Parallel Databases

These slides are a modified version of the slides of the book "Database System Concepts" (Chapter 18), 5th Ed., McGraw-Hill, by Silberschatz, Korth and Sudarshan.
Original slides are available at www.db-book.com

Parallel Databases

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

Introduction

- Parallel machines are becoming quite common and affordable
  - Prices of microprocessors, memory and disks have dropped sharply
  - Recent desktop computers feature multiple processors and this trend is projected to accelerate
- 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:
  - storing large volumes of data
  - processing time-consuming decision-support queries
  - providing high throughput for transaction processing

Parallelism in Databases

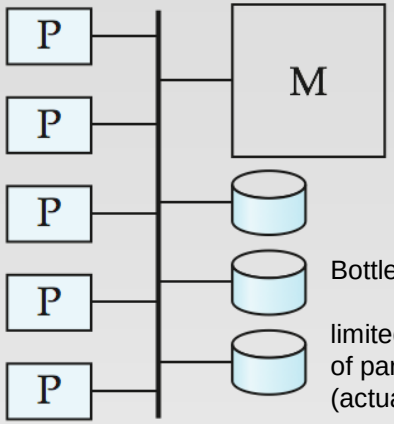
- Data can be partitioned across multiple disks for parallel I/O.
- Individual relational operations (e.g., sort, join, aggregation) can be executed in parallel
  - data can be partitioned and each processor can work independently on its own partition.
- Queries are expressed in high level language (SQL, 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.

Parallel Database Architectures

Basic architectural models for parallel machines

- **Shared memory** -- processors share a common memory
- **Shared disk** -- processors share a common disk
- **Shared nothing** -- processors share neither a common memory nor common disk
- **Hierarchical** -- hybrid of the above architectures

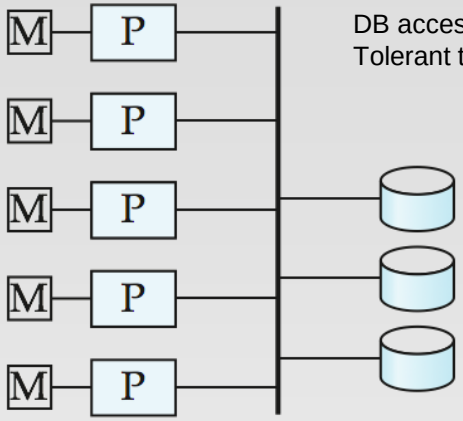
Parallel Database Architectures



Bottleneck: memory access

limited by the bus 16-32 degree of parallelism
(actually 4 up to 8 degree of parallelism)

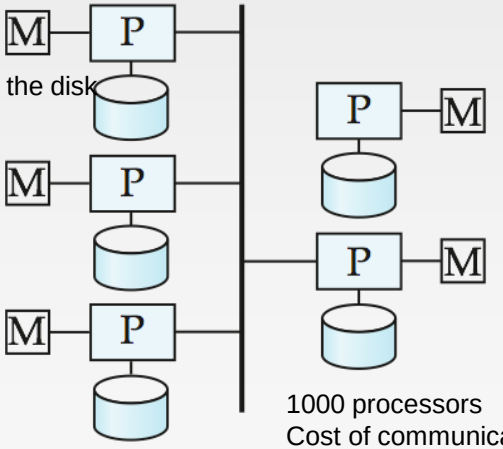
(a) shared memory



DB accessible from all processors
Tolerant to processor failure

(b) shared disk

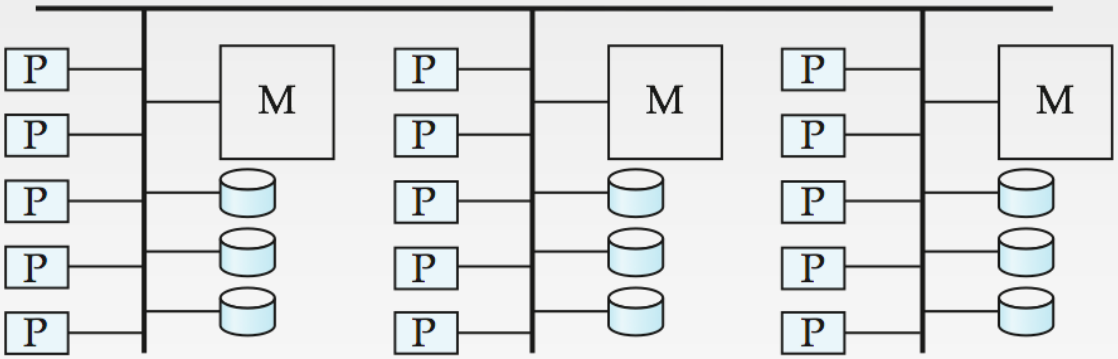
server for the data on the disk



1000 processors
Cost of communications and non-local disk access

(c) shared nothing

Shared nothing



(d) hierarchical

Shared Memory

- Processors and disks have access to a common memory, typically via a bus or through an interconnection network.
- Extremely efficient communication between processors — data in shared memory can be accessed by any processor without having to move it using software.
- Downside – architecture is not scalable beyond 32 or 64 processors since the bus or the interconnection network becomes a bottleneck
- Widely used for lower degrees of parallelism (4 to 8).

Shared Disk

- All processors can directly access all disks via an interconnection network, but the processors have private memories.
  - The memory bus is not a bottleneck
  - Architecture provides a degree of **fault-tolerance** — if a processor fails, the other processors can take over its tasks since the database is resident on disks that are accessible from all processors.
- Examples: IBM Sysplex and DEC clusters (now part of Compaq) running Rdb (now Oracle Rdb) were early commercial users
- Downside: bottleneck now occurs at interconnection to the disk subsystem.
- Shared-disk systems can scale to a somewhat larger number of processors, but communication between processors is slower.

Shared Nothing

- Node consists of a processor, memory, and one or more disks. Processors at one node communicate with another processor at another node using an interconnection network. A node functions as the server for the data on the disk or disks the node owns.
- Examples: Teradata, Tandem, Oracle-n CUBE
- Data accessed from local disks (and local memory accesses) do not pass through interconnection network, thereby minimizing the interference of resource sharing.
- Shared-nothing multiprocessors can be scaled up to thousands of processors without interference.
- Main drawback: cost of communication and non-local disk access; sending data involves software interaction at both ends.

Hierarchical

- Combines characteristics of shared-memory, shared-disk, and shared-nothing architectures.
- Top level is a shared-nothing architecture – nodes connected by an interconnection network, and do not share disks or memory with each other.
- Each node of the system could be a shared-memory system with a few processors.
- Alternatively, each node could be a shared-disk system, and each of the systems sharing a set of disks could be a shared-memory system.

I/O 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 tothe 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 $[v_0, v_1, ..., v_{n-2}]$ is chosen.
  - Let x be the partitioning attribute value of a tuple. Tuples such that $v_i \le x < v_{i+1}$ go to disk $i + 1$. Tuples with $x < v_0$ go to disk 0 and tuples with $x \ge v_{n-2}$ go to disk n-1.

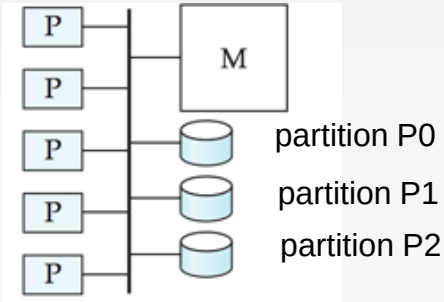
    E.g., with a partitioning vector [5,11], a tuple with partitioning attribute value of 2 will go to disk 0, a tuple with value 8 will go to disk 1, while a tuple with value 20 will go to disk2.

Example:
shared memory architecture, n=3

```
select  *
  from  R
```

⇩

```
select   *      select  *      select  *
 from P0         from P1        from P2
(Disk0)         (Disk1)        (Disk2)
```



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:

- 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:

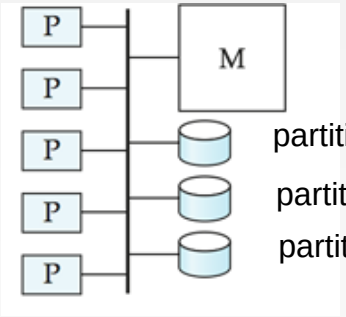
- Good for sequential access
  - Assuming hash function is good, and partitioning attributes form a key, tuples will be equally distributed between disks
  - Retrieval work is then well balanced between disks.
- **Good for point queries on partitioning attribute**
  - **Can lookup single disk, leaving 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

```
select  *
 from  R
where A=xxx
```

H(xxx) = j

⇩

```
select   *
  from Pj
  (Diskj)
```



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

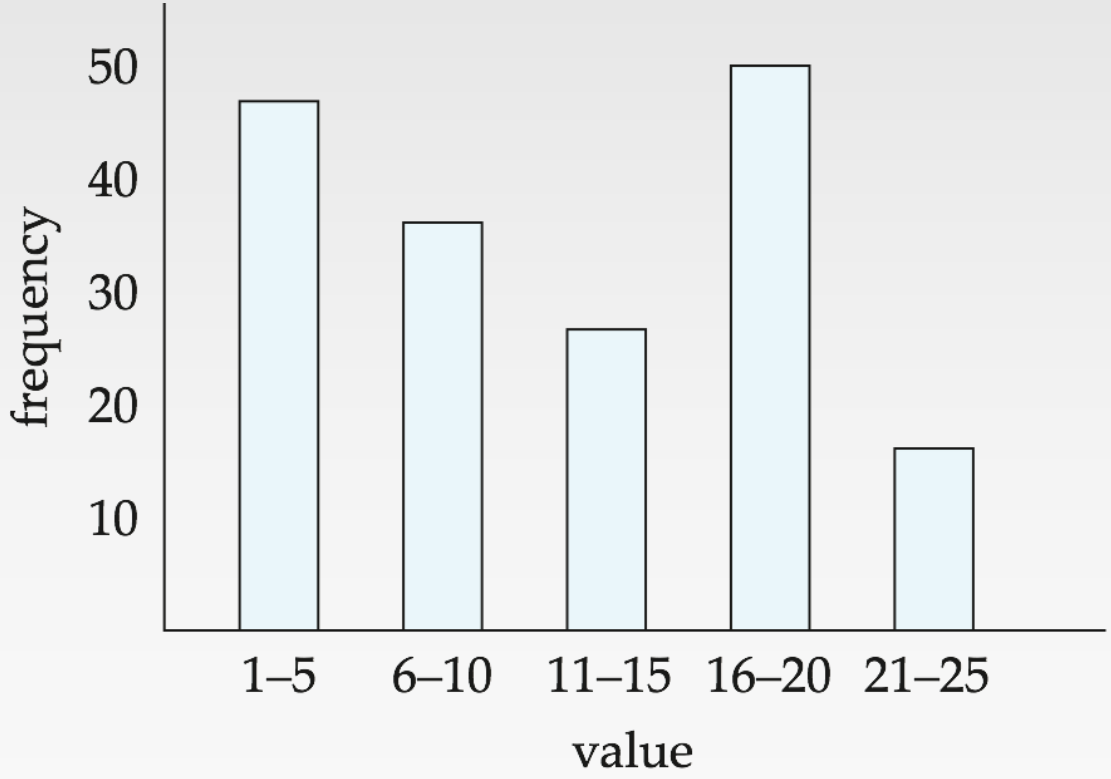
- The distribution of tuples to disks may be **skewed** — that is, some disks have many tuples, while others may have fewer tuples.
- **Types of skew:**
  - **Attribute-value skew**.
    - Some values appear in the partitioning attributes of many tuples; all the tuples with the same value for the partitioning 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

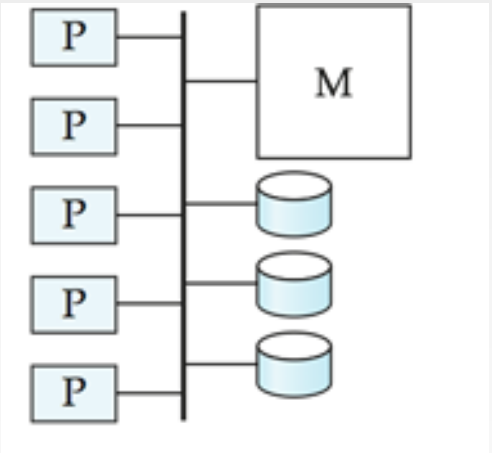
- Balanced partitioning vector can be constructed from histogram in a relatively straightforward fashion
  - Assume uniform distribution within each range of the histogram
- Histogram can be constructed by scanning relation, or sampling (blocks containing) tuples of the relation



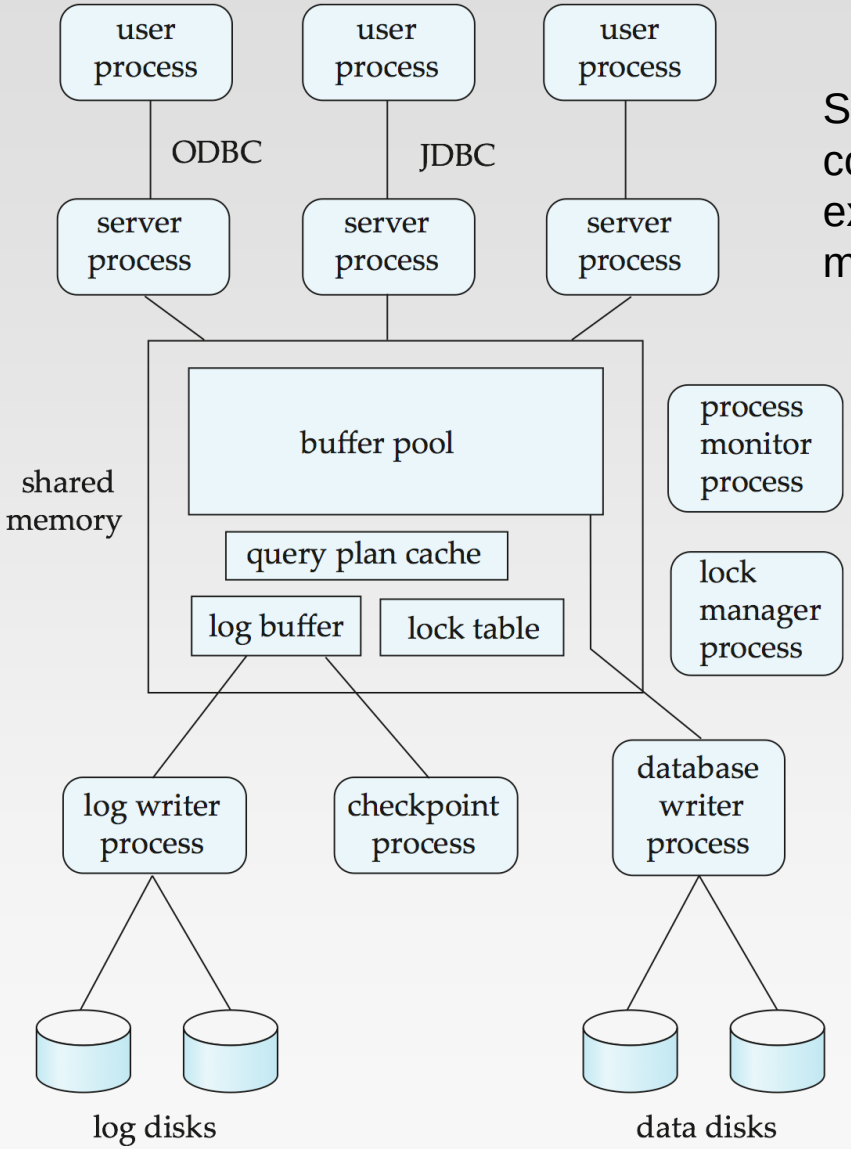
Interquery Parallelism

Interquery Parallelism

- Each query is run sequentially
- 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.



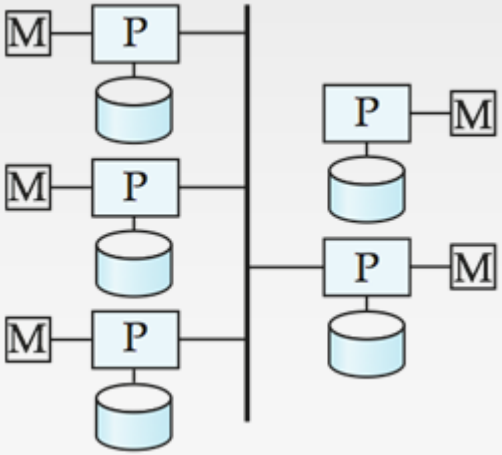
Transaction System Processes (Sequential systems)



Sequential database systems support concurrent processing of transactions executed in time-shared concurrent manner

Interquery Parallelism

- More complicated to implement on shared-disk or shared-nothing architectures
  - Locking and logging must be coordinated by passing messages between processors (2PL, 2PC, ….).
  - 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.



Two processors do not update the same data independently at the same time.

When a processor access or update data, the DBMS must ensure that the process has the latest version of the data in its buffer pool.

Intraquery Parallelism

Intraquery Parallelism

- Execution of a single query in parallel on multiple processors/disks; important for speeding up long-running queries

- Consider a query that requires a relation to be sorted on attribute A Assume the relation has been partitioned by range-partition on the same attribute A. We can
  - sort each partition in parallel
  - concatenate the sorted partitions to get the final sorted relation

  We have parallelized the query by parallelizing the sort operation.

- The operator tree for a query can contain multiple operations

  We can parallelize the operations that do not depend on one another; and we may be able to pipeline the output of one operation to another operation.

Intraquery Parallelism

- 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*.

The two forms can be used simultaneously in a query.

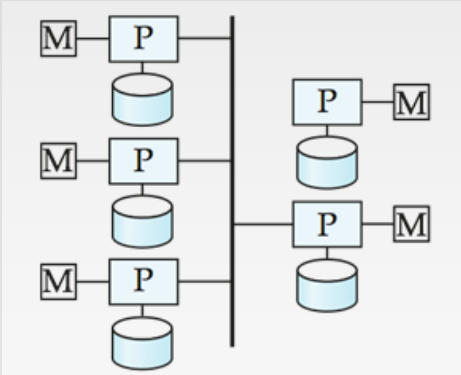
Parallel Processing of Relational Operations

The algorithms for parallelizing query evaluation depends on the machine architecture.

- 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.

Intraoperation Parallelism

Parallel Sort



Range-Partitioning Sort

- Choose processors P_0, ..., P_m, where $m \leq n$ -1 to do sorting.

Step 1:

- Create range-partition vector with m entries, on the sorting attribute (each partition the same number of tuples)
- 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.
  - This step requires I/O and communication overhead.

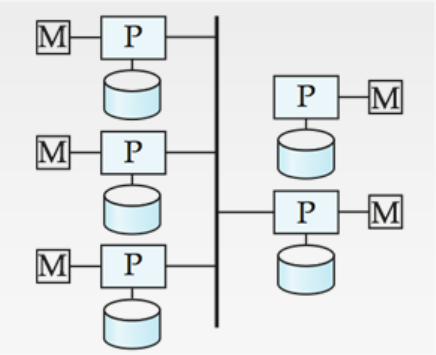
Step 2:

- Each processor P_i sorts its partition of the relation locally.
- Each processor 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 <= i < j <= 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, ..., 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_i performs a merge on the streams as they are received, to get a single sorted run.
  - The sorted runs on processors P_0,..., P_{m-1} are concatenated to get the final result.



m = 3
Sort partition P0 (run0)
Sort partition P1 (run1)
Sort partition P2 (run2)

⇨ Parallelized Merge

range-partitioned V = [5, 20]

P0: SRun0 x <=5	P1: SRun0 5<x<=20	P2: SRun0>=20
SRun1 x <=5	SRun1 5<x<=20	SRun1>=20
SRun3 x <=5	SRun2 5<x<=20	SRun2>=20

Merge **Merge** **Merge**

Concatenation

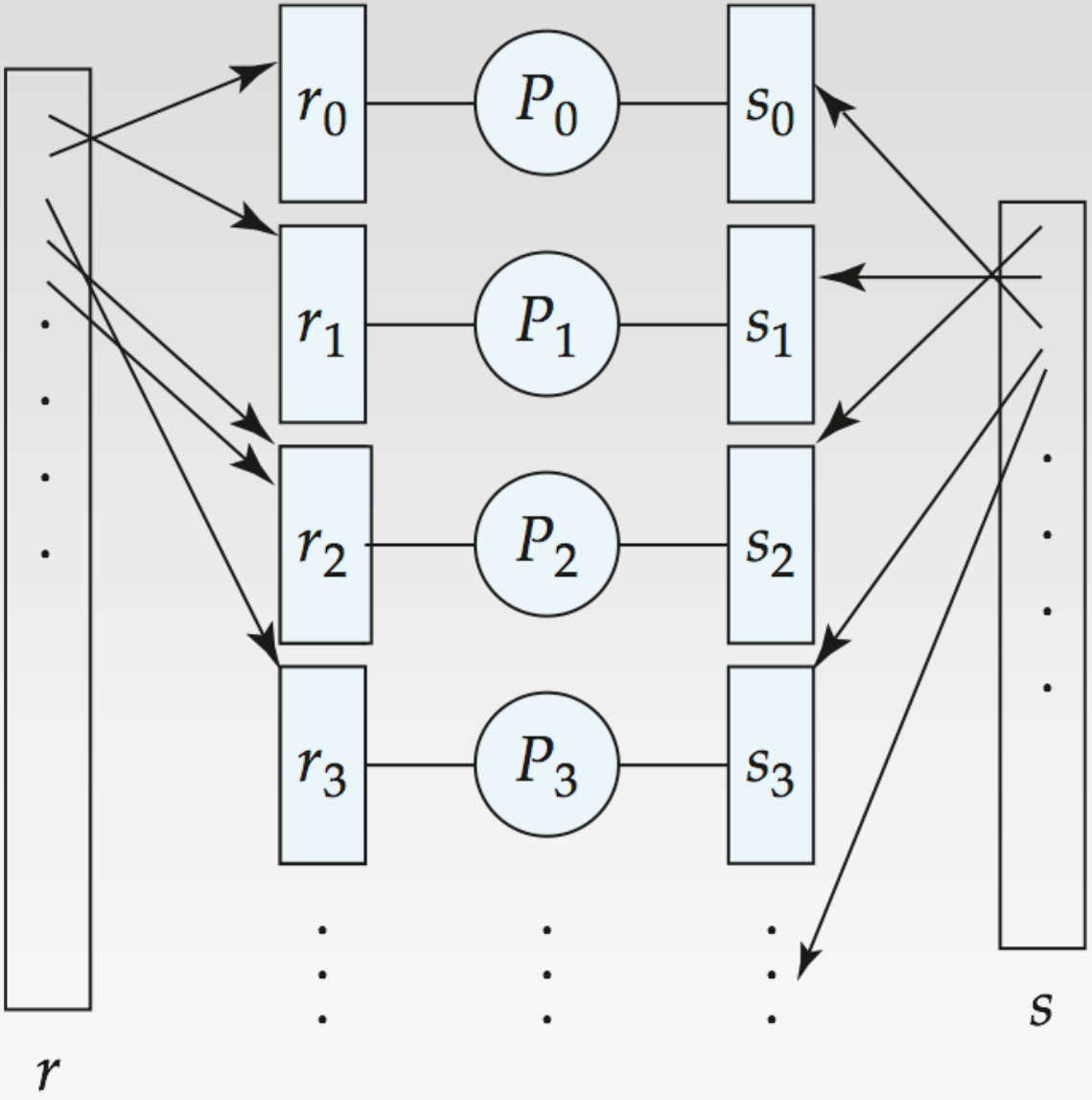
Parallel Join

- 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 $r_0, r_1, ..., r_{n-1}$ 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 $r_i \bowtie_{ri.A=si.B} s_i$. Any of the standard join methods can be used.

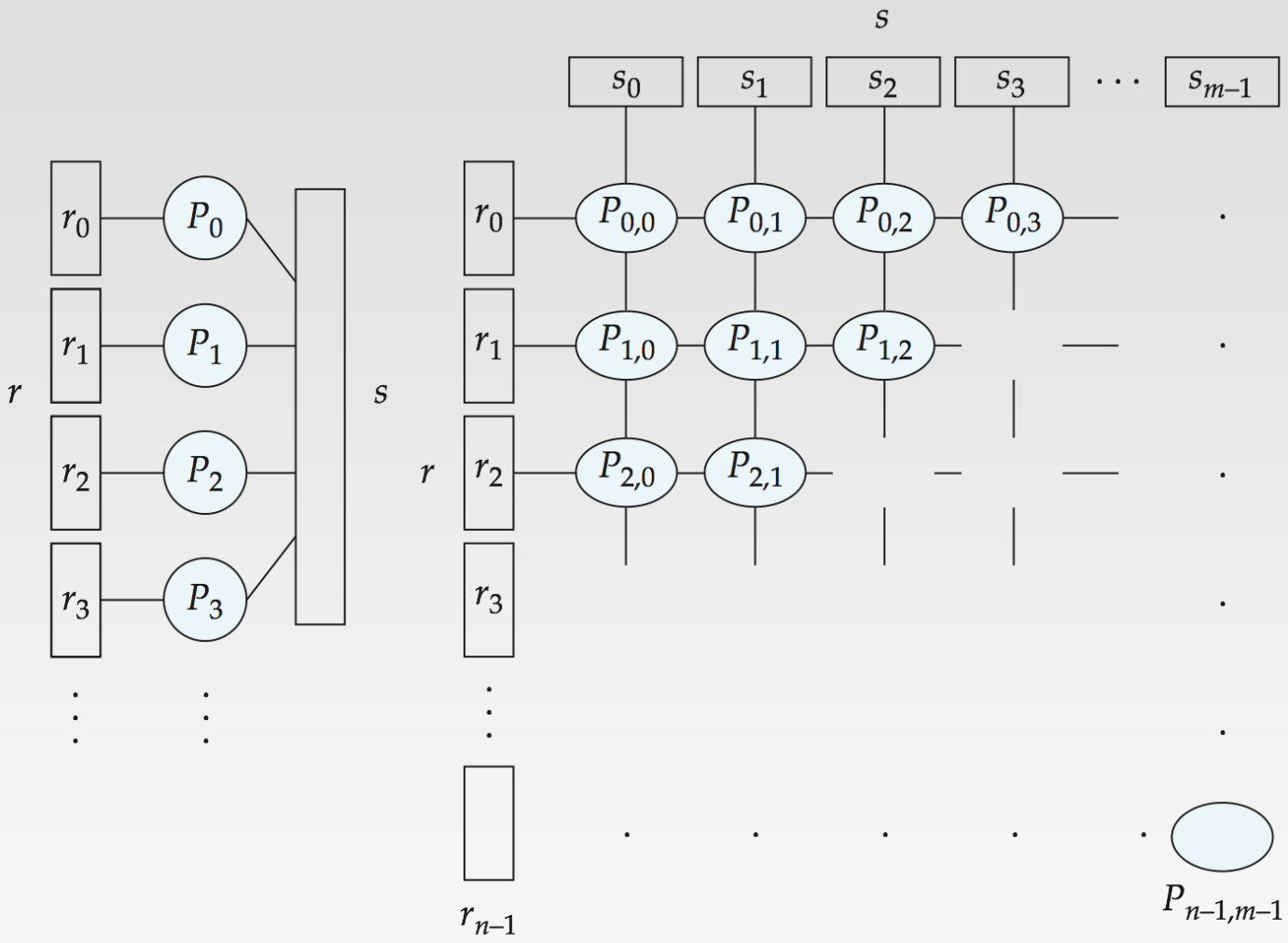
Partitioned Join (Cont.)



Fragment-and-Replicate Join

- Partitioning not possible for some join conditions
  - E.g., non-equijoin conditions, such as r.A > s.B.
  - Not easy way of partitioning r and s such that tuple in r_i join only tuples in s_i
- For joins were 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_j. 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 $P_{i,j}$.

Fragment-and-Replicate Join (Cont.)

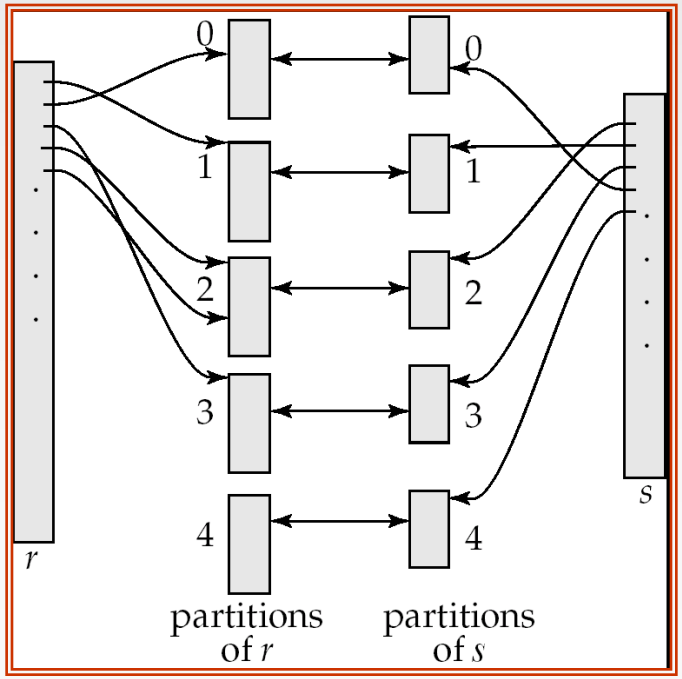
- Both versions of fragment-and-replicate work with any join condition, since every tuple in *r* can be tested with every tuple in *s*.
- Usually has a **higher cost** than partitioning, since one of the relations (for asymmetric fragment-and-replicate) or both relations (for general fragment-and-replicate) 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

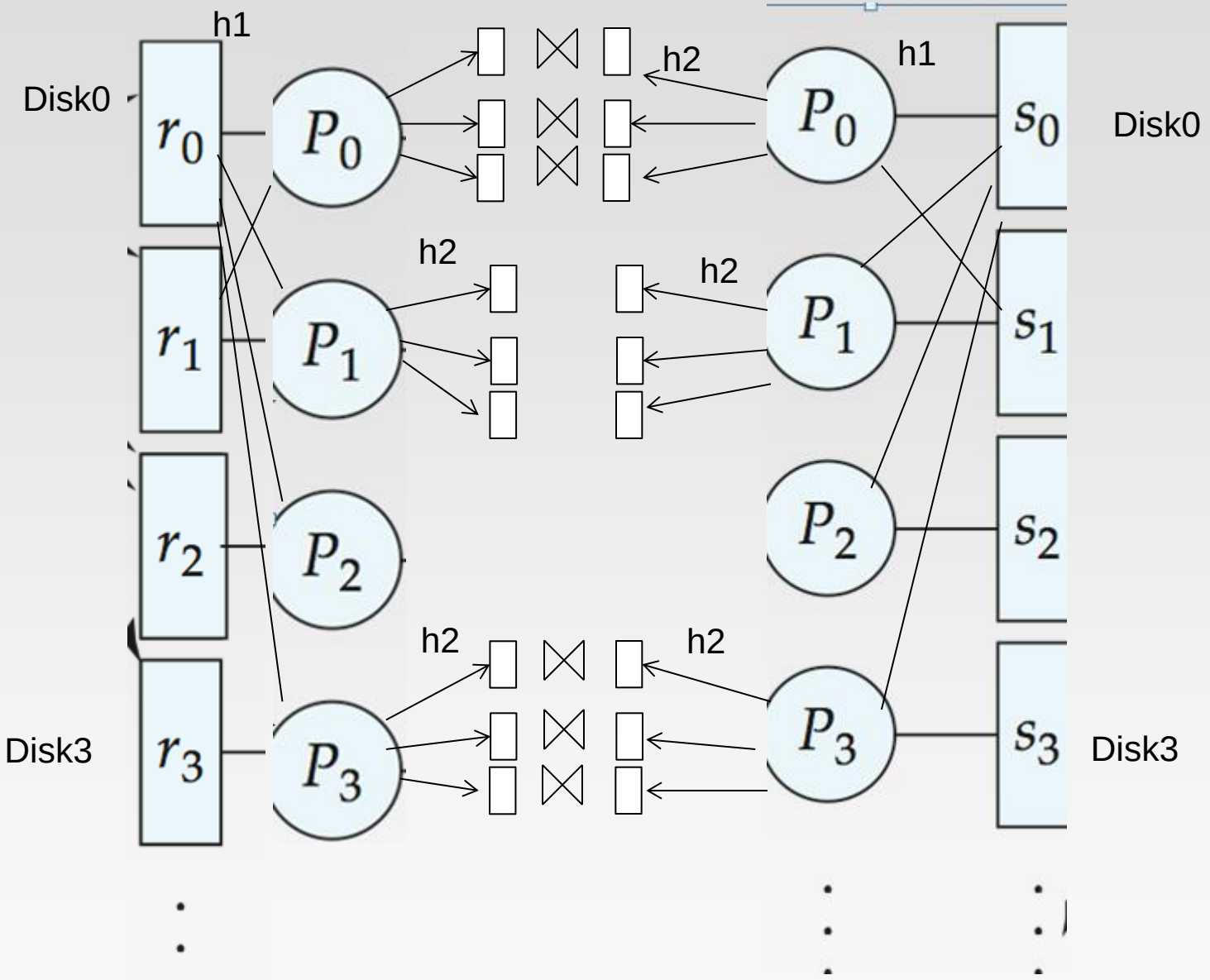
The partitioned hash join can be parallelized:

- 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 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.

HASH JOIN



Partitioned Parallel Hash-Join



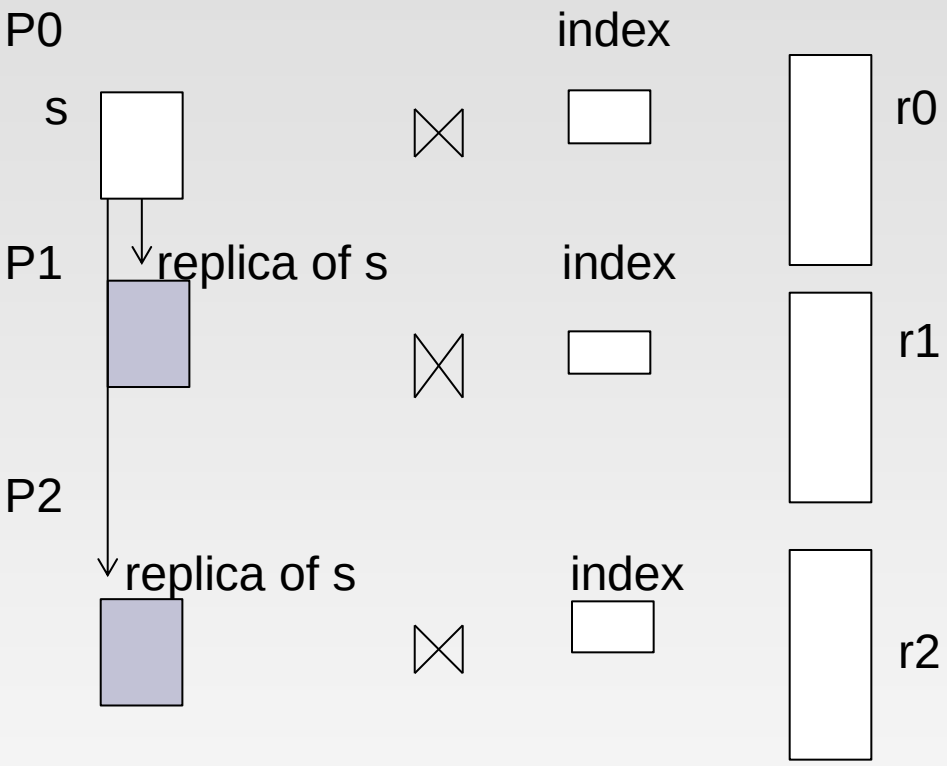
Partitioned Parallel Hash-Join (Cont.)

- 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.

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



indexed nested-loop join of *s* with the i^{th} partition of relation *r*

asymmetric fragment-and-replicate

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_i the selection is performed at a single processor.
- If θ is of the form $i <= a_i <= u$ (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.

Cost of Parallel Evaluation of Operations

- If there is no skew in the partitioning, and there is no overhead due to the parallel evaluation, a parallel operation using **n** processors will take **1/n** times as long as the same operation on a single processor
- The time cost of parallel processing would be **1/n** of the time cost of sequential processing of the operation.

- If skew and overheads are also to be taken into account, the time taken by a parallel operation can be estimated as

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

  - 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

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 = $r_1 \bowtie r_2$
    - And P2 be assigned the computation of temp2 = temp1 $\bowtie$ r_3
    - And P3 be assigned the computation of temp2 $\bowtie$ r_4
  - 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 pipelineable join evaluation algorithm (e.g., indexed nested loops join) is used

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 P_3 be assigned the computation of temp1 $\bowtie$ $temp_2$
    - P_1 and P_2 can work **independently in parallel**
    - P_3 has to wait for input from P_1 and P_2
      - Can pipeline output of P_1 and P_2 to P_3, 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.

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.
- 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

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).