Chapter 17: Parallel Databases

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Introduction

- Parallel machines are becoming quite common and affordable
  - Prices of microprocessors, memory and disks have dropped sharply
- Databases 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 database systems increasingly used for:
  - processing time-consuming decision-support queries
  - providing high throughput for transaction processing

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 ith 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 $0 \ldots n-1$.
- 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.)

- Partitioning techniques (cont.):

  Range partitioning :

  - Choose an attribute as the partitioning attribute.
  - A partitioning vector $[v_0, v_1, \ldots, v_{n-2}]$ is chosen
  - Let v be the partitioning attribute value of a tuple. Tuples such that $v_i \leq v < v_{i+1}$ go to disk $i + 1$. Tuples with $v < v_0$ go to disk 0 and tuples with $v \geq v_{n-2}$ go to disk $n - 1$.

  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 20 will go to disk 2.

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., $10 \leq r.A < 25$.

Comparison of Partitioning Techniques (Cont.)

- **Round-robin.**
  - 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** — i.e., 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.
- Alternative technique based on *histograms* used in practice (will see later).

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, $P_0, \ldots, P_{n-1}$, and n disks $D_0, \ldots, D_{n-1}$, where disk D_i is associated with processor P_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 $P_0, \ldots, P_m$, where $m \leq n - 1$ 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 i^{th} range are sent to processor P_i
  - P_i stores the tuples it received temporarily on disk D_i.
- 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 $1 \leq i < j \leq m$, the key values in processor P_i are all less than the key values in P_j.

Parallel Sort (Cont.)

Parallel External Sort-Merge

- Assume the relation has already been partitioned among disks $D_0, \ldots, D_{n-1}$ (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 $P_0, \ldots, P_{m-1}$.
  - Each processor P_i performs a merge on the streams as they are received, to get a single sorted run.
  - The sorted runs on processors $P_0, \ldots, P_{m-1}$ are concatenated to get the final result.

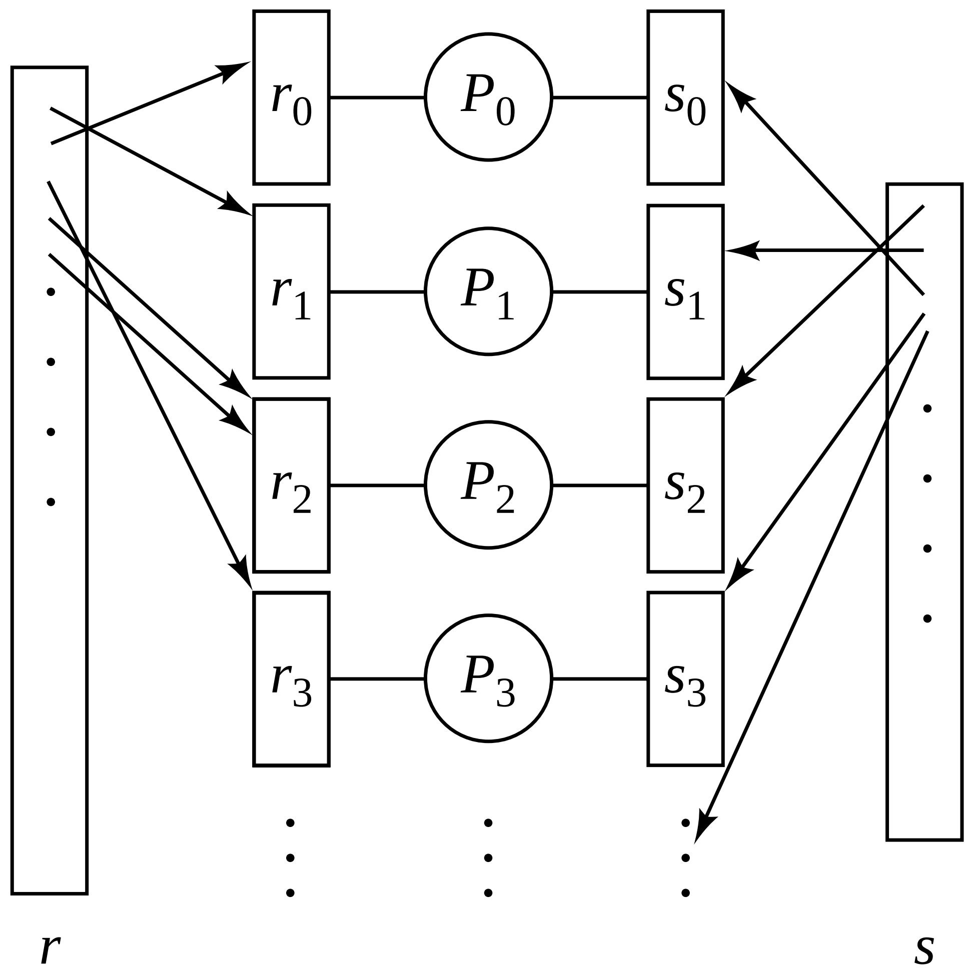
Parallel Join

- 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 $r \bowtie_{r.A=s.B} s$.
- r and s each are partitioned into n partitions, denoted $r_0, r_1, \ldots, r_{n-1}$ and $s_0, s_1, \ldots, s_{n-1}$.
- 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 $r_i \bowtie_{r_i.A=s_i.B} s_i$. Any of the standard join methods can be used.

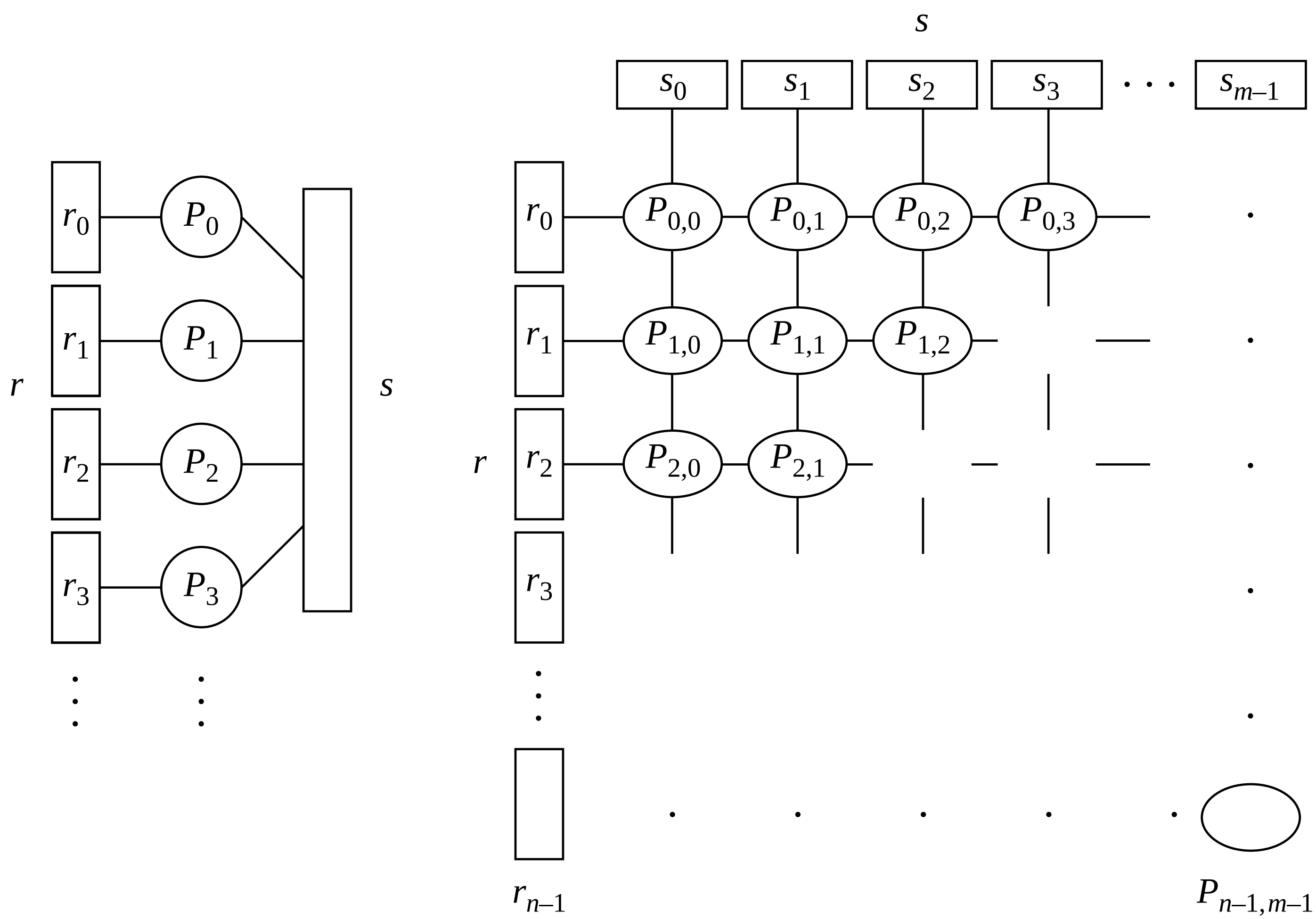
Partitioned Join (Cont.)



Fragment-and-Replicate Join

- Partitioning not possible for some join conditions
  - e.g., non-equijoin conditions, such as $r.A > s.B$.
- For joins were partitioning is not applicable, parallelization can be accomplished by *fragment and replicate* technique.
- 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, $r_0, r_1, \ldots, r_{n-1}$; s is partitioned into m partitions, $s_0, s_1, \ldots, s_{m-1}$.
  - Any partitioning technique may be used.
  - There must be at least $m * n$ processors.
  - Label the processors as $P_{0,0}, P_{0,1}, \ldots, P_{0,m-1}, P_{1,0}, \ldots, P_{n-1,m-1}$.
  - $P_{i,j}$ computes the join of r_i with s_j. In order to do so, r_i is replicated to $P_{i,0}, P_{i,1}, \ldots, P_{i,m-1}$, while s_i is replicated to $P_{0,i}, P_{1,i}, \ldots, P_{n-1,i}$.
  - Any join technique can be used at each processor $P_{i,j}$.

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

Also assume s is smaller than r and therefore s is chosen as the build relation.

- A hash function h_1 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 h_1. 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, h_2, 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 h_1. 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 h_2 (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_i 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_j where a partition of relation *s* is stored reads the tuples of relation *s* stored in D_j, and replicates the tuples to every other processor P_i. 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 *i*th partition of relation *r*.

Parallel Nested-Loop Join (Cont.)

- The indexed nested-loop join can actually be overlapped with the distribution of tuples of relation *s*, to reduce the cost of writing the tuples of relation *s* to disk and reading them back.

- However, the replication of relation *s* must be synchronized with the join so that there is enough space in in-memory buffers at each processor P_i to hold the tuples of relation *s* that have been received but not yet used in the join.

Other Relational Operations

Parallelizing the evaluation of other relational operations:

Selection Example: $\sigma_\theta(r)$

- θ is of the form $a_i = v$ where a_i is an attribute and v a value.
  - If r is partitioned on a_i, the selection is performed at a single processor.
- θ is of the form $l \leq a_i \leq u$ (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.
- 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; with the optimization of eliminating 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.

Other Relational Operations (Cont.)

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

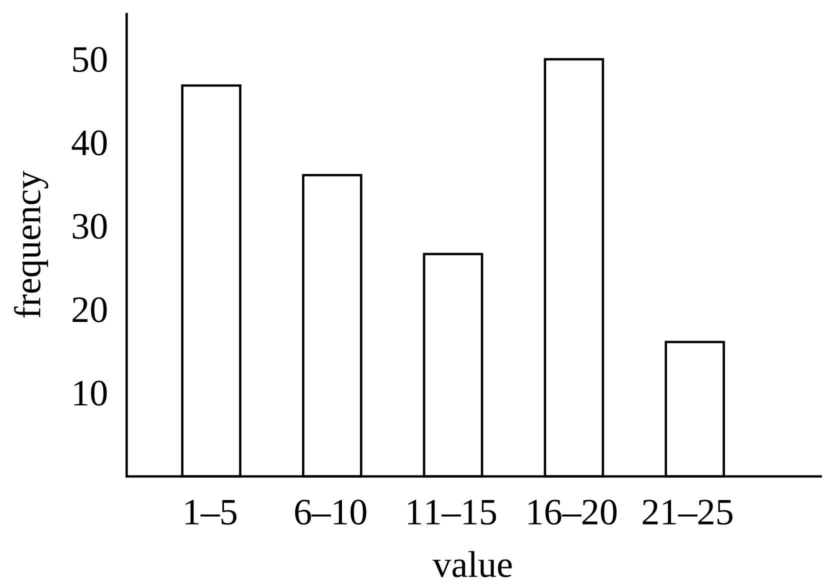
$$T_{\text{part}} + T_{\text{asm}} + \max(T_0, T_1, \ldots, T_{n-1})$$

  - 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_i; this needs to be estimated taking into account the skew, and the time wasted in contentions.

Handling Skew

One way to handle skew in joins with range-partitioning

- construct and store a frequency table (or *histogram*) of the attribute values for each attribute of each relation.
- Construct a load-balanced range-partition vector using the histogram



Interoperation 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 processor P_1 be assigned the computation of $temp_1 \leftarrow r_1 \bowtie r_2$ and let P_2 be assigned the computation of $r_3 \bowtie temp_1$.
- As P_1 computes tuples in $r_1 \bowtie r_2$, it makes these tuples available to processor P_2.
- Thus, P_2 has available to it some of the tuples in $r_1 \bowtie r_2$ before P_1 has finished its computation. P_2 can use those tuples to begin computation of $temp_1 \bowtie r_3$ even before $r_1 \bowtie r_2$ is fully computed by P_1.
- As P_2 computes tuples in $(r_1 \bowtie r_2) \bowtie r_3$, it makes these tuples available to P_3, which computes the join of these tuples with r_4.

Factors Limiting Utility of Pipeline Parallelism

- Pipelined parallelism is useful because 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 (i.e., 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

- Operations in a query expression that do not depend on each other can be executed in parallel.
- Consider the join $r_1 \bowtie r_2 \bowtie r_3 \bowtie r_4$.
- Compute $temp_1 \leftarrow r_1 \bowtie r_2$ in parallel with $temp_2 \leftarrow r_3 \bowtie r_4$.
- When these two computations complete, we compute:

$$temp_1 \bowtie temp_2$$

- To get further parallelism, the tuples in $temp_1$ and $temp_2$ can be pipelined into the computation of $temp_1 \bowtie temp_2$, which is itself carried out using pipelined join.
- Does not provide a high degree of parallelism; less useful in a highly parallel system, although it is useful with a lower degree of parallelism.

Query Optimization

- Query optimization in parallel databases is significantly more complex than query optimization in sequential databases.
- Cost models are more complicated, since we must take into account partitioning costs and issues such as skew and resource contention.
- When scheduling execution tree in parallel system, must decide:
  - How to parallelize each operation and how many processors to use for it.
  - What operations to pipeline, what operations to execute independently in parallel, and what operations to execute sequentially, one after the other.
- Determining the amount of resources to allocate for each operation is a problem. E.g., allocating more processors than optimal can result in high communication overhead.

Query Optimization (Cont.)

- Long pipelines should be avoided as the final operation may wait a lot for inputs, while holding precious resources
- The number of parallel evaluation plans from which to choose from is much larger than the number of sequential evaluation plans. Therefore heuristics are needed while optimization
- Two alternative heuristics for choosing parallel plans:
  1. No pipelining and inter-operation pipelining; just parallelize every operation across all processors.
     – Finding best plan is now much easier — use standard optimization technique, but with new cost model
  2. First choose most efficient sequential plan and then choose how best to parallelize the operations in that plan.
     – Can explore pipelined parallelism as an option
- Choosing a good physical organization (partitioning technique) is important to speed up queries.

Design of Parallel Systems

Some issues in the design of parallel systems:

- Parallel loading of data from external sources is needed in order to handle large volumes of incoming data.
- Resilience to failure of some processors or disks.
  - Probability of some disk or processor failing is higher in a parallel system.
  - Operation (perhaps with degraded performance) should be possible in spite of failure.
  - Redundancy achieved by storing extra copy of every data item at another processor.

Design of Parallel Systems (Cont.)

- On-line reorganization of data and schema changes must be supported.
  - For example, index construction on terabyte databases can take hours or days even on a parallel system.
    - Need to allow other processing (insertions/deletions/updates) to be performed on relation even as index is being constructed.
    - Basic idea: index construction tracks changes and “catches up” on changes at the end.
  - Also need support for on-line repartitioning and schema changes (executed concurrently with other processing).