CompSci 516
Database Systems

Lecture 20

Parallel DBMS

Instructor: Sudeepa Roy

Reading Material

- [RG]
  - Parallel DBMS: Chapter 22.1-22.5
- [GUW]
  - Parallel DBMS and map-reduce: Chapter 20.1-20.2

Acknowledgement:
The following slides have been created adapting the instructor material of the [RG] book provided by the authors Dr. Ramakrishnan and Dr. Gehrke.

Reading Material

- [RG]
  - Parallel DBMS: Chapter 22.1-22.5
  - Distributed DBMS: Chapter 22.6 – 22.14
- [GUW]
  - Parallel DBMS and map-reduce: Chapter 20.1-20.2
  - Distributed DBMS: Chapter 20.3, 20.4.1-20.4.2, 20.5-20.6
- Recommended readings:
  - Chapter 2 (Sections 1,2,3) of Mining of Massive Datasets, by Rajaraman and Ullman: http://i.stanford.edu/~ullman/mmds.html
  - Original Google MR paper by Jeff Dean and Sanjay Ghemawat, OSDI' 04: http://research.google.com/archive/mapreduce.html

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Parallel and Distributed Data Processing

- so far, one machine
- now: data and operation distribution
- Parallelism
  - performance
- Data distribution
  - increased availability, e.g. when a site goes down
  - distributed local access to data (e.g. an organization may have branches in several cities)
  - analysis of distributed data

Parallel vs. Distributed DBMS

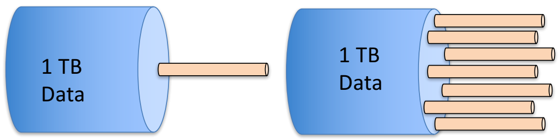
Parallel DBMS	Distributed DBMS (Lecture 18)
• Parallelization of various operations – e.g. loading data, building indexes, evaluating queries	• Data is physically stored across different sites – Each site is typically managed by an independent DBMS
• Data may or may not be distributed initially	• Location of data and autonomy of sites have an impact on Query opt., Conc. Control and recovery
• Distribution is governed by performance consideration	• Also governed by other factors: – increased availability for system crash – local ownership and access

Parallel DBMS

Why Parallel Access To Data?

At 10 MB/s
1.2 days to scan

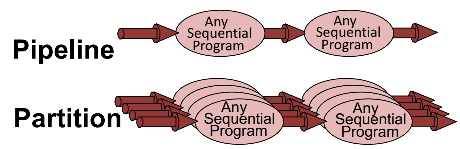
1,000 x parallel
1.5 minute to scan.



Parallelism:
divide a big problem
into many smaller ones
to be solved in parallel.

Parallel DBMS

- Parallelism is natural to DBMS processing
  - Pipeline parallelism: many machines each doing one step in a multi-step process.
  - Data-partitioned parallelism: many machines doing the same thing to different pieces of data.
  - Both are natural in DBMS!



outputs split N ways, inputs merge M ways

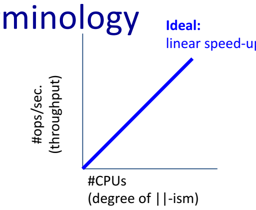
DBMS: The parallel Success Story

- DBMSs are the most successful application of parallelism
  - Teradata (1979), Tandem (1974, later acquired by HP),..
  - Every major DBMS vendor has some parallel server
- Reasons for success:
  - Bulk-processing (= partition parallelism)
  - Natural pipelining
  - Inexpensive hardware can do the trick
  - Users/app-programmers don't need to think in parallel

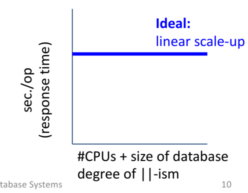
Some || Terminology

Ideal graphs

- Speed-Up
  - More resources means proportionally less time for given amount of data.



- Scale-Up
  - If resources increased in proportion to increase in data size, time is constant.



Some || Terminology

In practice

- Due to overhead in parallel processing
- Start-up cost

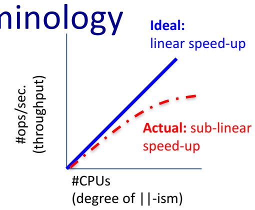
Starting the operation on many processor, might need to distribute data

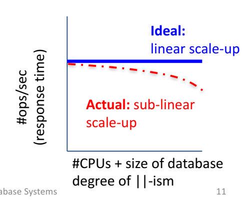
- Interference

Different processors may compete for the same resources

- Skew

The slowest processor (e.g. with a huge fraction of data) may become the bottleneck





Architecture for Parallel DBMS

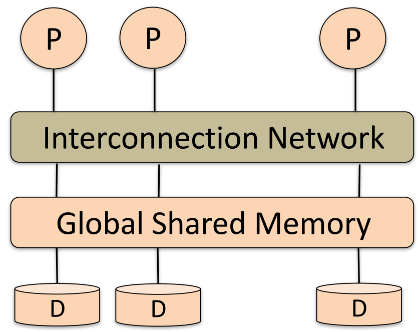
- Among different computing units
  - Whether memory is shared
  - Whether disk is shared

Basics of Parallelism

- Units: a collection of processors
  - assume always have local cache
  - may or may not have local memory or disk (next)
- A communication facility to pass information among processors
  - a shared bus or a switch

Shared Memory

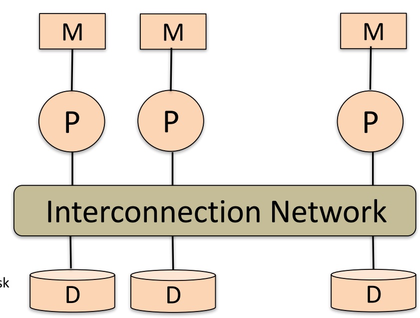
shared memory



Shared Disk

local memory

shared disk

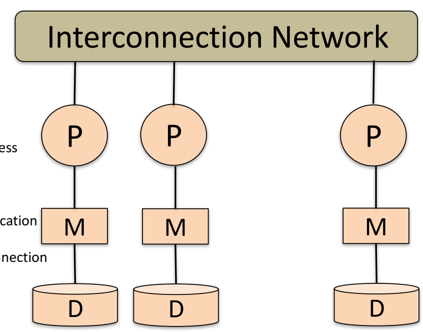


Shared Nothing

local memory and disk

no two CPU can access the same storage area

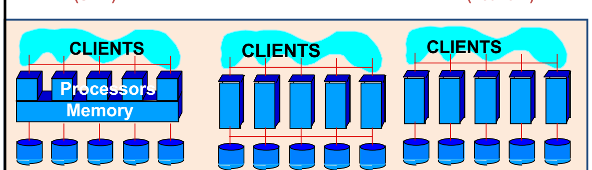
all communication through a network connection



Architecture: At A Glance

we will assume shared nothing

Shared Memory (SMP)	Shared Disk	Shared Nothing (network)



Shared Memory (SMP)
- Easy to program
- Expensive to build
- Low communication overhead: shared mem.
- Difficult to scaleup (memory contention)

Sequent, SGI, Sun

Shared Disk
- Trade-off but still interference like shared-memory (contention of memory and nw bandwidth)

VMScluster, Sysplex

Shared Nothing (network)
- Hard to program and design parallel algos
- Cheap to build
- Easy to scaleup and speedup
- Considered to be the best architecture

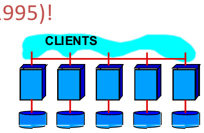
Tandem, Teradata, SP2

What Systems Worked This Way

NOTE: (as of 9/1995)!

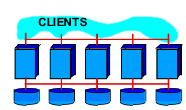
Shared Nothing

Teradata:	400 nodes
Tandem:	110 nodes
IBM / SP2 / DB2:	128 nodes
Informix/SP2	48 nodes
ATT & Sybase	? nodes



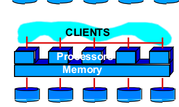
Shared Disk

Oracle	170 nodes
DEC Rdb	24 nodes



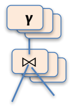
Shared Memory

Informix	9 nodes
RedBrick	? nodes

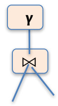


Different Types of DBMS Parallelism

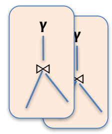
- Intra-operator parallelism
  - get all machines working to compute a given operation (scan, sort, join)
  - OLAP (decision support)



- Inter-operator parallelism
  - each operator may run concurrently on a different site (exploits pipelining)
  - For both OLAP and OLTP



- Inter-query parallelism
  - different queries run on different sites
  - For OLTP



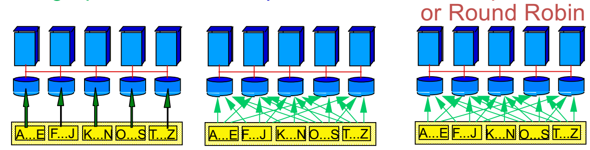
- We'll focus on intra-operator parallelism

Ack:
Slide by Prof. Dan Suciu

Data Partitioning

Horizontally Partitioning a table (why horizontal?):

Range-partition | Hash-partition | Block-partition or Round Robin



Range-partition:
- Good for equijoins, range queries, group-by
- Can lead to data skew

Hash-partition:
- Good for equijoins
- But only if hashed on that attribute
- Can lead to data skew

Block-partition or Round Robin:
- Send i-th tuple to i-mod-n processor
- Good to spread load
- Good when the entire relation is accessed

Shared disk and memory less sensitive to partitioning, Shared nothing benefits from "good" partitioning

Example

- R(<u>Key</u>, A, B)
- Can Block-partition be skewed?
  - no, uniform
- Can Hash-partition be skewed?
  - on the key: uniform with a good hash function
  - on A: may be skewed,
    - e.g. when all tuples have the same A-value

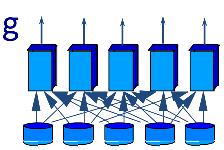
Parallelizing Sequential Evaluation Code

- "Streams" from different disks or the output of other operators
  - are "merged" as needed as input to some operator
  - are "split" as needed for subsequent parallel processing
- Different Split and merge operations appear in addition to relational operators
- No fixed formula for conversion
- Next: parallelizing individual operations

Parallel Scans

- Scan in parallel, and merge.
- Selection may not require all sites for range or hash partitioning
  - but may lead to skew
  - Suppose $\sigma_{A = 10}R$ and partitioned according to A
  - Then all tuples in the same partition/processor
- Indexes can be built at each partition

Parallel Sorting

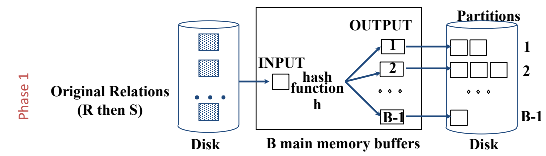


Idea:
- Scan in parallel, and range-partition as you go
  - e.g. salary between 10 to 210, #processors = 20
  - salary in first processor: 10-20, second: 21-30, third: 31-40, ….
- As tuples come in, begin "local" sorting on each
- Resulting data is sorted, and range-partitioned
- Visit the processors in order to get a full sorted order
- Problem: skew!
- Solution: "sample" the data at start to determine partition points.

Parallel Joins

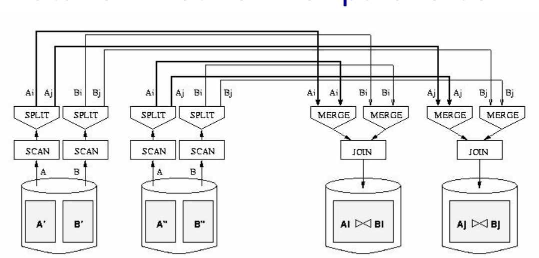
- Need to send the tuples that will join to the same machine
  - also for GROUP-BY
- Nested loop:
  - Each outer tuple must be compared with each inner tuple that might join
  - Easy for range partitioning on join cols, hard otherwise
- Sort-Merge:
  - Sorting gives range-partitioning
  - Merging partitioned tables is local

Parallel Hash Join



- In first phase, partitions get distributed to different sites:
  - A good hash function *automatically* distributes work evenly
- Do second phase at each site.
- Almost always the winner for equi-join

Dataflow Network for parallel Join

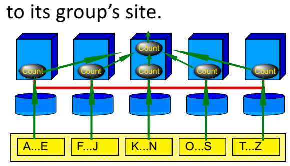


- Good use of split/merge makes it easier to build parallel versions of sequential join code.

Parallel Aggregates

- For each aggregate function, need a decomposition:
  - count(S) = Σ count(s(i)), ditto for sum()
  - avg(S) = (Σ sum(s(i))) / Σ count(s(i))
  - and so on...
- For group-by:
  - Sub-aggregate groups close to the source.
  - Pass each sub-aggregate to its group's site.
    - Chosen via a hash fn.

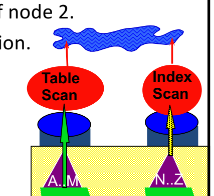
Which SQL aggregate operators are not good for parallel execution?



Jim Gray & Gordon Bell: VLDB 95 Parallel Database Systems Survey

Best serial plan may not be best ||

- Why?
- Trivial counter-example:
  - Table partitioned with local secondary index at two nodes
  - Range query: all of node 1 and 1% of node 2.
  - Node 1 should do a scan of its partition.
  - Node 2 should use secondary index.



Examples

Example problem: Parallel DBMS

R(a,b) is horizontally partitioned across N = 3 machines.

Each machine locally stores approximately 1/N of the tuples in R.

The tuples are randomly organized across machines (i.e., R is block partitioned across machines).

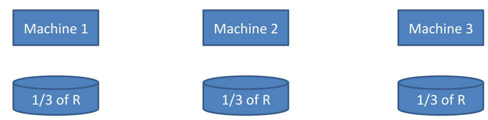
Show a RA plan for this query and how it will be executed across the N = 3 machines.

Pick an efficient plan that leverages the parallelism as much as possible.

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

R(a, b)

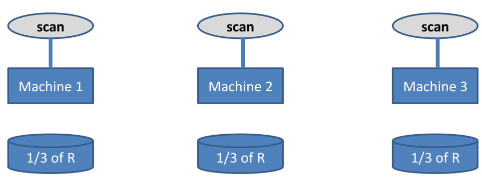
SELECT a, max(b) as topb
FROM R
WHERE a > 0
GROUP BY a



R(a, b)

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

If more than one relation on a machine, then "scan S", "scan R" etc



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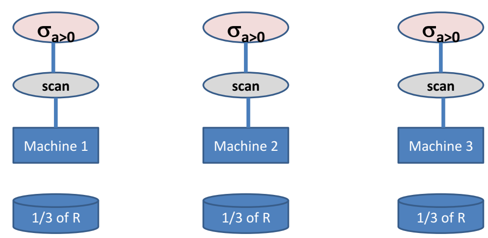

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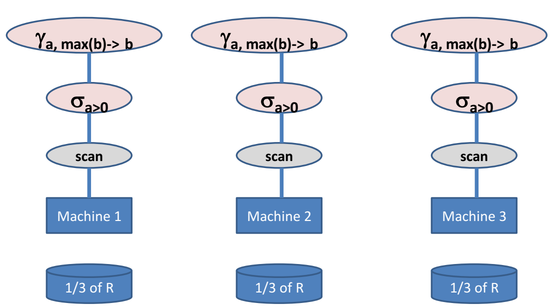

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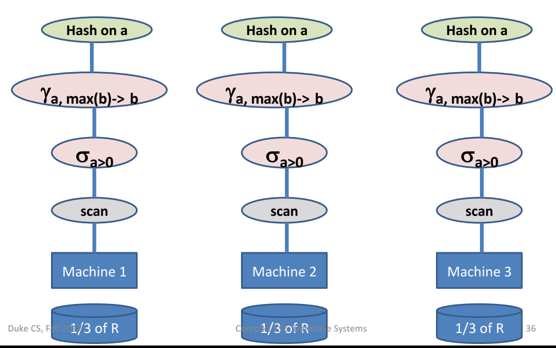
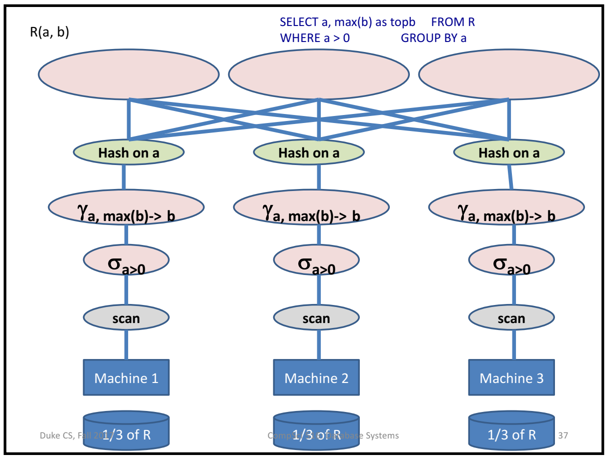
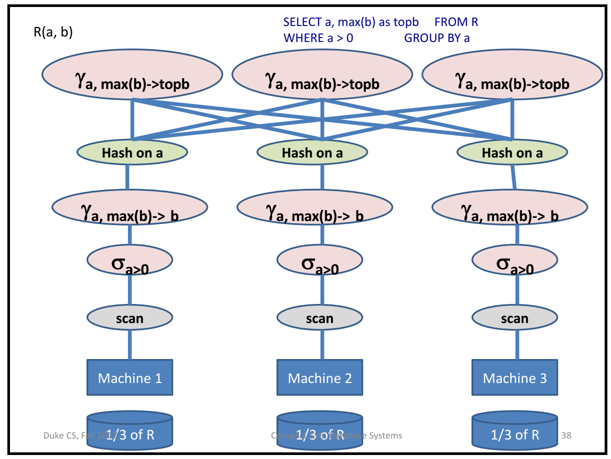






Same Example Problem: Map Reduce

Explain how the query will be executed in MapReduce (recall Lecture-3)

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

Specify the computation performed in the map and the reduce functions

Map

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

- Each map task
  - Scans a block of R
  - Calls the map function for each tuple
  - The map function applies the selection predicate to the tuple
  - For each tuple satisfying the selection, it outputs a record with key = a and value = b

•When each map task scans multiple relations, it needs to output something like **key = a and value = ('R', b)** which has the relation name 'R'

Shuffle

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

- The MapReduce engine reshuffles the output of the map phase and groups it on the intermediate key, i.e. the attribute a

•Note that the programmer has to write only the map and reduce functions, the shuffle phase is done by the MapReduce engine (although the programmer can rewrite the partition function), but you should still mention this in your answers

Reduce

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

- Each reduce task
  - computes the aggregate value **max(b) = topb** for each group (i.e. ***a***) assigned to it (by calling the reduce function)
  - outputs the final results: **(a, topb)**

A local combiner can be used to compute local max before data gets reshuffled (in the map tasks)

• Multiple aggregates can be output by the reduce phase like **key = a and value = (sum(b), min(b))** etc.

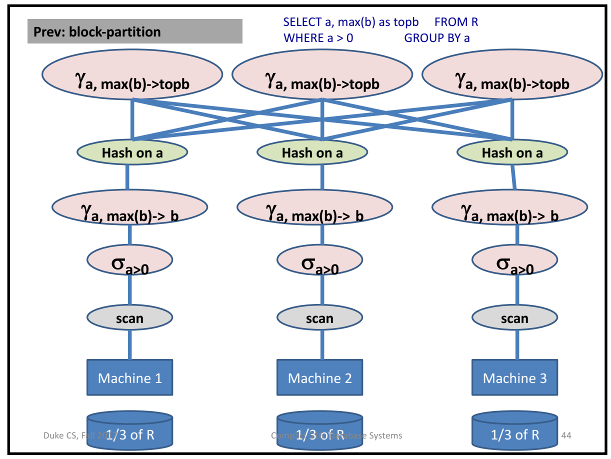
• Sometimes a second (third etc) level of Map-Reduce phase might be needed

Benefit of hash-partitioning

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

- What would change if we hash-partitioned R on R.a before executing the same query on the previous parallel DBMS and MR

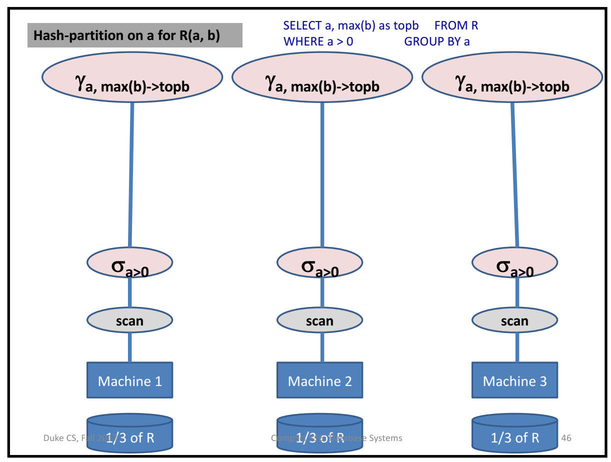
- First Parallel DBMS



Hash-partition on a for R(a, b)

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

- It would avoid the data re-shuffling phase
- It would compute the aggregates locally



Benefit of hash-partitioning

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

- **For MapReduce**
  - Logically, MR won't know that the data is hash-partitioned
  - MR treats map and reduce functions as black-boxes and does not perform any optimizations on them

- But, if a local combiner is used
  - Saves communication cost:
    - fewer tuples will be emitted by the map tasks
  - Saves computation cost in the reducers:
    - the reducers would have to do anything