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Lecture 17 -- Parallel Databases (DeWitt and Gray)

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Parallel/distributed databases: goal provide exactly the same API (SQL) and abstractions (relational tables), but partition data across a bunch of machines -- let us store more data and process it faster.

Parallel refers a single multi-processor machine, or a cluster of machines.

Huge market -- essentially all high performance databases work this way

Some notes:

- No "administrative boundaries" in parallel
- All sites cooperative in parallel
- Parallel machines don't need to be as tolerant to failures as distributed machines

Authors:
- Dewitt
- Gray

Many special purpose parallel architectures have failed. Why?

prohibitively expensive (no economy of scale)
slow to evolve
requires a tool set

Increasingly parallelism is achieved through software running on commodity HW

Performance metrics:

$$\text{Speed up} = \frac{\text{oldtime}}{\text{newtime}} \quad \text{for a given problem}$$

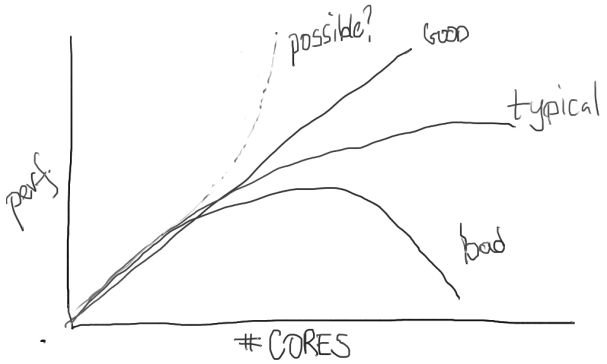
$$\text{Scale up} = \frac{\text{small system runtime on small problem}}{\text{large system runtime on large problem}}$$

Not necessarily identical -- a small problem may be harder to parallelize.

Transaction scaleup: N times as many TPC-C's for N machines
Batch scaleup : N times as big a query for N machines

What kind of speedups are we looking for?

Linear! (say that scaleup = 1 is "linear")



What are the key properties of a parallelizable workload?

Illustrates linear speedup.

Can be decomposed into small units that can be executed independently

What are the barriers to linear speedup:

Startup times (e.g., process per parallel operation may be a bad idea)

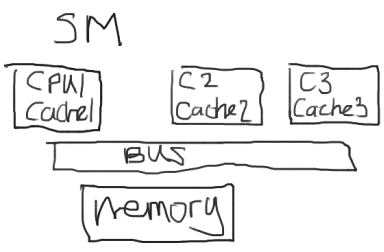
Interference (processors depend on some shared resource)

Skew (workload not of equal size on each processor)

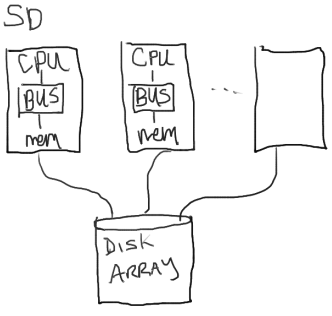
3 architectures

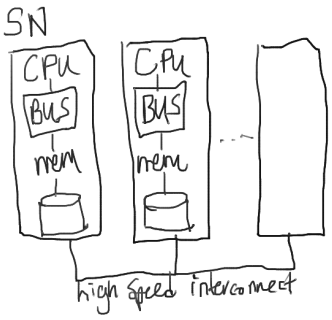
Shared memory, shared disk, shared nothing.

Show design.



Cache coherence protocols arbitrate concurrent accesses to main memory





Shared Memory:

+ easy to program	- perfomance/scalability
+ no changes to CC+R	- fault tolerance
	- cost

Shared Disk:

+ better scalability	- cost
+ better fault tolerance	- complex cache coherency
	- not very scalable

Shared Nothing (partitioned data):

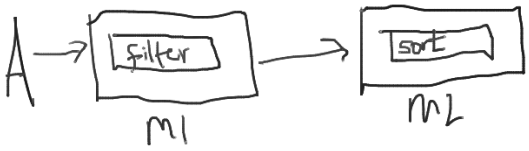
+ cost	- new CC+R
+ scalability	- new executor
+ fault tolerance	- maintenance

How does a ll DBMS provide linear scaleup in performance of a single query?

2 Types of parallelism:

Pipelined

Sequence of operators, each running on a different processor
output of nth stage used as input into n+1st stage. Diagram:



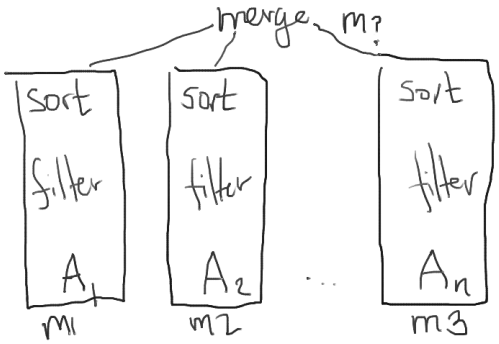
Why is pipelined parallelism hard to exploit?

Only works when each pipeline stage is about the same speed
Short pipelines
Inputs to stage i+1 depend on stage i
If stage i blocks, badness ensues

Partitioned

Identical subproblems each running on a subset of the data on a different processor

Diagram:



How should we partition data?

Three types of partitioning

	Pros	Cons
Round-robin	Perfect load balancing	All nodes process associative queries (e.g., ename = 'Smith')
Hash	Good load balancing Better associativity than RR	Clustering, range queries (e.g., sal > 2,000,000)
Range	Good sequential + associative perf. Good Clustering	Load balancing problems (Hot spots) -- skew

Typically, partitioning is specified by the database administrator apriori (e.g., data is pre-partitioned in some way prior to the query running.)

How to fix range partitioning problems?

Use different size partitions based on their popularity

Or create many small partitions (hash buckets) and babalcen those

Sometimes we can answer a query with data from just 1 site, depending on partitioning used. Often, however, we will have to combine data from many sites. How do we do that?

Which operators can be partitioned?

Scans, selections, projections, aggregates, joins

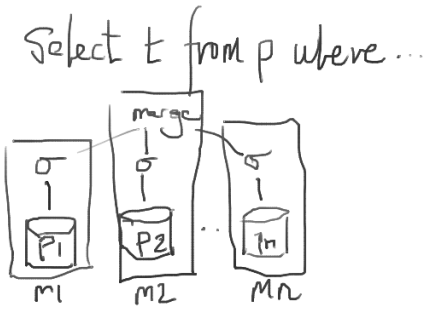
Need specialized operators to make this work

Split

and

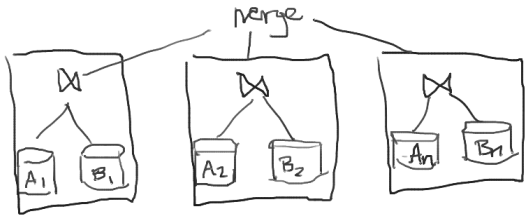
Merge

Selection Example



Joins are a little tricky -- must ensure that all tuples that could join see each other if we want to parallelize.
Example: partitioned on join attribute

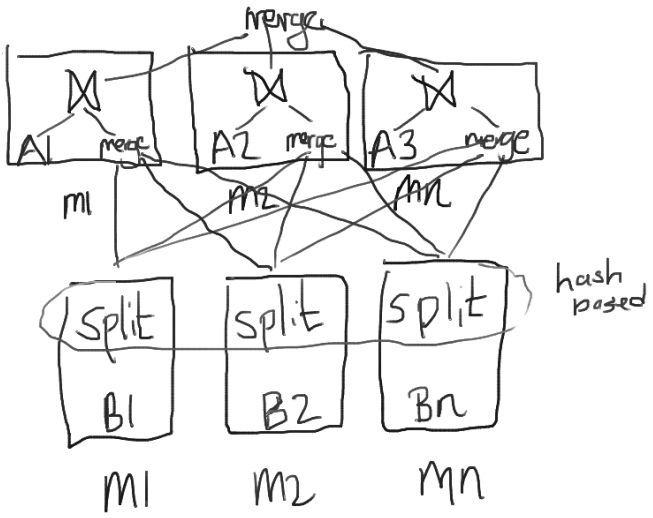
SELECT * FROM A,B WHERE A.a = B.b
n machines, hash fxn H
Hash A on a, H(a) -> 1..n
Hash B on b, B(b) -> 1..n



Example: not partitioned on join attribute

Have to repartition one of the tables

Hash B on c, H(c) -> 1..n



Can choose to repart A, repart B, or both.

Best choice depends on sizes of relations.

Other options for joins --

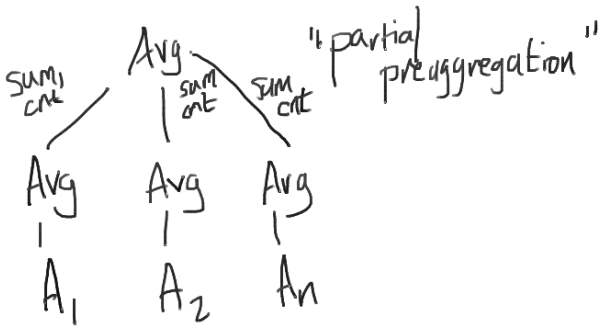
1) replicate small tables on all nodes -- avoid repartitioning altogether, if tables fit

2) "semijoin":
send list of all values in each partition of B to A,
then send list of matching tuples from A to B,
then compute join at B.

Good for selective joins of wide tables.

Aggregation:
Can run aggregates in parallel, then merge groups.
Example:

select avg(f) from A



Standard way of expressing aggregates:

INIT
MERGE
FINAL

Some other issues:

Scheduling -- what if one machine runs way ahead of another

Fault tolerance -- what to do if one machine fails
Transactions

...
Summary:
Databases workloads are "embarassingly parallelizable" -- one of the great advantages of the relational algebra.

Qs:

Is it always good to parallelize?

(No, not if there is a high startup cost).

Suppose we are running lots of little transactions, each of which does very little work on its own piece of the database? What is optimal partitioning strategy then?

(Partition according to pieces transactions operate on, so each can run in parallel.)

I heard that databases don't scale, is that true?

(No, not really. The workloads parallelize just fine -- extremely well, in fact, in most cases. In the wide area ("internet scale") making transactions work can be tricky, as we'll discuss next time.)

Some Themes in Parallel DBs
(that distinguish them from other parallel programming tasks):

o Hooray for the relational model
- apps don't change when you parallelize system (physical data independence!).
  can tune, scale system without informing apps too
- ability to partition records arbitrarily, w/o synchronization

o essentially no synchronization except setup & teardown
- no barriers, cache coherence, etc.
- DB transactions work fine in parallel

  + data updated in place, with 2-phase locking transactions
  + replicas managed only at EOT via 2-phase commit
  + coarser grain, higher overhead than cache coherency stuff

o Bandwidth much more important than latency
- often pump 1-1/n % of a table through the network
- aggregate net BW should match aggregate disk BW
- bus BW should match about 3x disk BW (NW send, NW receive, disk)
- Latency, schmatency. Insignificance makes a BIG difference in what
  architectures are needed.