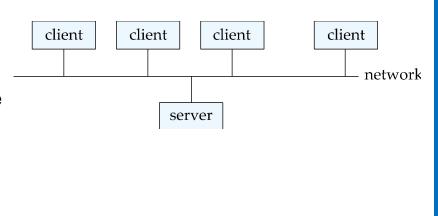
UMD DATA605 - Big Data Systems Parallel Systems and Databases

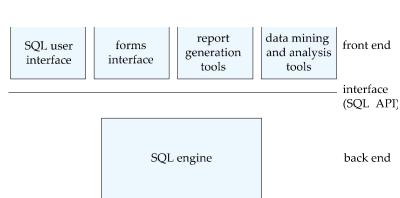
GP Saggese gsaggese@umd.edu

with thanks to Alan Sussman, Amol Deshpande

Client-Server Systems

- The client-server model is a distributed application structure that partitions tasks between:
 - Servers: the providers of a resource or service (e.g., a database)
 - Clients: service requesters (e.g., client applications)
- The architecture of a database system can be divided into:
 - Back-end (Server): manages access, query evaluation and optimization, concurrency control and recovery
 - Front-end (Clients): consists of tools such as forms, report-writers, and graphical user interface (GUI)
- The interface between the front-end and the back-end is through:
 - SQL; or
 - An application programming interface (API)





Parallel Databases: Introduction

Parallel machines have become common and affordable

- Prices of microprocessors, memory, and disks keep dropping sharply
- Desktop / laptop computers feature multiple processors
- This trend will continue

DBs are growing increasingly large

- Large volumes of transaction data are collected and stored for later analysis
- Multimedia objects like images are increasingly stored in databases

Large-scale parallel DBs increasingly used for:

- Storing large volumes of data
- Processing time-consuming queries
- Providing high throughput for transaction processing

Parallel vs Distributed Computing

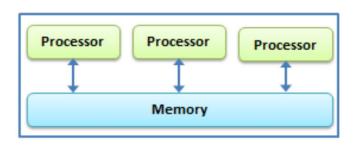
Parallel computing

- One computer with multiple CPUs
- Cluster = many similar computers
 with multiple CPUs
- Homogenous and close
- Working on one task

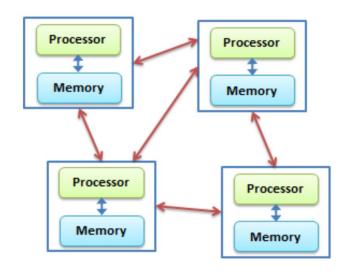
Distributed computing

- Several autonomous (often geographically separate)
 computers systems
- Heterogeneous and distant
- Working on divided tasks

Parallel Computing



Distributed Computing



Parallel Systems

- Parallel systems consist of:
 - Multiple processors
 - Multiple memories
 - Multiple disks
 - Connected by a fast interconnection network
- Coarse-grain parallel machine
 - Small number of powerful processors
 - E.g., your laptop with multiple CPUs
- Fine-grain parallel machine
 - Aka massively parallel
 - Thousands of smaller processors
 - E.g., GPUs, Connection Machine
 - Much larger degree of parallelism
 - Typically no shared memory





The Connection Machine, MIT, 1980s



Parallel Databases

- Internet / Big Data created the need for large and fast DBs, e.g.,
 - Store petabytes of data
 - Process thousands of transactions per second (e.g., commerce web-site)

Databases can be parallelized

- The set-oriented nature of DB queries often lends itself to parallelization
- Some database operations are embarrassingly parallel
 - E.g., a join between R and S on R.b = S.b can be done as MapReduce task

Parallel DBs

- More transactions per second, or less time per query
- Throughput vs response time
- Speed-up vs scale-up
- But, perfect speedup doesn't happen because of:
 - Start-up costs
 - Interference of tasks
 - Skew

How to Measure Parallel Performance

Throughput

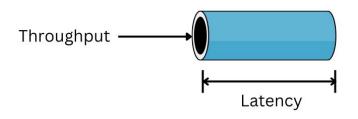
- = the number of tasks that can be completed in a given time interval
- Increase throughput by processing many tasks in parallel

Latency

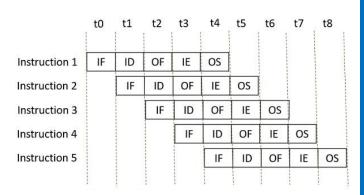
- = the amount of time it takes to complete a single task from the time it is submitted
- Decrease response time by performing subtasks of each task in parallel

Throughput and latency are related but are not the same thing

- E.g., increase throughput by reducing latency
- E.g., increase throughput by pipelining, i.e., overlapping execution of tasks
 - E.g., building a car takes weeks but one car is completed per hour







Pipelining of instructions in microprocessor

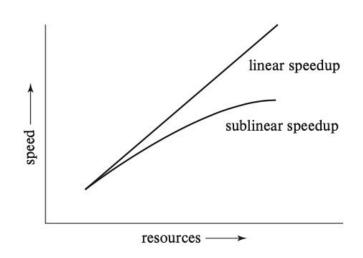
Speed-Up and Scale-Up: Intuition

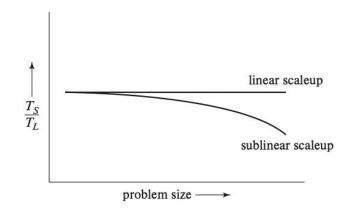
- You have a workload to execute
 - The amount of work can be changed (*M*)
 - Number of DB transactions; or
 - Amount of DB data to query
- You need to execute the workload on a machine
 - The amount of computing power can be changed (*N*)
 - Better CPU (scale vertically, scale up)
 - More CPUs (scale horizontally, scale out)
- Two ways for measuring efficiency when increasing workload and computing power
 - Speed-up
 - Keep constant problem size M
 - Increase the power of the machine N
 - Scale-up
 - Increase the problem size M
 - Increase the power of the machine N

Speed-Up vs Scale-Up

- The amount of computing power can be changed (N)
- The amount of work can be changed (M)
- Speed-up: a fixed-sized problem executing on a small system is given to a system which is N-times larger
 - Measured by:
 speed-up = small system elapsed time
 large system elapsed time
 - Speed-up is linear if equation equals N
- Scale-up: increase the size of both the problem
 (M) and the system (N)
 - N-times larger system to perform M-times larger job
 - Measured by: scale-up = small system / problem time big system / problem time

Scale-up is linear if equation equals 1





Factors Limiting Speed-up and Scale-up

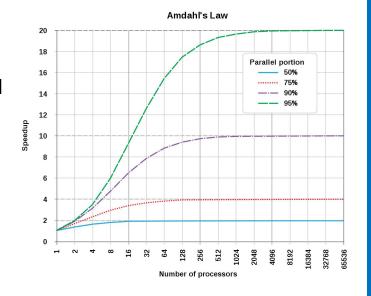
- Speed-up and scale-up are often sub-linear due to several issues
- Sequential computation
 - Some pieces of the computation can be executed in parallel, others must be executed sequentially

Amdahl's Law

- p = fraction of computation that can be parallelized
- s = nodes providing linear speed-up
- T = the execution time in the serial case
- T(p) = (1-p)T + (p / s)T
- Speedup = T / T(p)

$$S_{ ext{latency}}(s) = rac{1}{(1-p) + rac{p}{s}}$$

- E.g., if 90% is parallelizable, the max speed-up is 10x
- If 50% is parallelizable, the max speed-up is 2x even with infinite amount of nodes!)



Factors Limiting Speed-up and Scale-up

Startup costs

Cost of starting up many processes may dominate computation time

Interference

- Processes accessing shared resources (e.g., system bus, disks, or locks) compete with each other
- Time spent waiting on other processes, rather than performing useful work
- Same problem of hiring many developers

Cost of synchronization

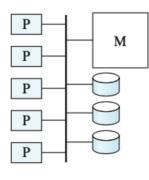
 The smaller the pieces to work on, the more complex is the synchronization between the workers

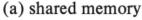
Skew

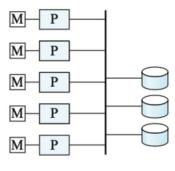
- Increasing the degree of parallelism increases the variance in response time of parallely executed tasks
- Difficult to keep a task split in equally sized parts
- Overall execution time determined by slowest of parallely executing tasks

Topology of Parallel Systems

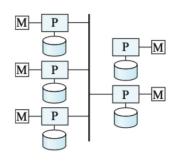
- Several ways to organize computation and storage
 - M = memory
 - P = processors
 - D = disks
- Topology
 - Shared memory
 - Shared disk
 - Shared-nothing
 - Hierarchical
- Problems are:
 - Cache coherency
 - Data communication
 - Fault tolerance
 - Resource congestion



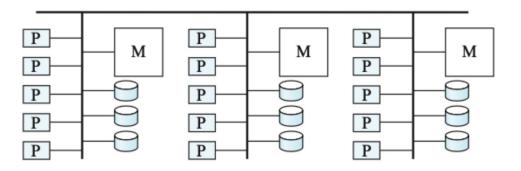




(b) shared disk



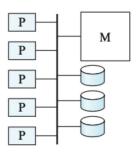
(c) shared nothing



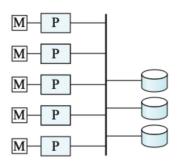
(d) hierarchical

Topology of Parallel Systems: Comparison

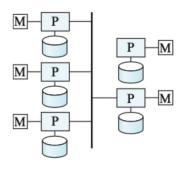
	Shared Memory	Shared Disk	Shared Nothing
Communication between processors	Extremely fast	Disk interconnect is very fast	Over a LAN, so slowest
Scalability?	Not beyond 32 or 64 or so (memory bus is the bottleneck)	Not very scalable (disk interconnect is the bottleneck)	Very very scalable
Notes	Cache-coherency an issue	Transactions complicated; natural fault-tolerance.	Distributed transactions are complicated (deadlock detection etc);
Main use	Low degrees of parallelism	Not used very often	Everywhere



(a) shared memory



(b) shared disk



(c) shared nothing

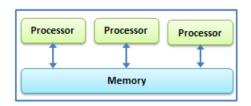
Parallel Databases

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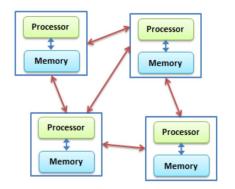
Distributed Databases

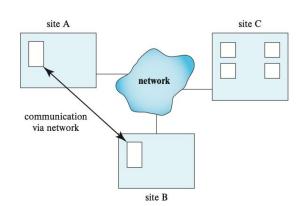
- The DB is stored on nodes located at geographically separated sites
 - Communicate through dedicated high-speed private networks or Internet
- Done because of necessity, e.g.,
 - A large corporation with offices all over the world
 - For redundancy and for disaster recovery reasons
 - Typically not done for performance reasons
 - Use a parallel system to achieve high performance
- Wide-area networks (WAN)
 - Lower bandwidth
 - Higher latency
 - Greater probability of failures (compared to networks in a single data center)
 - Network-link failures may result in network partition
 - vs Local-area networks (LAN)
- No sharing of memory or disks
- Replication across geographically separated centers
 - Achieve high-availability despite failures
 - E.g., natural disasters, power outage, hacker attacks
- Nodes can have different size and functions
 - Parallel DBs have nodes that are similar

Parallel Computing



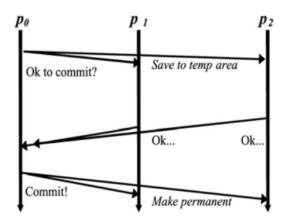
Distributed Computing





Consistency Issues in Distributed DB Systems

- Parallel and distributed and DBs work well for query processing
 - Since we are only reading the data
- When updating a parallel or distributed DB consistency needs to be enforced
- Atomicity issues
 - Problem: transaction is all-or-nothing across multiple nodes
 - Two-phase commit (2PC)
 - Each node executes the transaction, reaching a "ready state"
 - The commit decision is delegated to a single coordinator node
 - If each node reaches the ready state, the coordinator decides to commit
 - If a node aborts at any code, the coordinator aborts the transaction
 - If a node fails in ready state, it recovers from failure (e.g., write-ahead logs on stable storage) and it can either commit or abort
 - Paxos
 - Distributed consensus (e.g., blockchain)
- Concurrency issues
 - Problem: multiple processes writing and reading at the same time
 - Locks / deadlock management
- Autonomy issues
 - Problem: Even within an organization, people tend to be protective of their unit / department
 - E.g., for administering systems, patching, updating



```
Coordinator:
   multicast: ok to commit?
   collect replies
    all ok => send commit
    else => send abort

Participant:
   ok to commit =>
    save to temp area, reply ok
   commit =>
    make change permanent
   abort =>
    delete temp area
```

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BACKUP

Parallel Databases

- Introduction
- I/O Parallelism
- Interquery Parallelism
- Intraquery Parallelism
- Intraoperation Parallelism
- Interoperation Parallelism
- Design of Parallel Systems

Silbershatz: Chap 22

Parallelism in Databases

- Data can be partitioned across multiple disks for parallel I/O
- Individual relational operations (e.g., sort, join, aggregation) can be executed in parallel
 - Data can be partitioned and each processor can work independently on its own partition
- Queries are expressed in high level language (SQL, translated to relational algebra)
 - makes parallelization easier
- Different queries can be run in parallel with each other
 - Concurrency control takes care of conflicts
- Thus, databases naturally lend themselves to parallelism

I/O Parallelism

- Reduce the time required to retrieve relations from disk by partitioning the relations on multiple disks
- Horizontal partitioning tuples of a relation are divided among many disks such that each tuple resides on one disk
- Partitioning techniques (number of disks = n):

Round-robin:

Send the i^{th} tuple inserted in the relation to disk i mod n.

Hash partitioning:

- Choose one or more attributes as the partitioning attributes.
- Choose hash function h with range 0...n 1
- Let i denote result of hash function h applied to the partitioning attribute value of a tuple. Send tuple to disk i.

I/O Parallelism (Cont.)

Range partitioning:

20 will go to disk2.

- Choose an attribute as the partitioning attribute.
- A partitioning vector $[v_0, v_1, ..., v_{n-2}]$ is chosen.
- Let v be the partitioning attribute value of a tuple. Tuples such that $v_i \le v_{i+1}$ go to disk l+1. Tuples with $v < v_0$ go to disk 0 and tuples with $v \ge v_{n-2}$ go to disk l+1. E.g., with a partitioning vector [5,11], a tuple with partitioning attribute value of 2 will go to disk 0, a tuple with value 8 will go to disk 1, while a tuple with value

Comparison of Partitioning Techniques

- Evaluate how well partitioning techniques support the following types of data access:
 - 1. Scanning the entire relation.
 - 2. Locating a tuple associatively **point queries**.
 - E.g., r.A = 25.
 - 3. Locating all tuples such that the value of a given attribute lies within a specified range range queries.
 - $E.g., 10 \le r.A < 25.$

Comparison of Partitioning Techniques (Cont.)

Round robin:

- Advantages
 - Best suited for sequential scan of entire relation on each query.
 - All disks have almost an equal number of tuples; retrieval work is thus well balanced between disks.
- Range queries are difficult to process
 - No clustering -- tuples are scattered across all disks

Comparison of Partitioning Techniques (Cont.)

Hash partitioning:

- Good for sequential access
 - Assuming hash function is good, and partitioning attributes form a key, tuples will be equally distributed between disks
 - Retrieval work is then well balanced between disks.
- Good for point queries on partitioning attribute
 - Can lookup single disk, leaving others available for answering other queries.
 - Index on partitioning attribute can be local to disk, making lookup and update more efficient
- No clustering, so difficult to answer range queries

Comparison of Partitioning Techniques (Cont.)

- Range partitioning:
- Provides data clustering by partitioning attribute value.
- Good for sequential access
- Good for point queries on partitioning attribute: only one disk needs to be accessed.
- For range queries on partitioning attribute, one to a few disks may need to be accessed
 - Remaining disks are available for other queries.
 - Good if result tuples are from one to a few blocks.
 - If many blocks are to be fetched, they are still fetched from one to a few disks, and potential parallelism in disk access is wasted

• Example of execution skew.

Partitioning a Relation across Disks

- If a relation contains only a few tuples which will fit into a single disk block, then assign the relation to a single disk.
- Large relations are preferably partitioned across all the available disks.
- If a relation consists of m disk blocks and there are n disks available in the system, then the relation should be allocated min(m,n) disks.

Handling of Skew

- The distribution of tuples to disks may be skewed
 - Some disks have many tuples, while others may have fewer tuples

Types of skew:

- Attribute-value skew.
 - Some values appear in the partitioning attributes of many tuples; all the tuples with the same value for the partitioning attribute end up in the same partition.
 - Can occur with range-partitioning and hash-partitioning.

Partition skew.

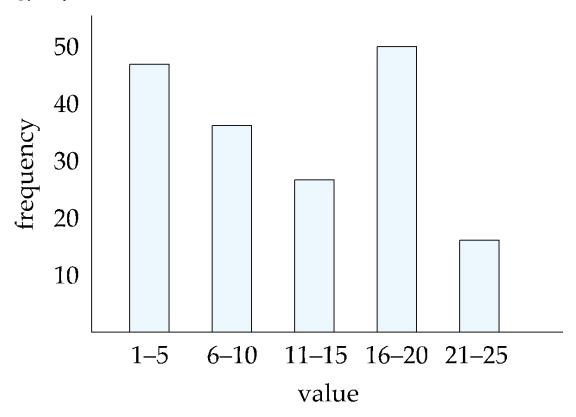
- With range-partitioning, badly chosen partition vector may assign too many tuples to some partitions and too few to others.
- Less likely with hash-partitioning if a good hash-function is chosen.

Handling Skew in Range-Partitioning

- To create a balanced partitioning vector (assuming partitioning attribute forms a key of the relation):
 - Sort the relation on the partitioning attribute.
 - Construct the partition vector by scanning the relation in sorted order as follows.
 - After every $1/n^{th}$ of the relation has been read, the value of the partitioning attribute of the next tuple is added to the partition vector.
 - n denotes the number of partitions to be constructed.
 - Duplicate entries or imbalances can result if duplicates are present in partitioning attributes.
- Alternative technique based on histograms used in practice

Handling Skew using Histograms

- Balanced partitioning vector can be constructed from histogram in a relatively straightforward fashion
 - Assume uniform distribution within each range of the histogram
- Histogram can be constructed by scanning relation, or sampling (blocks containing) tuples of the relation



Handling Skew Using Virtual Processor Partitioning

- Skew in range partitioning can be handled elegantly using virtual processor partitioning:
 - create a large number of partitions (say 10 to 20 times the number of processors)
 - Assign virtual processors to partitions either in round-robin fashion or based on estimated cost of processing each virtual partition

Basic idea:

- If any normal partition would have been skewed, it is very likely the skew is spread over a number of virtual partitions
- Skewed virtual partitions get spread across a number of processors, so work gets distributed evenly!

Interquery Parallelism

- Queries/transactions execute in parallel with one another.
- Increases transaction throughput; used primarily to scale up a transaction processing system to support a larger number of transactions per second.
- Easiest form of parallelism to support, particularly in a shared-memory parallel database, because even sequential database systems support concurrent processing.
- More complicated to implement on shared-disk or shared-nothing architectures
 - Locking and logging must be coordinated by passing messages between processors.
 - Data in a local buffer may have been updated at another processor.
 - Cache-coherency has to be maintained reads and writes of data in buffer must find latest version of data.

Cache Coherency Protocol

- Example of a cache coherency protocol for shared disk systems:
 - Before reading/writing to a page, the page must be locked in shared/exclusive mode.
 - On locking a page, the page must be read from disk
 - Before unlocking a page, the page must be written to disk if it was modified.
- More complex protocols with fewer disk reads/writes exist.
- Cache coherency protocols for shared-nothing systems are similar. Each database page is assigned a home processor. Requests to fetch the page or write it to disk are sent to the home processor.

Intraquery Parallelism

- Execution of a single query in parallel on multiple processors/disks; important for speeding up long-running queries.
- Two complementary forms of intraquery parallelism:
 - Intraoperation Parallelism parallelize the execution of each individual operation in the query.
 - Interoperation Parallelism execute the different operations in a query expression in parallel.
- The first form scales better with increasing parallelism because the number of tuples processed by each operation is typically more than the number of operations in a query.

Parallel Processing of Relational Operations

- Our discussion of parallel algorithms assumes:
 - read-only queries
 - shared-nothing architecture
 - n processors, $P_0, ..., P_{n-1}$, and n disks $D_0, ..., D_{n-1}$, where disk D_i is associated with processor P_i .
- If a processor has multiple disks they can simply simulate a single disk D_i.
- Shared-nothing architectures can be efficiently simulated on shared-memory and shared-disk systems.
 - Algorithms for shared-nothing systems can thus be run on shared-memory and shared-disk systems.

However, some optimizations may be possible.

Parallel Sort

Range-Partitioning Sort

- Choose processors P_0 , ..., P_m , where $m \le n$ -1 to do sorting.
- Create range-partition vector with m entries, on the sorting attributes
- Redistribute the relation using range partitioning
 - all tuples that lie in the ith range are sent to processor P_i
 - $-P_i$ stores the tuples it received temporarily on disk D_i .
 - This step requires I/O and communication overhead.
- Each processor P_i sorts its partition of the relation locally.
- Each processors executes same operation (sort) in parallel with other processors, without any interaction with the others (data parallelism).
- Final merge operation is trivial: range-partitioning ensures that, for 1 j m, the key values in processor Pⁱ are all less than the key values in P_i.

Parallel Sort (Cont.)

Parallel External Sort-Merge

- Assume the relation has already been partitioned among disks $D_0, ..., D_{n-1}$ (in whatever manner).
- Each processor P_i locally sorts the data on disk D_i.
- The sorted runs on each processor are then merged to get the final sorted output.
- Parallelize the merging of sorted runs as follows:
 - The sorted partitions at each processor P_i are range-partitioned across the processors P_0 , ..., P_{m-1} .
 - Each processor P, performs a merge on the streams as they are received, to get a single sorted run.
 - The sorted runs on processors P_0, \dots, P_{m-1} are concatenated to get the final result.

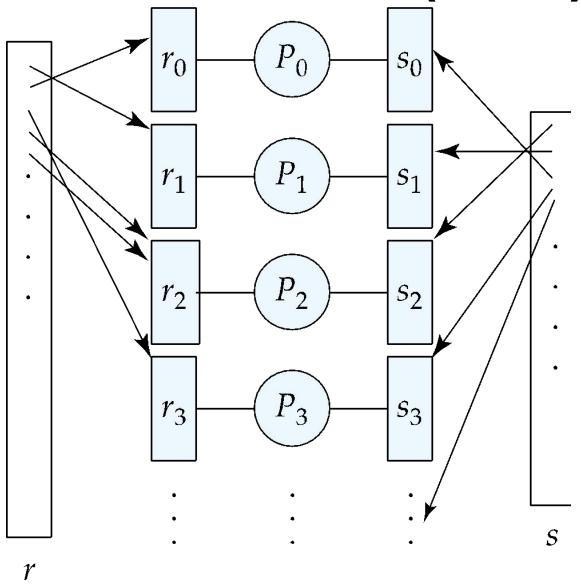
Parallel Join

- The join operation requires pairs of tuples to be tested to see if they satisfy the join condition, and if they do, the pair is added to the join output.
- Parallel join algorithms attempt to split the pairs to be tested over several processors.
 Each processor then computes part of the join locally.
- In a final step, the results from each processor can be collected together to produce the final result.

Partitioned Join

- For equi-joins and natural joins, it is possible to partition the two input relations across the processors, and compute the join locally at each processor.
- Let r and s be the input relations, and we want to compute $r \bowtie_{rA=s.B} s$.
- r and s each are partitioned into n partitions, denoted r_0 , r_1 , ..., r_{n-1} and s_0 , s_1 , ..., s_{n-1} .
- Can use either range partitioning or hash partitioning.
- r and s must be partitioned on their join attributes r.A and s.B), using the same range-partitioning vector or hash function.
- Partitions r_i and s_i are sent to processor P_i ,
- Each processor P_i locally computes $r \bowtie r_{i,A=si,B}$ s_i. Any of the standard join methods can be used.

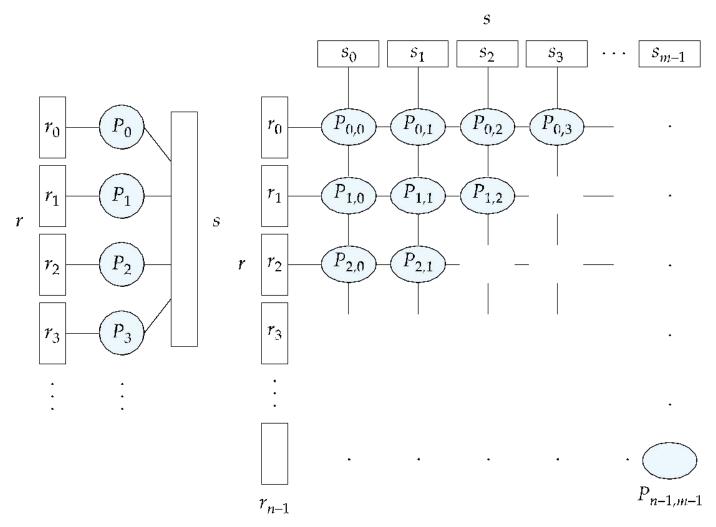
Partitioned Join (Cont.)



Fragment-and-Replicate Join

- Partitioning not possible for some join conditions
 - E.g., non-equijoin conditions, such as r.A > s.B.
- For joins where partitioning is not applicable, parallelization can be accomplished by fragment and replicate technique
 - Depicted on next slide
- Special case asymmetric fragment-and-replicate:
 - One of the relations, say r, is partitioned; any partitioning technique can be used.
 - The other relation, s, is replicated across all the processors.
 - Processor P_i then locally computes the join of r_i with all of s using any join technique.

Depiction of Fragment-and-Replicate Joins



(a) Asymmetric fragment and replicate

(b) Fragment and replicate

Fragment-and-Replicate Join (Cont.)

- General case: reduces the sizes of the relations at each processor.
 - -r is partitioned into n partitions, $r_0, r_1, ..., r_{n-1}$; s is partitioned into m partitions, $s_0, s_1, ..., s_{m-1}$.
 - Any partitioning technique may be used.
 - There must be at least m * n processors.
 - Label the processors as

 - $-P_{0,0}, P_{0,1}, ..., P_{0,m-1}, P_{1,0}, ..., P_{n-1m-1}$ $-P_{i,j}$ computes the join of r_i with s_i . In order to do so, r_i is replicated to $P_{i,0}, P_{i,1}, ..., P_{i,m-1}$, while s_i is replicated to $P_{0,i}, P_{1,i}, ..., P_{n-1,i}$
 - Any join technique can be used at each processor P_{ii} .

Fragment-and-Replicate Join (Cont.)

- Both versions of fragment-and-replicate work with any join condition, since every tuple in r can be tested with every tuple in s.
- Usually has a higher cost than partitioning, since one of the relations (for asymmetric fragment-and-replicate) or both relations (for general fragment-and-replicate) have to be replicated.
- Sometimes asymmetric fragment-and-replicate is preferable even though partitioning could be used.
 - E.g., say s is small and r is large, and already partitioned. It may be cheaper to replicate s across all processors, rather than repartition r and s on the join attributes.

Partitioned Parallel Hash-Join

Parallelizing partitioned hash join:

- Assume s is smaller than r and therefore s is chosen as the build relation.
- A hash function h₁ takes the join attribute value of each tuple in s and maps this tuple to one of the n processors.
- Each processor P_i reads the tuples of s that are on its disk D_i, and sends each tuple to the appropriate processor based on hash function h₁. Let s_i denote the tuples of relation s that are sent to processor P_i.
- As tuples of relation s are received at the destination processors, they are partitioned further using another hash function, h₂, which is used to compute the hash-join locally. (Cont.)

Partitioned Parallel Hash-Join (Cont.)

- Once the tuples of s have been distributed, the larger relation r is redistributed across the m processors using the hash function h₁
 - Let r_i denote the tuples of relation r that are sent to processor P_i.
- As the r tuples are received at the destination processors, they are repartitioned using the function h₂
 - (just as the probe relation is partitioned in the sequential hash-join algorithm).
- Each processor P_i executes the build and probe phases of the hash-join algorithm on the local partitions r_i and s of r and s to produce a partition of the final result of the hash-join.
- Note: Hash-join optimizations can be applied to the parallel case
 - e.g., the hybrid hash-join algorithm can be used to cache some of the incoming tuples in memory and avoid the cost of writing them and reading them back in.

Parallel Nested-Loop Join

- Assume that
 - relation s is much smaller than relation r and that r is stored by partitioning.
 - there is an index on a join attribute of relation r at each of the partitions of relation r.
- Use asymmetric fragment-and-replicate, with relation s being replicated, and using the existing partitioning of relation r.
- Each processor P, where a partition of relation s is stored reads the tuples of relation s stored in D, and replicates the tuples to every other processor P,
 - At the end of this phase, relation s is replicated at all sites that store tuples of relation r.
- Each processor P_i performs an indexed nested-loop join of relation s with the ith partition of relation r.

Other Relational Operations

Selection $\sigma_{\theta}(r)$

- If θ is of the form $a_i = v$, where a_i is an attribute and v a value.
 - If r is partitioned on a the selection is performed at a single processor.
- If θ is of the form $I \le a_i \le u$ (i.e., θ is a range selection) and the relation has been range-partitioned on a_i
 - Selection is performed at each processor whose partition overlaps with the specified range of values.
- In all other cases: the selection is performed in parallel at all the processors.

Other Relational Operations (Cont.)

- Duplicate elimination
 - Perform by using either of the parallel sort techniques
 - eliminate duplicates as soon as they are found during sorting.
 - Can also partition the tuples (using either range- or hash- partitioning) and perform duplicate elimination locally at each processor.

Projection

- Projection without duplicate elimination can be performed as tuples are read in from disk in parallel.
- If duplicate elimination is required, any of the above duplicate elimination techniques can be used.

Grouping/Aggregation

- Partition the relation on the grouping attributes and then compute the aggregate values locally at each processor.
- Can reduce cost of transferring tuples during partitioning by partly computing aggregate values before partitioning.
- Consider the sum aggregation operation:
 - Perform aggregation operation at each processor P_i on those tuples stored on disk D_i
 - results in tuples with partial sums at each processor.
 - Result of the local aggregation is partitioned on the grouping attributes, and the aggregation performed again at each processor P_i to get the final result.
- Fewer tuples need to be sent to other processors during partitioning.

Cost of Parallel Evaluation of Operations

- If there is no skew in the partitioning, and there is no overhead due to the parallel evaluation, expected speed-up will be 1/n
- If skew and overheads are also to be taken into account, the time taken by a parallel operation can be estimated as

$$T_{part} + T_{asm} + max(T_0, T_1, ..., T_{n-1})$$

- T_{part} is the time for partitioning the relations
 T_{asm} is the time for assembling the results
 T_i is the time taken for the operation at
- processor P
 - this needs to be estimated taking into account the skew, and the time wasted in contentions.

Interoperator Parallelism

Pipelined parallelism

Consider a join of four relations

```
• r_1 \bowtie r_2 \bowtie r_3 \bowtie r_4
```

- Set up a pipeline that computes the three joins in parallel
 - Let P1 be assigned the computation of temp1 = r₁ ⋈ r₂

 - And P3 be assigned the computation of temp2 ⋈ r₄
- Each of these operations can execute in parallel, sending result tuples it computes to the next operation even as it is computing further results
 - Provided a pipelinable join evaluation algorithm (e.g., indexed nested loops join) is used

Factors Limiting Utility of Pipeline Parallelism

- Pipeline parallelism is useful since it avoids writing intermediate results to disk
- Useful with small number of processors, but does not scale up well with more processors. One reason is that pipeline chains do not attain sufficient length.
- Cannot pipeline operators which do not produce output until all inputs have been accessed (e.g., aggregate and sort)
- Little speedup is obtained for the frequent cases of skew in which one operator's execution cost is much higher than the others.

Independent Parallelism

Independent parallelism

Consider a join of four relations

```
r_1 \bowtie r_2 \bowtie r_3 \bowtie r_4
```

- Let P_1 be assigned the computation of temp1 = $r_1 \bowtie r_2$
- And P_2 be assigned the computation of temp2 = $r_3 \bowtie r_4$
- And P₃ be assigned the computation of temp1⋈ temp₂
- P₁ and P₂ can work independently in parallel
- P₃ has to wait for input from P₁ and P₂
 - Can pipeline output of P₁ and P₂ to P₃, combining independent parallelism and pipelined parallelism
- Does not provide a high degree of parallelism
 - useful with a lower degree of parallelism.
 - less useful in a highly parallel system.

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