# Introduction to Data Management CSE 344

## Lecture 24: Parallel Databases

# Announcements

- Quiz 7 due Thursday
- HW7 due next Tuesday
- HW8 will be posted by end of week
  – Will take more hours than other HWs (complex setup, queries run for many hours) – Plan ahead!
  – Details in sections this week – a bit too soon, but no sections next week
- Next several lectures: parallel databases
  – Traditional, MapReduce+PigLatin

# Parallel Computation Today

Two Major Forces Pushing towards Parallel Computing:

- Change in Moore's law

- Cloud computing

# Parallel Computation Today

1. Change in Moore's law* (exponential growth in transistors per chip density) no longer results in increased clock speeds
   – Increased hw performance available only through parallelism
   – Think multicore: 4 cores today, perhaps 64 in a few years

* Moore's law says that the number of transistors that can be placed inexpensively on an integrated circuit doubles approximately every two years [Intel co-founder Gordon E. Moore described the trend in his 1965 paper and predicted that it will last for at least 10 years]

# Parallel Computation Today

2. Cloud computing commoditizes access to large clusters
   – Ten years ago, only Google could afford 1000 servers;
   – Today you can rent this from Amazon Web Services (AWS)

Cheap!

Jeff Dean, SOCC'2010:

## Numbers Everyone Should Know

| | |
|---|---|
| L1 cache reference | 0.5 ns |
| Branch mispredict | 5 ns |
| L2 cache reference | 7 ns |
| Mutex lock/unlock | 25 ns |
| Main memory reference | 100 ns |
| Compress 1K w/cheap compression algorithm | 3,000 ns |
| Send 2K bytes over 1 Gbps network | 20,000 ns |
| Read 1 MB sequentially from memory | 250,000 ns |
| Round trip within same datacenter | 500,000 ns |
| Disk seek | 10,000,000 ns |
| Read 1 MB sequentially from disk | 20,000,000 ns |
| Send packet CA->Netherlands->CA | 150,000,000 ns |

Google

Memory access

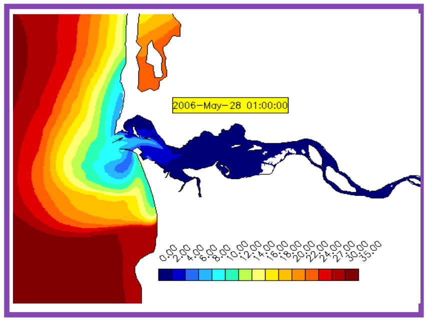
Local access is significantly faster than communication

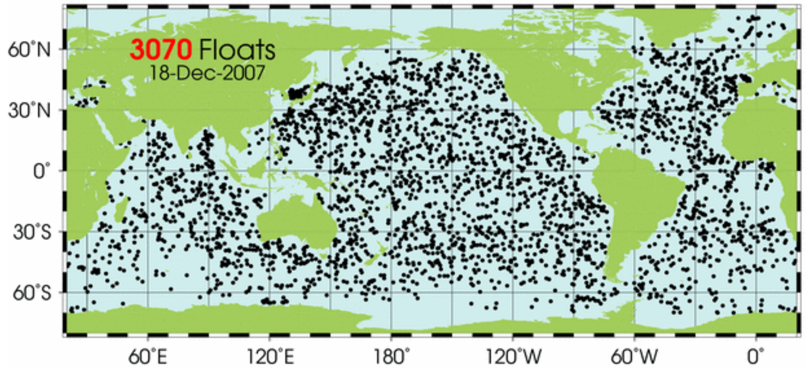
Communication

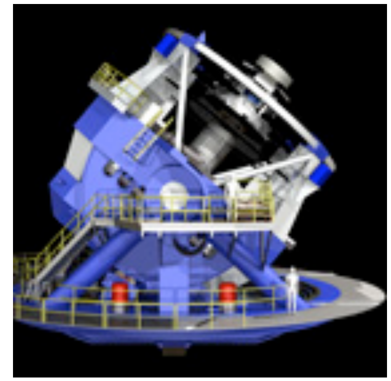
# Science is Facing a Data Deluge!

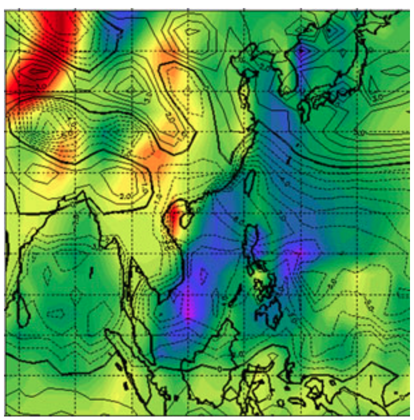
- Astronomy: Large Synoptic Survey Telescope LSST: 30TB/night (high-resolution, high-frequency sky surveys)
- Physics: Large Hadron Collider 25PB/year
- Biology: lab automation, high-throughput sequencing
- Oceanography: high-resolution models, cheap sensors, satellites
- Medicine: ubiquitous digital records, MRI, ultrasound

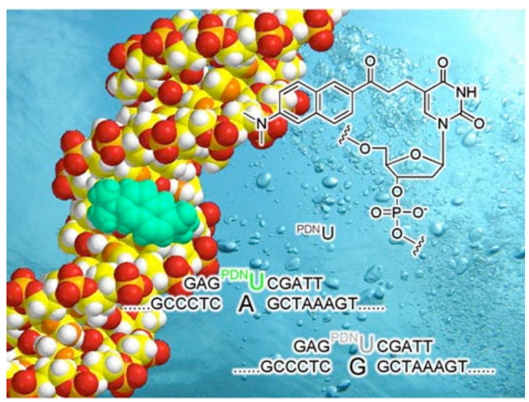
# Science is Facing a Data Deluge!





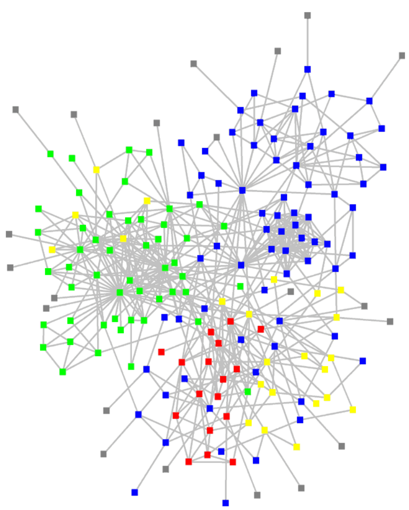


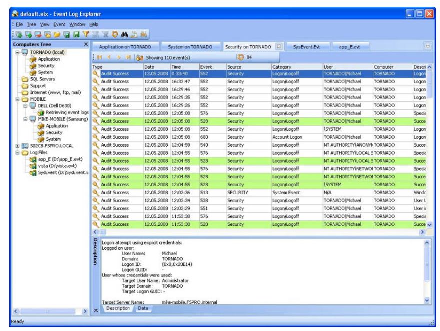

# Industry is Facing a Data Deluge!

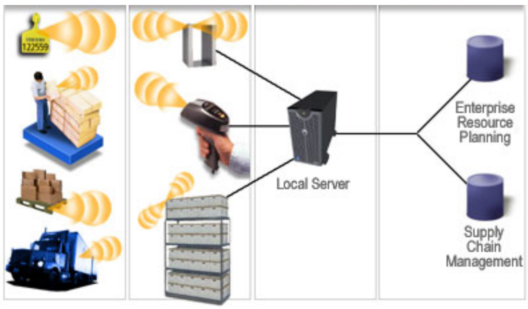
Clickstreams, search logs, network logs, social networking data, RFID data, etc.

- Facebook:
  - 15PB of data in 2010
  - 60TB of new data every day
- Google:
  - In May 2010 processed 946PB of data using MapReduce
- Twitter, Google, Microsoft, Amazon, Walmart, etc.

# Industry is Facing a Data Deluge!







# Big Data

- Companies, organizations, scientists have data that is **too big, too fast, and too complex** to be managed without changing tools and processes

- Relational algebra and SQL are easy to parallelize and parallel DBMSs have already been studied in the 80's!

# Data Analytics Companies

As a result, we are seeing an explosion of and a huge success of db analytics companies

- Greenplum founded in 2003 acquired by EMC in 2010; A parallel shared-nothing DBMS (this lecture)
- Vertica founded in 2005 and acquired by HP in 2011; A parallel, column-store shared-nothing DBMS (see 444 for discussion of column-stores)
- DATAllegro founded in 2003 acquired by Microsoft in 2008; A parallel, shared-nothing DBMS
- Aster Data Systems founded in 2005 acquired by Teradata in 2011; A parallel, shared-nothing, MapReduce-based data processing system (next lecture). SQL on top of MapReduce
- Netezza founded in 2000 and acquired by IBM in 2010. A parallel, shared-nothing DBMS.

Great time to be in the data management, data mining/statistics, or machine learning!

# Two Kinds to Parallel Data Processing

- Parallel databases, developed starting with the 80s (this lecture)
  - OLTP (Online Transaction Processing)
  - OLAP (Online Analytic Processing, or Decision Support)
- MapReduce, first developed by Google, published in 2004 (next lecture)
  - Only for Decision Support Queries

Today we see convergence of the two approaches (Greenplum,Dremmel)

# 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

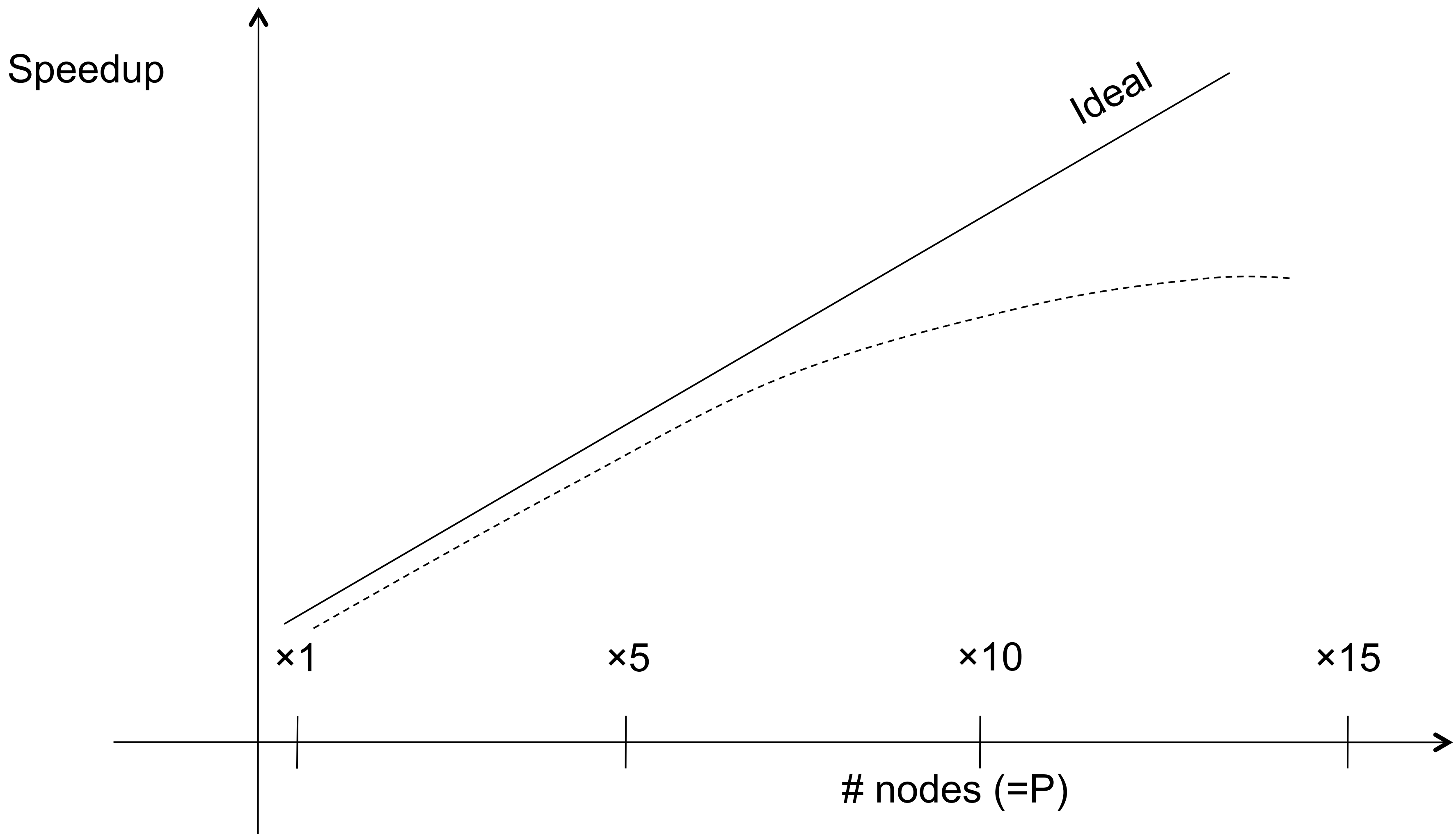
# Performance Metrics for Parallel DBMSs

P = the number of nodes (processors, computers)

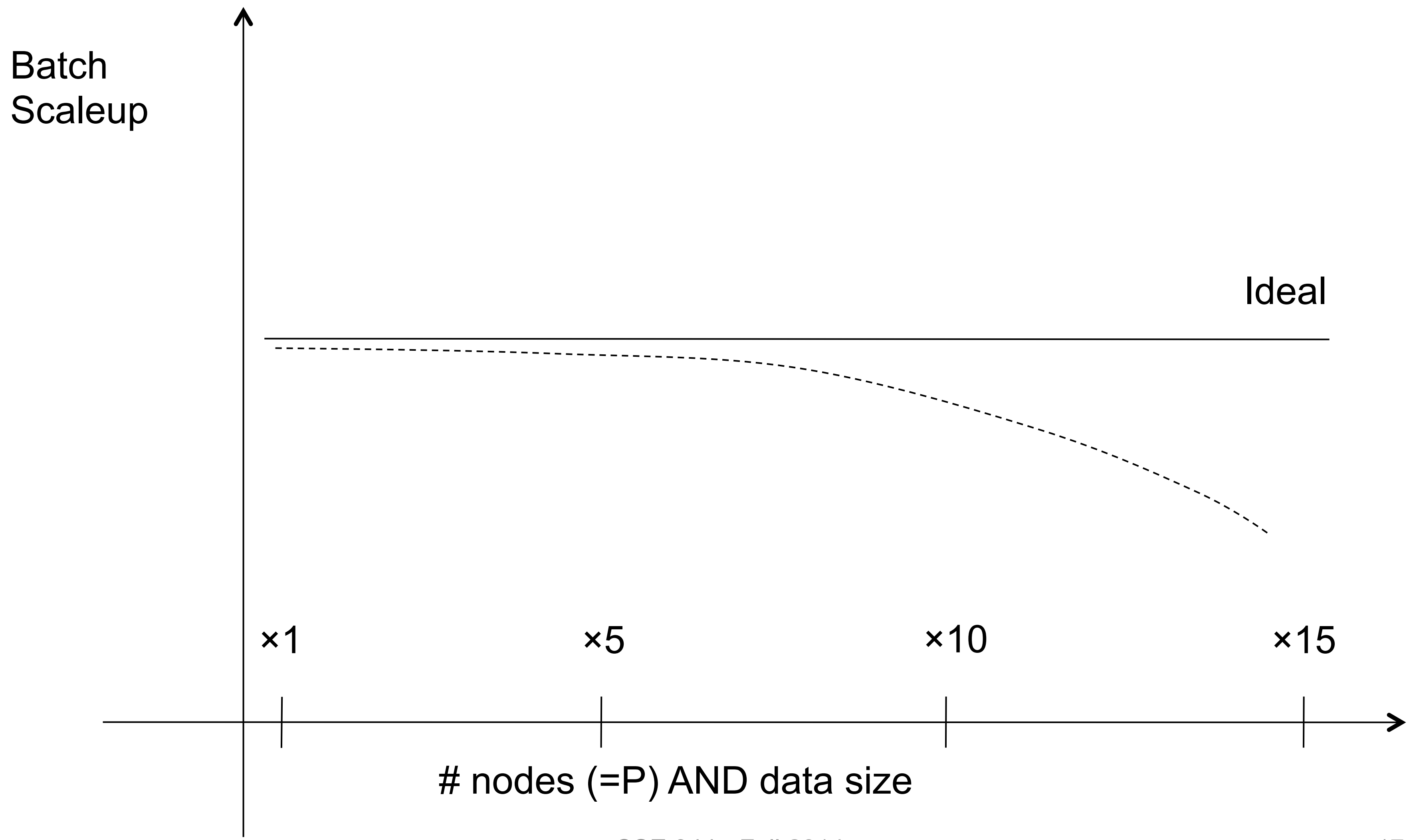
- Speedup:
  - More nodes, same data ➔ higher speed
- Scaleup:
  - More nodes, more data ➔ same speed

- OLTP: "Speed" = transactions per second (TPS)
- Decision Support: "Speed" = query time

# Linear v.s. Non-linear Speedup



# Linear v.s. Non-linear Scaleup



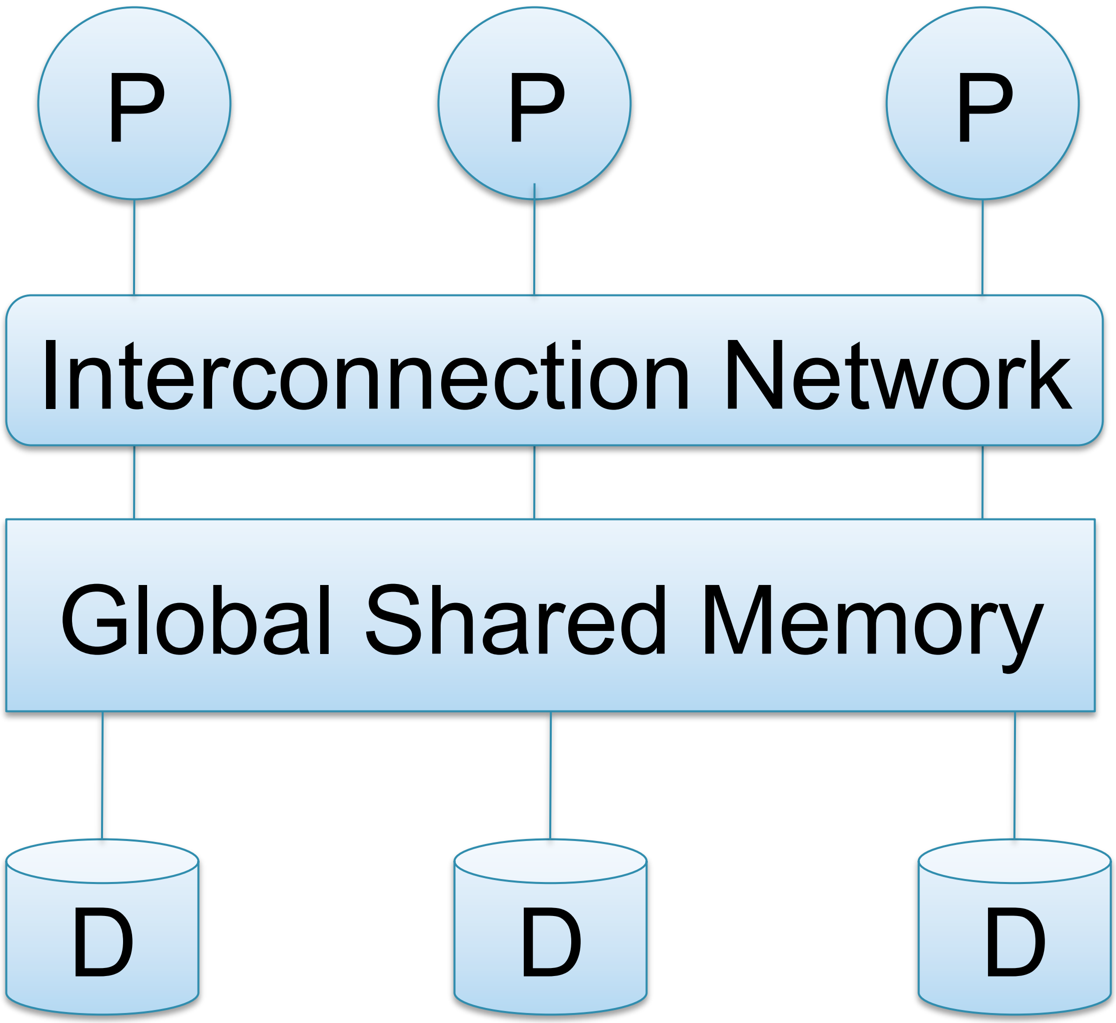
# Challenges to Linear Speedup and Scaleup

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

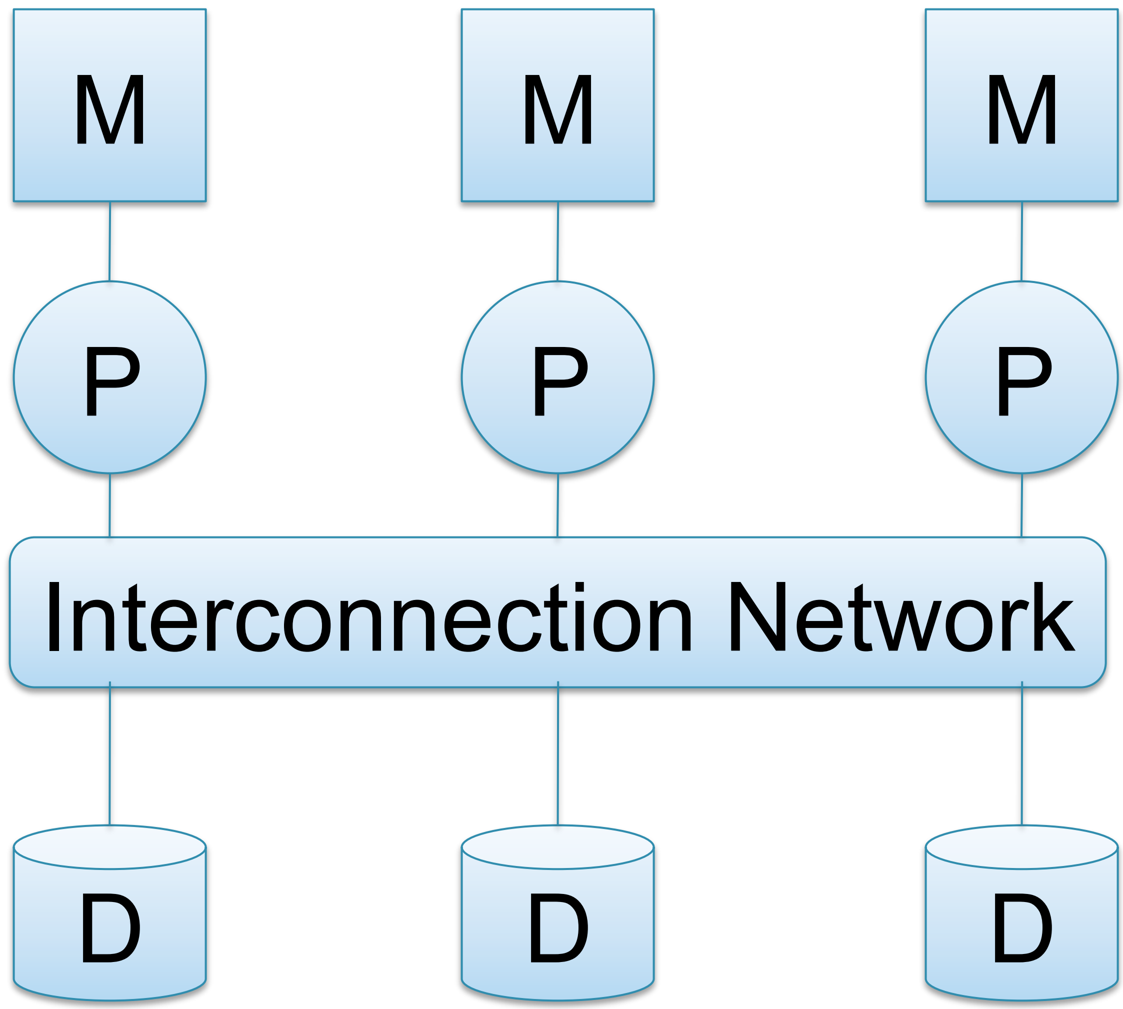
# Architectures for Parallel Databases

- Shared memory
- Shared disk
- Shared nothing

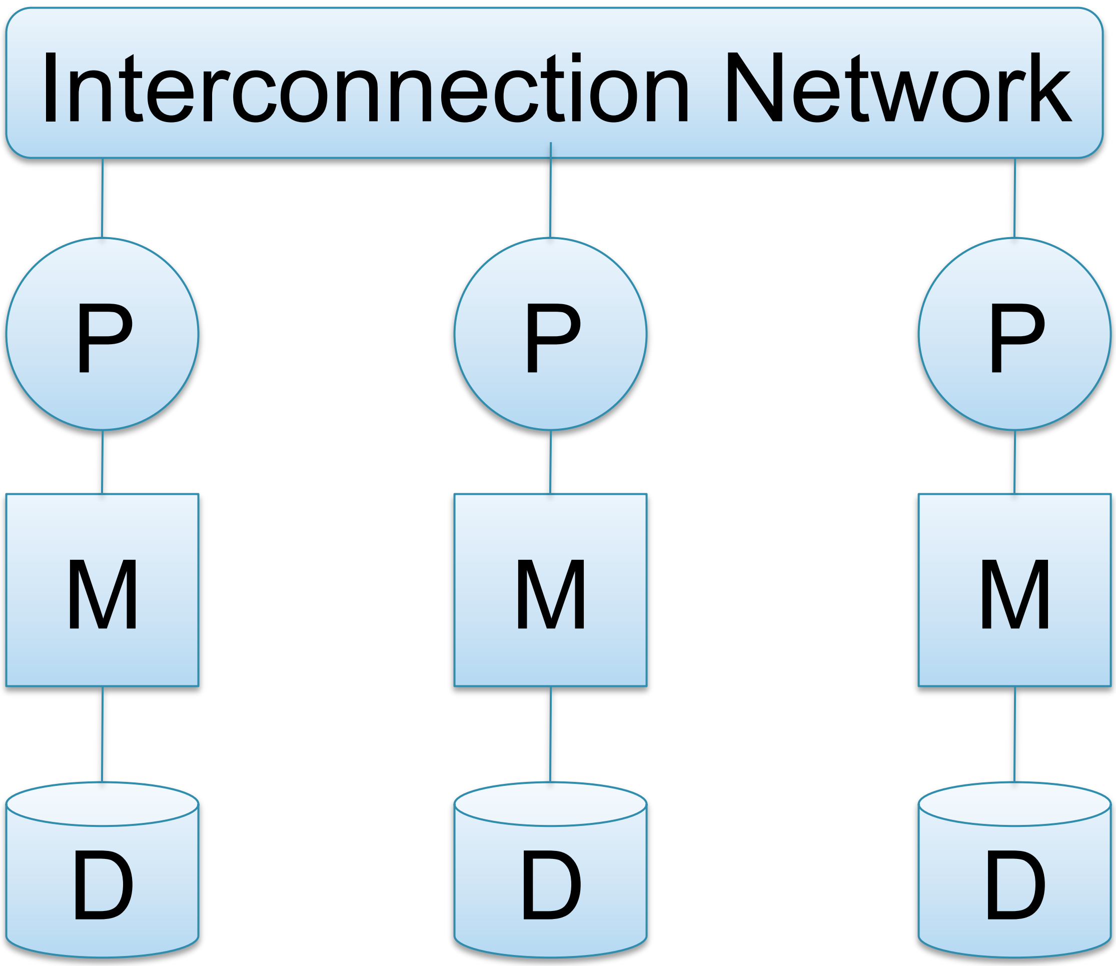
# Shared Memory



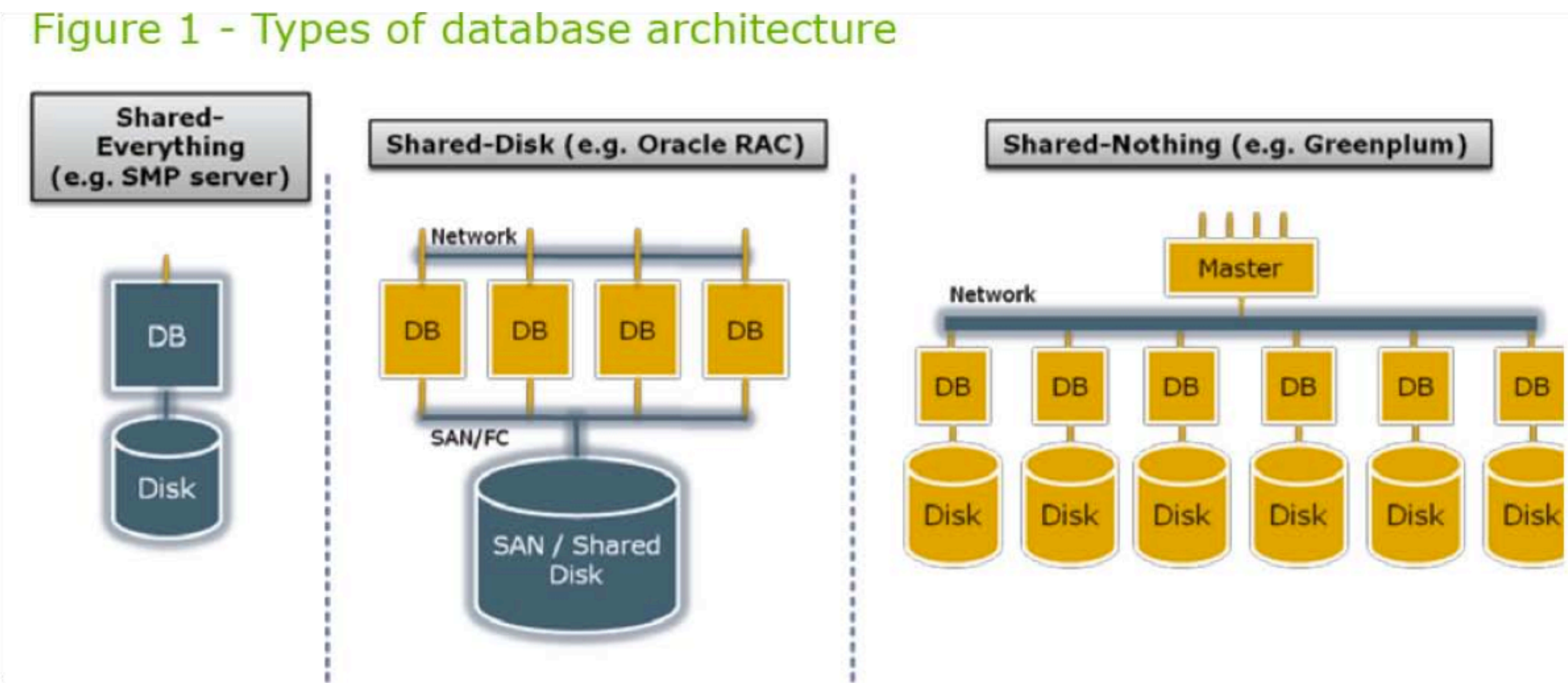
# Shared Disk



# 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 and can leverage many threads to get a query to run faster (see query plans)

- Easy to use and program
- But very expensive to scale: last remaining cash cows in the hardware industry

# 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.

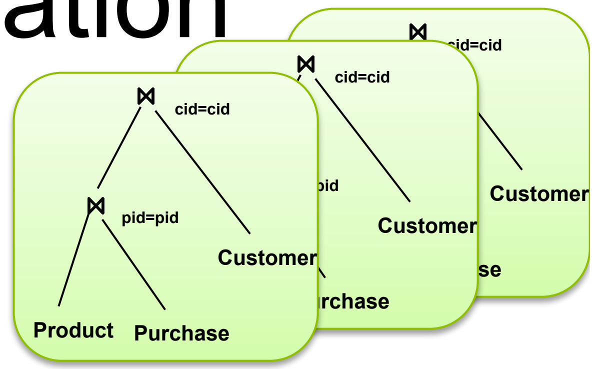
We discuss only Shared Nothing in class

# In Class

- You have a parallel machine.  Now what?

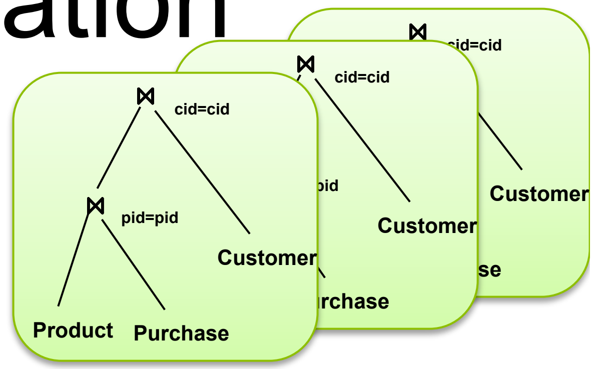
- How do you speed up your DBMS?

# Approaches to Parallel Query Evaluation




- Inter-query parallelism
  - Transaction per node
  - OLTP

# Approaches to Parallel Query Evaluation

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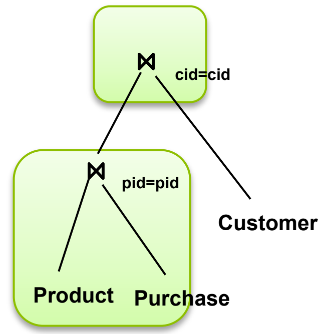


- Inter-operator parallelism
  - Operator per node
  - Both OLTP and Decision Support

# Approaches to Parallel Query Evaluation

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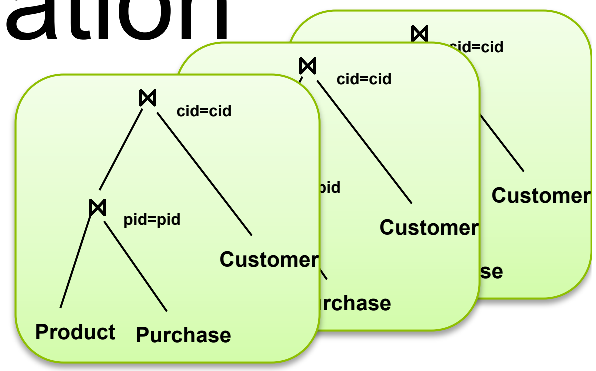


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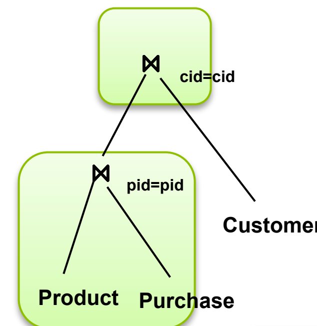
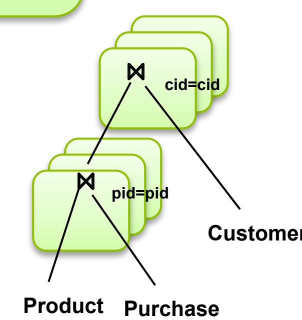



- Intra-operator parallelism
  - Operator on multiple nodes
  - Decision Support



# Approaches to Parallel Query Evaluation

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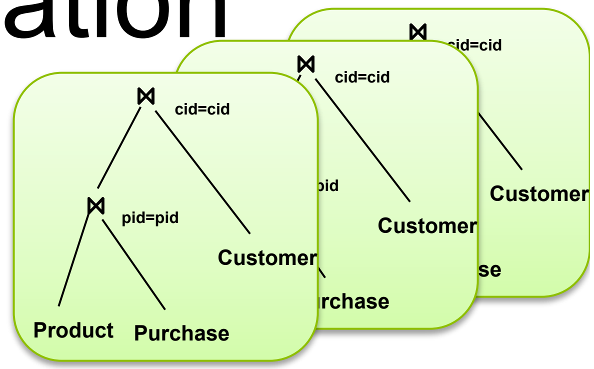


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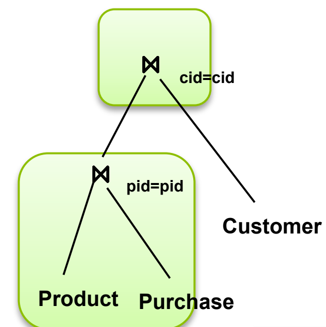


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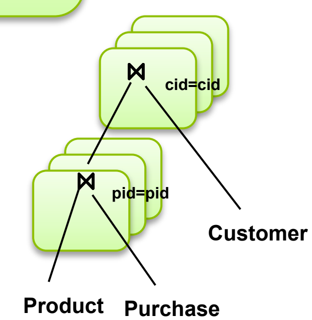



We study only intra-operator parallelism: most scalable

# Basic Query Processing: Quick Review in Class

Basic query processing on one node.

Given relations R(A,B) and S(B, C), no indexes, how do we compute:

- Selection: $\sigma_{A=123}(R)$
- Group-by: $\gamma_{A,sum(B)}(R)$
- Join: $R \bowtie S$

# Basic Query Processing: Quick Review in Class

Basic query processing on one node.

Given relations R(A,B) and S(B, C), no indexes, how do we compute:

- Selection: $\sigma_{A=123}(R)$
  - Scan file R, select records with A=123
- Group-by: $\gamma_{A,sum(B)}(R)$
  - Scan file R, insert into a hash table using attr. A as key
  - When a new key is equal to an existing one, add B to the value
- Join: $R \bowtie S$
  - Scan file S, insert into a hash table using attr. B as key
  - Scan file R, probe the hash table using attr. B

# Parallel Query Processing

How do we compute these operations on a shared-nothing parallel db?

- Selection: $\sigma_{A=123}(R)$ (that's easy, won't discuss…)
- Group-by: $\gamma_{A,sum(B)}(R)$
- Join: $R \bowtie S$

Before we answer that: how do we store R (and S) on a shared-nothing parallel db?

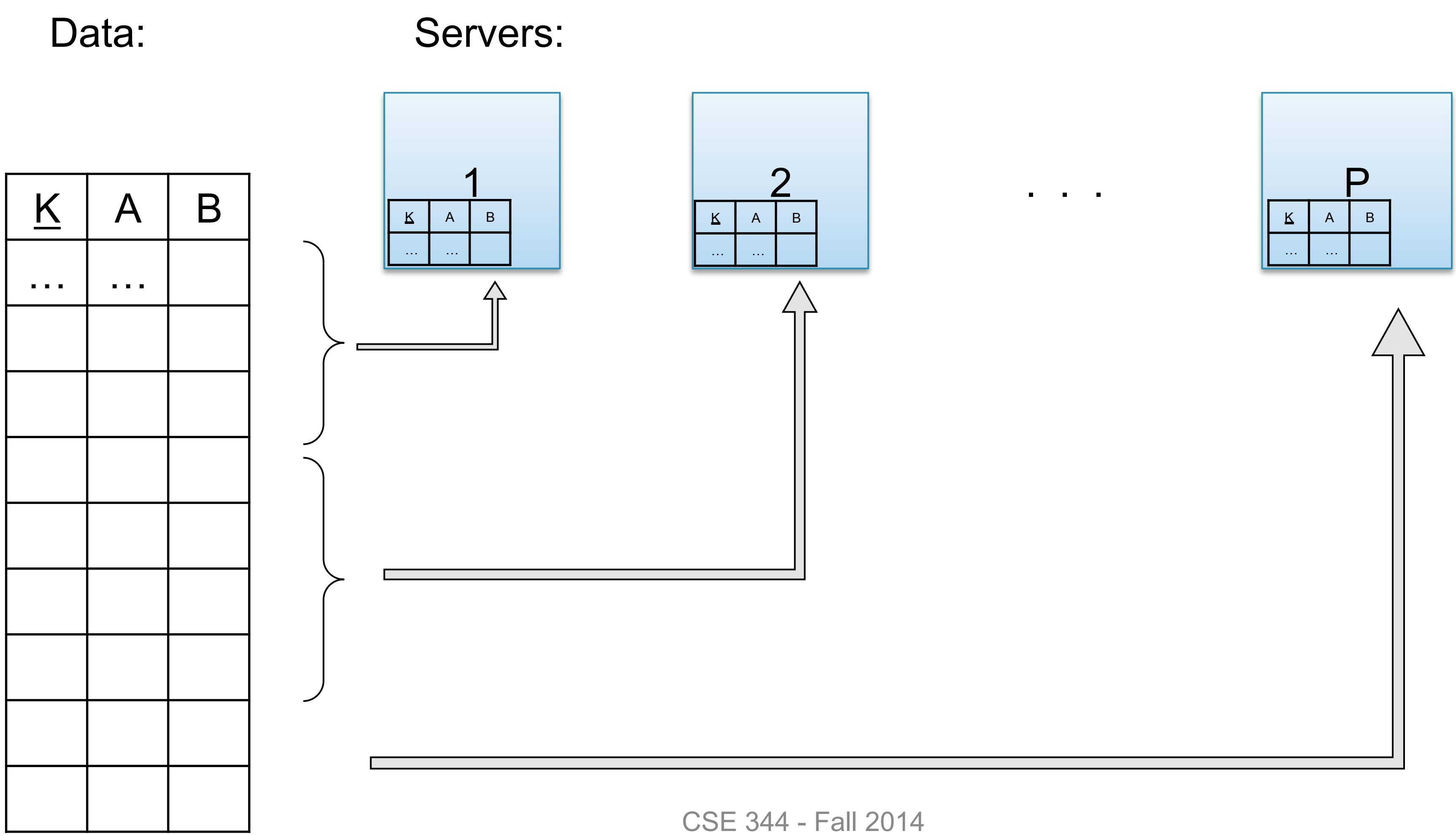
# Horizontal Data Partitioning

Data:

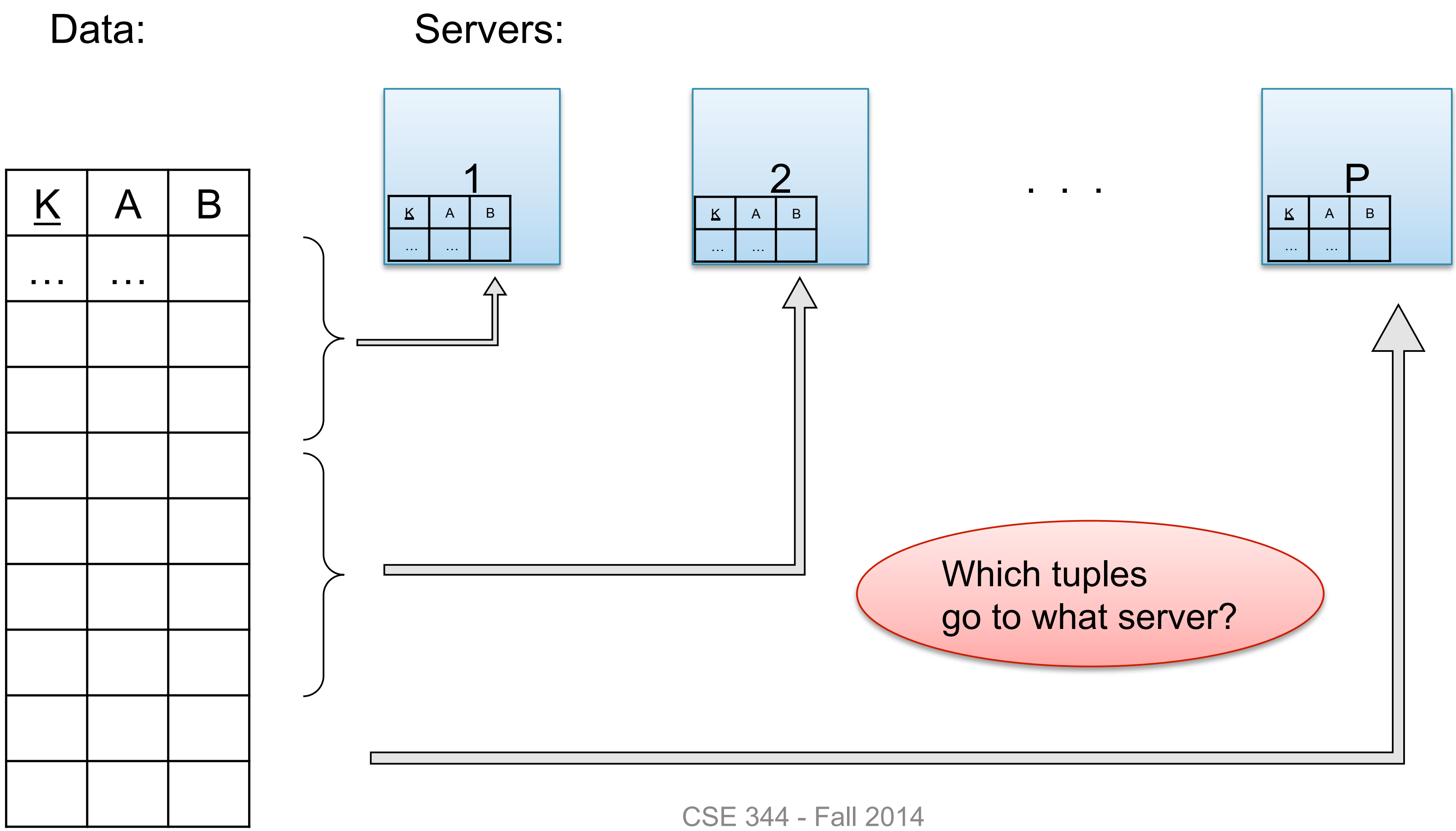
| K | A | B |
|---|---|---|
| … | … | |
| | | |
| | | |
| | | |
| | | |
| | | |
| | | |
| | | |
| | | |

Servers:

# Horizontal Data Partitioning



# Horizontal Data Partitioning



# Horizontal Data Partitioning

- Block Partition:
  - Partition tuples arbitrarily s.t. $size(R_1) \approx \ldots \approx size(R_P)$
- 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 $v_{i-1} < t.A < v_i$

# Parallel GroupBy

Data: R(K,A,B,C)
Query: $\gamma_{A,sum(C)}(R)$
Discuss in class how to compute in each case:

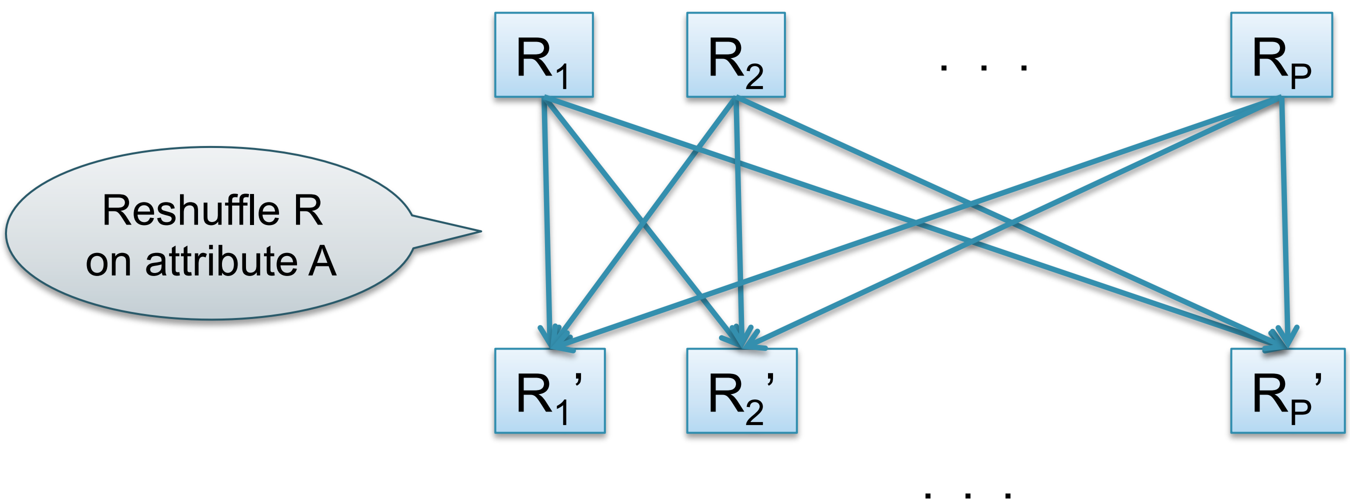
- R is hash-partitioned on A
- R is block-partitioned
- R is hash-partitioned on K

# Parallel GroupBy

Data: R(K,A,B,C)

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

- R is block-partitioned or hash-partitioned on K



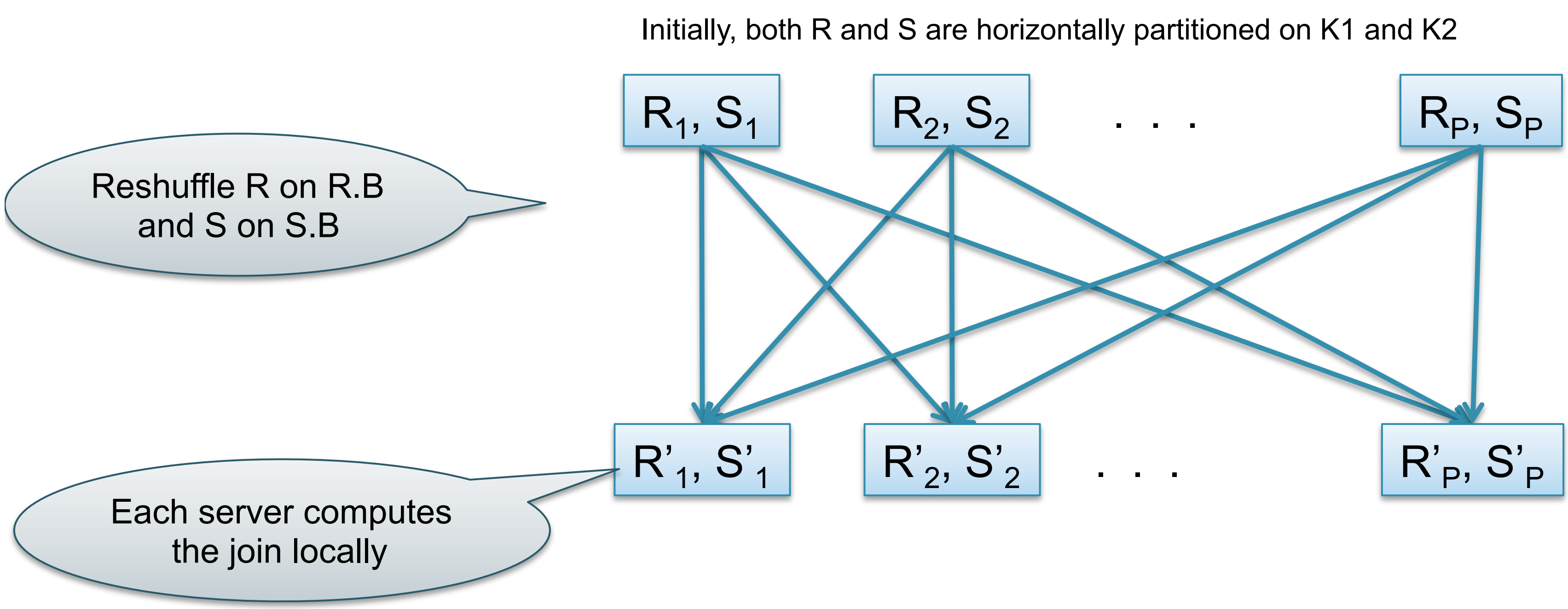
# Parallel Join

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

Initially, both R and S are horizontally partitioned on K1 and K2

# Parallel Join

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



# 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)

# Uniform Data v.s. Skewed Data

- Let R(<u>K</u>,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

May be skewed

Assuming good hash function

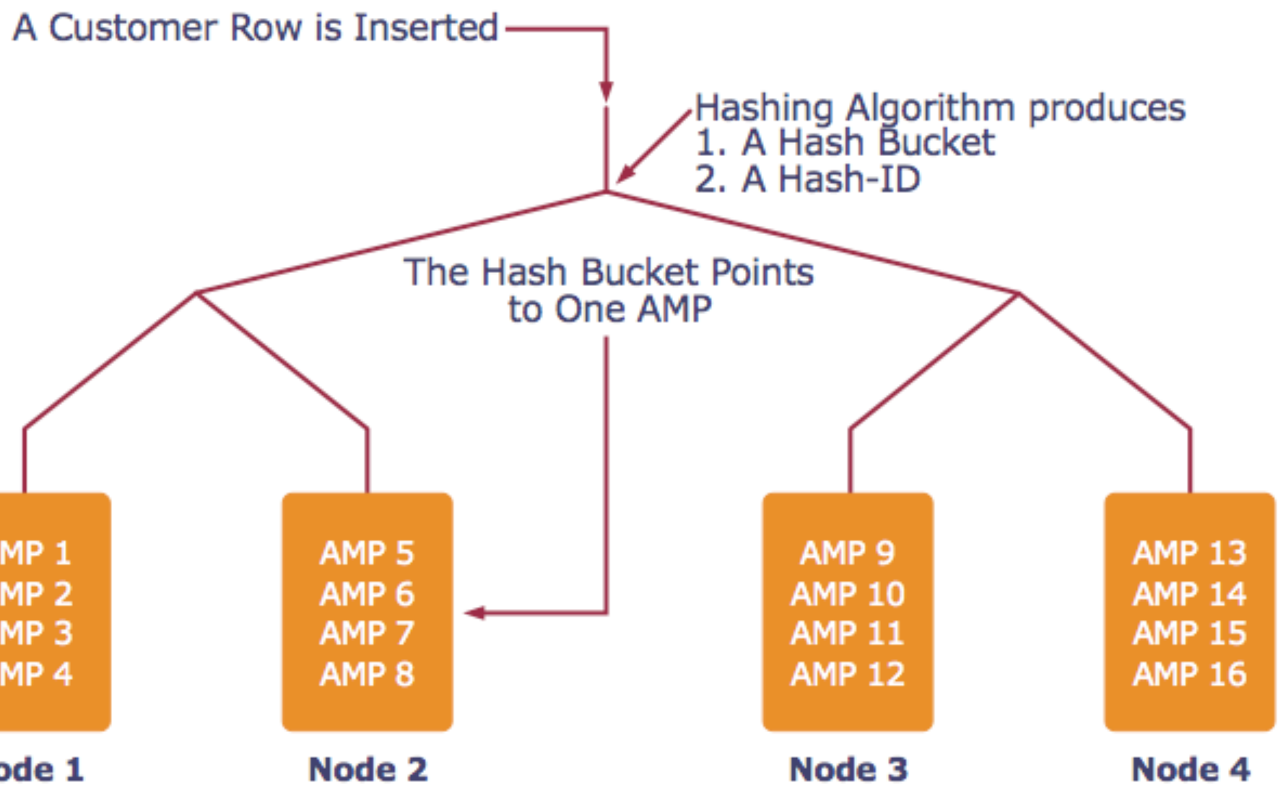
E.g. when all records have the same value of the attribute A, then all records end up in the same partition

# Parallel DBMS

- Parallel query plan: tree of parallel operators
  Intra-operator parallelism
  - Data streams from one operator to the next
  - Typically all cluster nodes process all operators
- Can run multiple queries at the same time
  Inter-query parallelism
  - Queries will share the nodes in the cluster
- Notice that user does not need to know how his/her SQL query was processed

# Loading Data into a Parallel DBMS

*Example using Teradata System*



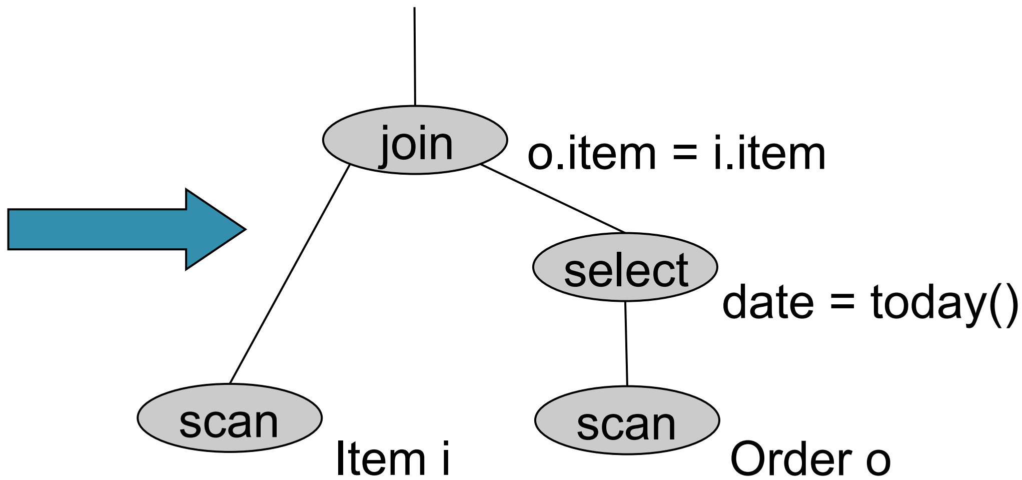

*AMP = "Access Module Processor" = unit of parallelism*

Order(oid, item, date), Line(item, …)

# Example Parallel 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()
```



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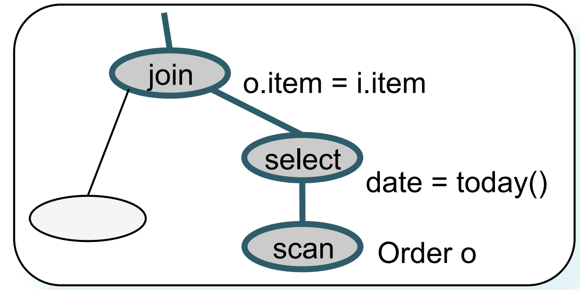


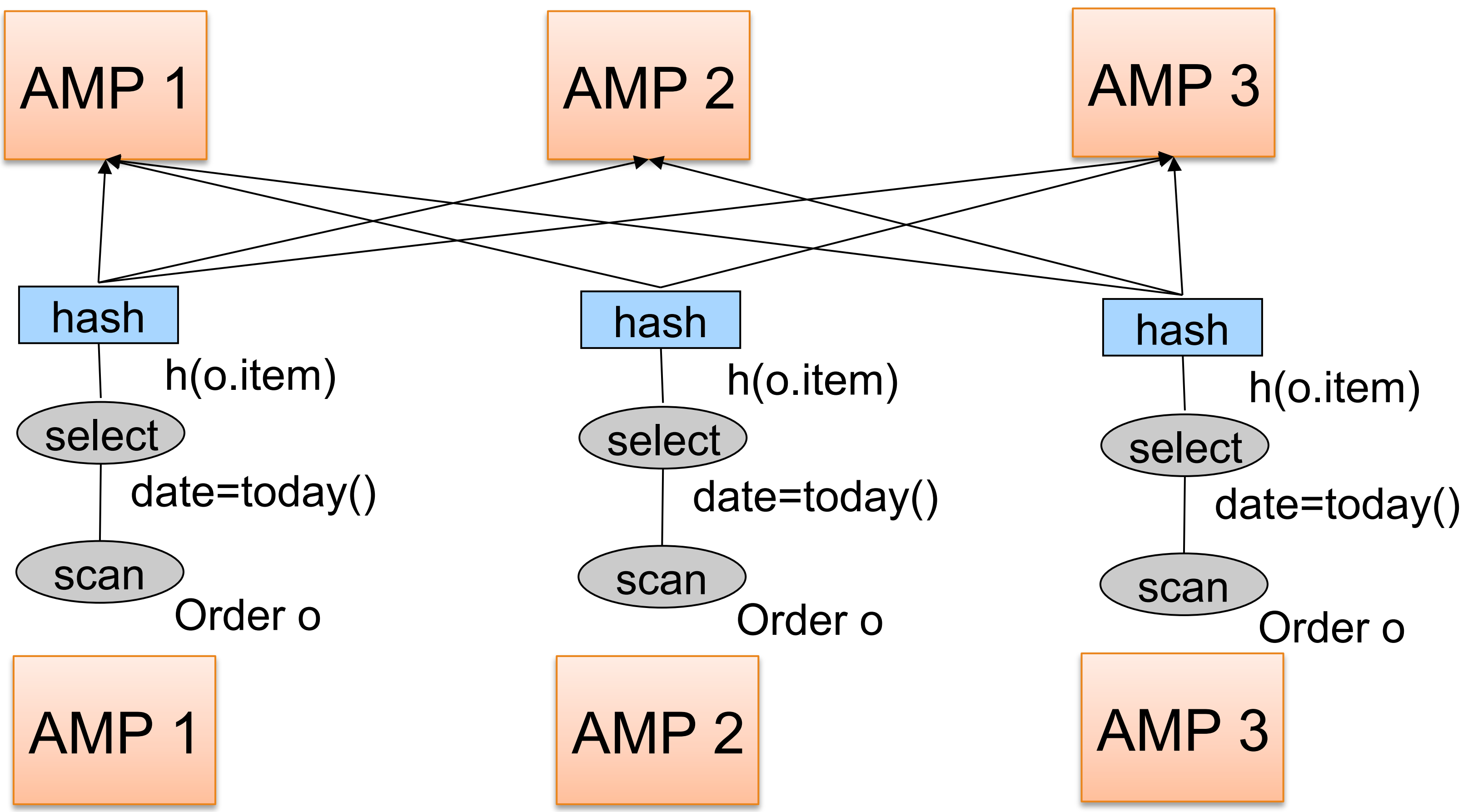

Order(<u>oid</u>, item, date), Line(item, …)

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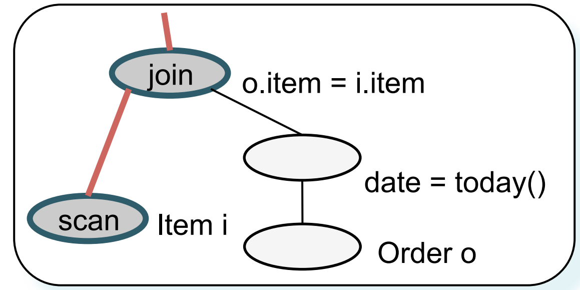


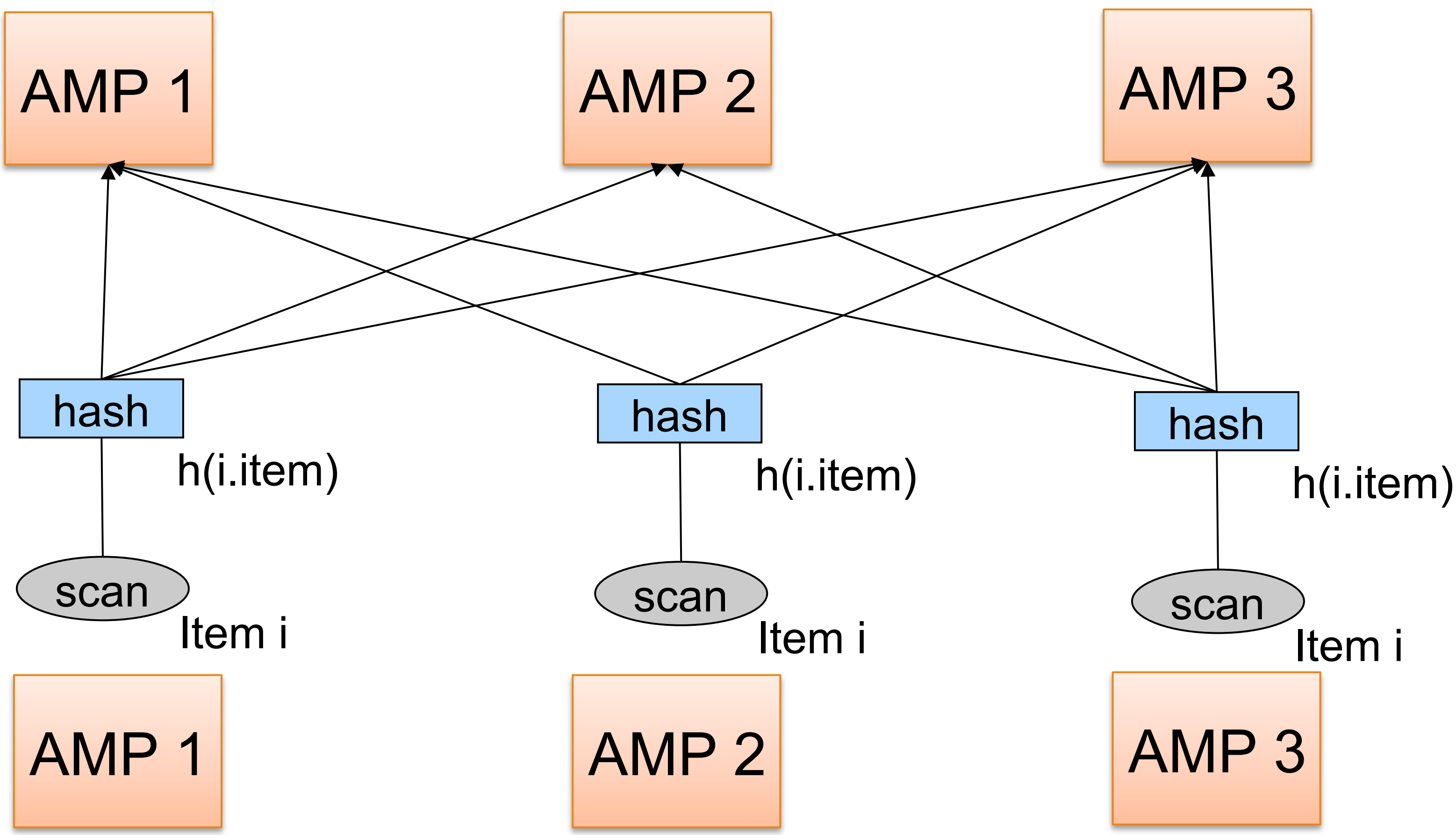

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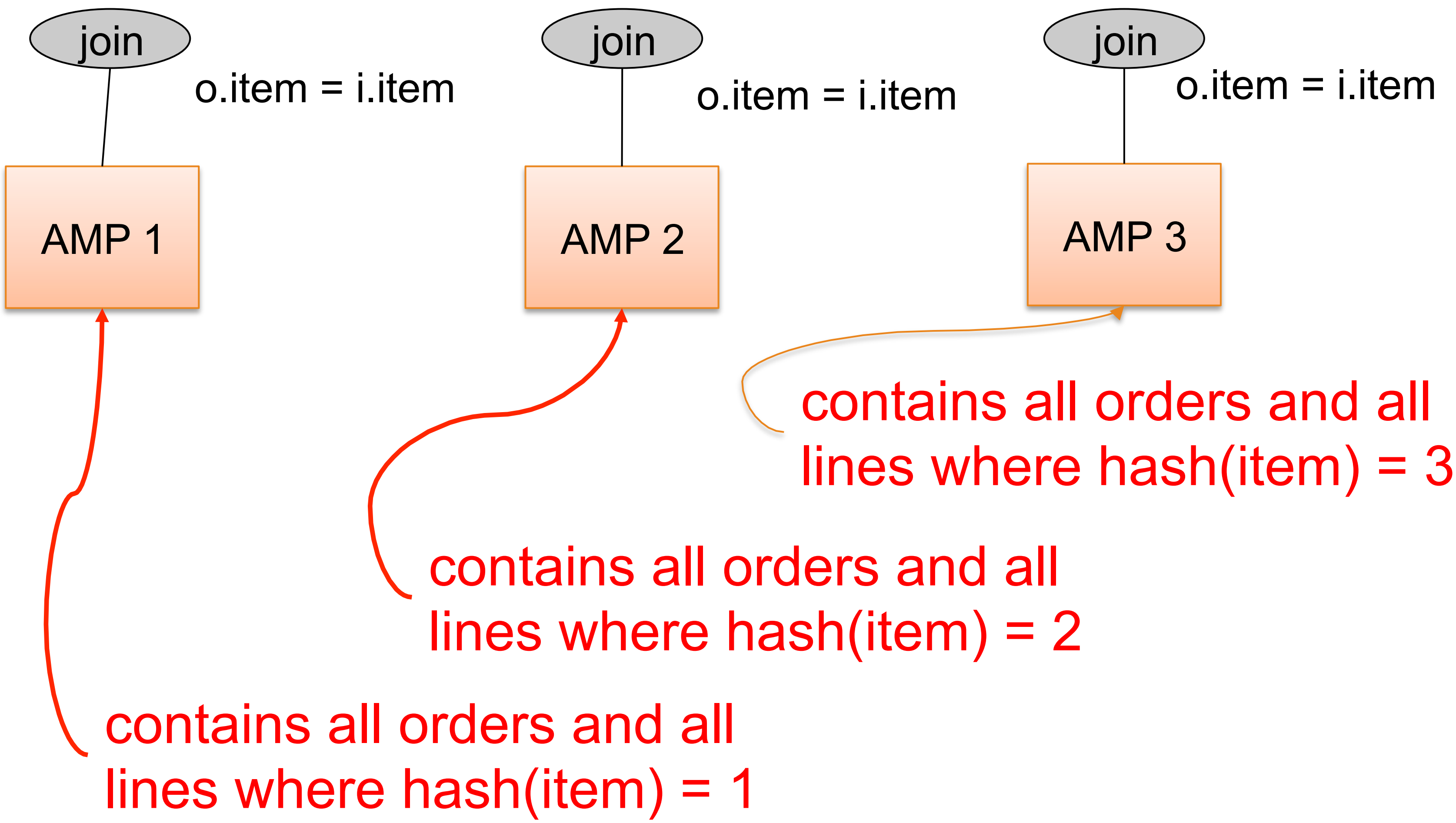

# Parallel Dataflow Implementation

- 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
- You will use this extensively in 444