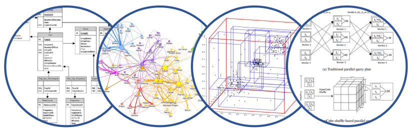


Database System Internals

Intro to Parallel DBMSs

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

1

Announcements

- Quiz 3+4 canceled ☺

2

What We Have Already Learned

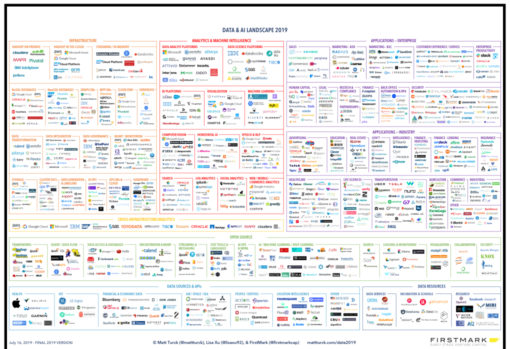
- Phase 1: Query Execution
  - Data Storage and Indexing
  - Buffer management
  - Query evaluation and operator algorithms
  - Query optimization
- Phase 2: Transaction Processing
  - Concurrency control: pessimistic and optimistic
  - Transaction recovery: undo, redo, and undo/redo
- Phase 3: Parallel Processing & Distributed Transactions

3

Where We Are Headed Next

- Scaling the execution of a query
  - Parallel DBMS
  - MapReduce
  - Spark
- Scaling transactions
  - Distributed transactions
  - Replication

4



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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**

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Building Our Parallel DBMS

Data model? Relational (SimpleDB!)

9

Building Our Parallel DBMS

Data model? Relational (SimpleDB!)

Scaleup goal?

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Scaling Transactions Per Second

- OLTP: Transactions per second
  "Online Transaction Processing"
- Amazon
- Facebook
- Twitter
- … your favorite Internet application…
- Goal is to increase transaction throughput
- We will get back to this next week

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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

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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!

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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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Building Our Parallel DBMS

Data model? Relational

Scaleup goal? OLAP

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Building Our Parallel DBMS

Data model? Relational

Scaleup goal? OLAP

Architecture?

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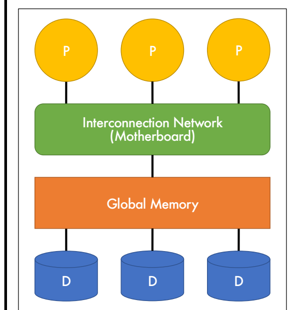
Shared-Memory Architecture



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

Microsoft SQL Server
PostgreSQL
SQLite
MySQL

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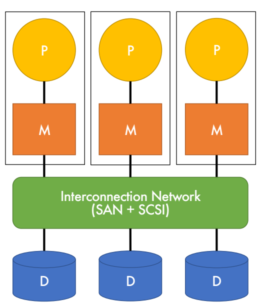
Shared-Disk Architecture



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

ORACLE
DATABASE

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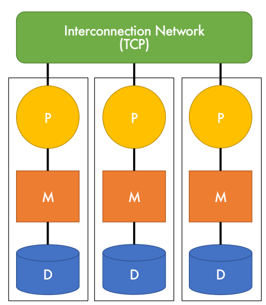
Shared-Nothing Architecture



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

teradata.
APACHE Spark
MySQL Cluster

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Building Our Parallel DBMS

Data model? Relational

Scaleup goal? OLAP

Architecture? Shared-Nothing

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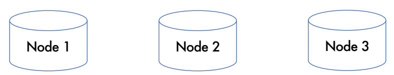
Shared-Nothing Execution Basics

- 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



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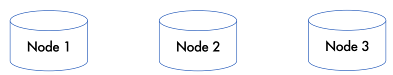
Shared-Nothing Database

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

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



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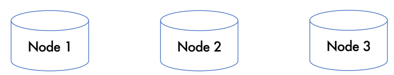
Shared-Nothing Database

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



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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

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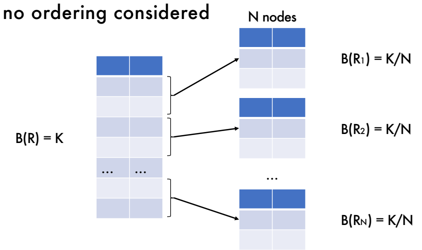
Option 2: Block Partitioning

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



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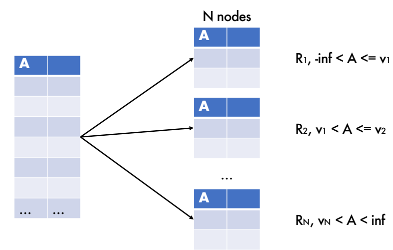
Option 3: Range Partitioning

Node contains tuples in chosen attribute ranges



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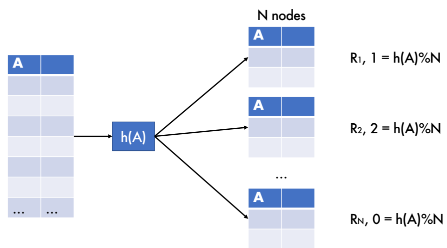
Option 4: Hash Partitioning

Node contains tuples with chosen attribute hashes



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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

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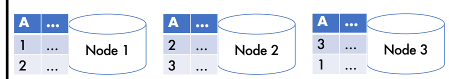
Parallel Selection

Assume:
R is block partitioned

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



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Parallel Selection

```
SELECT *
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```

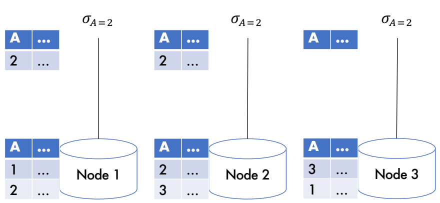

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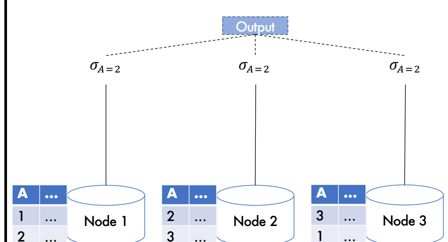
Implicit Union

Parallel query plans implicitly union at the end



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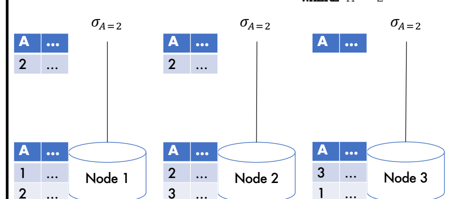
Parallel Selection

Data-parallel!

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



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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:

33

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

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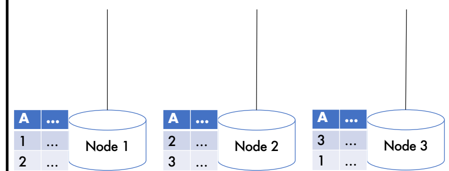
Parallel Selection

What if this query is not data-parallel?

Assume:
R is block partitioned

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



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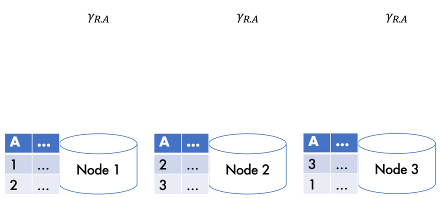
Partitioned Aggregation

Assume:
R is block partitioned

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



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Partitioned Aggregation

Assume:
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```
SELECT *
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```

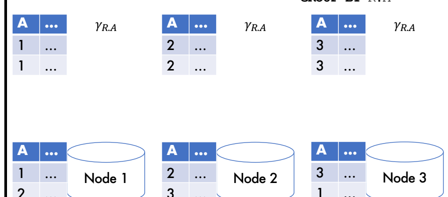

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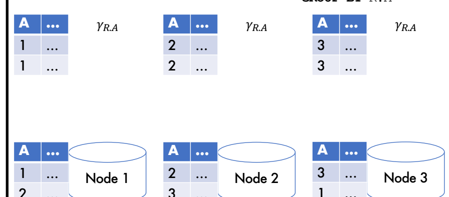
Partitioned Aggregation

1. Hash shuffle tuples

Assume:
R is block partitioned

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



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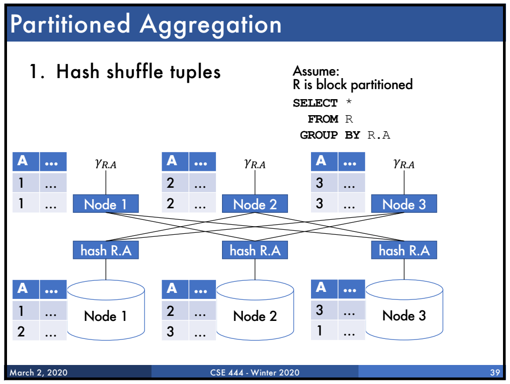

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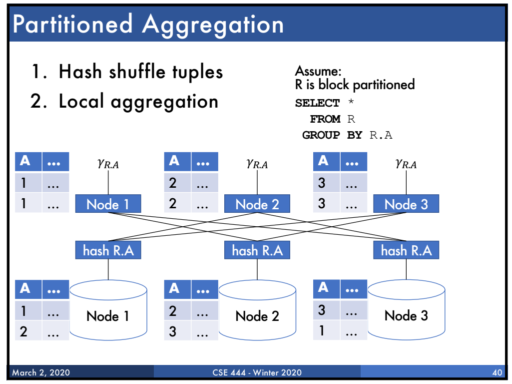

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Parallel Query Evaluation

New operator: Shuffle

- Serves to re-shuffle data between processes
  - Handles data routing, buffering, and flow control
- Two parts: ShuffleProducer and ShuffleConsumer
- Producer:
  - Pulls data from child operator and sends to n consumers
  - Producer acts as driver for operators below it in query plan
- Consumer:
  - Buffers input data from n producers and makes it available to operator through getNext() interface

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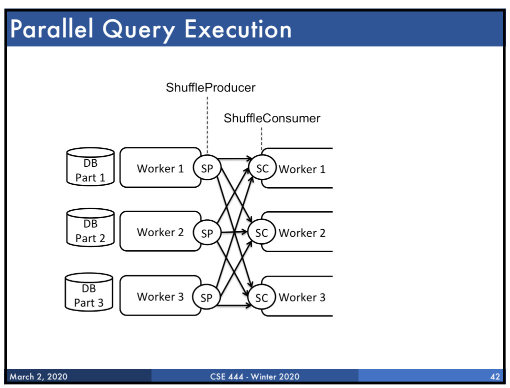

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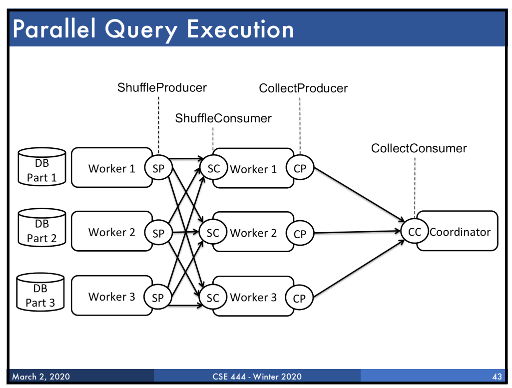

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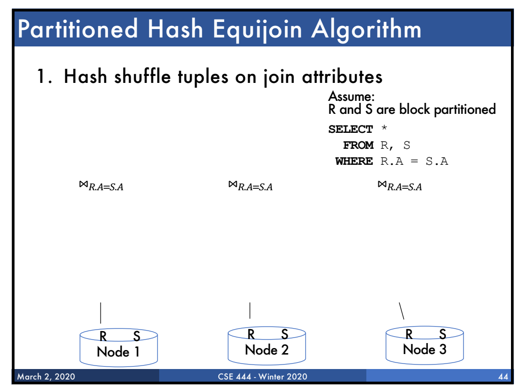

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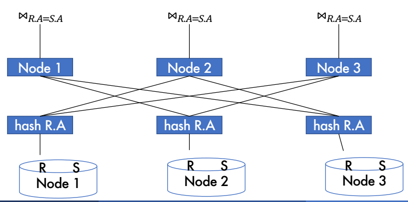
Partitioned Hash Equijoin Algorithm

1. Hash shuffle tuples on join attributes

Assume:
R and S are block partitioned

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



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Partitioned Hash Equijoin Algorithm

1. Hash shuffle tuples on join attributes

Assume:
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```
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  FROM R, S
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```

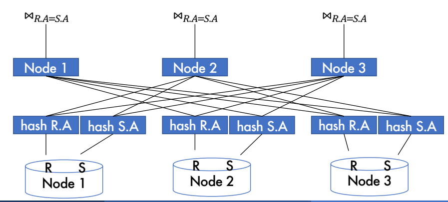

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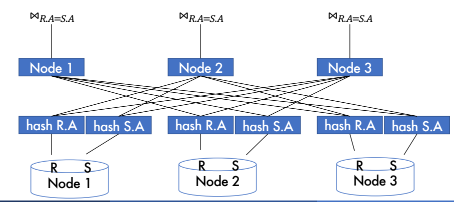
Partitioned Hash Equijoin Algorithm

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

Assume:
R and S are block partitioned

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



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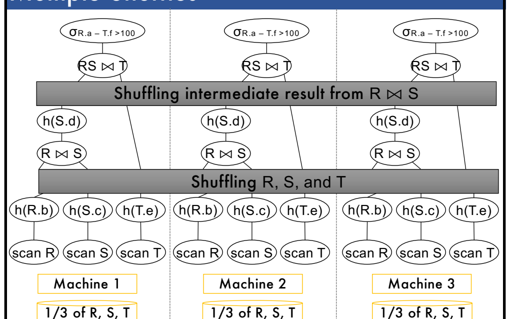
Multiple Shuffles



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Summary

- With one new operator, we've made SimpleDB an OLAP-ready parallel DBMS!
- Next lecture:
  - Skew handling
  - Algorithm refinements

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Speedup and Scaleup

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

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Speedup and Scaleup

- Consider:
  - Query: $\gamma_{A,sum(C)}(R)$
  - 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 ½ as many chunks)
- If we double both P and the size of R, what is the new running time?

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Speedup and Scaleup

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

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Basic Parallel GroupBy

Can we do better?

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

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Basic Parallel GroupBy

Can we do better?

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

Distributive	Algebraic	Holistic
$sum(a_1+a_2+...+a_9)= sum(sum(a_1+a_2+a_3)+ sum(a_4+a_5+a_6)+ sum(a_7+a_8+a_9))$	avg(B) = sum(B)/count(B)	median(B)

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Basic Parallel GroupBy

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- Count?
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YES

- Compute partial aggregates before shuffling

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Basic Parallel GroupBy

Can we do better?

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- Count?
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Distributive	Algebraic	Holistic
$sum(a_1+a_2+...+a_9)= sum(sum(a_1+a_2+a_3)+ sum(a_4+a_5+a_6)+ sum(a_7+a_8+a_9))$	avg(B) = sum(B)/count(B)	median(B)

YES

- Compute partial aggregates before shuffling

MapReduce implements this as “Combiners”

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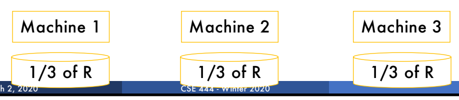
Exercise (www.draw.io is fast!)

Example Query with Group By

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



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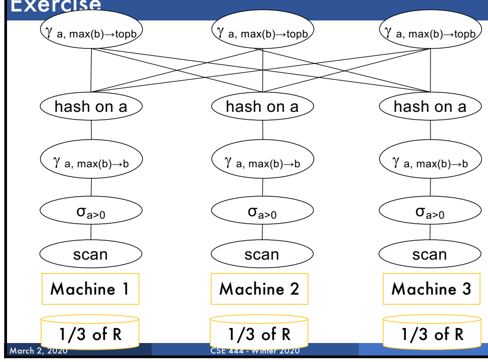
Exercise



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

- Data: R(<u>K1</u>,A, C), S(<u>K2</u>, B, D)
- Query: R(<u>K1</u>,A,C) ⋈ S(<u>K2</u>,B,D)

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

- Data: R(<u>K1</u>,A, C), S(<u>K2</u>, B, D)
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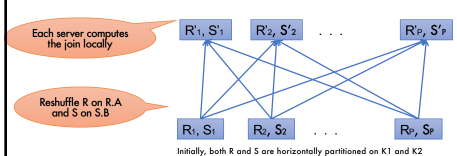

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Parallel Join: R $\bowtie_{A=B}$ S

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

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Optimization for Small Relations

When joining R and S

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

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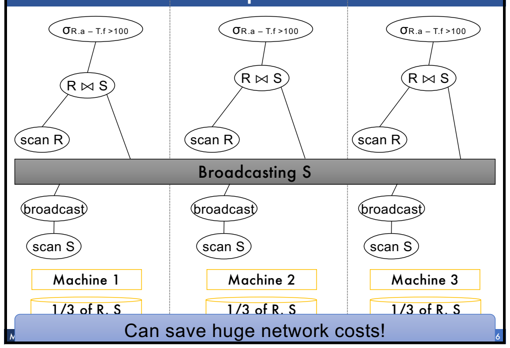
Broadcast Join Example



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Justin Biebers Re-visited

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

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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 } → [1,2] and [3,6]
- Eq-depth v.s. eq-width histograms

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Some Skew Handling Techniques

Create more partitions than nodes

- And be smart about scheduling the partitions
  - E.g. One node ONLY does Justin Biebers
- Note: MapReduce uses this technique

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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

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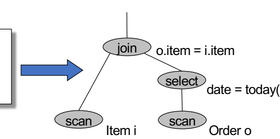
Example: Teradata – Query Execution

Order(oid, item, date), Line(item, ...)

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()
```



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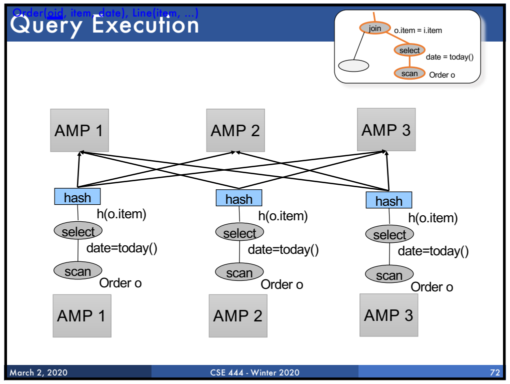

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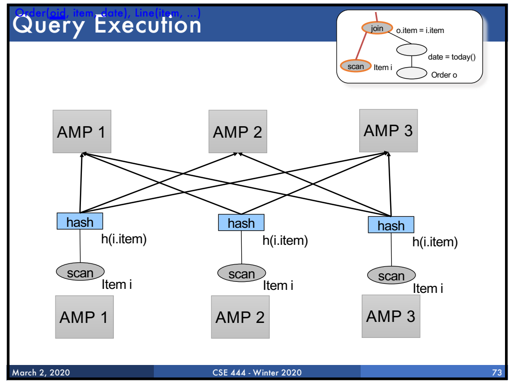

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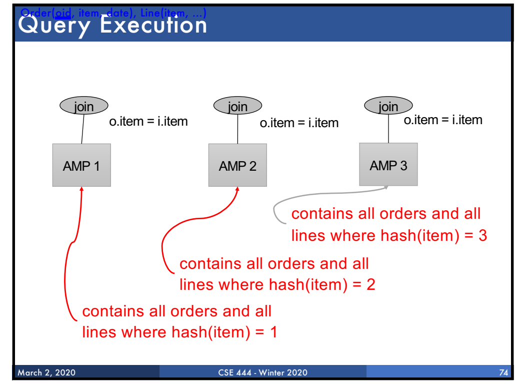

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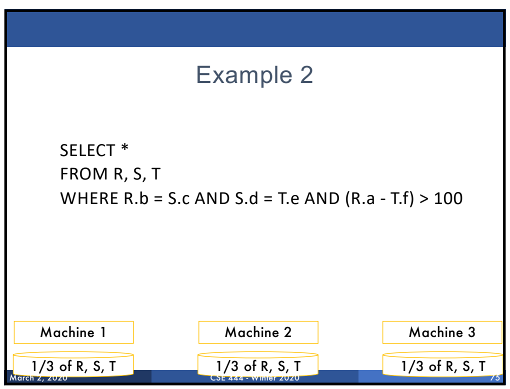

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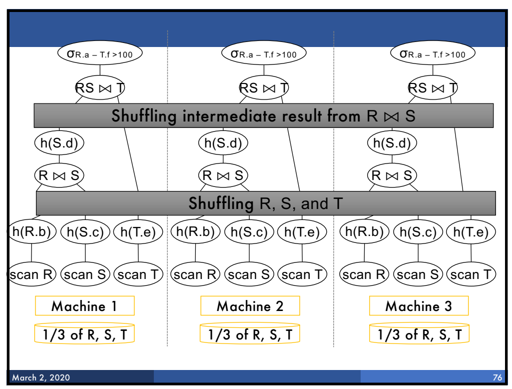

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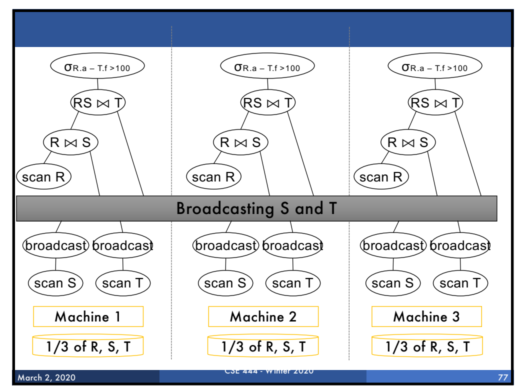

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