Parallel Databases; Map-Reduce

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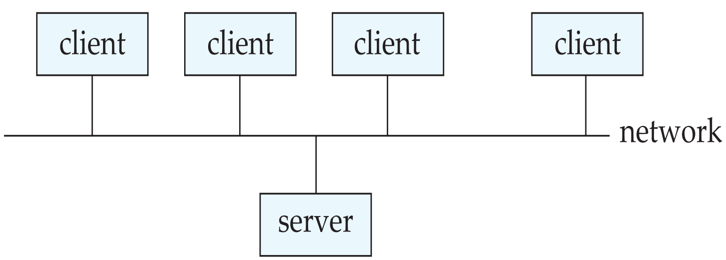
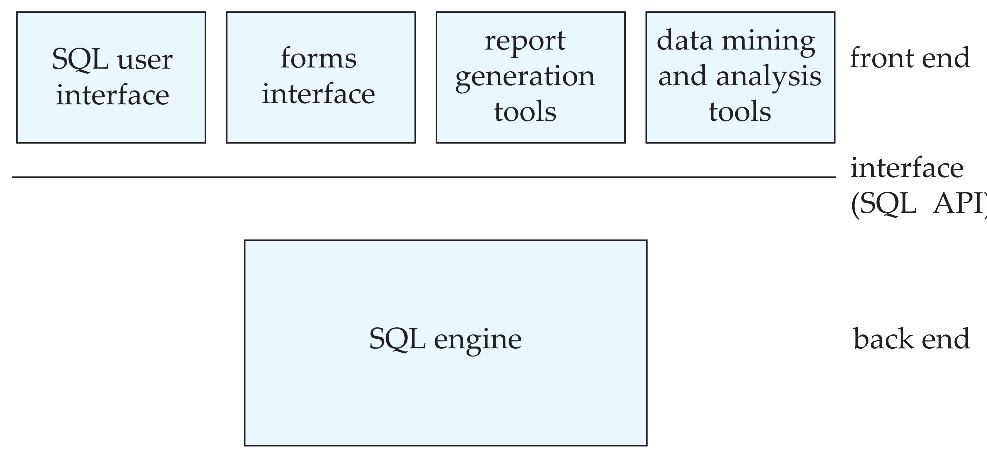
CMSC424

Client-Server Systems

- Database functionality can be divided into:
  - **Back-end**: manages access structures, query evaluation and optimization, concurrency control and recovery.
  - **Front-end**: consists of tools such as *forms*, *report-writers*, and graphical user interface facilities.
- The interface between the front-end and the back-end is through SQL or through an application program interface.





Parallel Databases

- Why ?
  - More transactions per second, or less time per query
  - Throughput vs. Response Time
  - Speedup vs. Scaleup
- Database operations are *embarrassingly parallel*
  - E.g. Consider a join between R and S on R.b = S.b
- But, perfect speedup doesn't happen
  - Start-up costs
  - Interference
  - Skew

Parallel Systems

- Parallel database systems consist of multiple processors and multiple disks connected by a fast interconnection network.
- A **coarse-grain parallel** machine consists of a small number of powerful processors
- A **massively parallel** or **fine grain parallel** machine utilizes thousands of smaller processors.
- Two main performance measures:
  - **throughput** --- the number of tasks that can be completed in a given time interval
  - **response time** --- the amount of time it takes to complete a single task from the time it is submitted

Speed-Up and Scale-Up

- **Speedup**: a fixed-sized problem executing on a small system is given to a system which is *N*-times larger.
  - Measured by:

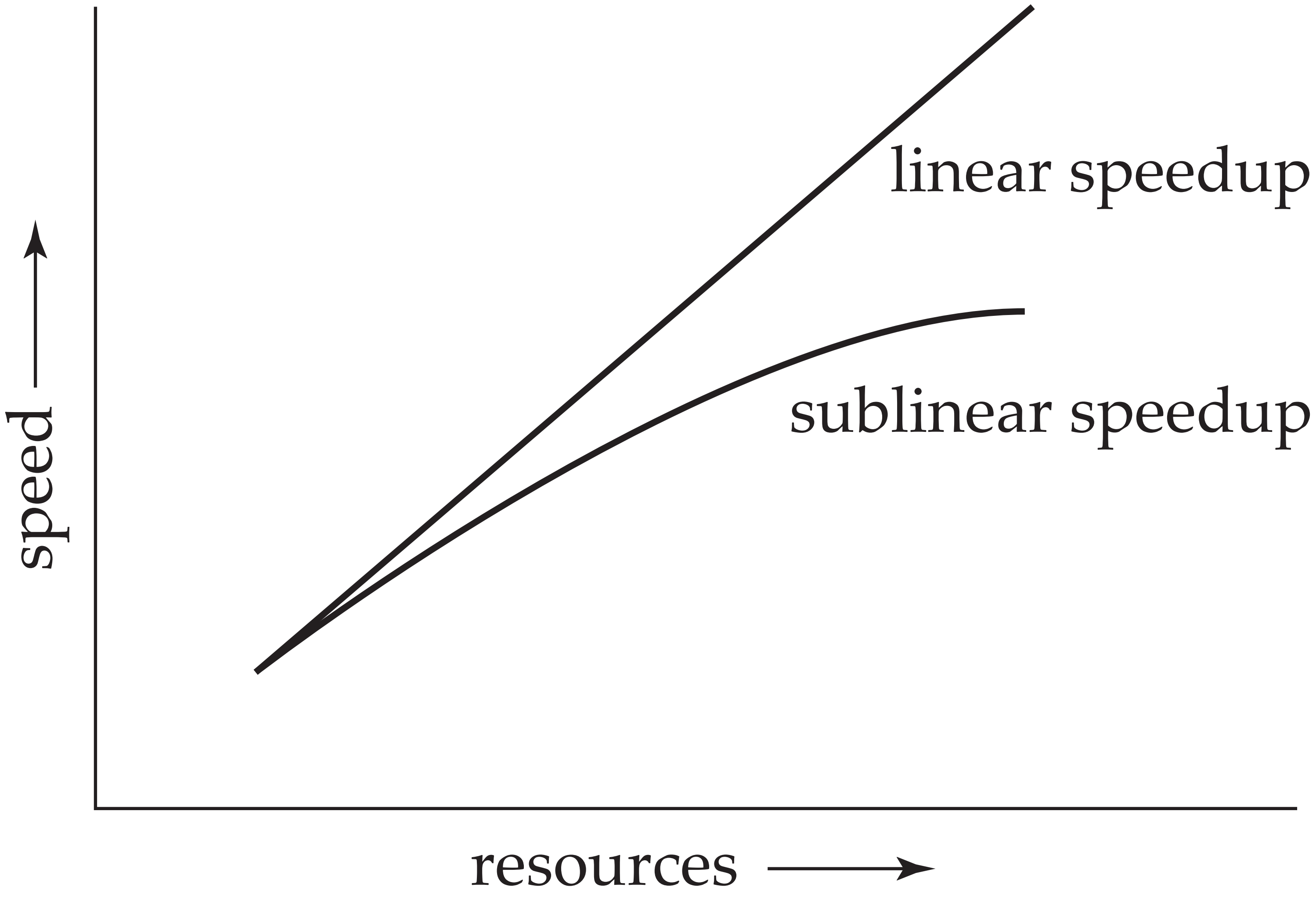
$$\textit{speedup} = \frac{\textit{small system elapsed time}}{\textit{large system elapsed time}}$$

  - Speedup is **linear** if equation equals N.
- **Scaleup**: increase the size of both the problem and the system
  - *N*-times larger system used to perform *N*-times larger job
  - Measured by:

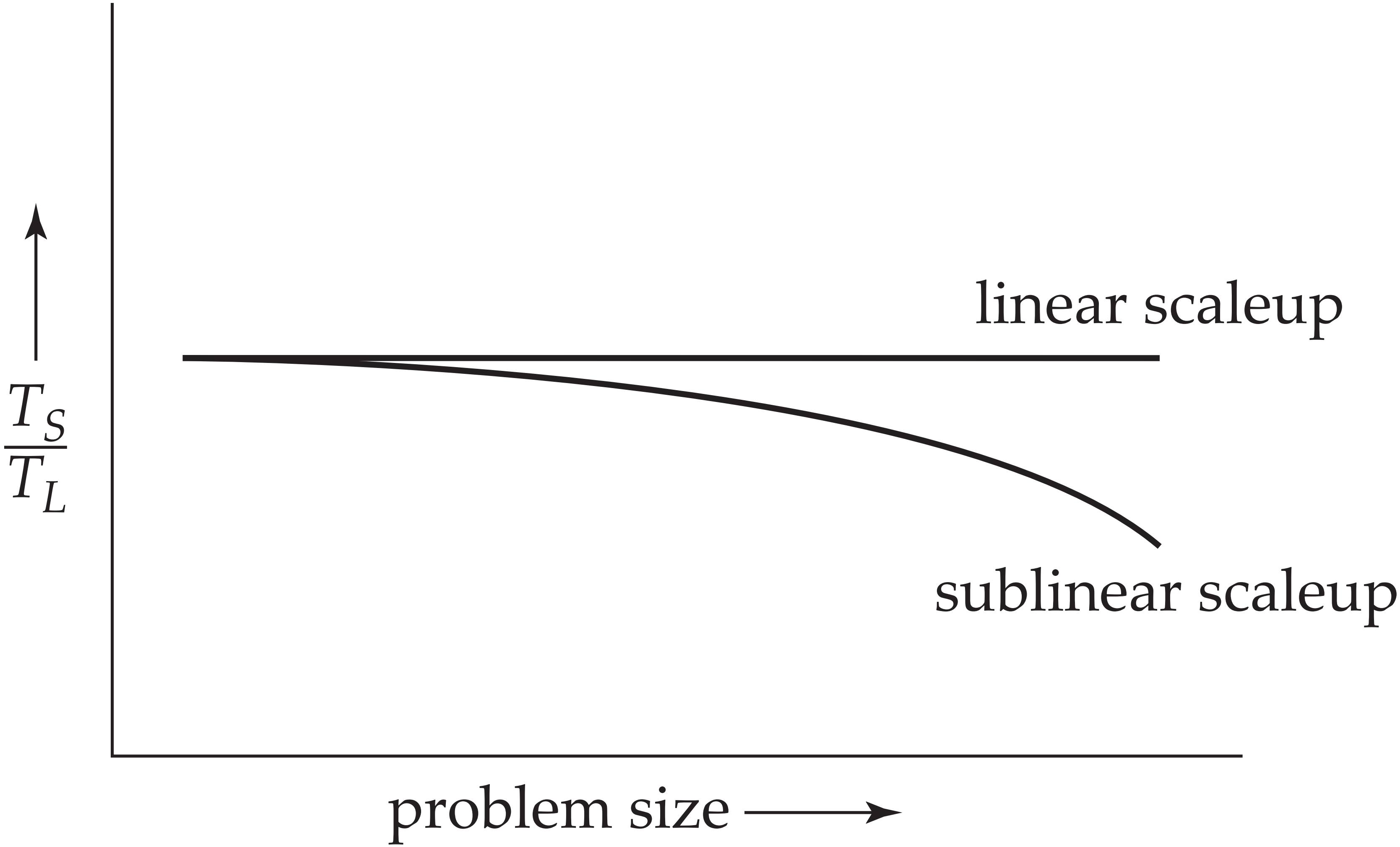
$$\textit{scaleup} = \frac{\textit{small system small problem elapsed time}}{\textit{big system big problem elapsed time}}$$

  - Scale up is **linear** if equation equals 1.

Speedup



Scaleup



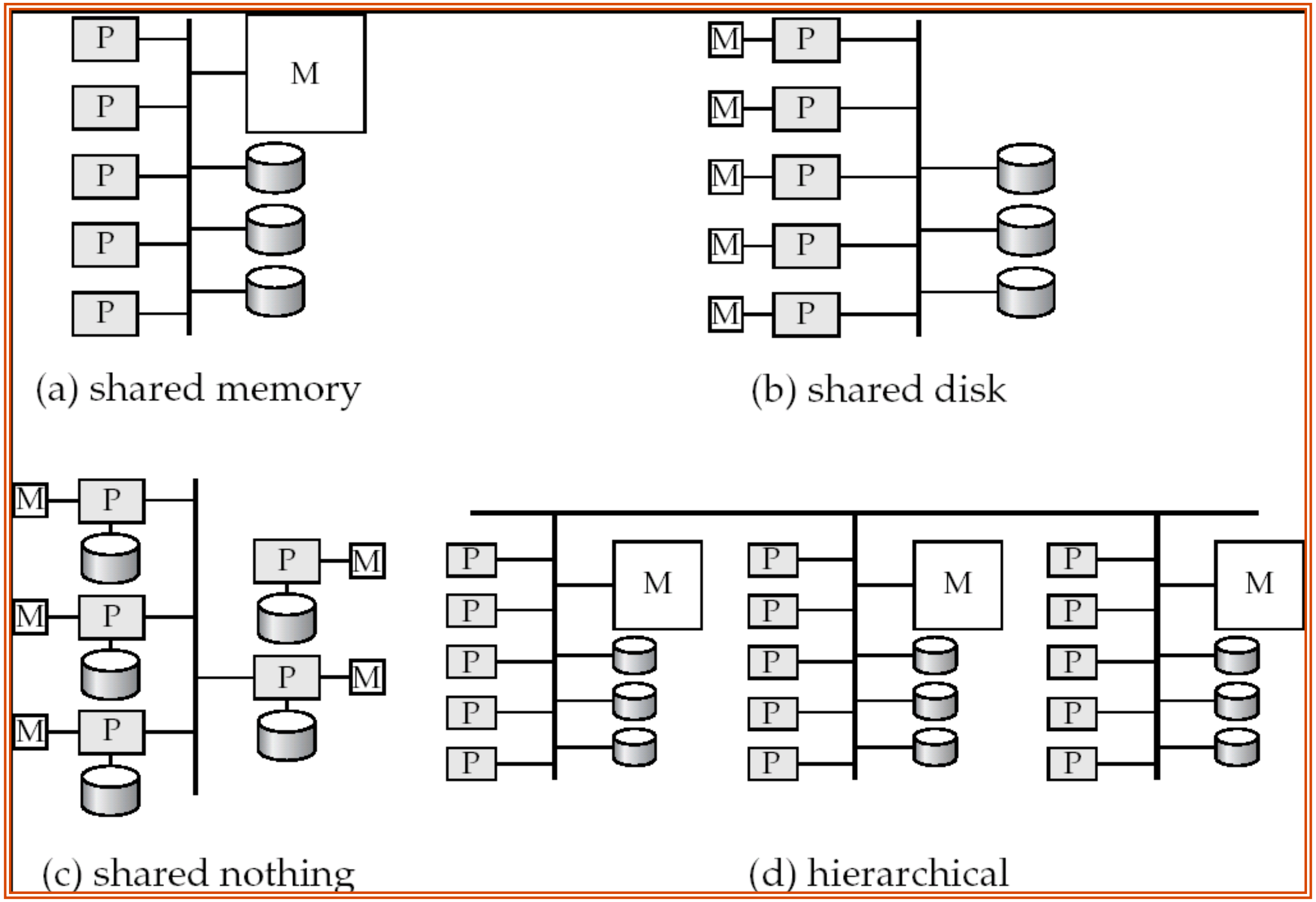
Factors Limiting Speedup and Scaleup

Speedup and scaleup are often sublinear due to:

- **Startup costs**: Cost of starting up multiple processes may dominate computation time, if the degree of parallelism is high.
- **Interference**: Processes accessing shared resources (e.g., system bus, disks, or locks) compete with each other, thus spending time waiting on other processes, rather than performing useful work.
- **Skew**: Increasing the degree of parallelism increases the variance in service times of parallely executing tasks. Overall execution time determined by **slowest** of parallely executing tasks.

Parallel Databases

- Shared-nothing vs. shared-memory vs. shared-disk



Parallel Databases

	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

Distributed Systems

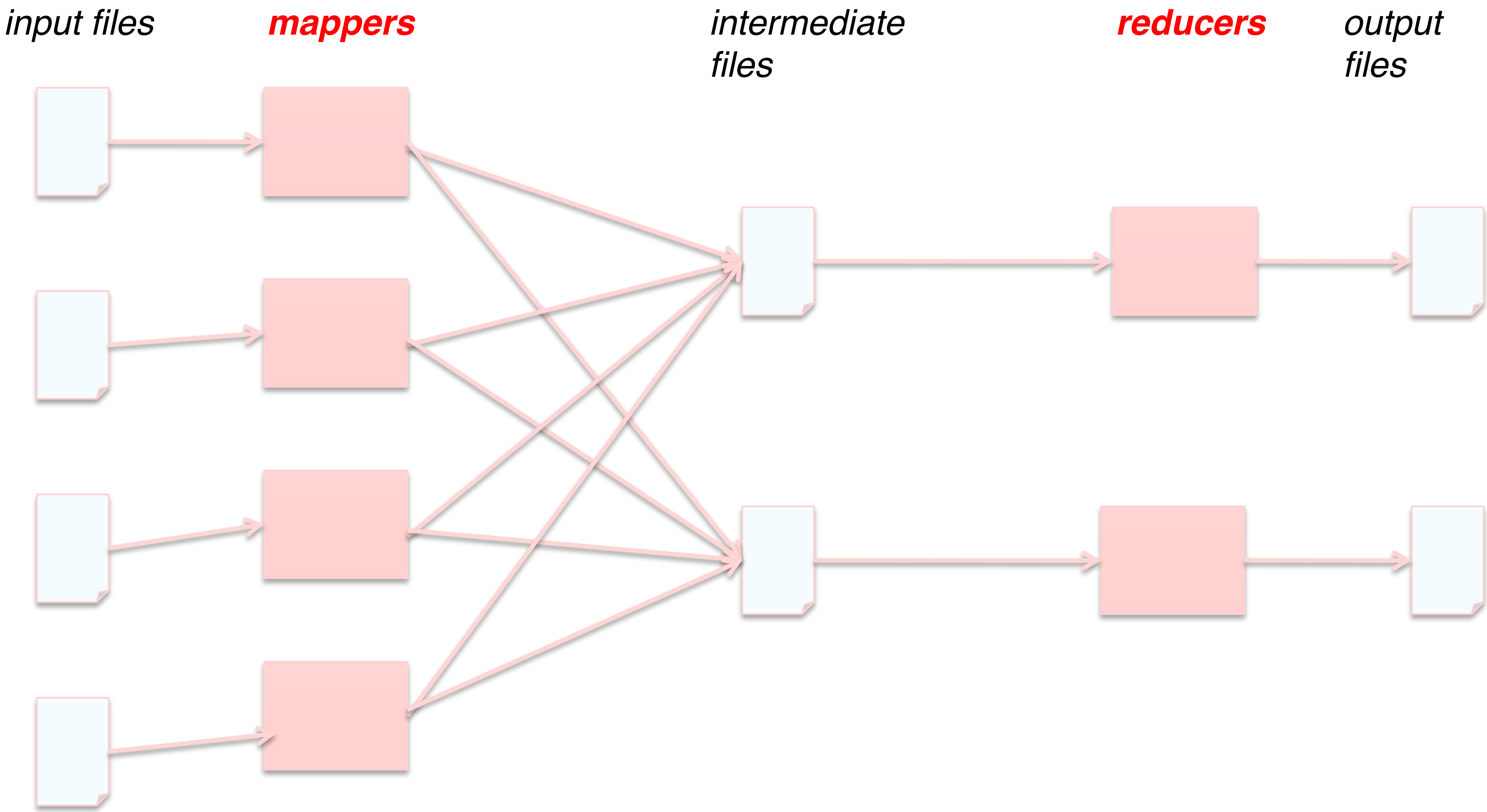
- Over a wide area network
- Typically not done for *performance reasons*
  - For that, use a parallel system
- Done because of necessity
  - Imagine a large corporation with offices all over the world
  - Also, for redundancy and for disaster recovery reasons
- Lot of headaches
  - Especially if trying to execute transactions that involve data from multiple sites
    - Keeping the databases in sync
      - *2-phase commit* for transactions uniformly hated
    - Autonomy issues
      - Even within an organization, people tend to be protective of their unit/ department
    - Locks/Deadlock management
  - Works better for query processing
    - Since we are only reading the data

MapReduce Framework

- Provides a fairly restricted, but still powerful abstraction for programming

- Programmers write a pipeline of functions, called *map* or *reduce*
  - map programs
    - inputs: a list of “records” (record defined arbitrarily – could be images, genomes etc…)
    - output: for each record, produce a set of “(key, value)” pairs
  - reduce programs
    - input: a list of “(key, {values})” grouped together from the mapper
    - output: whatever
  - Both can do arbitrary computations on the input data as long as the basic structure is followed

MapReduce Framework

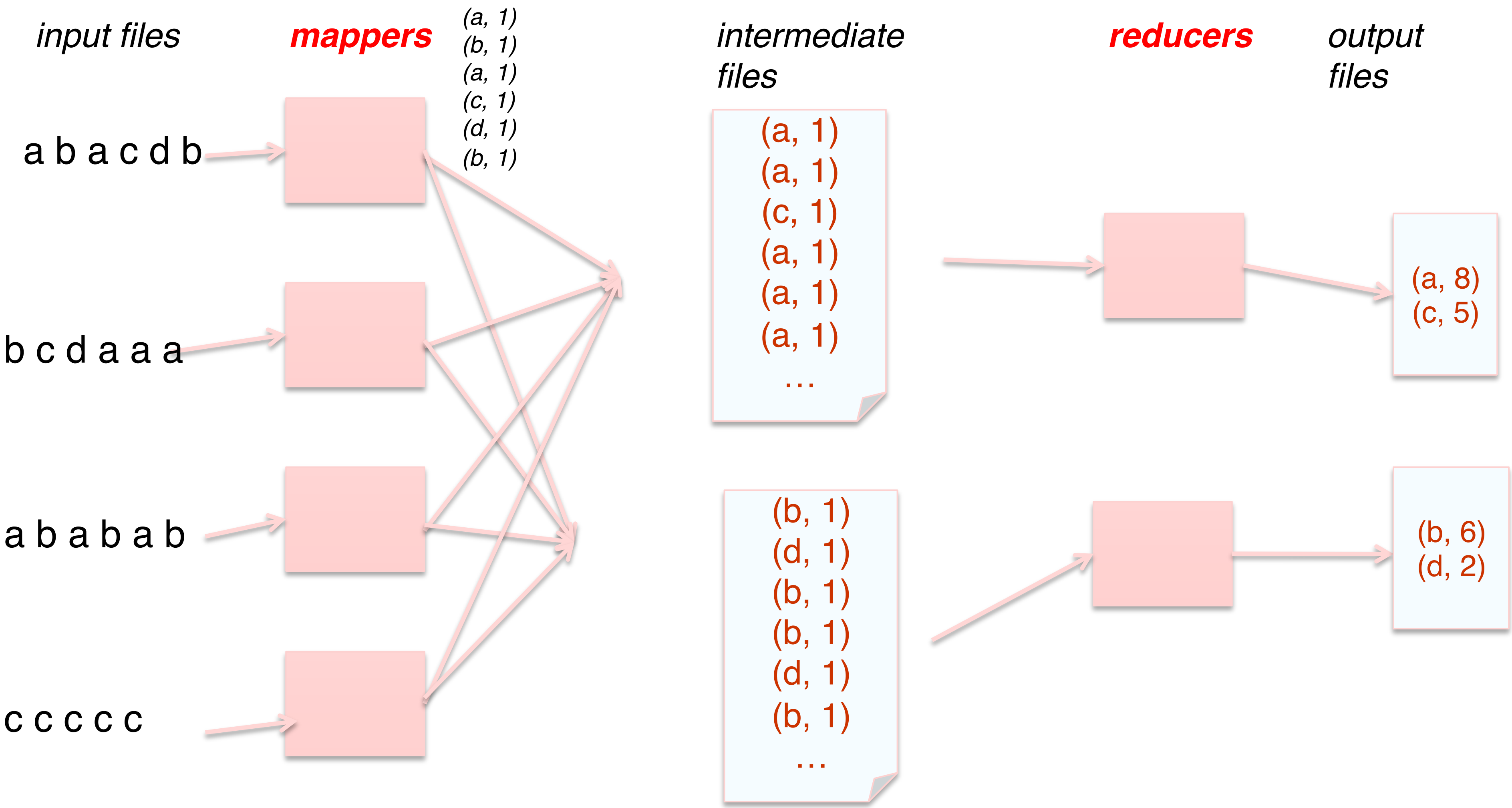


Word Count Example

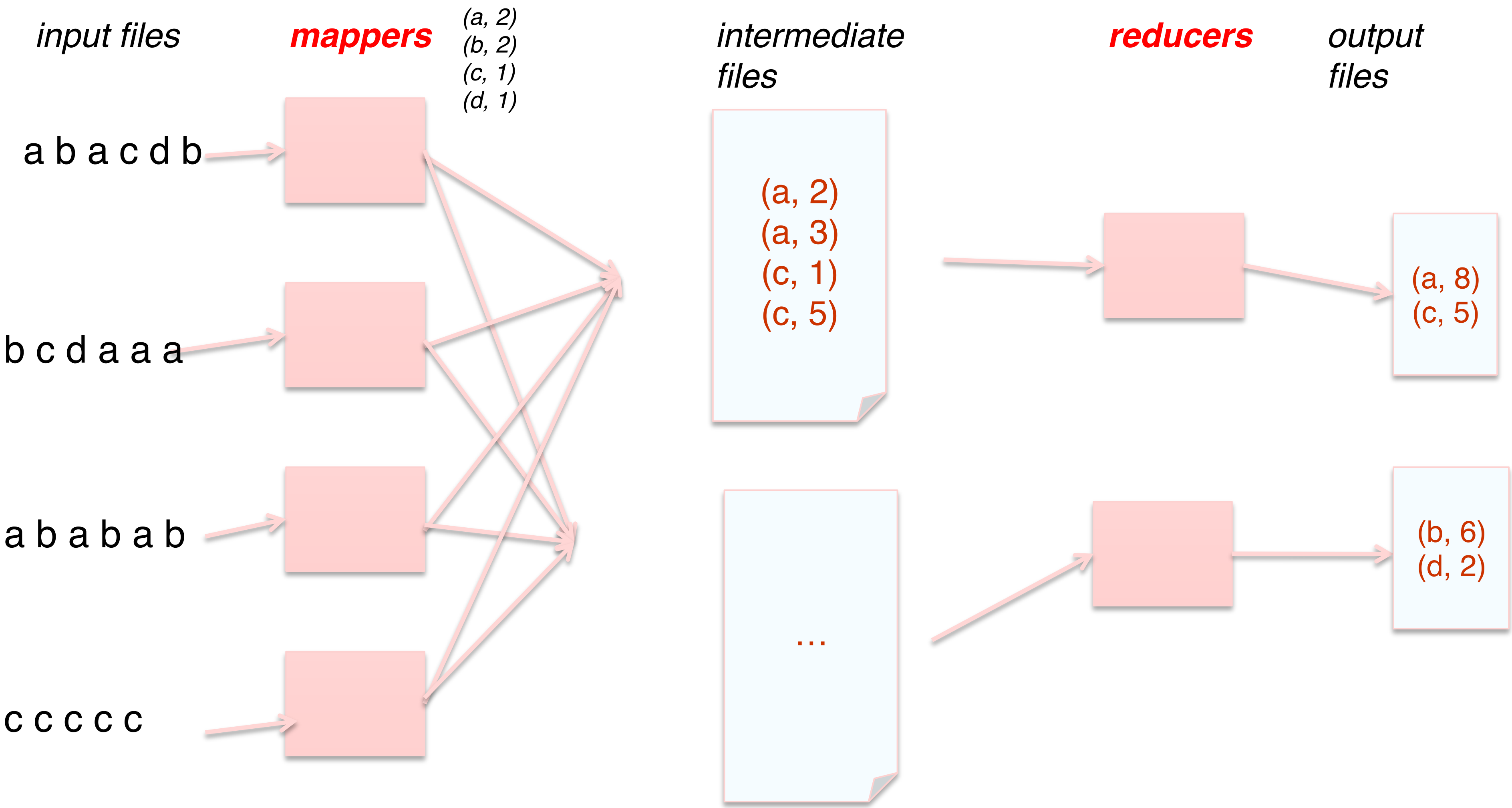
```
map(String key, String value):
  // key: document name
  // value: document contents
  for each word w in value:
    EmitIntermediate(w, "1");

reduce(String key, Iterator values):
  // key: a word
  // values: a list of counts
  int result = 0;
  for each v in values:
    result += ParseInt(v);
  Emit(AsString(result));
```

MapReduce Framework: Word Count



More Efficient Word Count



Called “mapper-side” combiner

Chapter 18: 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.

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_o, 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 $I + 1$. Tuples with $v < v_0$ go to disk 0 and tuples with $v \ge v_{n-2}$ 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.

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

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

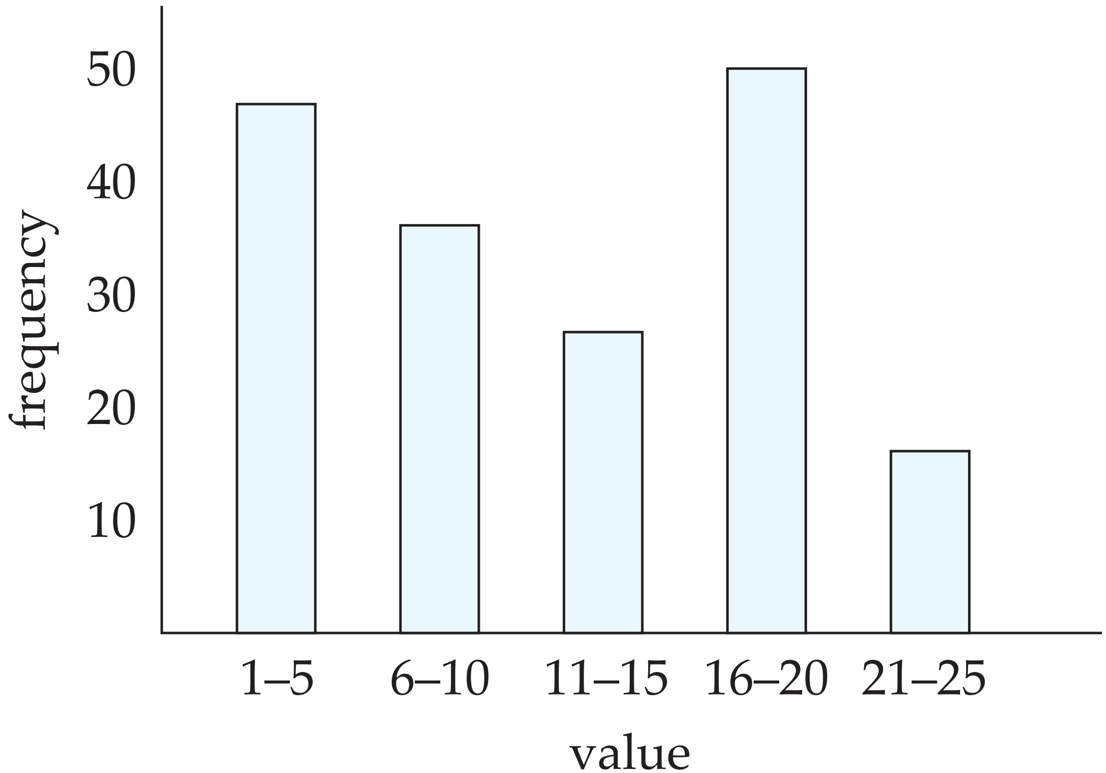
- The distribution of tuples to disks may be **skewed** — that is, some disks have many tuples, while others may have fewer tuples.
- **Types of skew:**
  - **Attribute-value skew**.
    - Some values appear in the partitioning attributes of many tuples; all the tuples with the same value for the partitioning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



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, $P_0, \ldots, P_{n-1}$, and n disks $D_0, \ldots, D_{n-1}$, 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 $m \leq n$ -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.
  - 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 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.

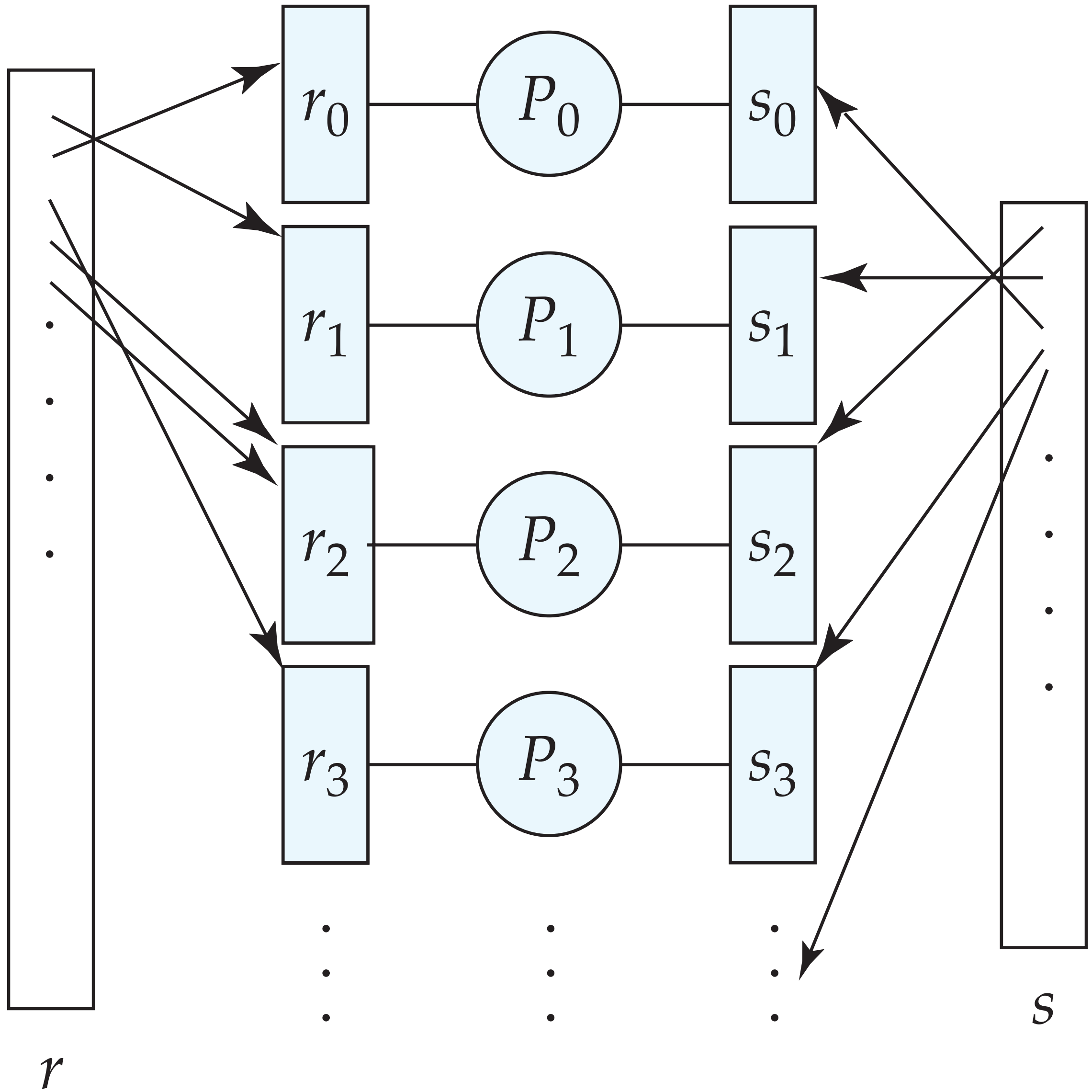
Parallel Join

- 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.

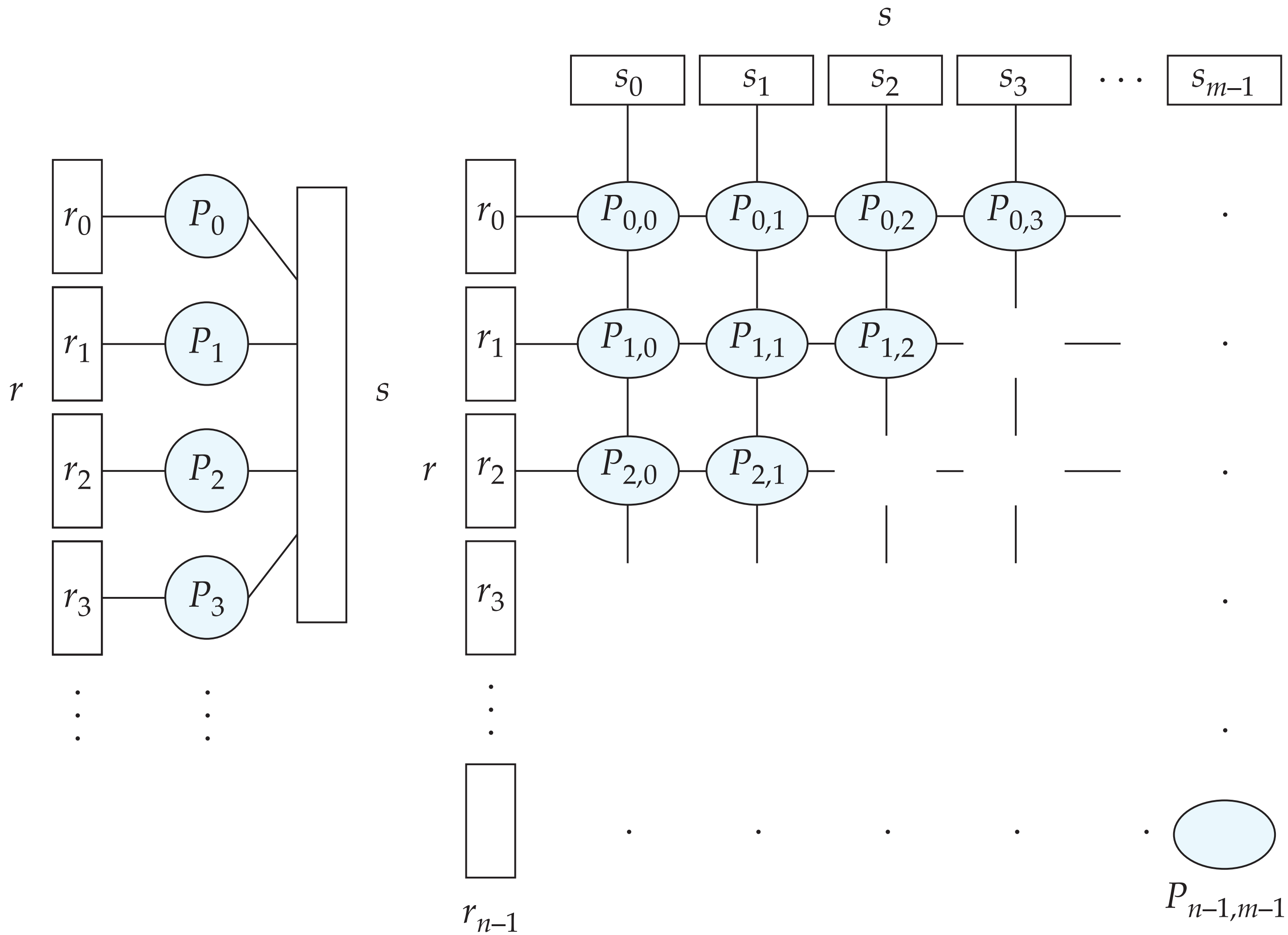
Partitioned Join (Cont.)



Fragment-and-Replicate Join

- Partitioning not possible for some join conditions
  - E.g., non-equijoin conditions, such as r.A > s.B.
- 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

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 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* 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*.

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 $l <= a_i <= u$ (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.

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

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

  - 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.

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

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 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.

