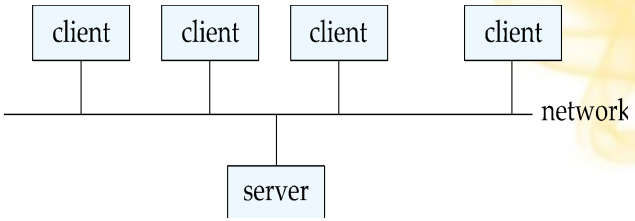
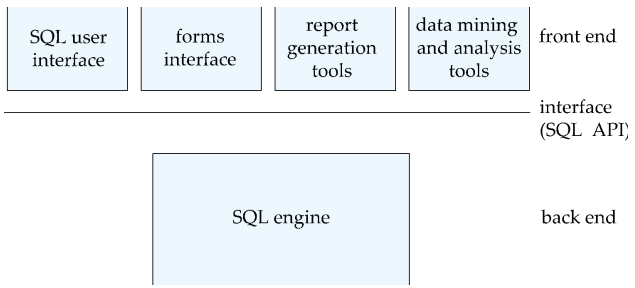
UMD DATA605 - Big Data Systems Parallel Systems and Databases

GP Saggese gsaggese@umd.edu with thanks to Alan Sussman, Amol Deshpande

Client-Server Architecture

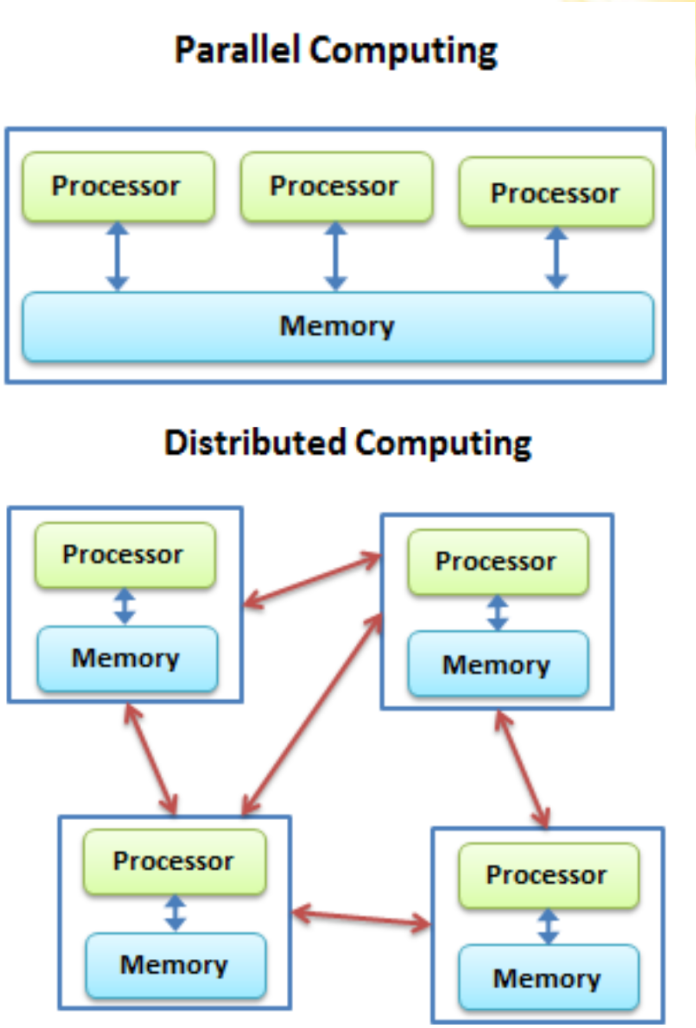
- The **client-server** is a model for distributed applications that partitions tasks between:
  - **Clients**: request a service (e.g., dashboard, GUI, client applications)
  - **Servers**: provide resource or service (e.g., a database)
- The **architecture of a database system** can be divided into:
  - **Back-end** (Server): manage access, query evaluation and optimization, concurrency control, and recovery
  - **Front-end** (Clients): consist 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 vs Distributed Computing

- **Parallel computing**
  - One computer with multiple CPUs
  - Cluster = many similar computers with multiple CPUs
  - Homogenous and (geographically) close computing nodes
  - Working on one task
- **Distributed computing**
  - Several autonomous (often geographically separate) computers systems
  - Heterogeneous and distant
  - Working on separate tasks



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
  - Much larger degree of parallelism
  - With or without shared memory
  - E.g., GPUs, The Connection Machine

The Connection Machine, MIT, 1980s

Connection Machine's cameo in Jurassic Park

Connection Machine in Jurassic Park

Parallel Databases: Introduction

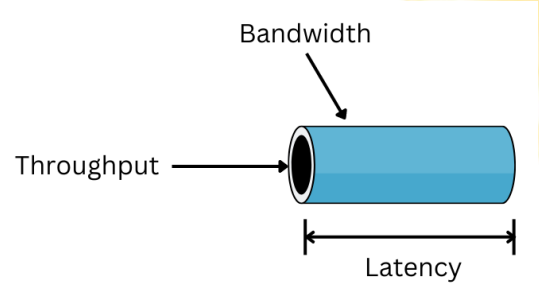
- **Parallel DBs were historically the standard approach before MapReduce**
- **Parallel machines have become common and affordable**
  - Prices of microprocessors, memory, and disks keep dropping sharply
  - Desktop / laptop computers feature multiple processors
  - This trend will continue
- **DBs are growing increasingly large**
  - Large volumes of transaction data are collected and stored for later analysis
  - Multimedia objects like data605/lectures_source/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

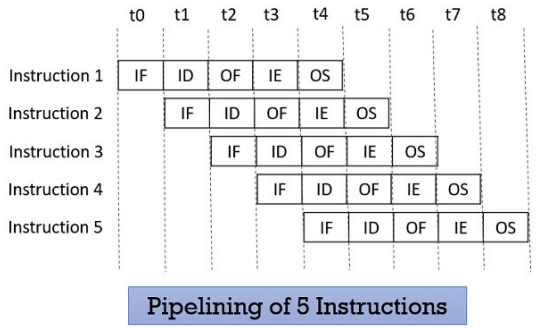
Parallel Databases

- 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 of microprocessor





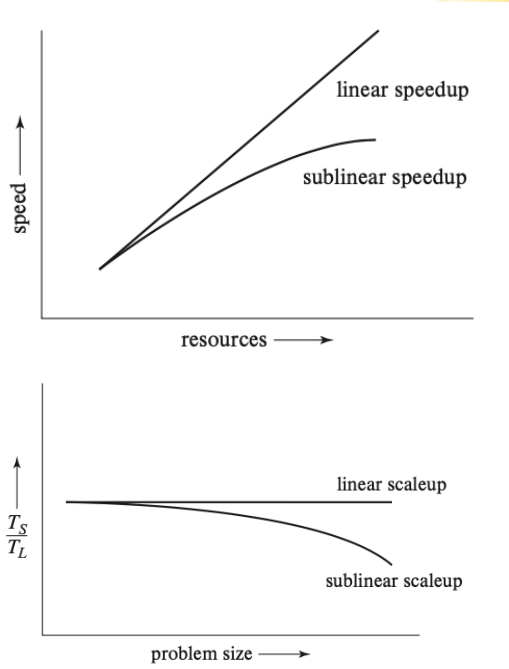
Pipelining of instructions in microprocessor

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**

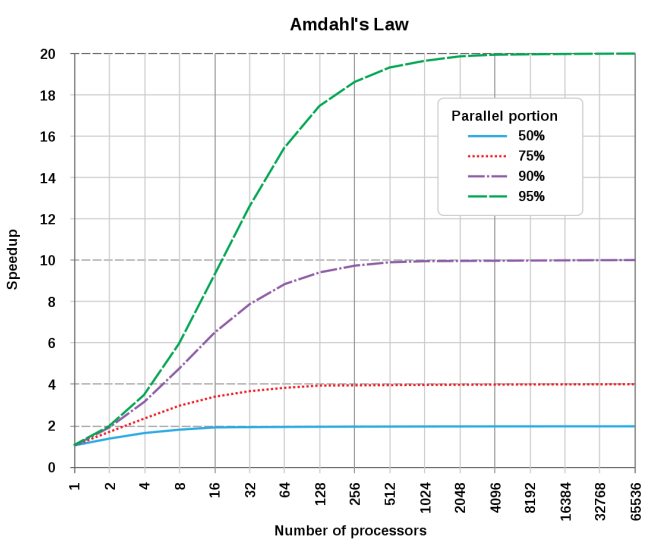


Factors Limiting Speed-up and Scale-up

- 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 = number of nodes
  - T = the execution time in the serial case
  - T(p) = the execution time on s nodes = (1-p)T + (p / s)T
  - Speedup(s) = T / T(s) =

$$S_{\text{latency}}(s) = \frac{1}{(1-p) + \frac{p}{s}}$$

  - 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!)



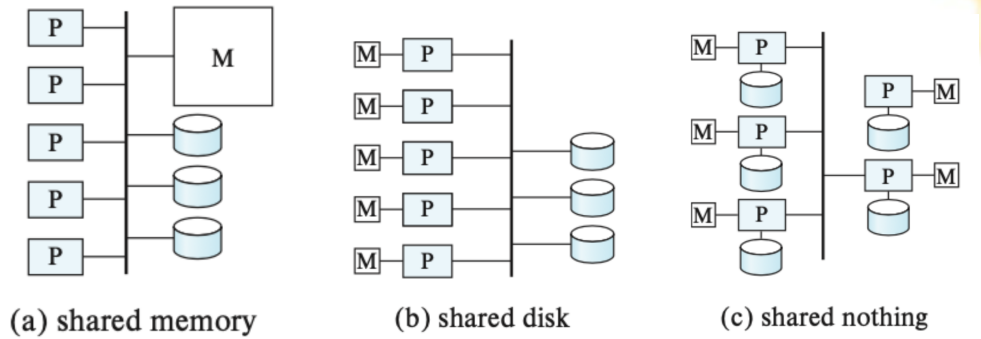
SCIENCE ACADEMY

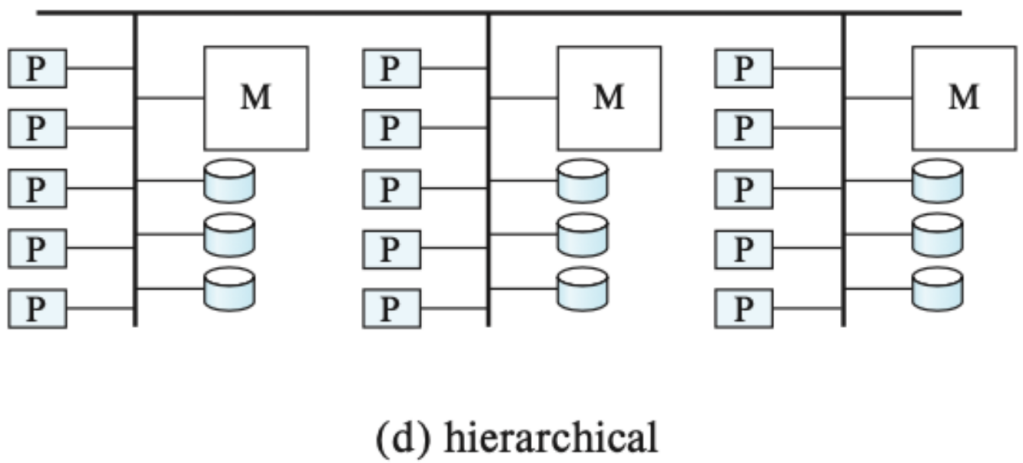
Factors Limiting Speed-up and Scale-up

- **Startup costs**
  - Cost of starting up many processes may dominate computation time
  - E.g., DBs create a pool of threads when they start, instead of waiting for requests
- **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
  - E.g., when lots of devs touch the same code creating merge conflicts
- **Cost of synchronization**
  - The smaller the pieces to work on, the more complex is synchronizing the workers
  - E.g., same problem when hiring many developers in a company
- **Skew**
  - Splitting the work to do 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

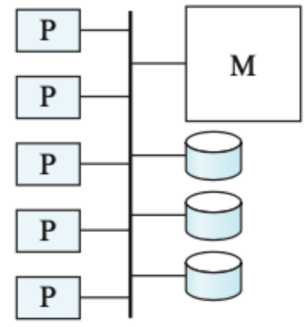
- Several ways to organize computation and storage
  - M = memory
  - P = processors
  - D = disks
- Topology
  - Shared memory
  - Shared disk
  - Shared nothing
  - Hierarchical
- Problems are:
  - Cache coherency
  - Data communication
  - Fault tolerance
  - Resource congestion



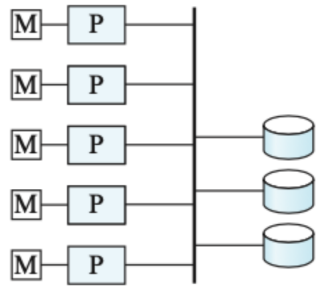


Topology of Parallel Systems: Comparison

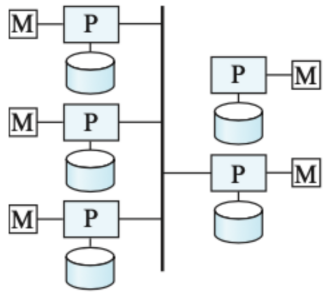
	Shared Memory	Shared Disk	Shared Nothing
Communication between processors	Extremely fast	Disk interconnect is very fast	Over a LAN, so slowest
Scalability?	Not beyond 32 or 64 or so (memory bus is the bottleneck)	Not very scalable (disk interconnect is the bottleneck)	Very very scalable
Notes	Cache-coherency 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



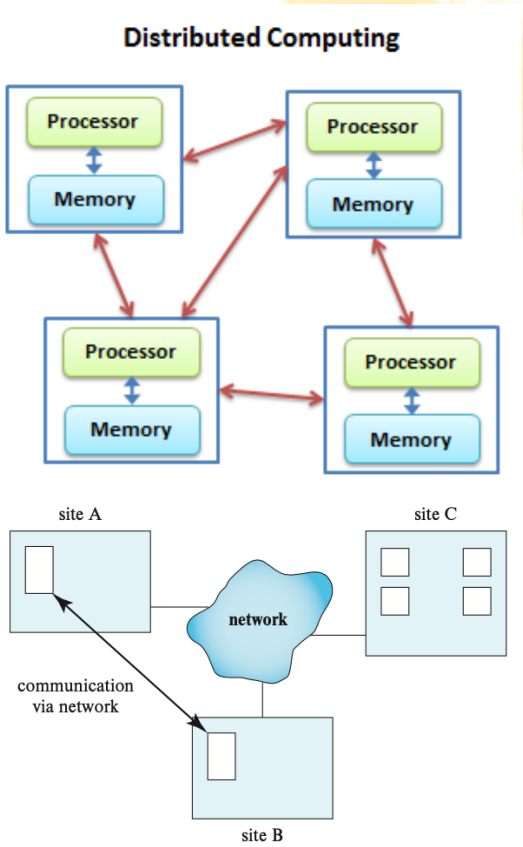
(b) shared disk



(c) shared nothing

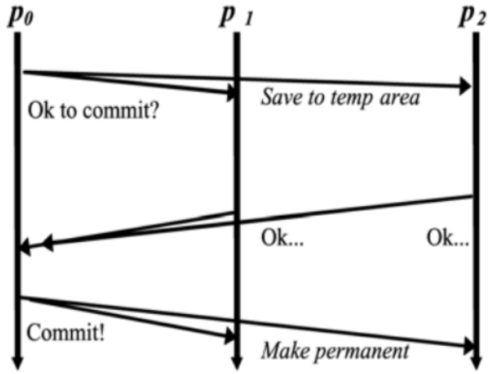
Distributed Databases

- **Distributed DBs**
  - 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 disaster recovery reasons
  - E.g., natural disasters, power outage, hacker attacks
  - Achieve high-availability despite failures
- Typically not done for performance reasons
  - Use a parallel DB to achieve high performance
- Wide-area networks (WAN) vs Local-area networks (LAN)
  - Lower bandwidth
  - Higher latency
  - Greater probability of failures (compared to networks in a single data center)
  - Network-link failures may result in network partition



Consistency Issues in Distributed DB Systems

- Parallel and distributed 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) is centralized approach
    - The commit decision is delegated to a single coordinator node
    - Each node executes the transaction, reaching a "ready state"
    - If each node reaches the ready state, the coordinator decides to commit
    - If a node fails in ready state, it can try to recover from failure (e.g., write-ahead logs on stable storage)
    - If a node aborts at any code, the coordinator aborts the transaction
  - Distributed consensus, e.g.,
    - Paxos
    - blockchain
- **Concurrency issues**



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

SCIENCE ACADEMY

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 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.)

- **Range partitioning**:
  - Choose an attribute as the partitioning attribute.
  - A partitioning vector `text [*v*o, *v*1, ..., *v*n-2]` is chosen.
- Let *v* be the partitioning attribute value of a tuple. Tuples such that *v*i <= *v*i+1 go to disk $I + 1$.Tuples with $v < v0$ go to disk 0 and tuples with $v >= v$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.

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., $10 <= r.A < 25$.

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

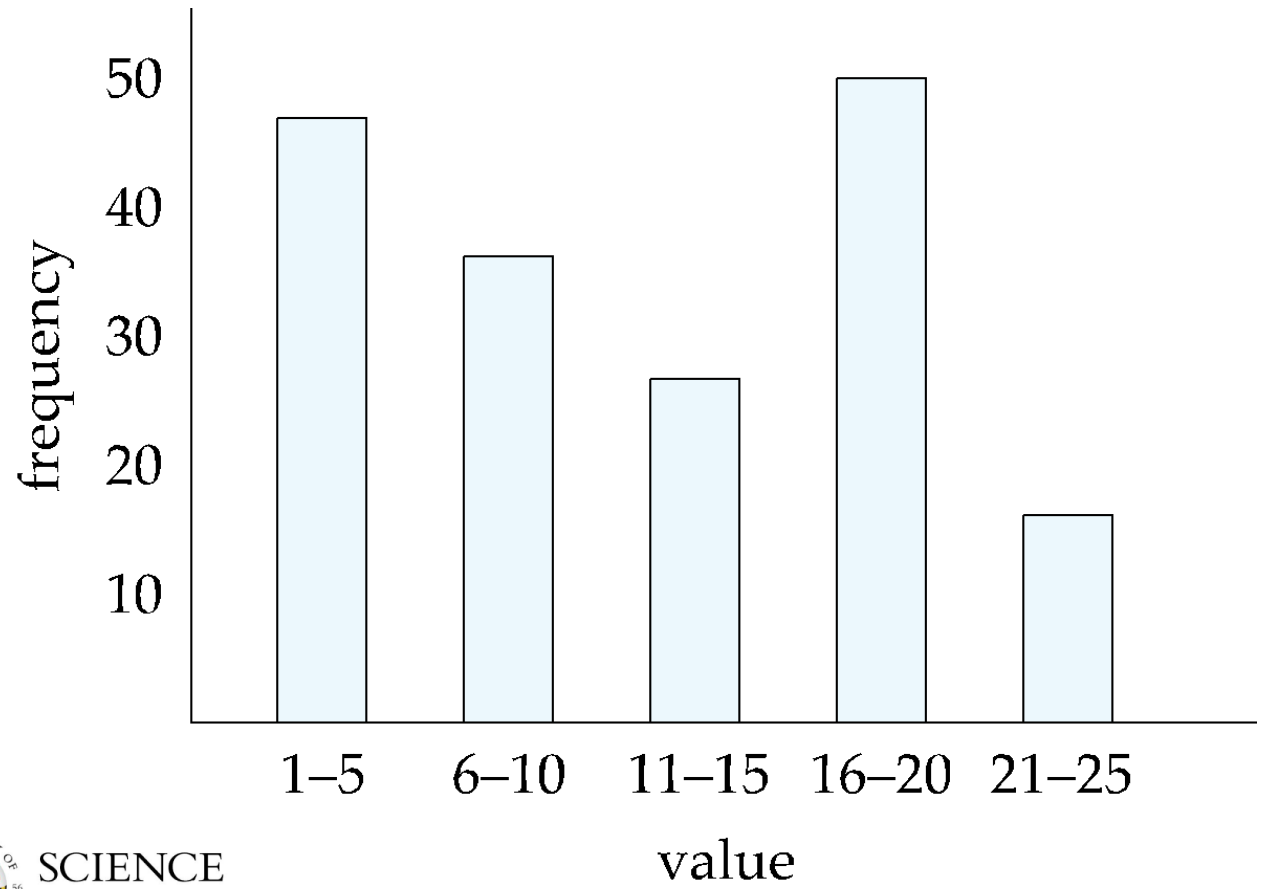
- The distribution of tuples to disks may be **skewed**
  - Some disks have many tuples, while others may have fewer tuples
- **Types of skew:**
  - **Attribute-value skew**.
    - Some values appear in the partitioning attributes of many tuples; all the tuples with the same value for the partitioning 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, $P0, \ldots, Pn\text{-}1$, and n disks $D0, \ldots, Dn\text{-}1$, where disk Di is associated with processor Pi.
- If a processor has multiple disks they can simply simulate a single disk Di.
- 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 $P0, \ldots, Pm$, where $m <= n$ -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 Pi
    - Pi stores the tuples it received temporarily on disk Di.
    - This step requires I/O and communication overhead.
  - Each processor Pi 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 Pj.

Parallel Sort (Cont.)

- **Parallel External Sort-Merge**
  - Assume the relation has already been partitioned among disks $D0, \ldots, Dn\text{-}1$ (in whatever manner).
  - Each processor Pi locally sorts the data on disk Di.
  - 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 Pi are range-partitioned across the processors $P0, \ldots, Pm\text{-}1$.
    - Each processor Pi performs a merge on the streams as they are received, to get a single sorted run.
    - The sorted runs on processors $P0, \ldots, Pm\text{-}1$ are concatenated to get the final result.

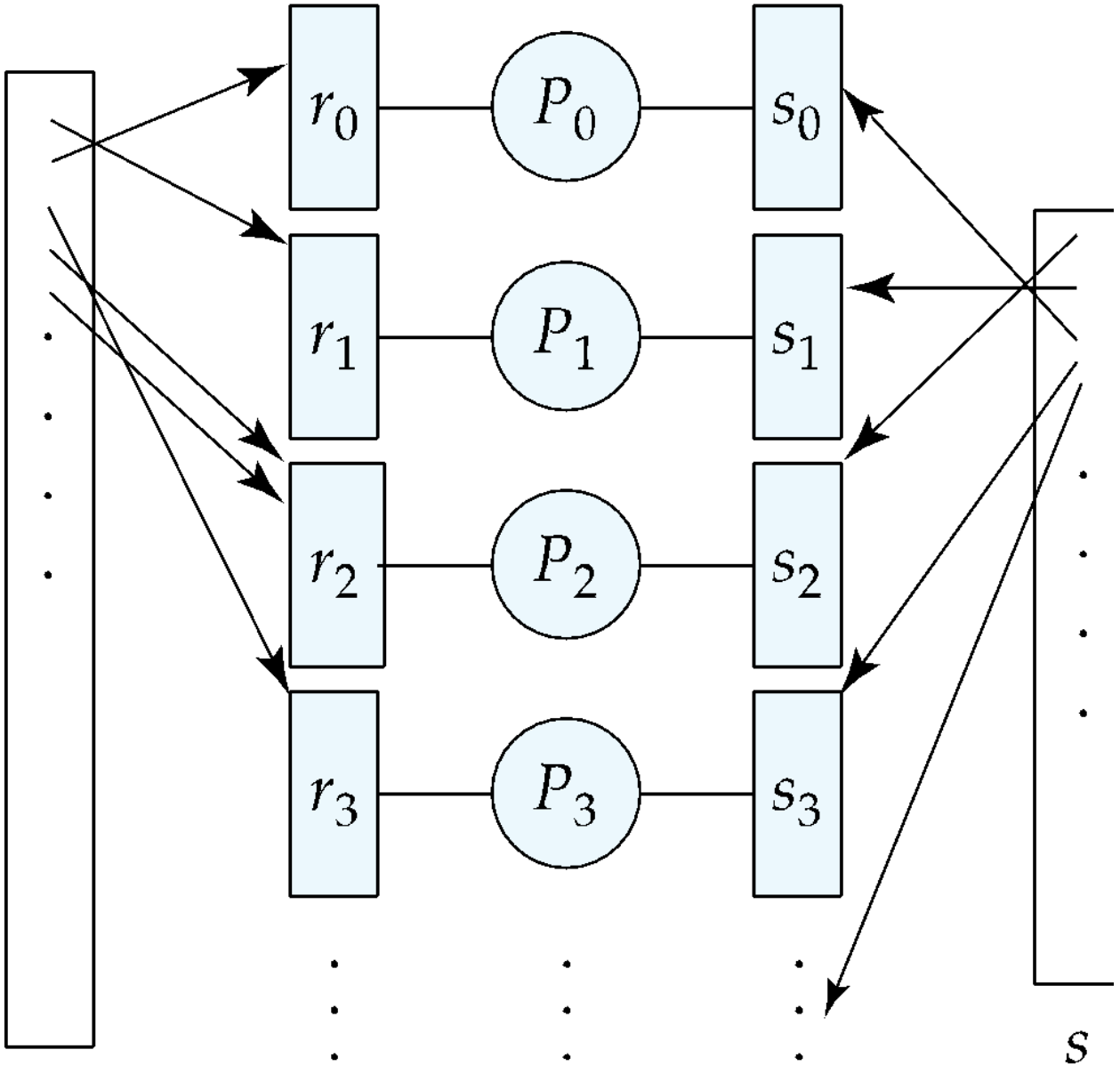
Parallel Join

- 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* *r.A=s.B* *s*.
- *r* and *s* each are partitioned into *n* partitions, denoted *r*0, *r*1, . . . , *m*-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 *r*i.A=si.B si. Any of the standard join methods can be used.

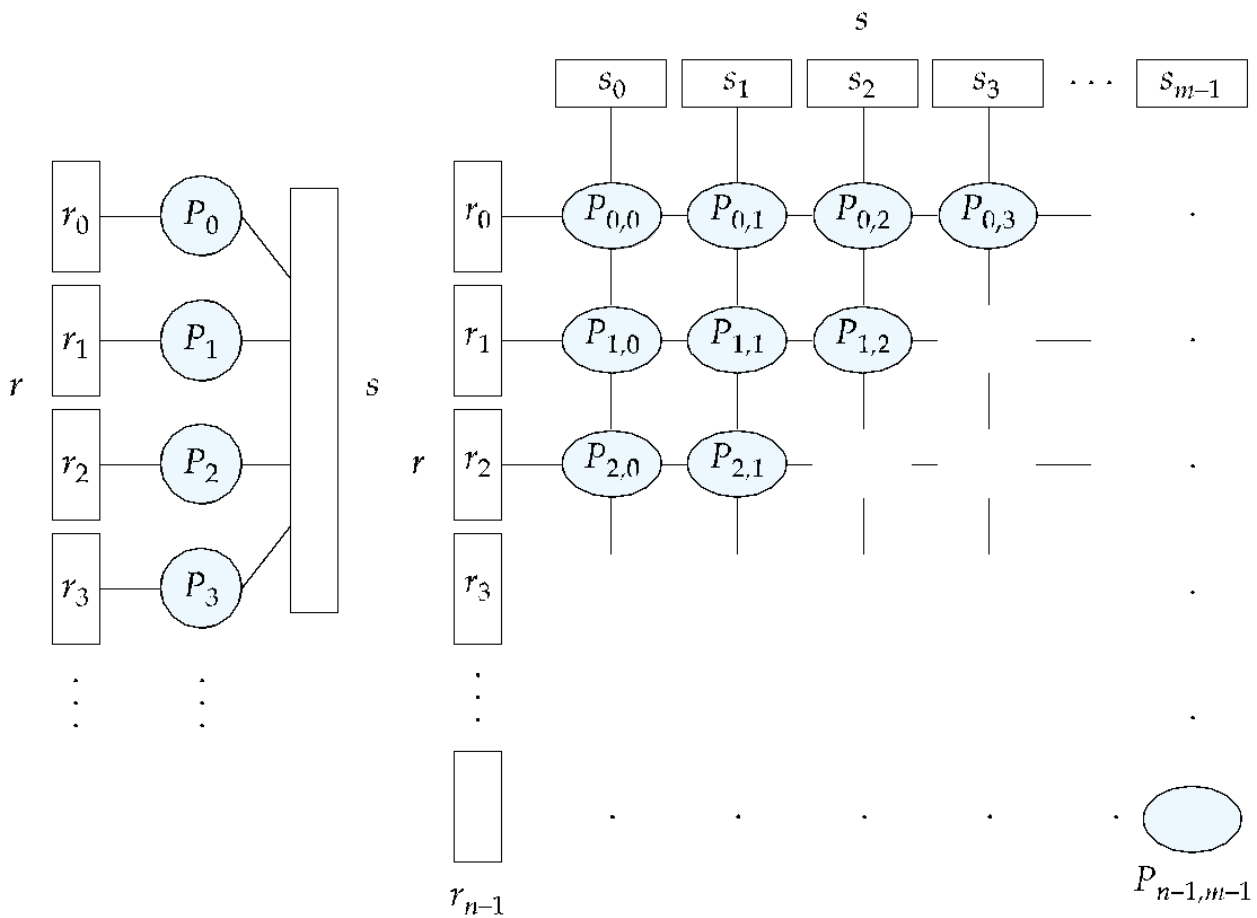
Partitioned Join (Cont.)



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*-1*m*-1.
  - *P**i,j* computes the join of *r**i* with ***sj. In order to do so, ri*** is replicated to ***Pi,0, Pi***,1, . . . , ***Pi,m-1, while si is replicated to P0,i, P1,i, . . . , Pn***-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

- Parallelizing partitioned hash join:
  - 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 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, *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 $h1$
  - Let ri 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 Pi 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**j* where a partition of relation *s* is stored reads the tuples of relation *s* stored in ***Dj, and replicates the tuples to every other processor Pi***.
  - 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
  - If thetha is of the form ai $=$ v, where ai is an attribute and v a value.
    - If r is partitioned on ai the selection is performed at a single processor.
  - If thetha is of the form l $<=$ ai $<=$ u (i.e., thetha is a range selection) and the relation has been range-partitioned on ai
    - 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 Pi on those tuples stored on disk Di
    - 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 Pi 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 Tpart + Tasm + max (T0, T1, . . . , Tn-1)
  - Tpart is the time for partitioning the relations
  - Tasm is the time for assembling the results
  - Ti is the time taken for the operation at processor Pi
    - 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
    - r1 $\bowtie$ r2 r3 r4
  - Set up a pipeline that computes the three joins in parallel
    - Let P1 be assigned the computation of temp1 = r1 r2
    - And P2 be assigned the computation of temp2 = temp1 r3
    - 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 r1 r2 r3 r4
    - Let P1 be assigned the computation of temp1 = r1 r2
    - And P2 be assigned the computation of temp2 = r3 r4
    - 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.