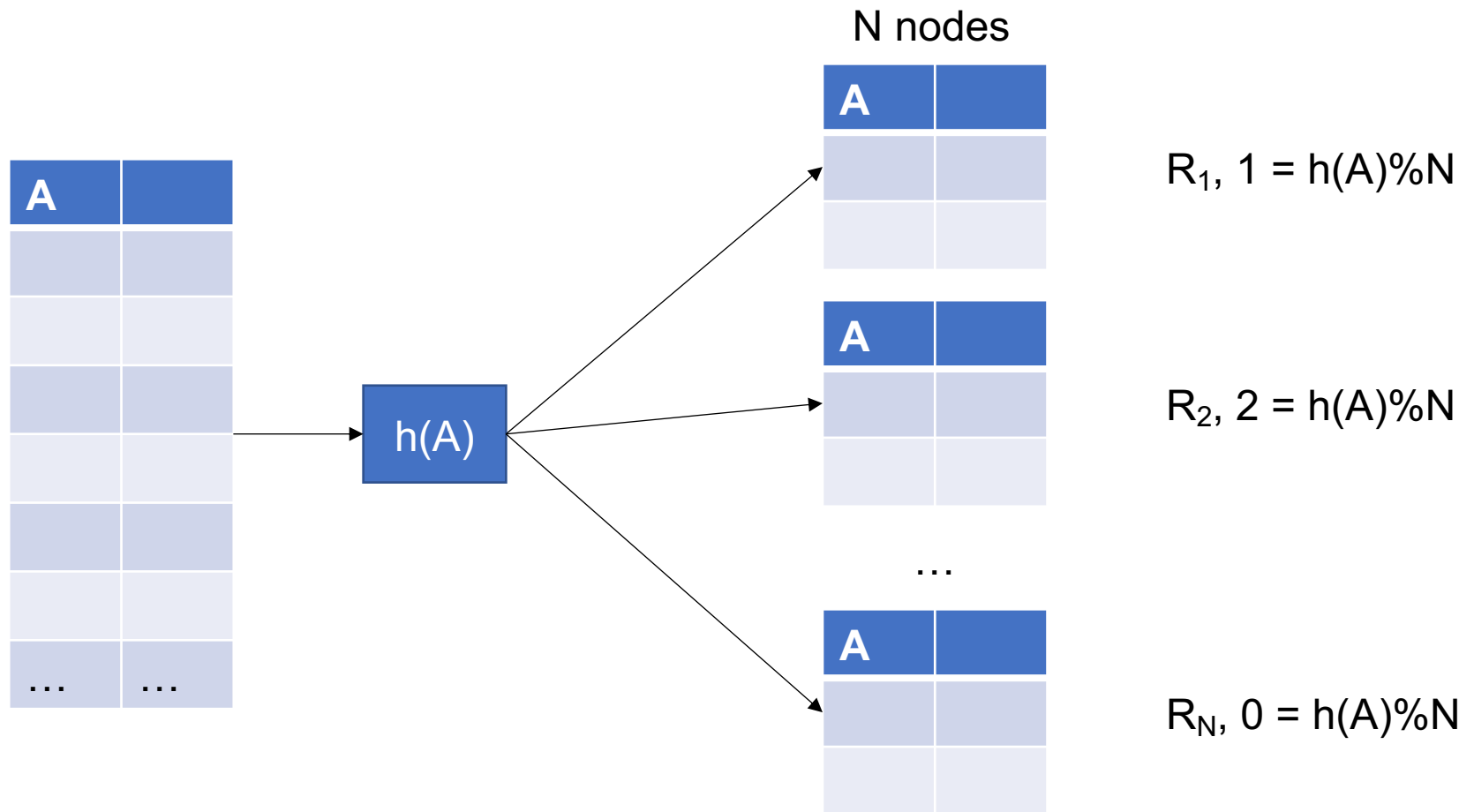
Option 3: Range Partitioning

Node contains tuples in chosen attribute ranges



Option 4: Hash Partitioning

Node contains tuples with chosen attribute hashes



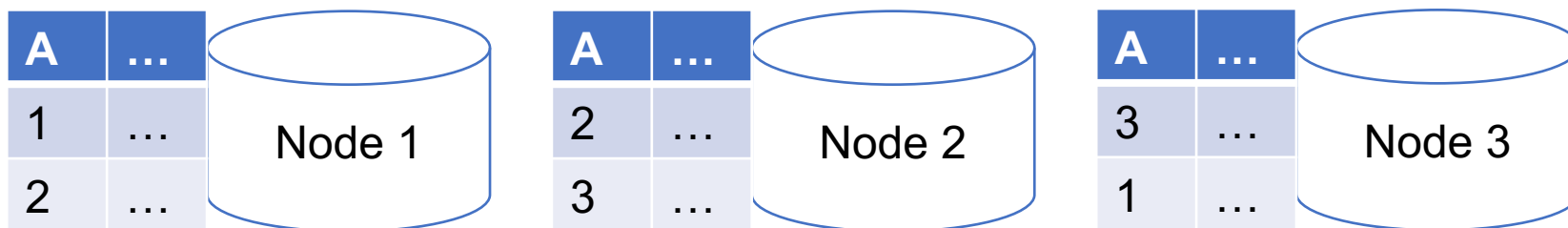
Skew: The Justin Bieber Effect

- Hashing data to nodes is very good when the attribute chosen better approximates a uniform distribution
- Keep in mind: Certain nodes will become bottlenecks if a poorly chosen attribute is hashed

Parallel Selection

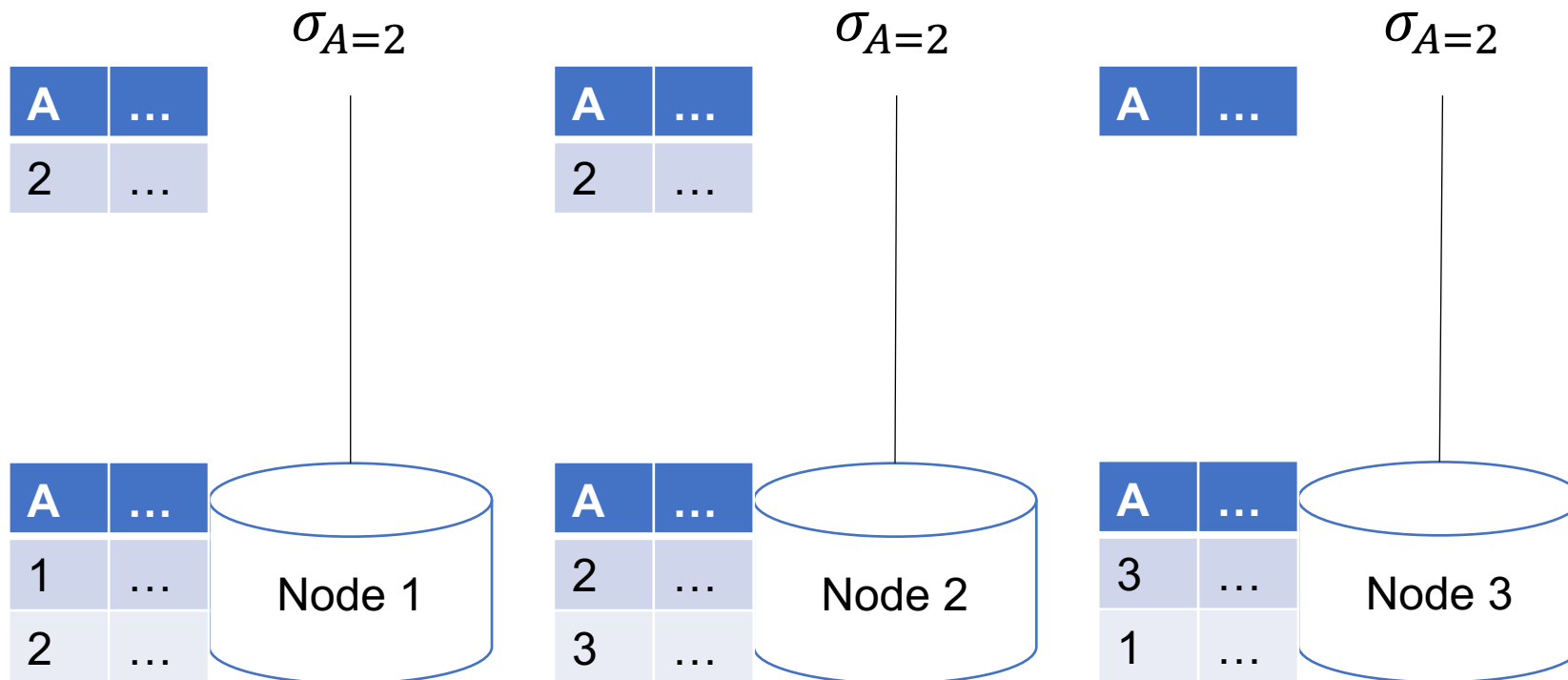
Assume:
R is block partitioned

```
SELECT *  
FROM R  
WHERE A = 2
```



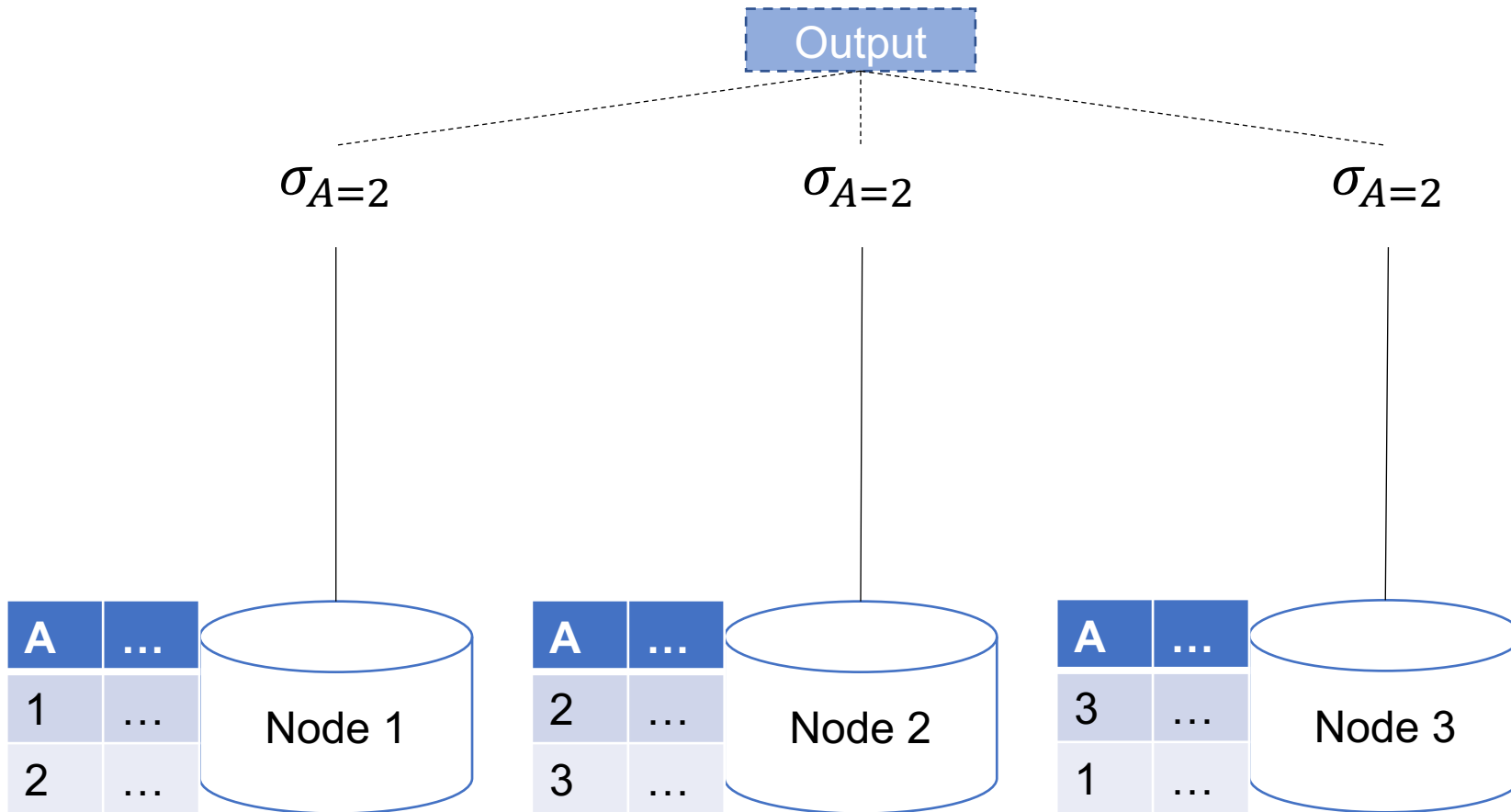
Parallel Selection

```
SELECT *  
FROM R  
WHERE A = 2
```



Implicit Union

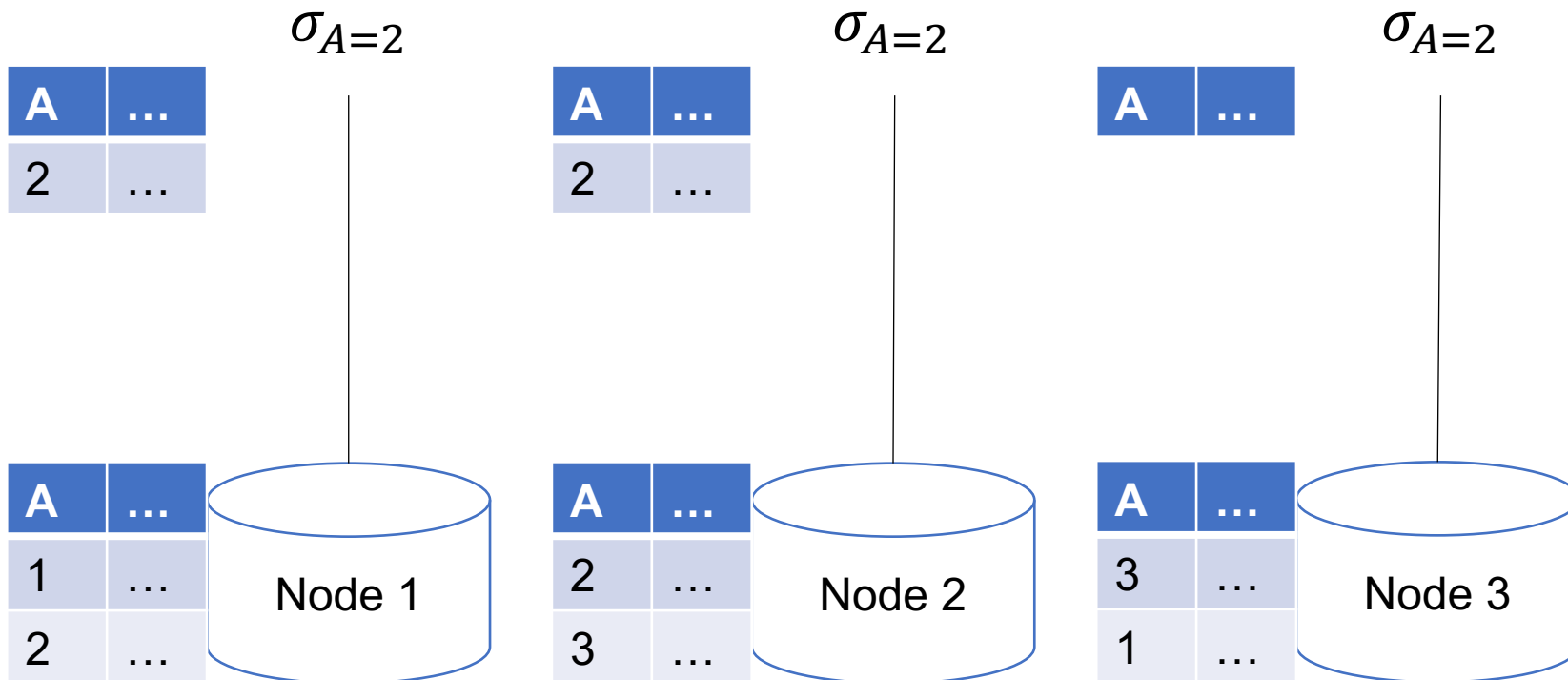
Parallel query plans implicitly union at the end



Parallel Selection

Data-parallel!

```
SELECT *  
FROM R  
WHERE A = 2
```



Parallel Selection

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

- On a conventional database: cost = **B(R)**

Q: What is the cost on each node for a database with N nodes ?

A:

Parallel Selection

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

- On a conventional database: cost = **B(R)**

Q: What is the cost on each node for a database with N nodes ?

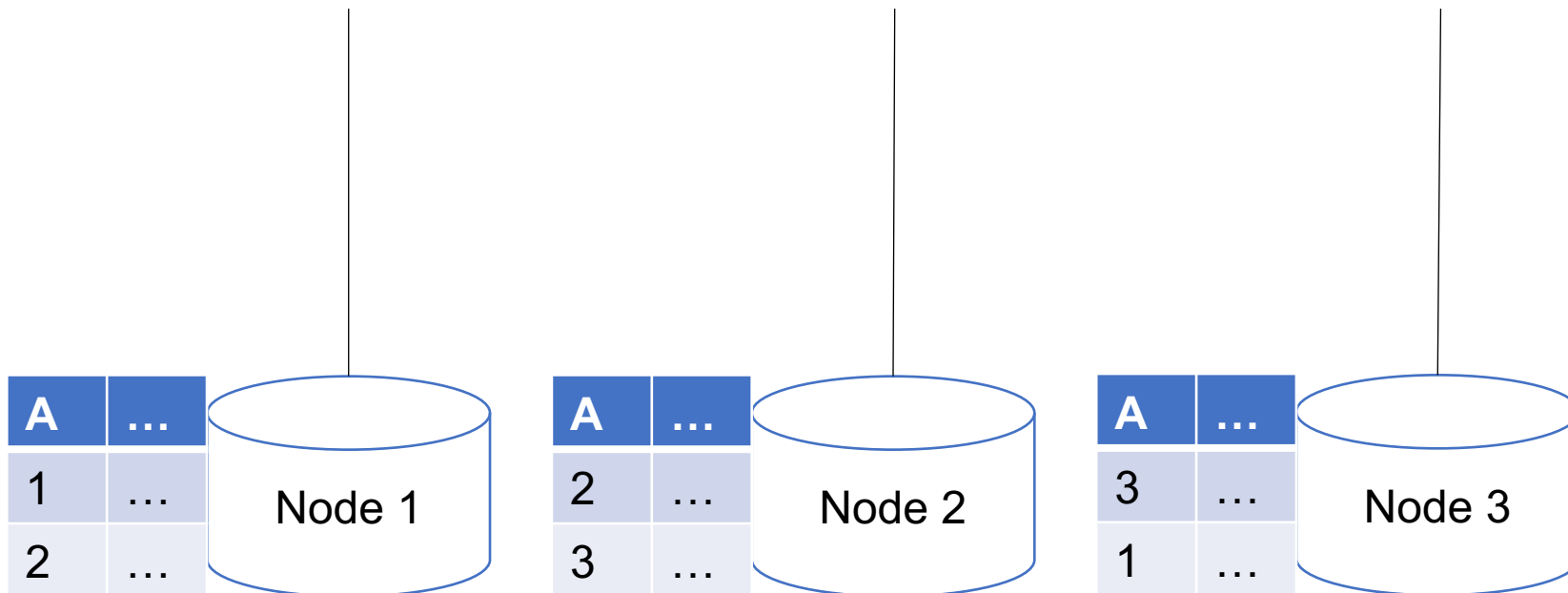
A: $B(R) / N$ block reads on each node

Parallel Selection

What if this query
is not data-parallel?

Assume:
R is block partitioned

```
SELECT *  
FROM R  
.....
```



Partitioned Aggregation

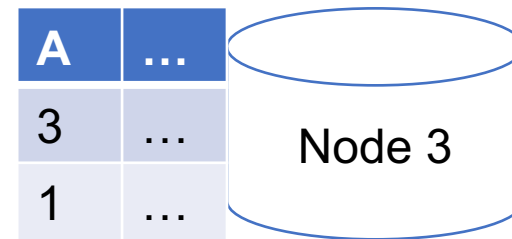
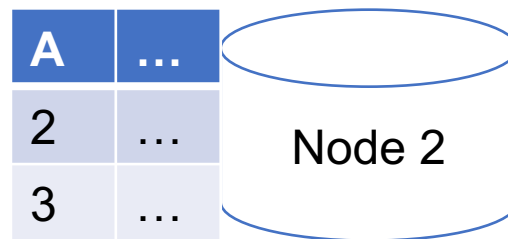
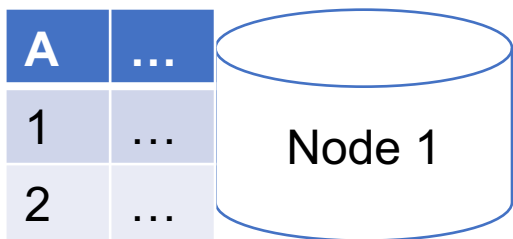
Assume:
R is block partitioned

```
SELECT *  
FROM R  
GROUP BY R.A
```

$\mathcal{V}_{R.A}$

$\mathcal{V}_{R.A}$

$\mathcal{V}_{R.A}$



Partitioned Aggregation

Assume:
R is block partitioned

```
SELECT *  
FROM R  
GROUP BY R.A
```

A	...
1	...
1	...

$\gamma_{R.A}$

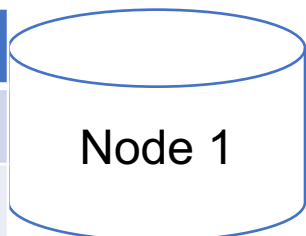
A	...
2	...
2	...

$\gamma_{R.A}$

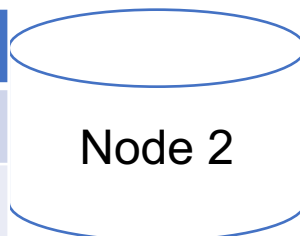
A	...
3	...
3	...

$\gamma_{R.A}$

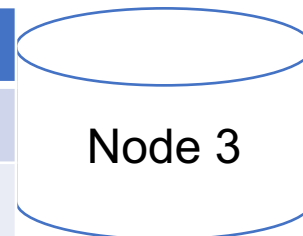
A	...
1	...
2	...



A	...
2	...
3	...



A	...
3	...
1	...



Partitioned Aggregation

1. Hash shuffle tuples

Assume:
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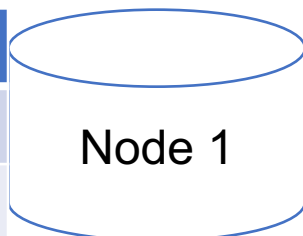
A	...
2	...
2	...

$\gamma_{R.A}$

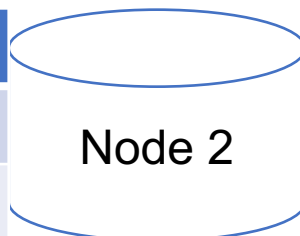
A	...
3	...
3	...

$\gamma_{R.A}$

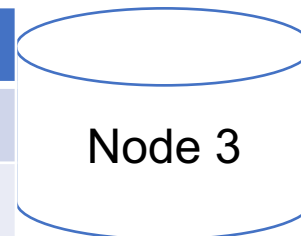
A	...
1	...
2	...



A	...
2	...
3	...



A	...
3	...
1	...

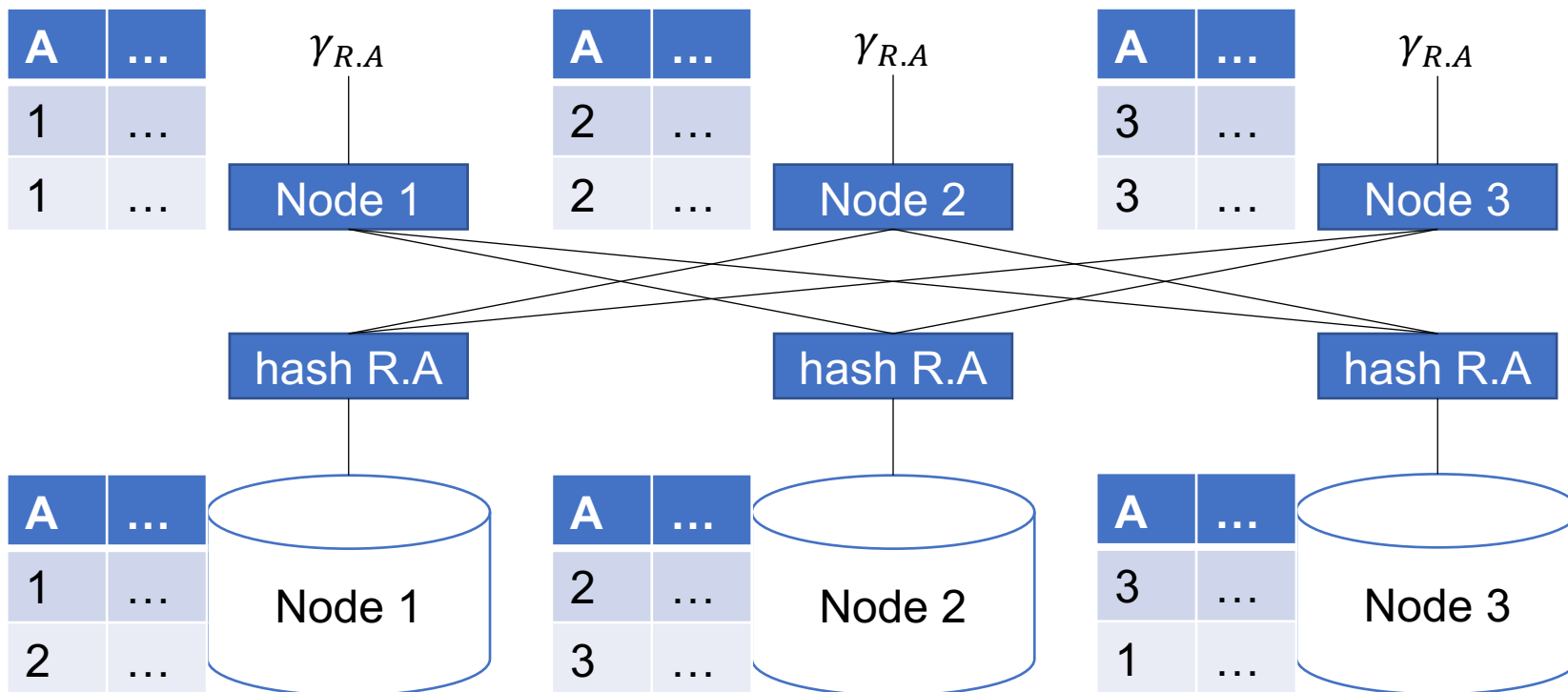


Partitioned Aggregation

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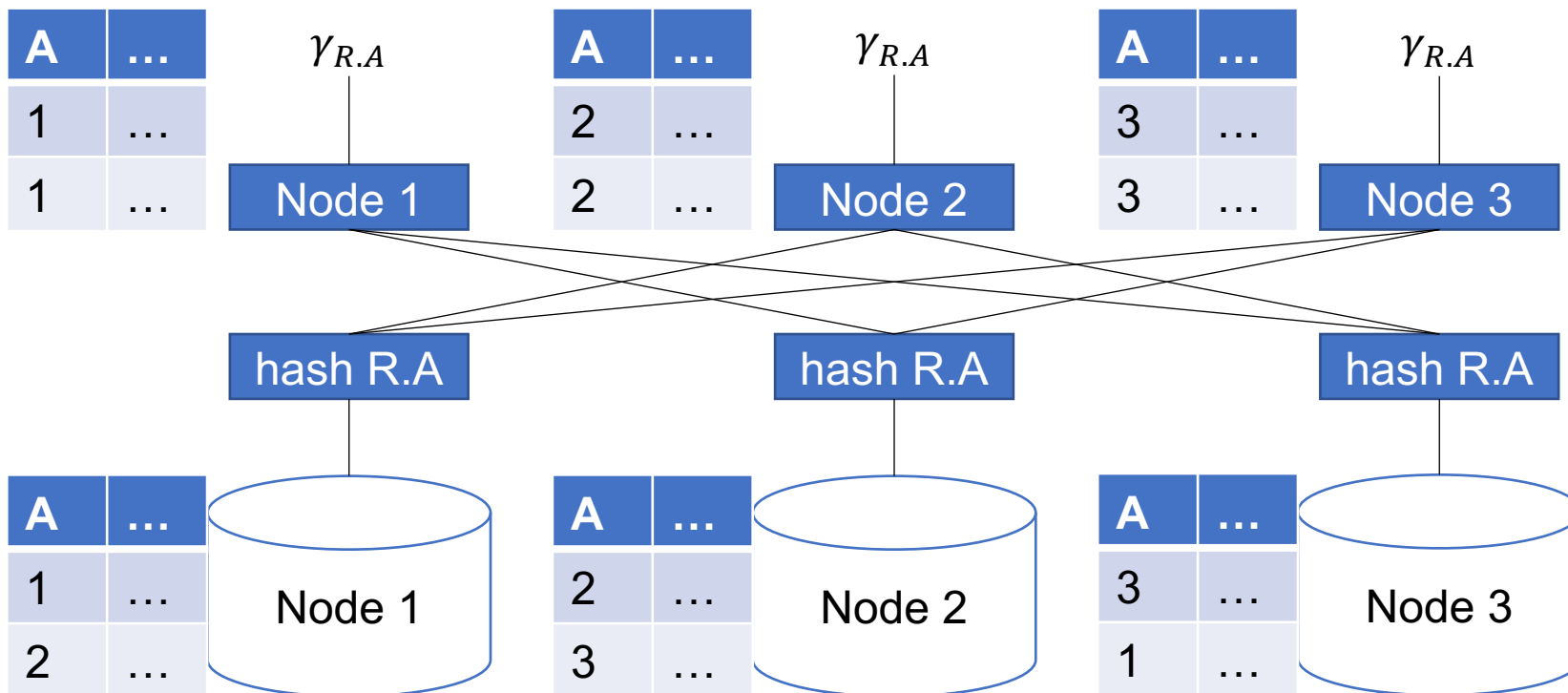


Partitioned Aggregation

1. Hash shuffle tuples
2. Local aggregation

Assume:
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SELECT *  
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GROUP BY R.A
```

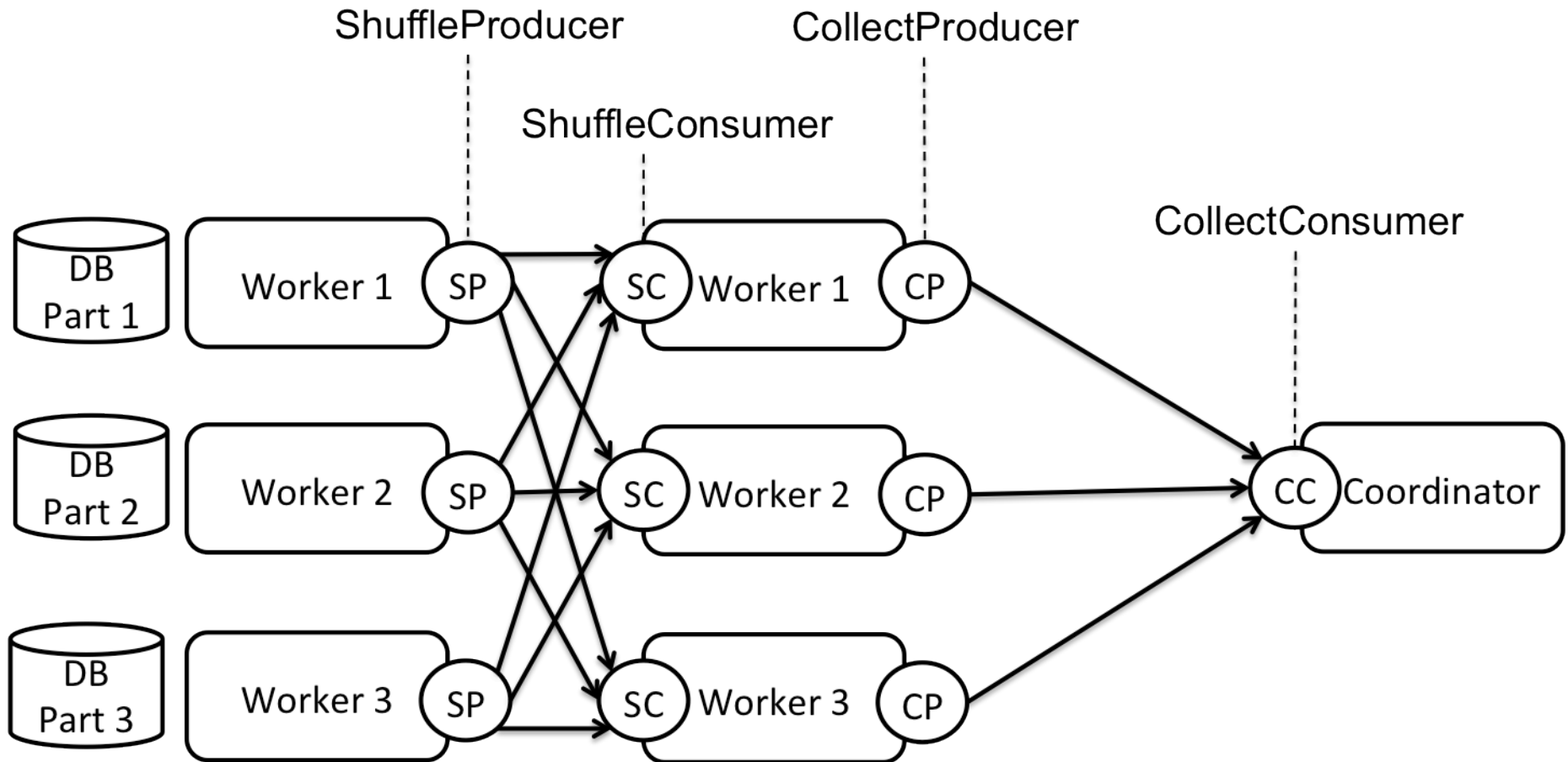


Parallel Query Evaluation

New operator: **Shuffle**

- Serves to re-shuffle data between processes
 - Handles data routing, buffering, and flow control
- Not relational algebra, but special operator in query plans

Parallel Query Execution



Partitioned Hash Equijoin Algorithm

1. Hash shuffle tuples on join attributes

Assume:

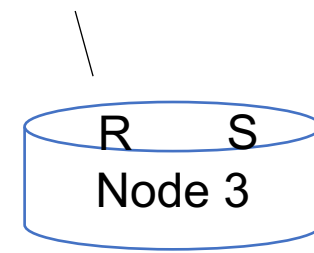
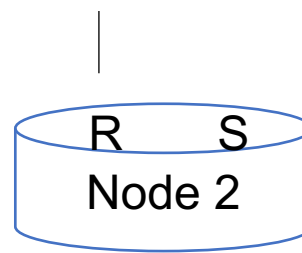
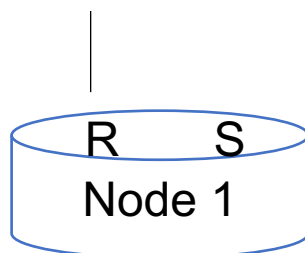
R and S are block partitioned

```
SELECT *  
FROM R, S  
WHERE R.A = S.A
```

$\bowtie_{R.A=S.A}$

$\bowtie_{R.A=S.A}$

$\bowtie_{R.A=S.A}$



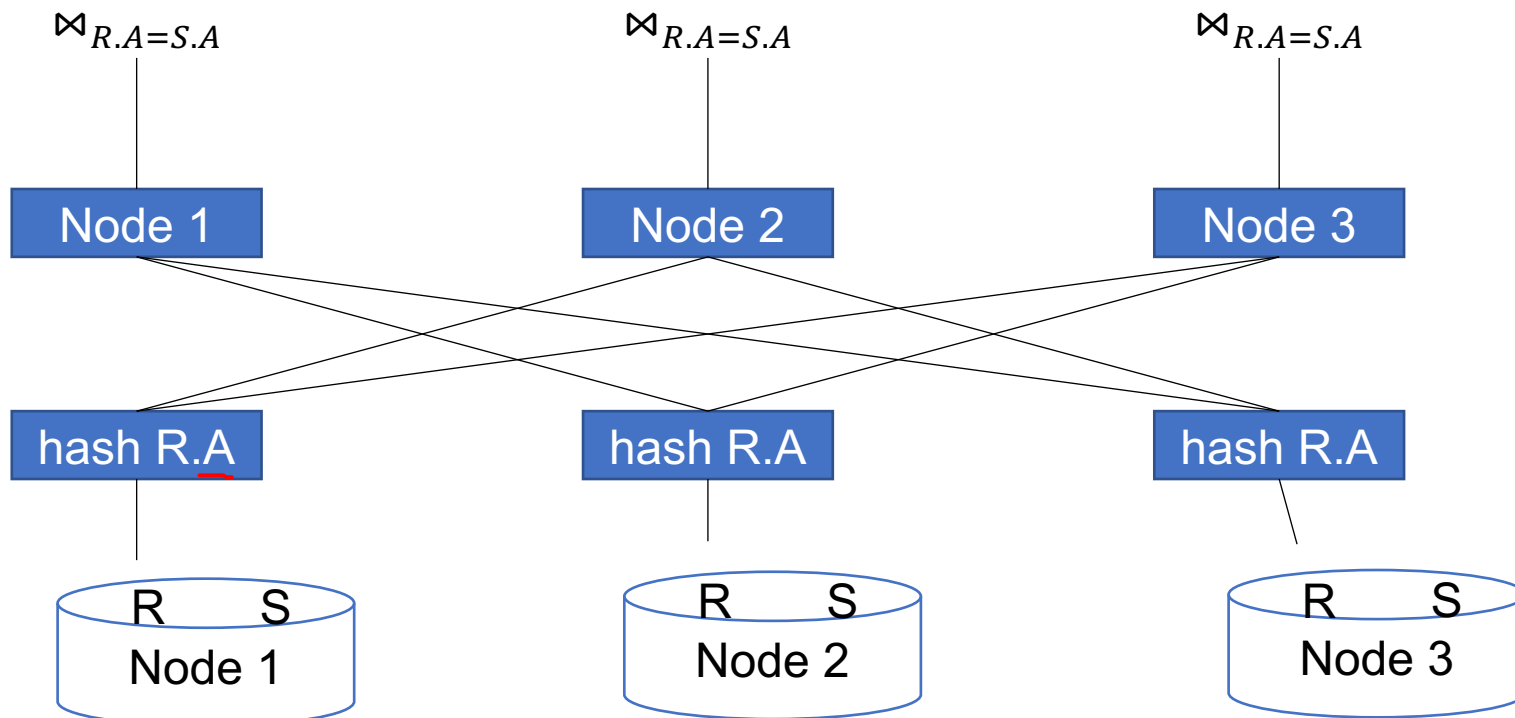
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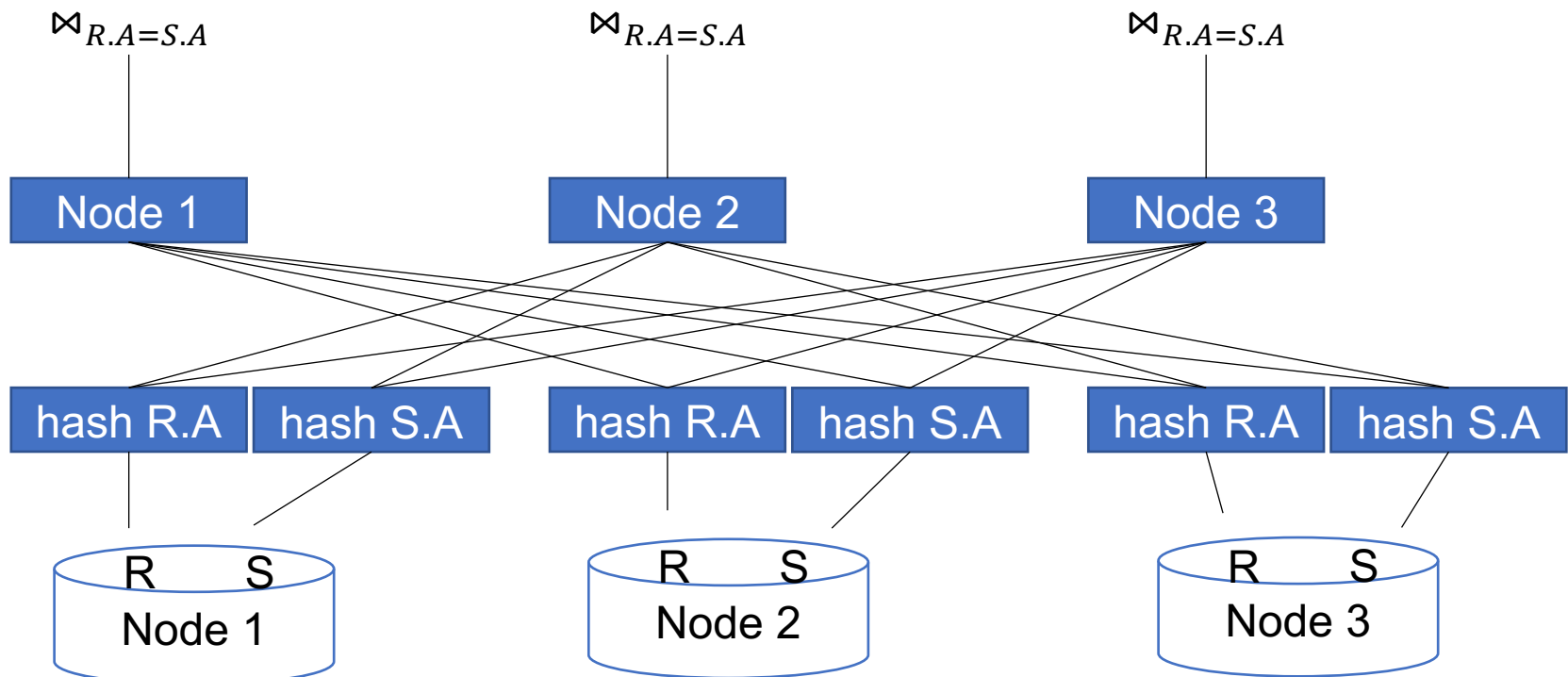
Partitioned Hash Equijoin Algorithm

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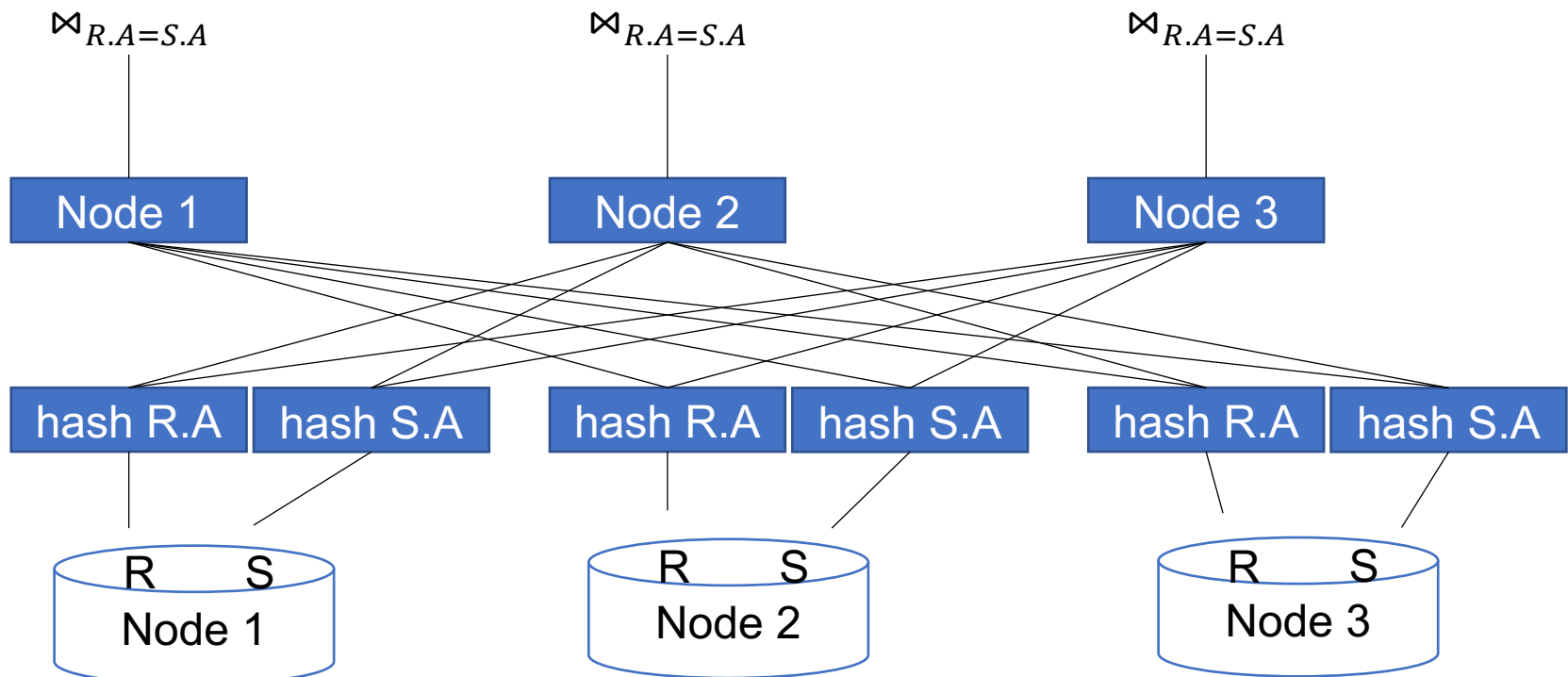
Partitioned Hash Equijoin Algorithm

1. Hash shuffle tuples on join attributes
2. Local join

Assume:

R and S are block partitioned

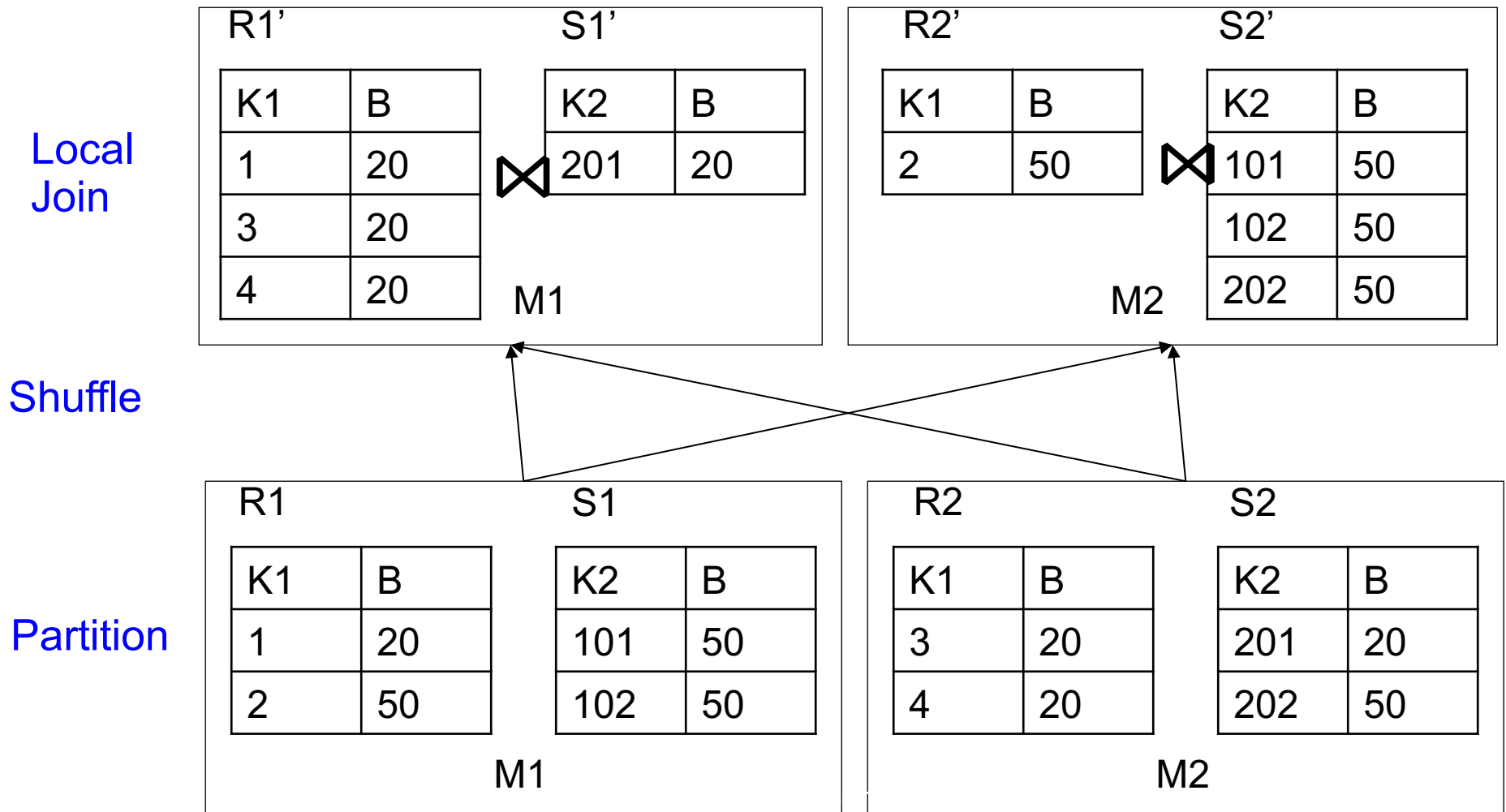
```
SELECT *  
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```



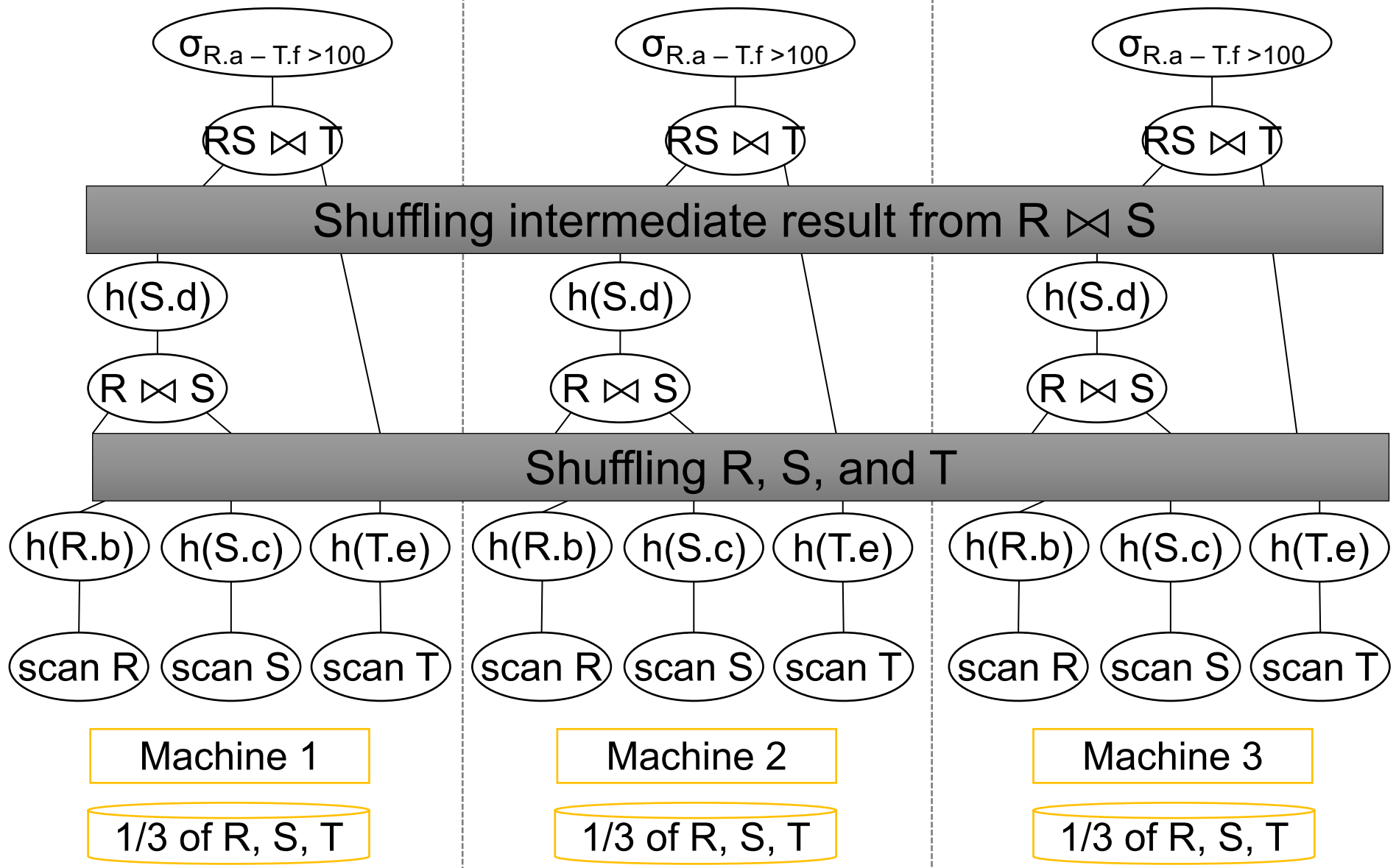
Data: R(K1,A, B), S(K2, B, C)

Query: R(K1,A,B) ⋈ S(K2,B,C)

Join on R.B = S.B



Multiple Shuffles



Summary

- With one new operator, we've made an OLAP-ready parallel DBMS!

Speedup and Scaleup

- Consider:
 - Query: $\gamma_{A, \text{sum}(C)}(R)$
 - Runtime: dominated by reading chunks from disk
- If we double the number of nodes P , what is the new running time?
- If we double both P and the size of R , what is the new running time?

Speedup and Scaleup

- Consider:
 - Query: $\gamma_{A, \text{sum}(C)}(R)$
 - Runtime: dominated by reading chunks from disk
- If we double the number of nodes P , what is the new running time?
 - **Half** (each server holds $\frac{1}{2}$ as many chunks)
- If we double both P and the size of R , what is the new running time?

Speedup and Scaleup

- Consider:
 - Query: $\gamma_{A, \text{sum}(C)}(R)$
 - Runtime: dominated by reading chunks from disk
- If we double the number of nodes P , what is the new running time?
 - **Half** (each server holds $\frac{1}{2}$ 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)

Basic Parallel GroupBy

Can we do better?

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

Basic Parallel GroupBy

Can we do better?

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

YES

- Compute partial aggregates before shuffling

Basic Parallel GroupBy

Can we do better?

- Sum?
- Count?
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Distributive	Algebraic	Holistic
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YES

- Compute partial aggregates before shuffling

MapReduce implements this as “Combiners”

Example Query with Group By

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

Machine 1

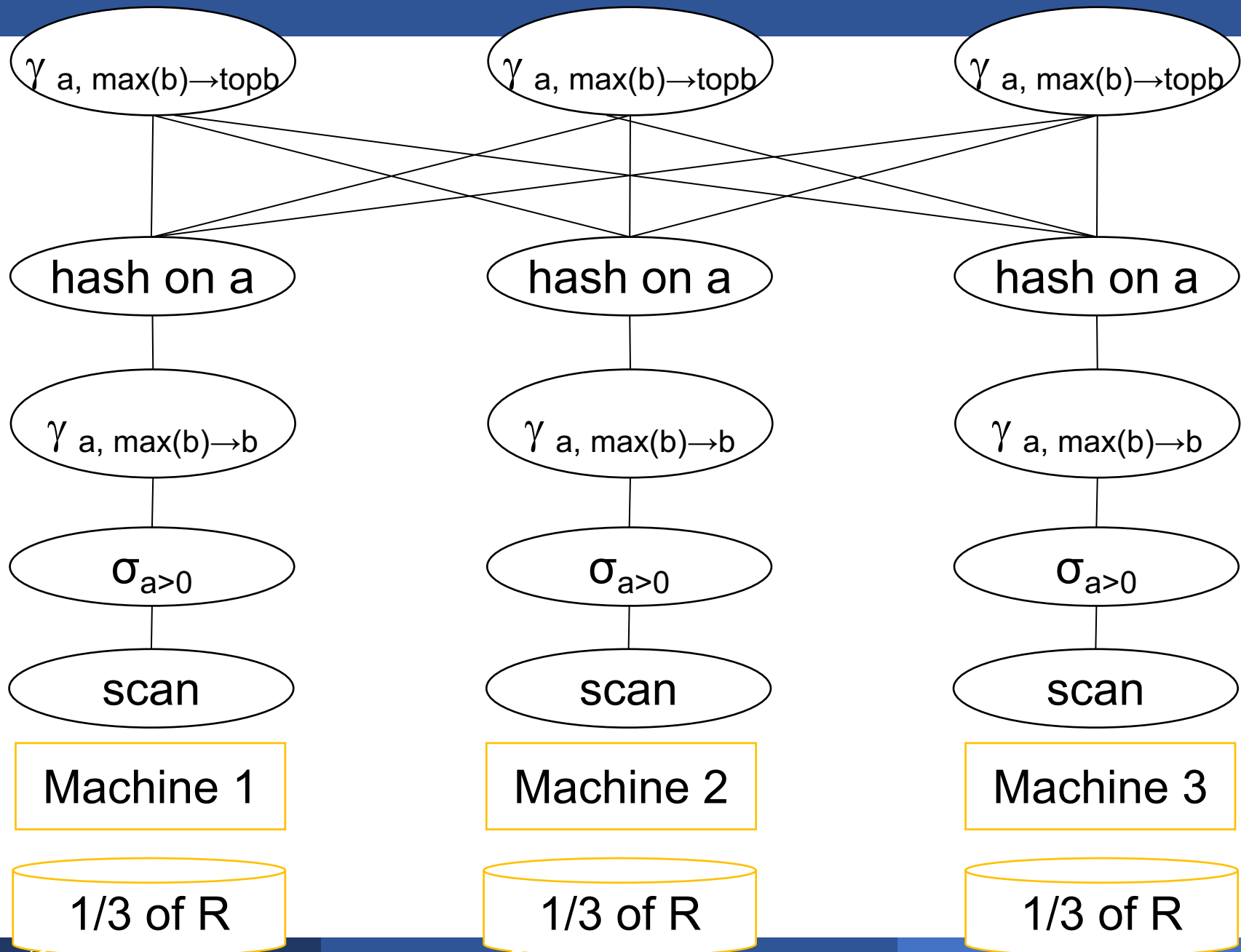
1/3 of R

Machine 2

1/3 of R

Machine 3

1/3 of R

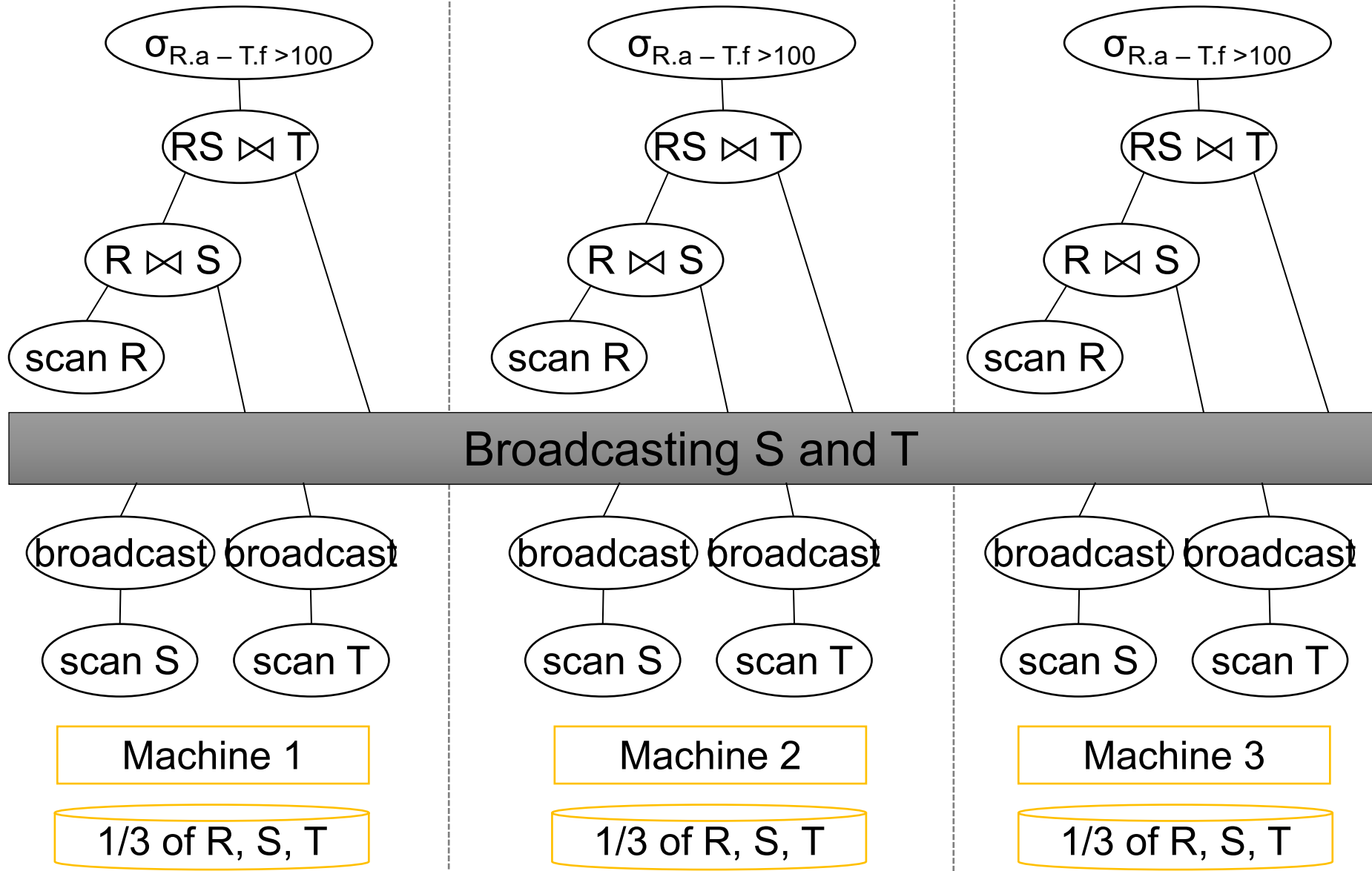


Optimization Joins for Small Relations

When joining R and S

- If $|R| \gg |S|$
 - Leave R where it is
 - Replicate entire S relation across nodes
- Also called a **small join** or a **broadcast join**

Optimization Joins for Small Relations



Some Skew Handling Techniques

Skew:

- Some partitions get more **input** tuples than others
- Reasons:
 - Range-partition instead of hash
 - Some values are very popular:
 - Heavy hitters values; e.g. 'Justin Bieber'
 - Selection before join with different selectivities
- Some partitions generate more **output** tuples than others

Some Skew Handling Techniques

If using range partition:

- Ensure each range gets same number of tuples
- E.g.: $\{1, 1, 1, 2, 3, 4, 5, 6\} \rightarrow [1,2]$ and $[3,6]$
- Eq-depth v.s. eq-width histograms

Some Skew Handling Techniques

Create more partitions than nodes

- And be smart about scheduling the partitions
- Note: MapReduce uses this technique

Some Skew Handling Techniques

Use subset-replicate (a.k.a. “skewedJoin”)

- Given $R \bowtie_{A=B} S$
- Given a heavy hitter value $R.A = 'v'$
(i.e. $'v'$ occurs very many times in R)
- Partition R tuples with value $'v'$ across all nodes
e.g. block-partition, or hash on other attributes
- Replicate S tuples with value $'v'$ to all nodes
- R = the build relation
- S = the probe relation

Summary of Parallel RDBMS

- Hash shuffle does it all
- Techniques have been around for decades
- We still get benefits of the relational database!