CSE 544
Principles of Database Management Systems

Lecture 12 – Parallel DBMSs

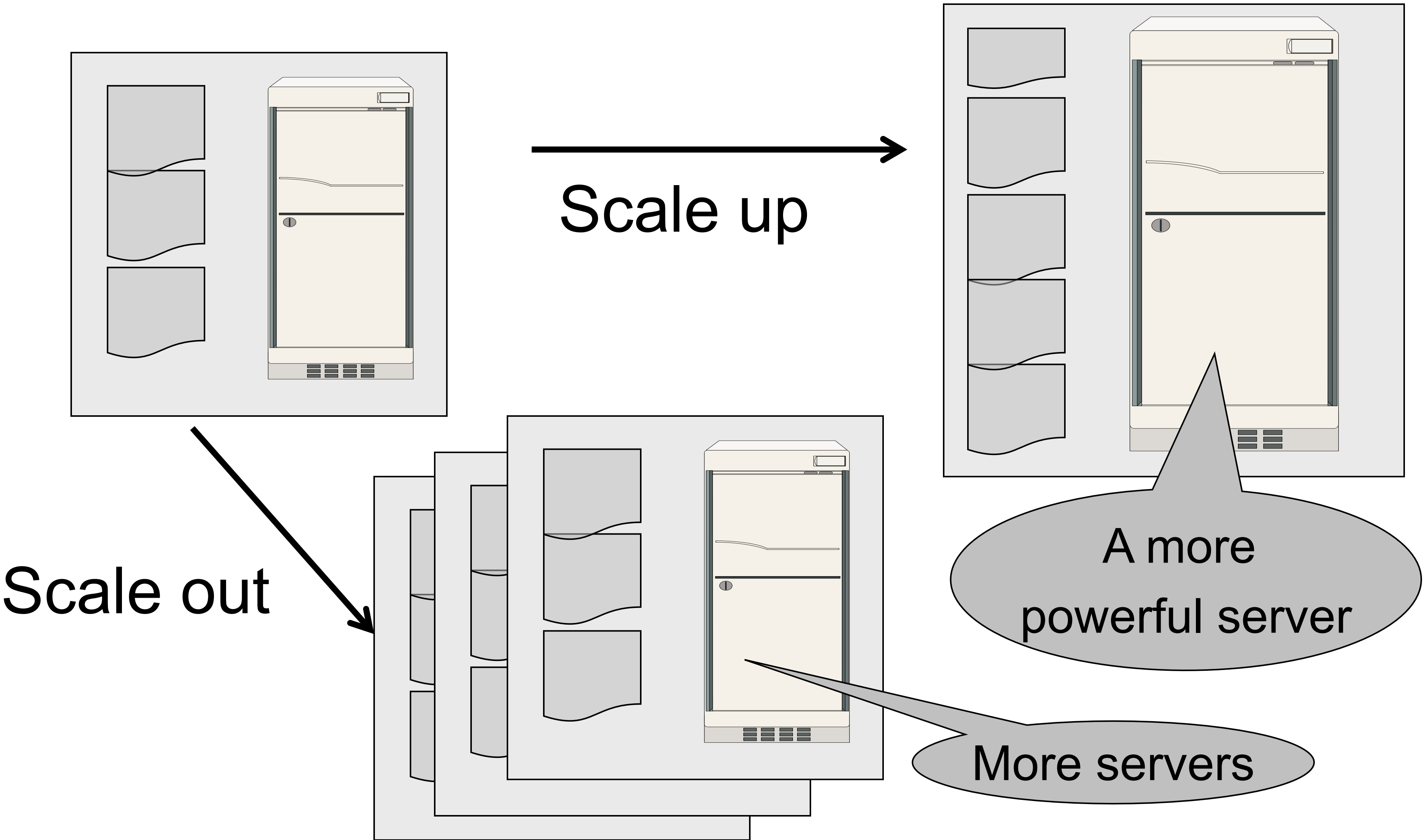
Announcements

- HW3 due on Friday!!!
- HW4 posted please apply for AWS credits asap
- Project, project, project, ...
- No class on Monday

Where We Are

- Relational data model: SQL, RA, datalog, FDs, ...
- Systems: disk I/Os, buffer, physical RA, iterator model, ...
- Today: scaling up to parallel computation

Two Ways to Scale a DBMS



Two Ways to Scale a DBMS

- Obviously this can be used to:
  - Execute multiple queries in parallel
  - Speed up a single query

- For now: how to speed up a single query

- We will worry about how to scale to multiple queries later

Parallel v.s. Distributed Databases

- Distributed database system:
  - Data is managed by **several sites**, each site capable of running independently

- Parallel database system:
  - Data is managed by a **single site**, but processed distributively, using parallel implementation

Parallel DBMSs

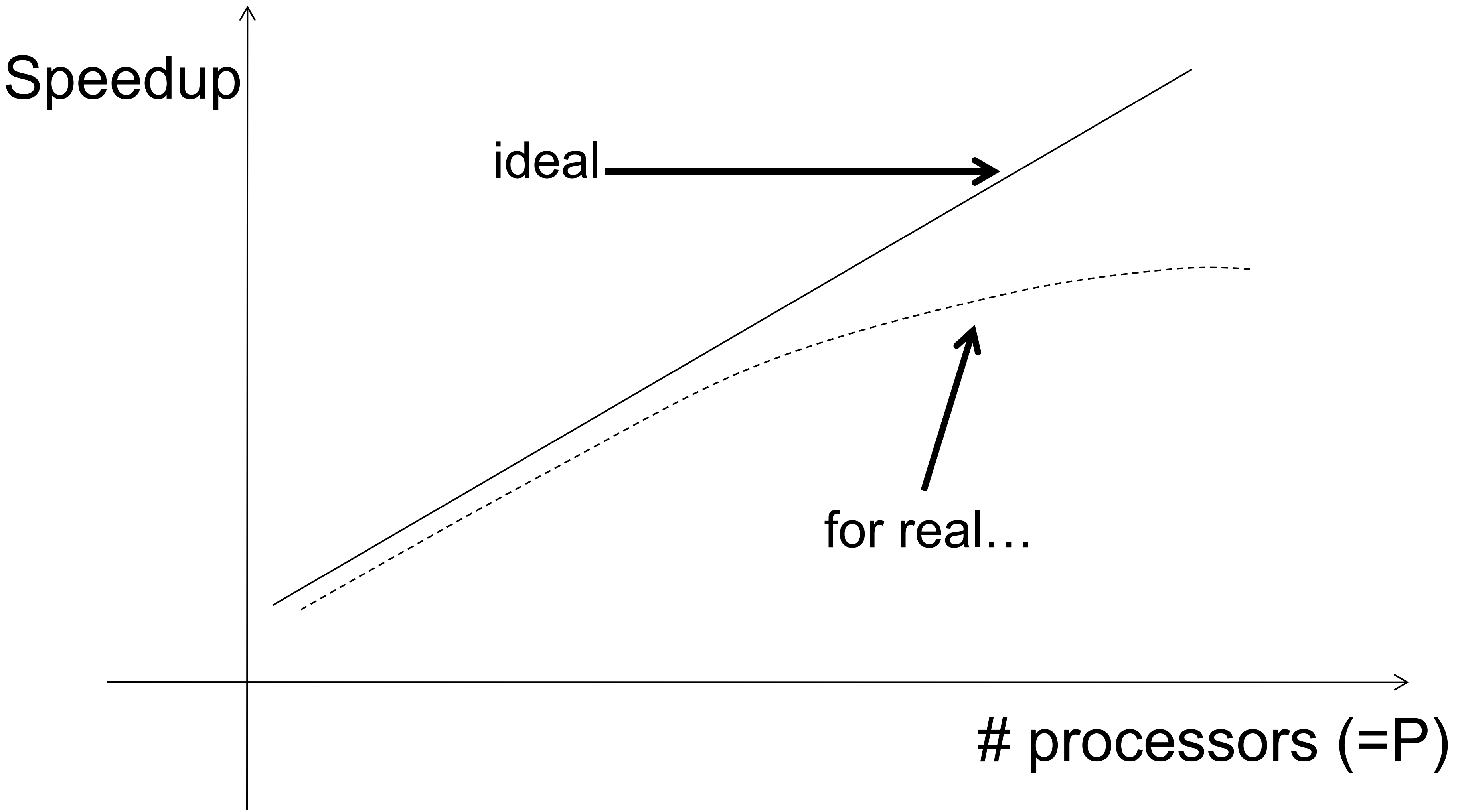
- Goal
  - Improve performance by executing multiple operations in parallel
- Key benefit
  - Cheaper to scale than relying on a single increasingly more powerful processor
- Key challenge
  - Ensure overhead and contention do not kill performance

Performance Metrics for Parallel DBMSs

Speedup

- More processors ➔ higher speed
- Individual queries should run faster
- Should do more transactions per second (TPS)
- Fixed problem size *overall*, vary # of processors ("strong scaling")

Linear v.s. Non-linear Speedup

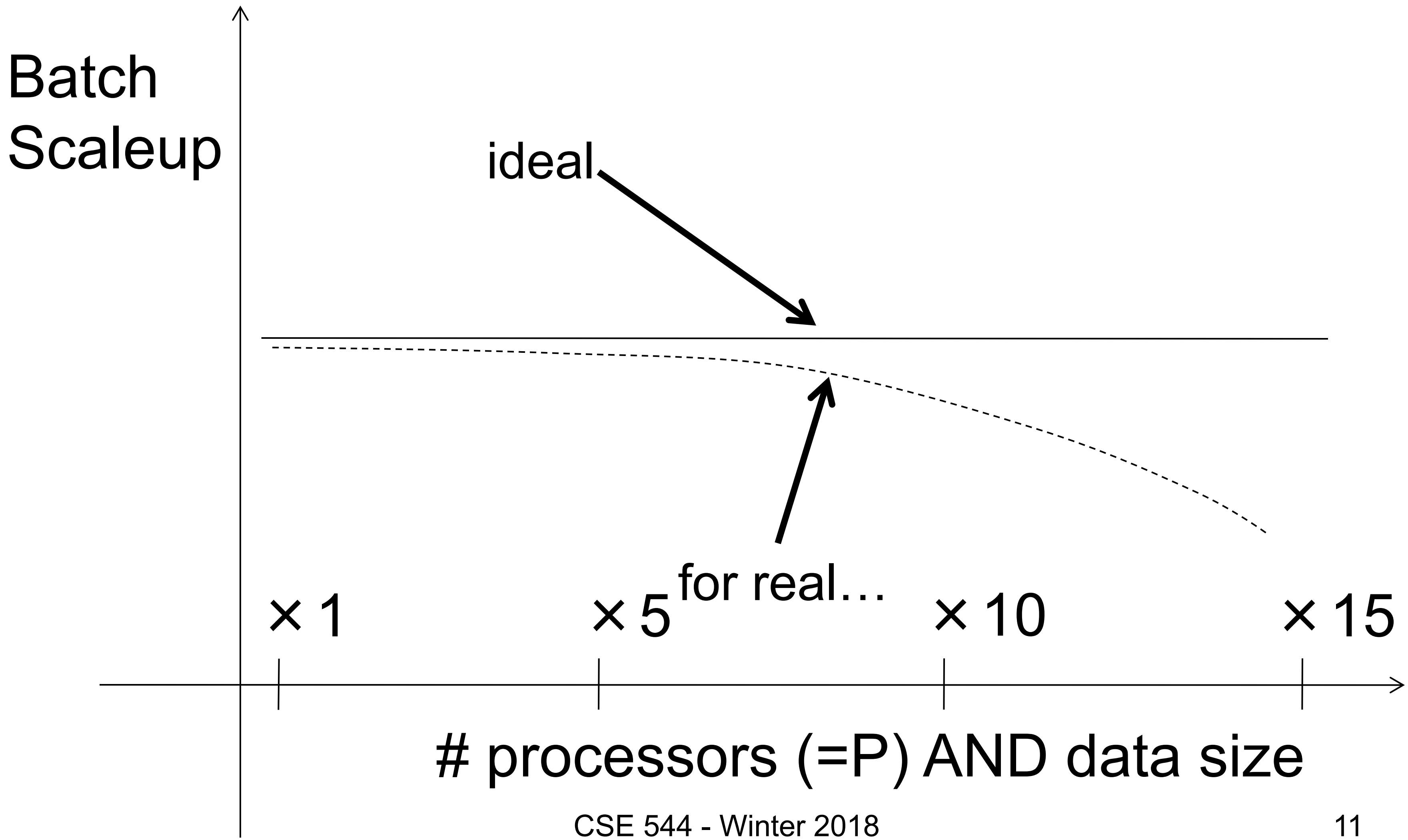


Performance Metrics for Parallel DBMSs

Scaleup

- More processors ➔ can process more data
- Fixed problem size *per processor,* vary # of processors ("weak scaling”)
- Batch scaleup
  - Same query on larger input data should take the same time
- Transaction scaleup
  - N-times as many TPS on N-times larger database
  - But each transaction typically remains small

Linear v.s. Non-linear Scaleup



Buzzwords, buzzwords

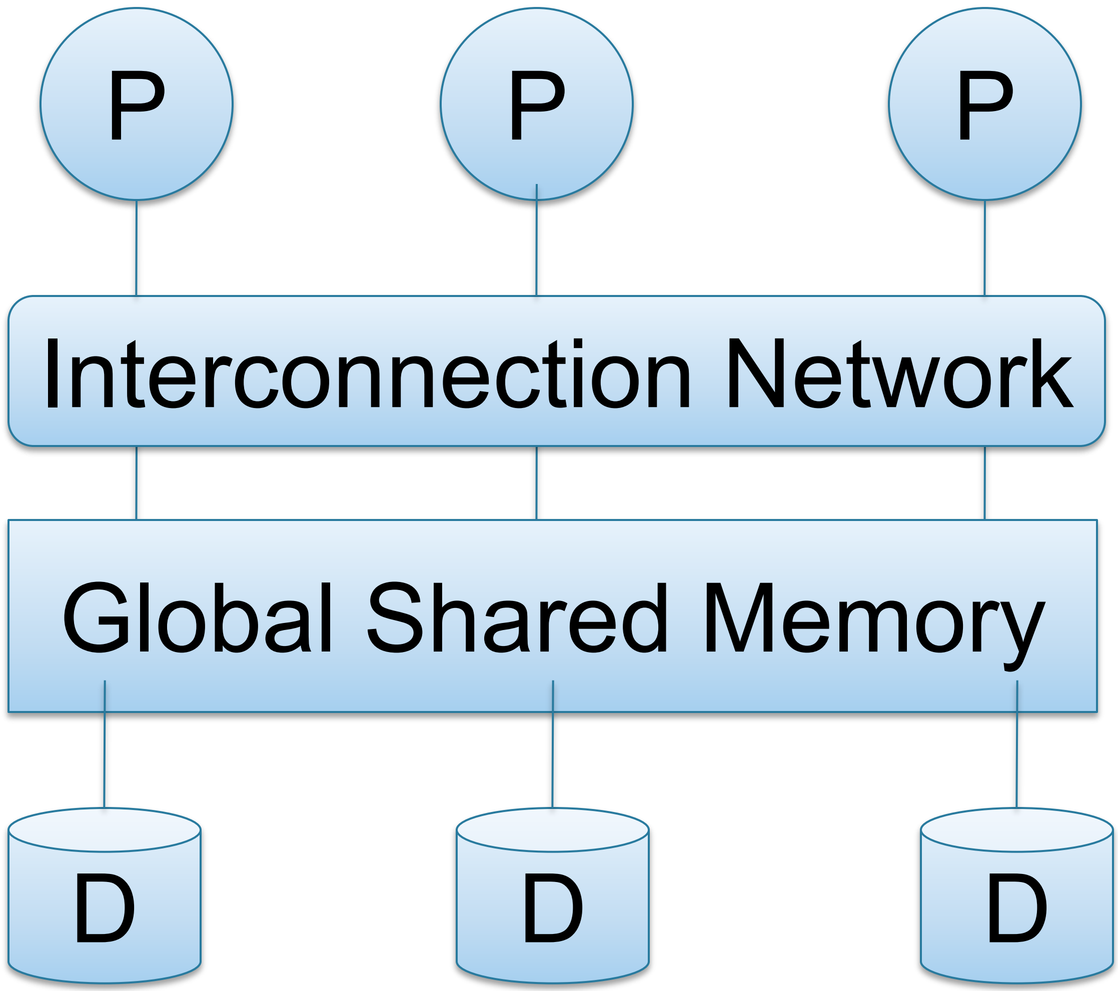
- Be careful. Commonly used terms today:
  - “scale up” = use an increasingly more powerful server
  - “scale out” = use a larger number of servers

Challenges to Linear Speedup and Scaleup

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

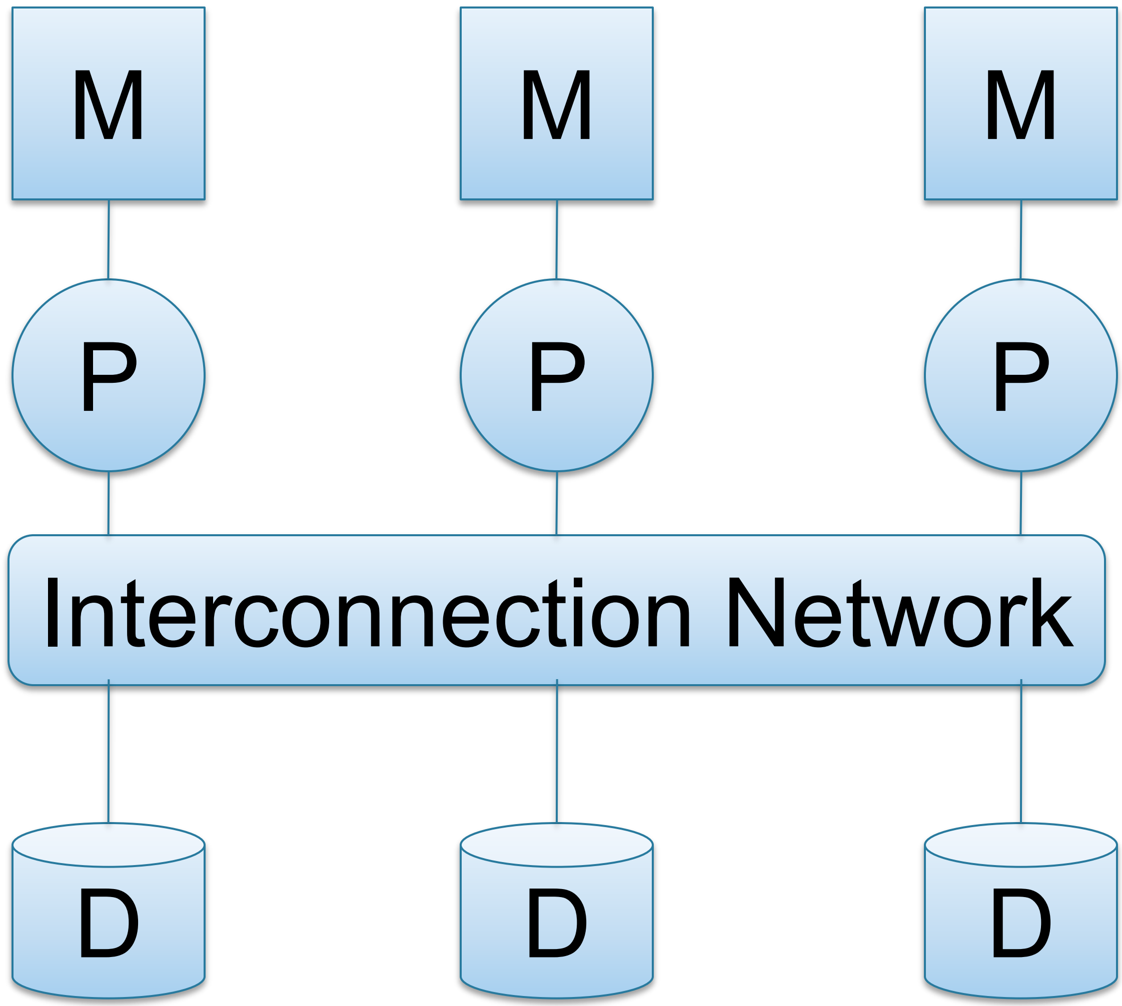
Parallel DBMS Architectures

Architecture for Parallel DBMS: Shared Memory

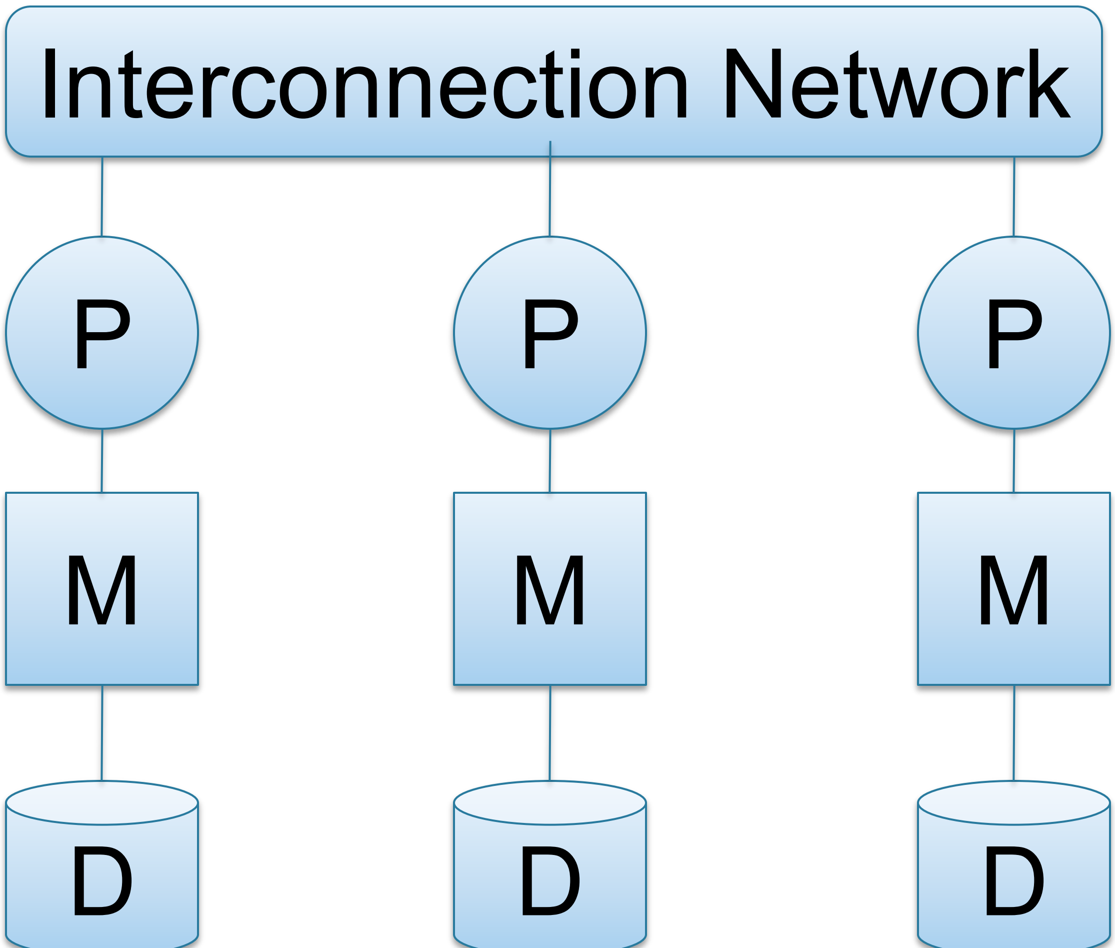


Aka SMP= symmetric multi processor

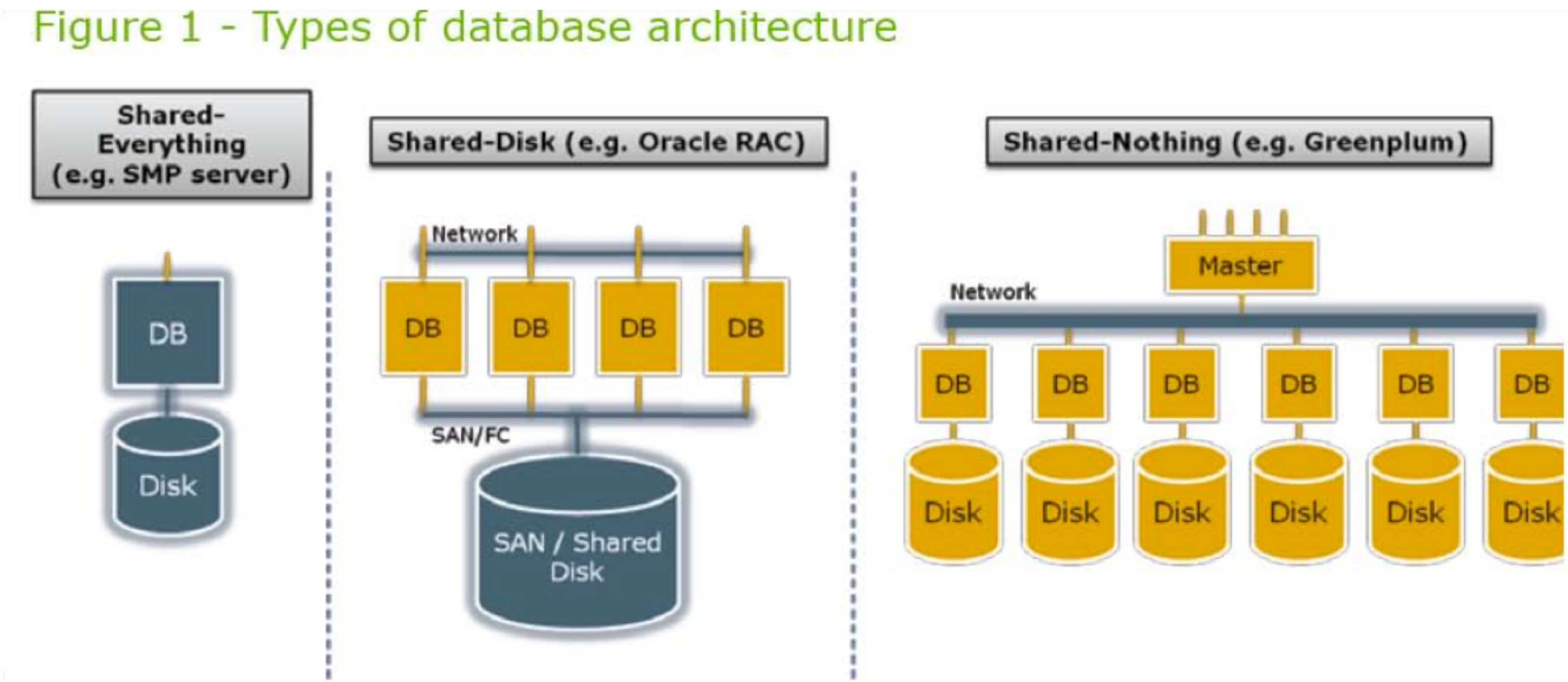
Architecture for Parallel DBMS: Shared Disk



Architecture for Parallel DBMS: Shared Nothing



A Professional Picture…



From: Greenplum Database Whitepaper

SAN = “Storage Area Network”

Shared Memory

- Nodes share both RAM and disk
- Dozens to hundreds of processors

Example: SQL Server runs on a single machine

- leverage many threads to get a query to run faster

Characteristics:

- Easy to use and program
- But very expensive to scale

Shared Disk

- All nodes access the same disks
- Found in the largest "single-box" (non-cluster) multiprocessors

Oracle dominates this class of systems

Characteristics:

- Also hard to scale past a certain point: existing deployments typically have fewer than 10 machines

Shared Nothing

- Cluster of machines on high-speed network
- Called "clusters" or "blade servers”
- Each machine has its own memory and disk: lowest contention.

NOTE: Because all machines today have many cores and many disks, then shared-nothing systems typically run many "nodes” on a single physical machine.

Characteristics:

- Today, this is the most scalable architecture.
- Most difficult to administer and tune.

We discuss only Shared Nothing in class

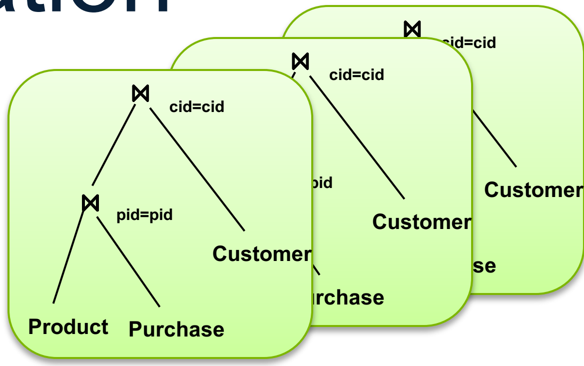
So…

- You have a parallel machine. Now what?

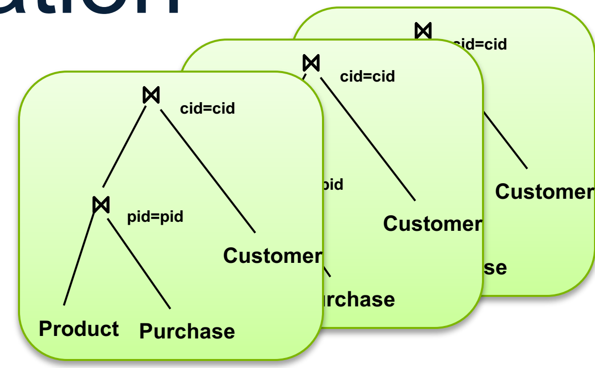
- How do you speed up your DBMS given a shared-nothing architecture?

Approaches to Parallel Query Evaluation

- Inter-query parallelism
  - Each query runs on one processor
  - Only for running multiple queries (OLTP)



Approaches to Parallel Query Evaluation



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- Inter-operator parallelism
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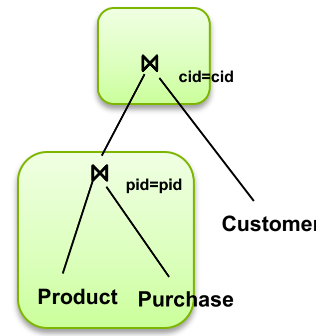
  - An operator runs on one processor
  - For both OLTP and Decision Support



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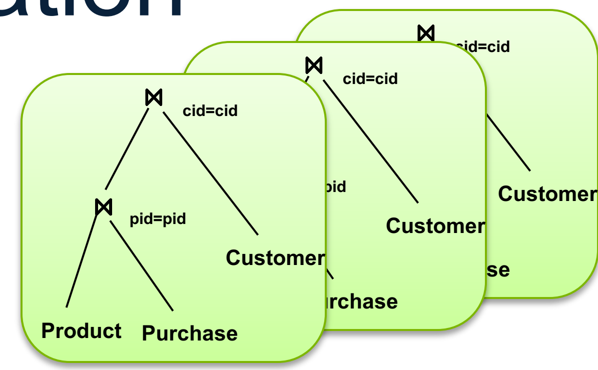

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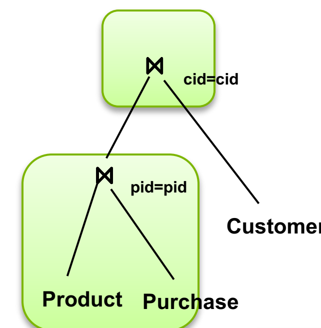

- Intra-operator parallelism
  - An operator runs on multiple processors
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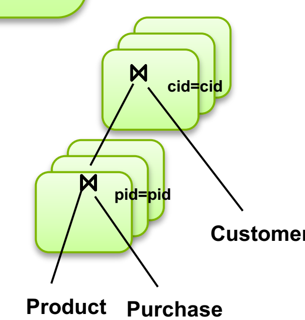

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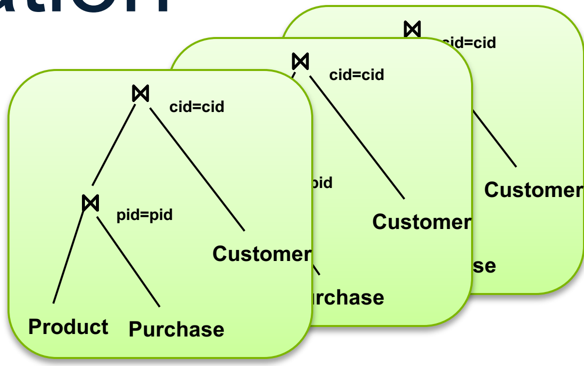

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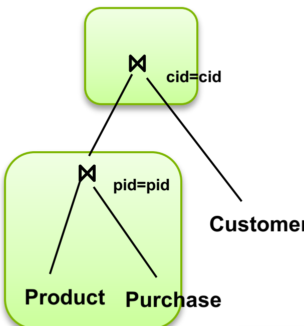

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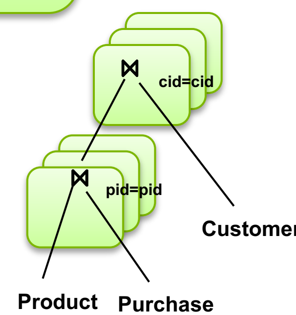


We study only intra-operator parallelism: most scalable

Data Partitioning

Horizontal Data Partitioning

- Relation R split into P chunks $R_0, \ldots, R_{P-1}$, stored at the P nodes

- Block partitioned
  - Each group of k tuples go to a different node

- Hash based partitioning on attribute A:
  - Tuple t to chunk h(t.A) mod P

- Range based partitioning on attribute A:
  - Tuple t to chunk i if $v_{i-1} < t.A < v_i$

Need to worry about **data skew**

Uniform Data v.s. Skewed Data

- Let R(K,A,B,C); which of the following partition methods may result in skewed partitions?

- Block partition

Uniform

- Hash-partition
  - On the key K
  - On the attribute A

Uniform

Assuming uniform hash function

May be skewed

E.g. when all records have the same value of the attribute A, then all records end up in the same partition

- Range-partition
  - On the key K
  - On the attribute A

May be skewed

Difficult to partition the range of A uniformly.

All You Need to Know About Skew

Hash-partition a m data values (with duplicates!) to p bins

Fact 1 Expected size of any **one** fixed bin is m/p

Fact 2 Say that data is *skewed* if some value has degree > m/p. Then **some** bin has load > m/p

Hiding log p factors

Fact 3 Conversely, if the database is *skew-free* then max size of **all** bins = $O(m/p)$ w.h.p.

Parallelizing Operator Implementations

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 a parallel database with P processors ?

- Block partitioned
- Hash partitioned
- Range partitioned

Parallel Selection

Q: What is the cost on a parallel database with P nodes ?

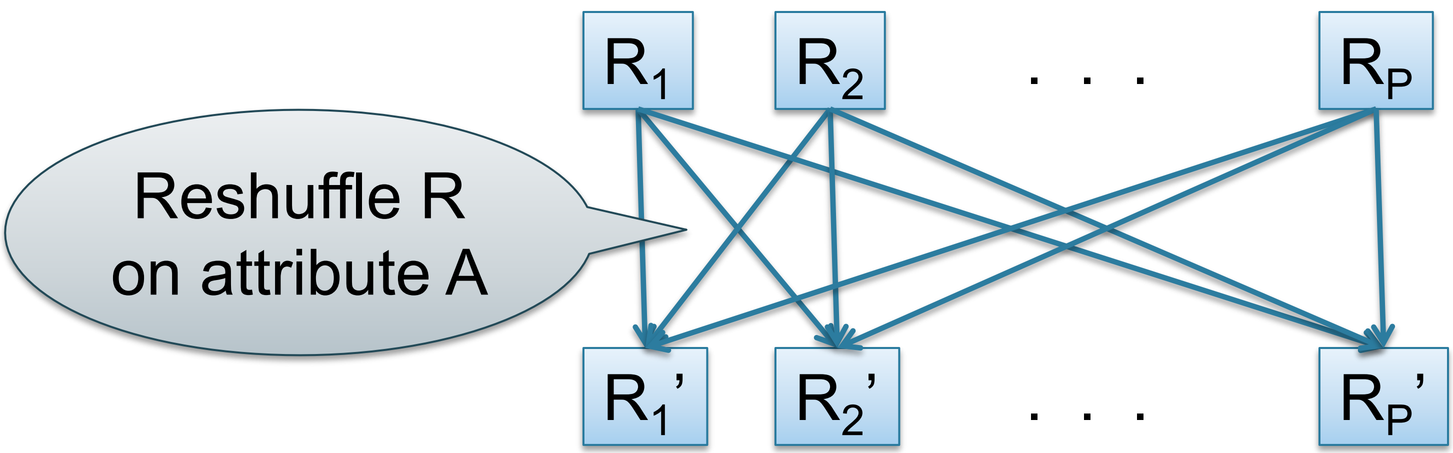
A: B(R) / P in all cases (except range) if cost is response time

However, not all processors are equal (workwise):

- Block: all servers do the same amount of work
- Hash: one server for $\sigma_{A=v}(R)$, all for $\sigma_{v1<A<v2}(R)$
- Range: some servers only

Parallel Group By: $\gamma_{A,\ sum(B)}(R)$

- If R is partitioned on A, then each node computes the group-by locally
- Otherwise, hash-partition R(K,A,B,C) on A, then compute group-by locally:



Parallel Group By: $\gamma_{A,\ sum(B)}(R)$

- Step 1: server i partitions chunk R_i using a hash function h(t.A) mod P: $R_{i0}, R_{i1}, \ldots, R_{i,P-1}$ (there are P servers total)
- Step 2: server i sends partition R_{ij} to server j
- Step 3: server j computes $\gamma_{A,\ sum(B)}$ on $R_{0j}, R_{1j}, \ldots, R_{P-1,j}$

Parallel Group By: $\gamma_{A,\ sum(B)}(R)$

Can we do better?

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

Parallel Group By: $\gamma_{A,\ sum(B)}(R)$

- $Sum(B) = Sum(B_0) + Sum(B_1) + \ldots + Sum(B_n)$
- $Count(B) = Count(B_0) + Count(B_1) + \ldots + Count(B_n)$
- $Max(B) = Max(Max(B_0), Max(B_1), \ldots, Max(B_n))$

distributive

- $Avg(B) = Sum(B) / Count(B)$

algebraic

- Median(B) = ???

holistic

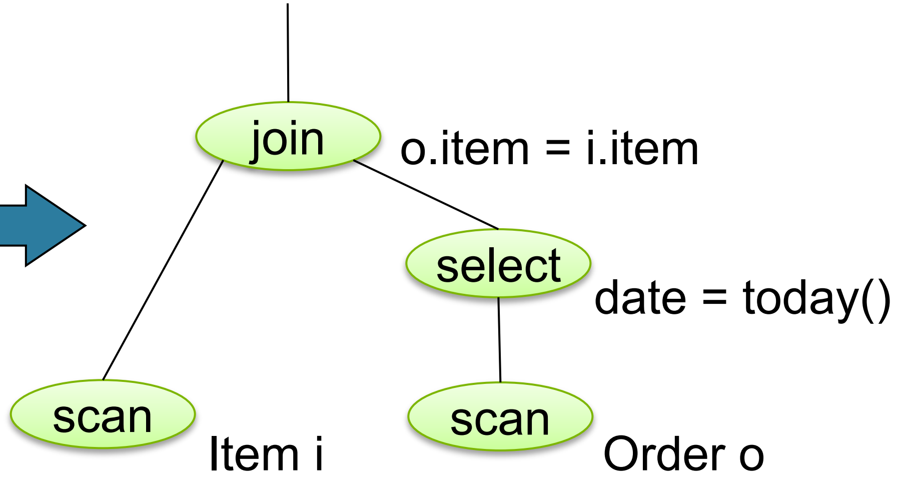
Parallel Join: $R \bowtie_{A=B} S$

- Step 1
  - For all servers in [0,k], server i partitions chunk R_i using a hash function h(t.A) mod P: R_{i0}, R_{i1}, …, $R_{i,P-1}$
  - For all servers in [k+1,P], server j partitions chunk S_j using a hash function h(t.A) mod P: S_{j0}, S_{j1}, …, $R_{j,P-1}$
- Step 2:
  - Server i sends partition R_{iu} to server u
  - Server j sends partition S_{ju} to server u
- Steps 3: Server u computes the join of R_{iu} with S_{ju}

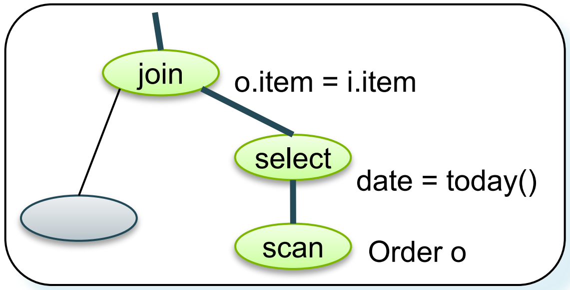
Example of Parallel Query Plan

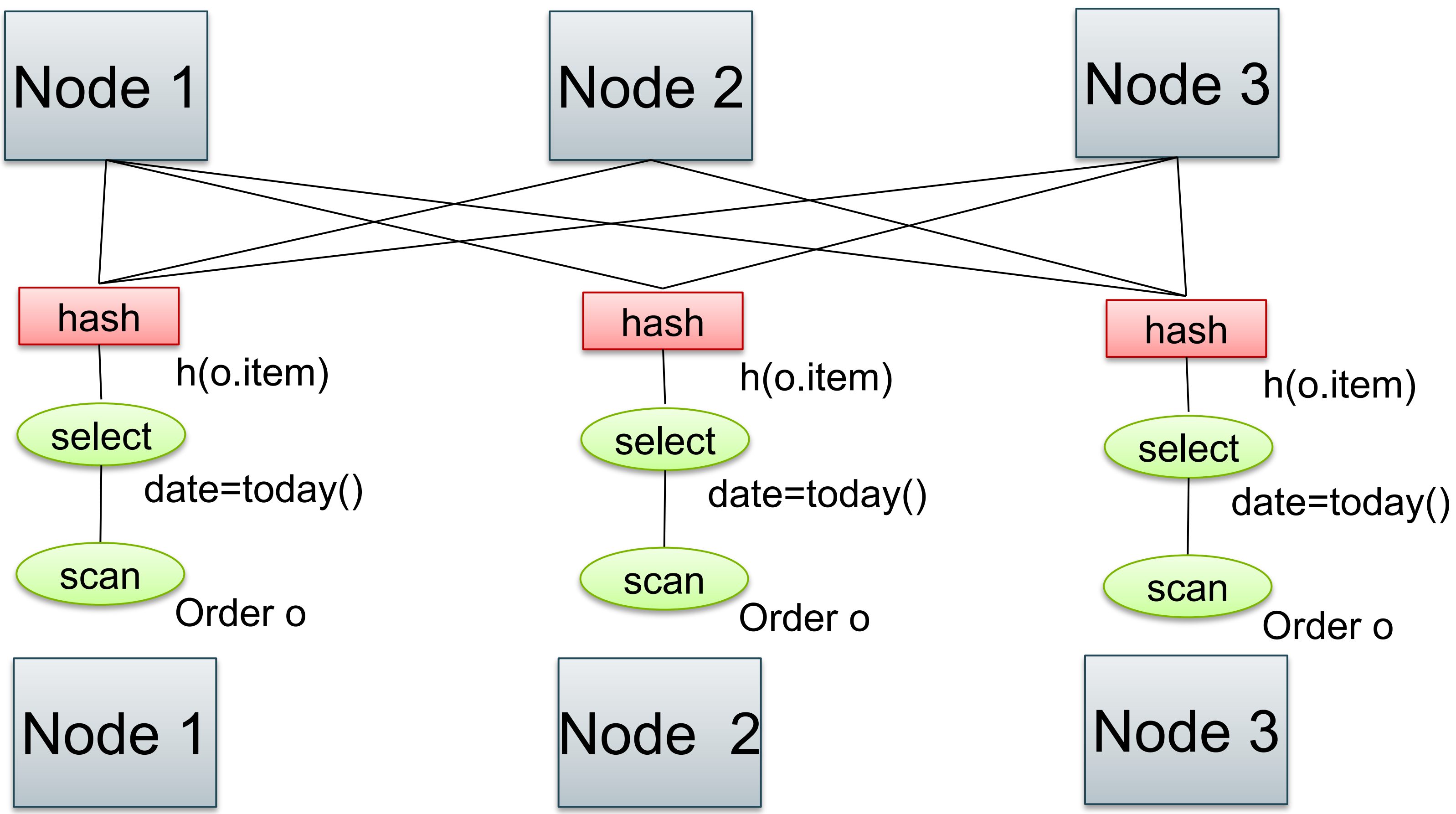
Find all orders from today, along with the items ordered

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



Example Parallel Plan





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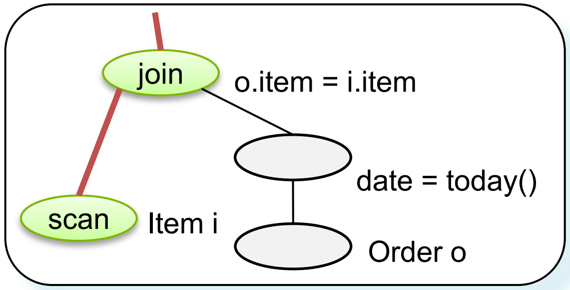

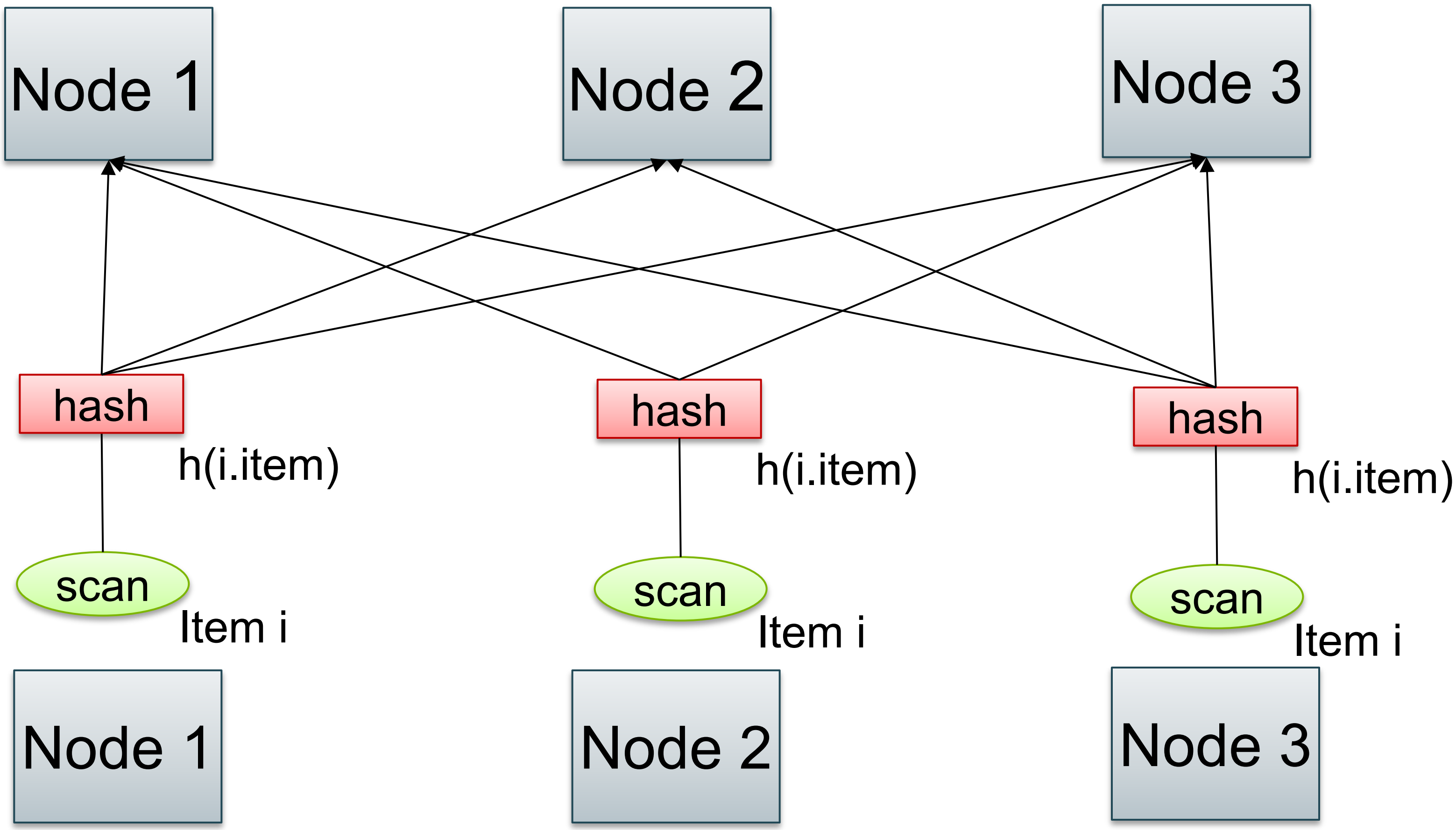

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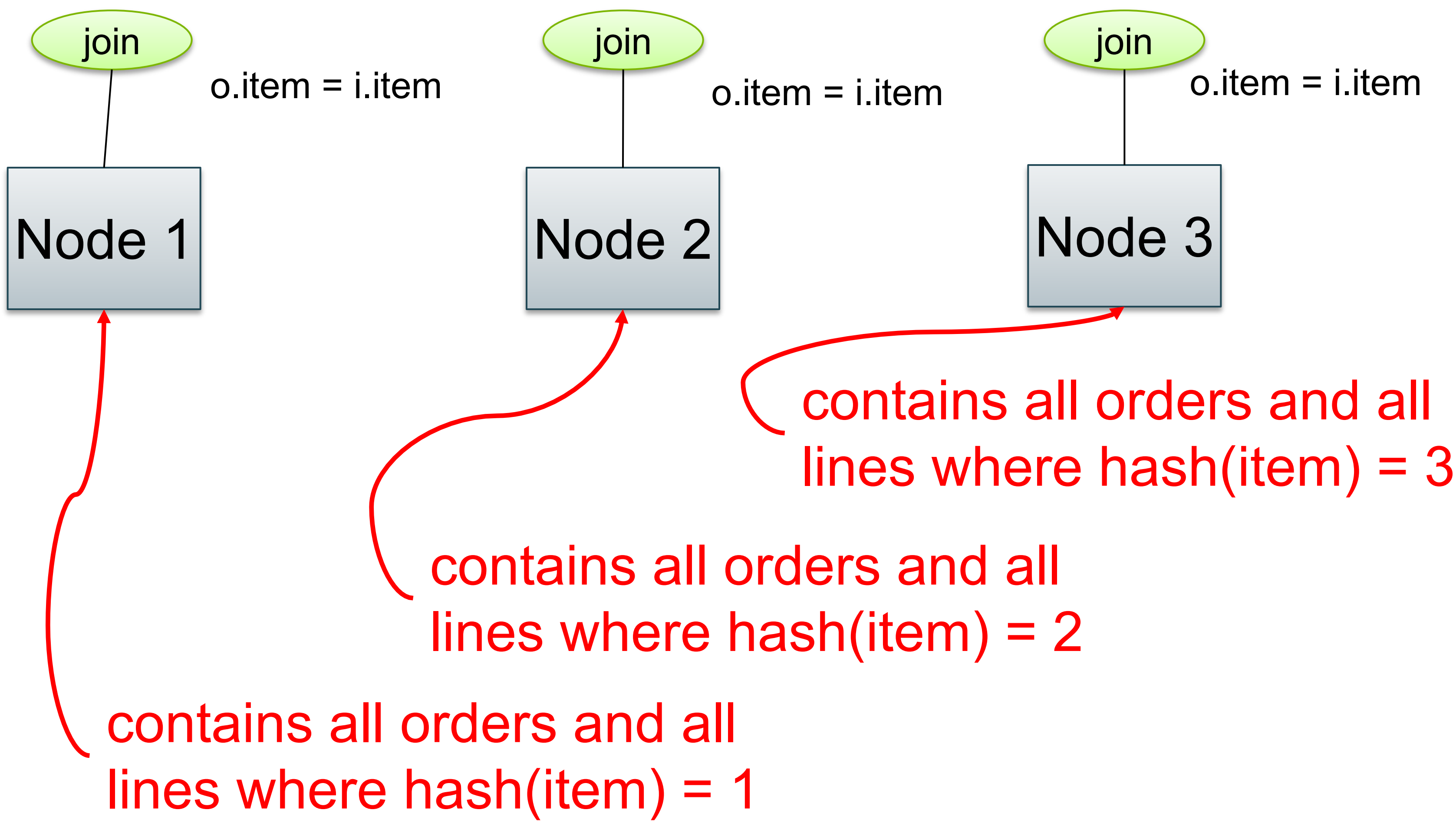

Optimization for Small Relations

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

- Sometimes called a “small join” or “broadcast join”

Other Interesting Parallel Join Implementation

Problem of skew during join computation

Some join partitions get more **input** tuples than others

- Reason 1: Base data unevenly distributed
  - Because used a range-partition function
  - Or used hashing but some values are very popular (Skew)
- Reason 2: Selection before join with different selectivities
- Reason 3: Input data got unevenly rehashed (or otherwise repartitioned before the join)

Some partitions **output** more tuples than others

Some Skew Handling Techniques

1. Use range- instead of hash-partitions
   – Ensure that each range gets same number of tuples
   – Example: {1, 1, 1, 2, 3, 4, 5, 6 } → [1,2] and [3,6]
2. Create more partitions than nodes
   – And be smart about scheduling the partitions
3. Use subset-replicate (i.e., “skewedJoin”)
   – Given an extremely common value ‘v’
   – Distribute R tuples with value v randomly across k nodes (R is the build relation)
   – Replicate S tuples with value v to same k machines (S is the probe relation)

Parallel Dataflow Implementation

Use relational operators unchanged

Add a special *shuffle* operator

- Handle data routing, buffering, and flow control
- Inserted between consecutive operators in the query plan
- Two components: ShuffleProducer and ShuffleConsumer
- Producer pulls data from 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

Conclusion

- Making databases parallel is another way to speed up query processing
- Many algorithms for parallelizing different relational operators
- Next time: MapReduce and Spark