CSE 444: Database Internals

Lectures 20-21
Parallel DBMSs

What We Have Already Learned

- Overall architecture of a DBMS
- Internals of query execution:
  - Data storage and indexing
  - Buffer management
  - Query evaluation including operator algorithms
  - Query optimization
- Internals of transaction processing:
  - Concurrency control: pessimistic and optimistic
  - Transaction recovery: undo, redo, and undo/redo

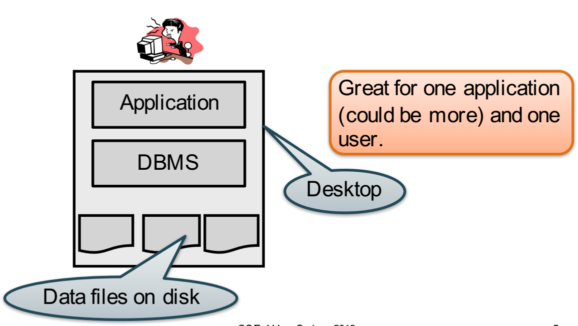
Where We Are Headed Next

- Scaling the execution of a query
  - Parallel DBMS
  - Distributed query processing
  - MapReduce
- Scaling transactions
  - Distributed transactions
  - Replication
- Scaling with NoSQL and NewSQL

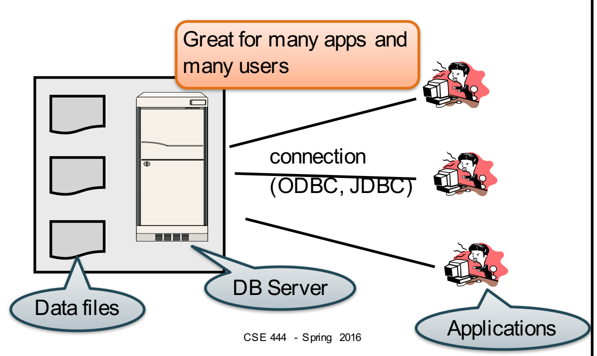
Reading Assignments

- Main textbook Chapter 20.1
- Database management systems.
  Ramakrishnan&Gehrke.
  Third Ed. Chapter 22.11

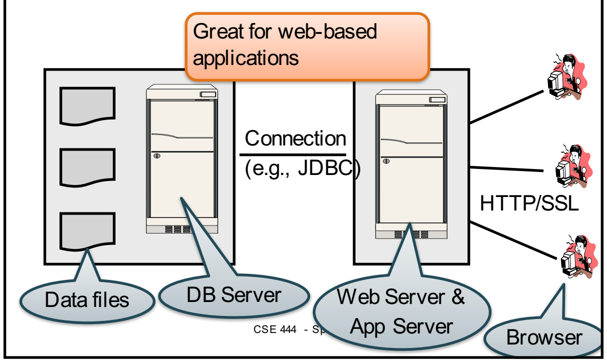
DBMS Deployment: Local



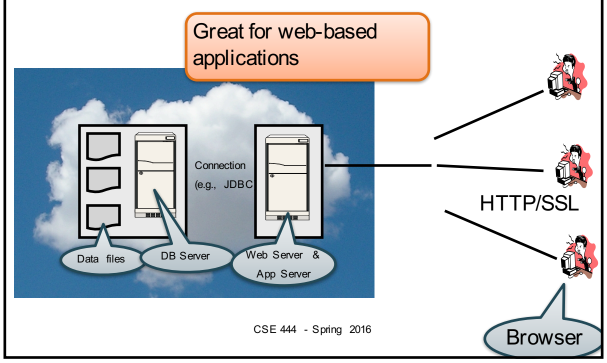
DBMS Deployment: Client/Server



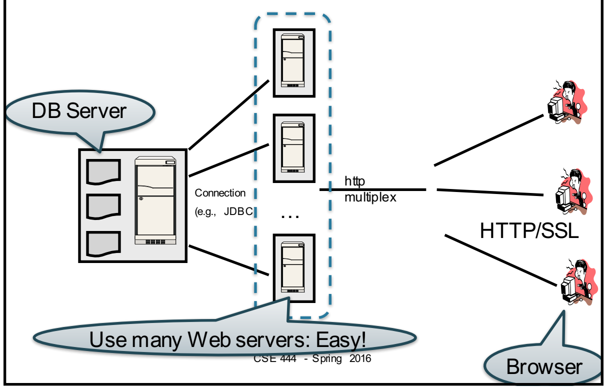
DBMS Deployment: 3 Tiers

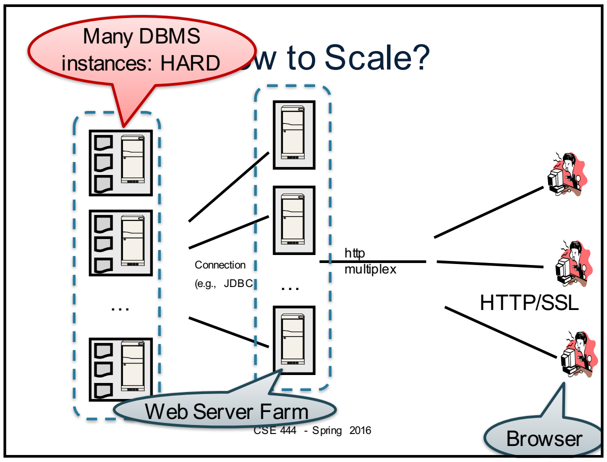


DBMS Deployment: Cloud



How to Scale?

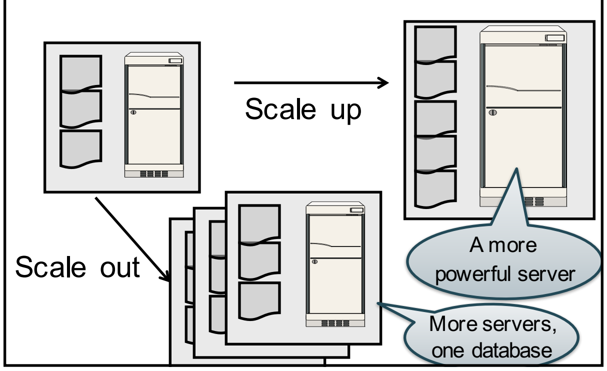




How to Scale?

- We 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

How to Scale a DBMS?



What to scale?

- OLTP: Transactions per second
  - OLTP = Online Transaction Processing
- OLAP: Query response time
  - OLAP = Online Analytical Processing

Scaling Transactions Per Second

- Amazon
- Facebook
- Twitter
- … your favorite Internet application…
- Goal is to scale OLTP workloads
- We will get back to this next week

Scaling Single Query Response Time

- Goal is to scale OLAP workloads
- That means the analysis of massive datasets

This Week: Focus on Scaling a Single Query

Big Data

- Buzzword?
- Definition from industry:
  - High Volume
  - High Variety
  - High Velocity

http://www.gartner.com/newsroom/id/1731916

Big Data

Volume is not an issue

- 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
- And you will implement it in lab 6

Big Data

New workloads are an issue

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

Data Analytics Companies

Explosion 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 paralle column-store shared-nothing DBMS
- 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 (in two lectures). SQL on top of MapReduc
- Netezza founded in 2000 and acquired by IBM in 2010. A parallel, shared-nothing DBMS.

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

Two Approaches to Parallel Data Processing

- Parallel databases, developed starting with the 80s (this lecture and next)
  - For both OLTP (transaction processing)
  - And for OLAP (decision support queries)
- MapReduce, first developed by Google, published in 2004 (in two lectures)
  - Only for decision support queries

Today we see convergence of the two approaches

Parallel DBMSs

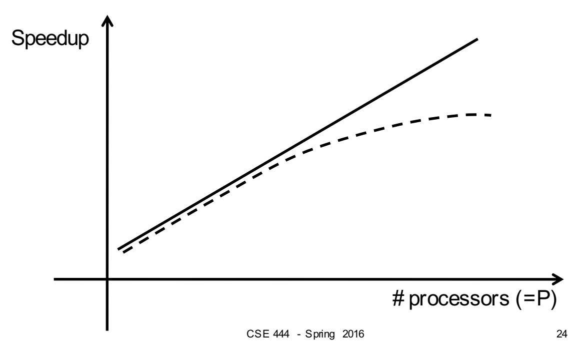
- Goal
  - Improve performance by executing multiple operations in parallel
- Key benefit
  - Cheaper to scale than relying on a single increasingly more powerful processor
- Key challenge
  - Ensure overhead and contention do not kill performance

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

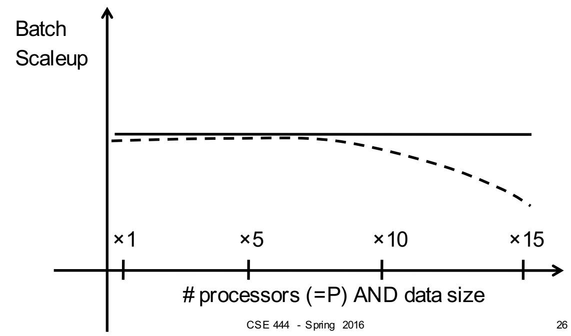


Performance Metrics for Parallel DBMSs

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



Warning

- 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

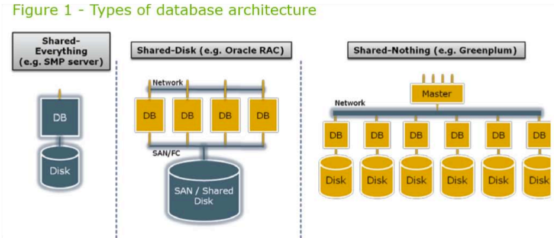
- Startup cost
  - Cost of starting an operation on many processors
- Interference
  - Contention for resources between processors
- Skew
  - Slowest processor becomes the bottleneck

Three Architectures for Parallel DB

- Shared memory
- Shared disk
- Shared nothing

Architectures for Parallel Databases

Figure 1 - Types of database architecture



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

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.

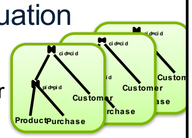
We discuss only Shared Nothing in class

In Class

- You have a parallel machine. Now what?
- How do you speed up your DBMS?

Taxonomy for Parallel Query Evaluation

- Inter-query parallelism
  - Each query runs on one processor



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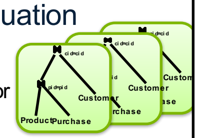
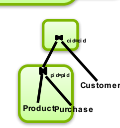


- Inter-operator parallelism
  - A query runs on multiple processors
  - An operator runs on one processor



Taxonomy for Parallel Query Evaluation

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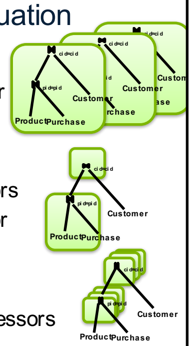
- Intra-operator parallelism
  - An operator runs on multiple processors



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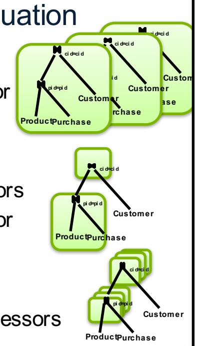


We study only intra-operator parallelism: most scalable

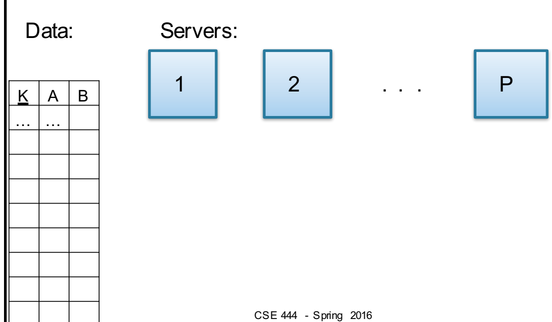
Parallel Query Processing

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

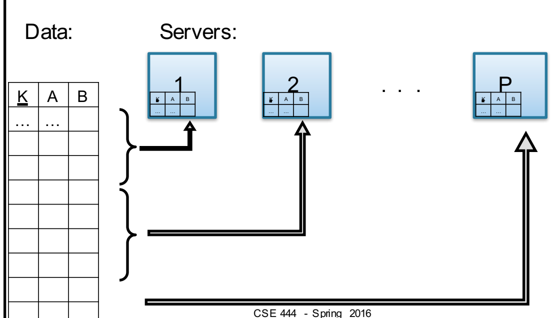
- Selection: $\sigma_{A=123}(R)$
- Group-by: $\gamma_{A,sum(B)}(R)$
- Join: $R \bowtie S$

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

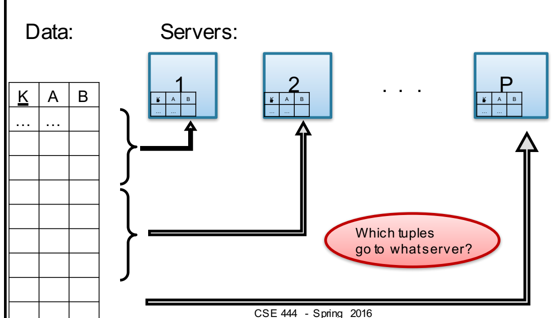
Horizontal Data Partitioning



Horizontal Data Partitioning



Horizontal 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 goes 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 $v_{i-1} < t.A < v_i$

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

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 — Uniform (Assuming uniform hash function)
  - On the attribute A
- Range-partition
  - On the key K
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Uniform Data v.s. Skewed Data

- Let R(K,A,B,C); which of the following partition methods may result in skewed partitions?
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Uniform Data v.s. Skewed Data

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  - On the key K — Uniform (Assuming uniform hash function)
  - On the attribute A — 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.)

Data Partitioning Revisited

What are the pros and cons ?

- Block based partitioning
  - Good load balance but always needs to read all the data
- Hash based partitioning
  - Good load balance
  - Can avoid reading all the data for equality selections
- Range based partitioning
  - Can suffer from skew (i.e., load imbalances)
  - Can help reduce skew by creating uneven partitions

Horizontal Data Partitioning

All three choices are just special cases:

- For each tuple, compute *bin = f(t)*
- Different properties of the function *f* determine hash vs. range vs. round robin vs. anything

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

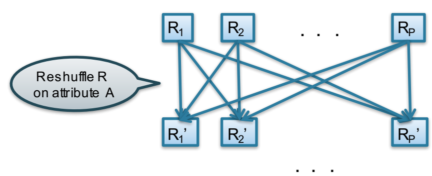
Compute $\sigma_{A=v}(R)$, or $\sigma_{v1<A<v2}(R)$

- On a conventional database: cost = B(R)
- Q: What is the cost on a parallel database with P processors ? A: B(R) / P, but
  - Block partitioned -- all servers do the work
  - Hash partitioned -- one server does the work
  - Range partitioned -- some servers do the work

Basic Parallel GroupBy

Data: R(<u>K</u>,A,B,C) -- hash-partitioned on K

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



Basic Parallel GroupBy

- Step 1: each server i partitions its chunk R_i using a hash function h(t.A) mod P: $R_{i,0}$, $R_{i,1}$, …, $R_{i,P-1}$
- Step 2: server j computes $\gamma_{A,\ sum(B)}$ on $R_{0,j}$, $R_{1,j}$, …, $R_{P-1,j}$

Basic Parallel GroupBy

Compute $\gamma_{A,sum(B)}(R)$

- On a conventional database: cost = B(R)
- Q: What is the cost on a parallel database with P processors ?

Basic Parallel GroupBy

Compute $\gamma_{A,sum(B)}(R)$

- On a conventional database: cost = B(R)
- Q: What is the cost on a parallel database with P processors ?
- A: B(R) / P

Basic Parallel GroupBy

Can we do better?

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

Basic Parallel GroupBy

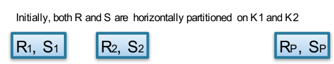
Can we do better?

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

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

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) $\bowtie$ S(<u>K2</u>,B,D)



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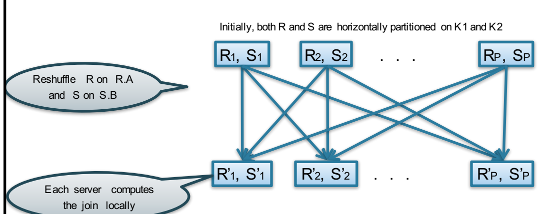


Parallel Join: $R \bowtie_{A=B} S$

- 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

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

Compute R $\bowtie_{A=B}$ S

- On a conventional database: cost = B(R)+B(S)
- Q: What is the cost on a parallel database with P processors ?

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

Compute R $\bowtie_{A=B}$ S

- On a conventional database: cost = B(R)+B(S)
- Q: What is the cost on a parallel database with P processors ?
- A: (B(R)+B(S)) / P

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?

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)

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

Other Interesting Parallel Join Implementation

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 } → [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

Parallel Query Evaluation

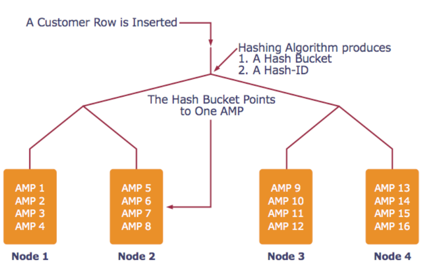
- Parallel query plan: tree of parallel operators
  Intra-operator parallelism
  - Data streams from one operator to the next
  - Typically all cluster nodes process all operators
- Can run multiple queries at the same time
  Inter-query parallelism
  - Queries will share the nodes in the cluster

Parallel Query Evaluation

New operator: Shuffle

- Origin: **Exchange** operator from Volcano system
- 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

Example: Teradata – Loading



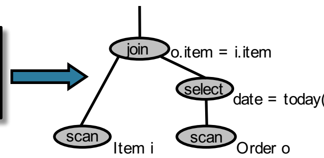
AMP = "Access Module Processor" = unit of parallelism

Order(oid, item, date), Line(item, …)

Example: Teradata – 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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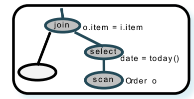
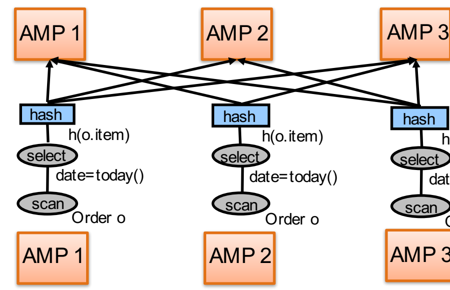
Query Execution





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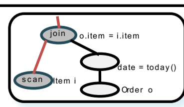

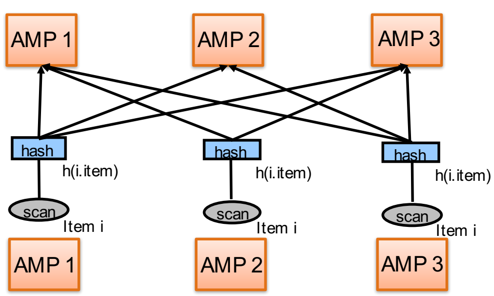

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Query Execution