Chapter 22: Parallel and Distributed Query Processing

Database System Concepts, 7th Ed.

Chapter 22: Parallel And Distributed Query Processing

- Overview
- Parallel Sort
- Parallel Join
- Other Operations
- Parallel Evaluation of Query Plans
- Query Processing on Shared Memory
- Query Optimization
- Distributed Query Processing

Parallel Query Processing

- Different queries/transactions can be run in parallel with each other.
  - **Interquery parallelism**
  - Concurrency control takes care of conflicts in case of updates
  - More on parallel transaction processing in Chapter 23
  - Focus in this chapter is on read-only queries
- 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.

Intraquery Parallelism

- **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
    - Supports high degree of parallelism
  - **Interoperation Parallelism** – execute the different operations in a query expression in parallel.
    - Limited degree of parallelism

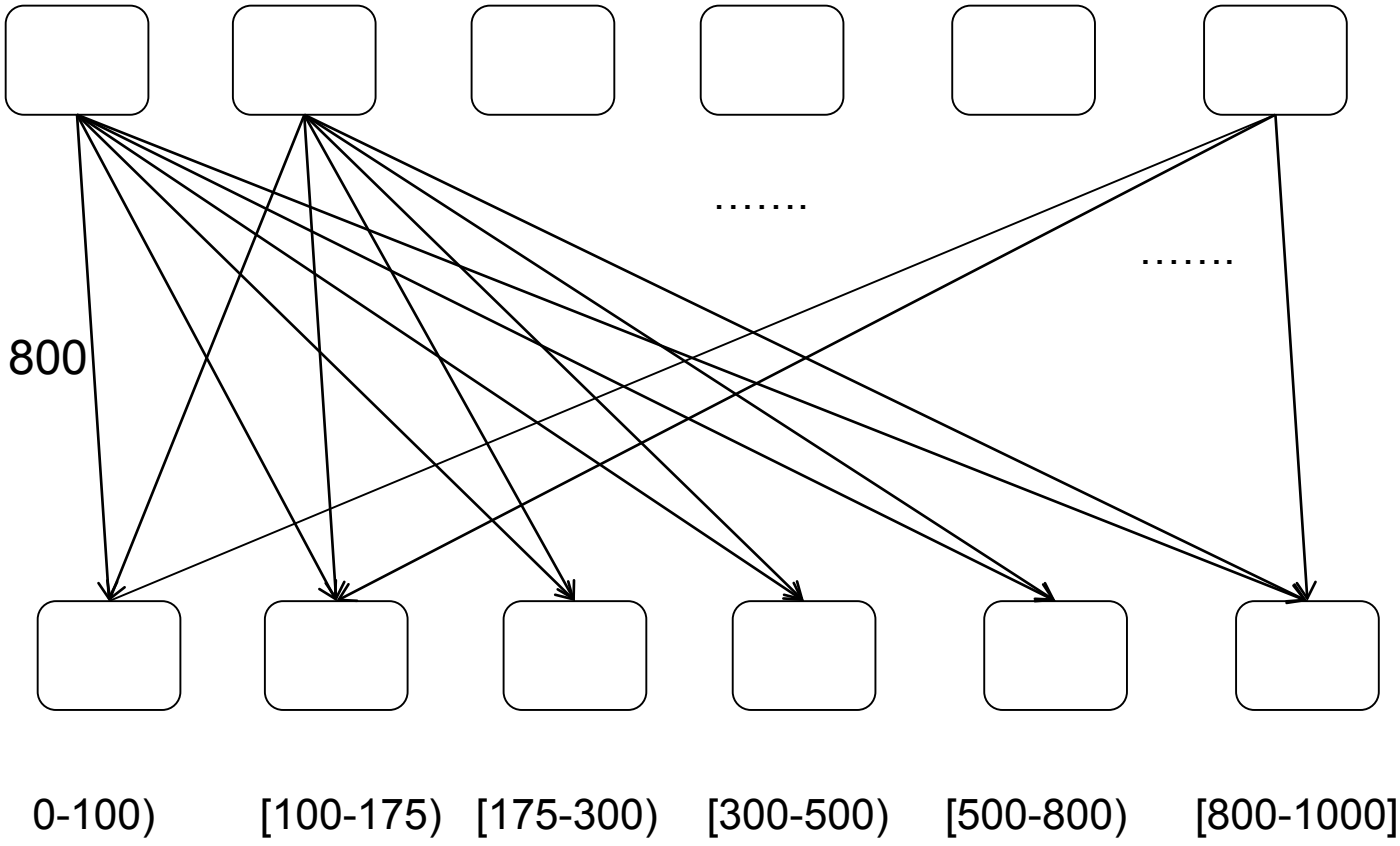
Parallel Processing of Relational Operations

- Our discussion of parallel algorithms assumes:
  - *read-only* queries
  - shared-nothing architecture
  - *n* nodes, N_1, ..., N_n
    - *Each assumed to have disks and processors*.
  - Initial focus on parallelization to a shared-nothing node
    - Parallel processing within a shared memory/shared disk node discussed later
  - 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

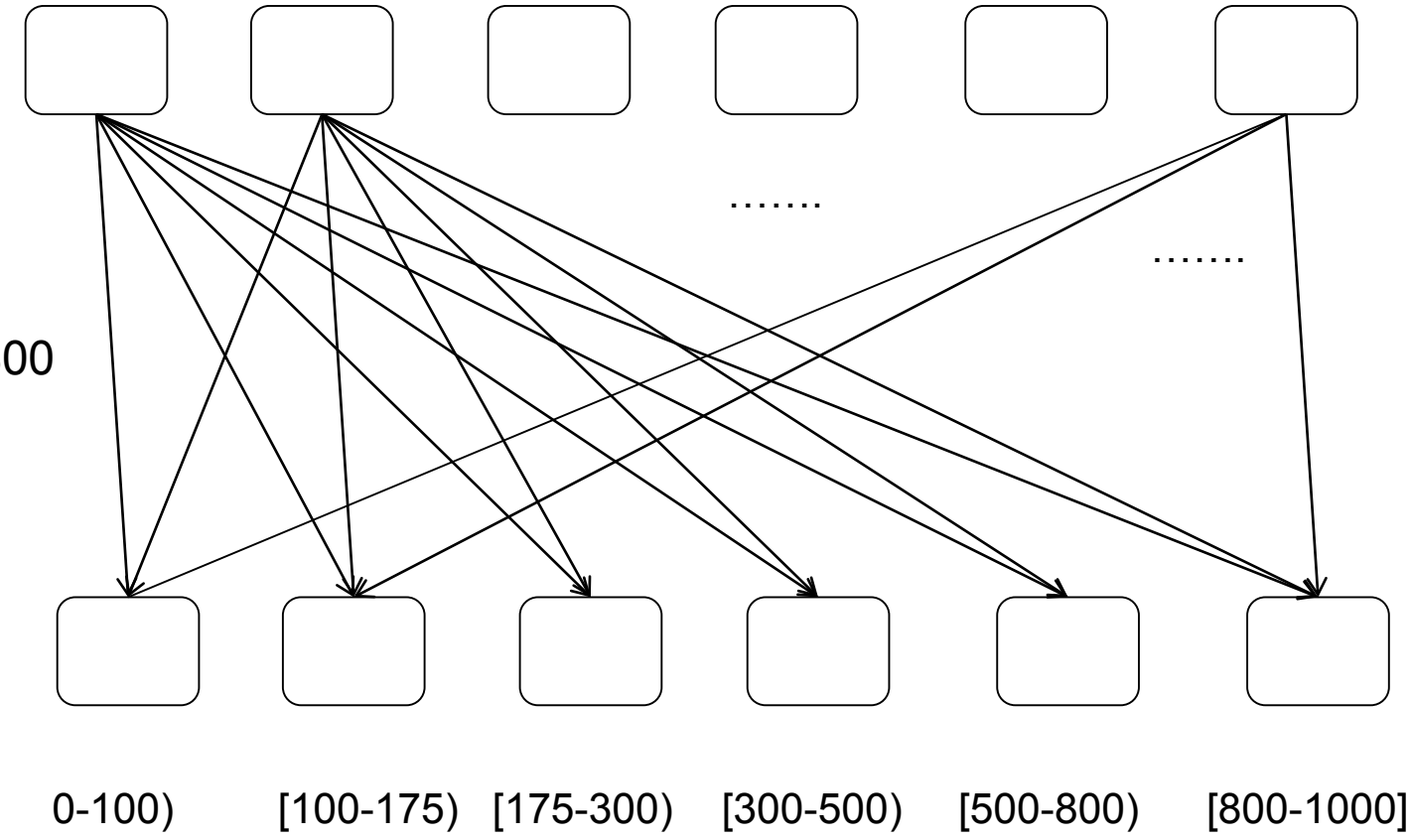
Range Partitioning

Redistribute using partitioning vector: 100, 175, 300, 500, 800



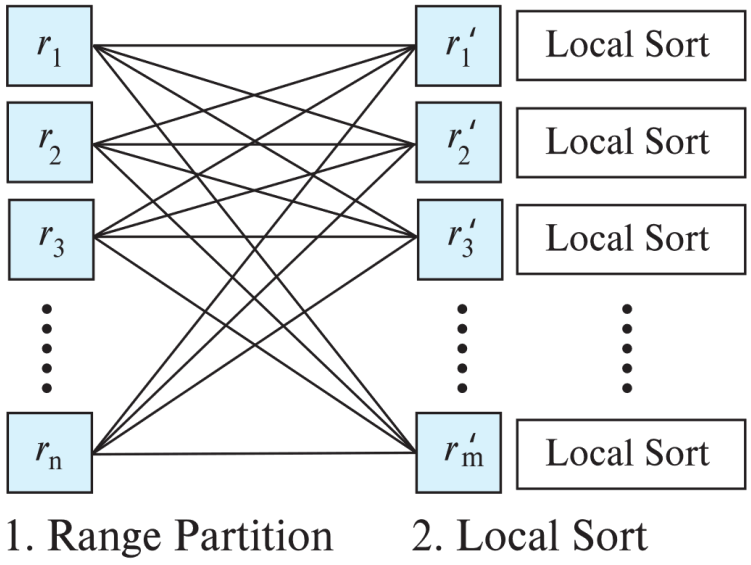
Range-Partitioning Parallel Sort

1) Redistribute using **partitioning vector**:
100, 175, 300, 500, 800

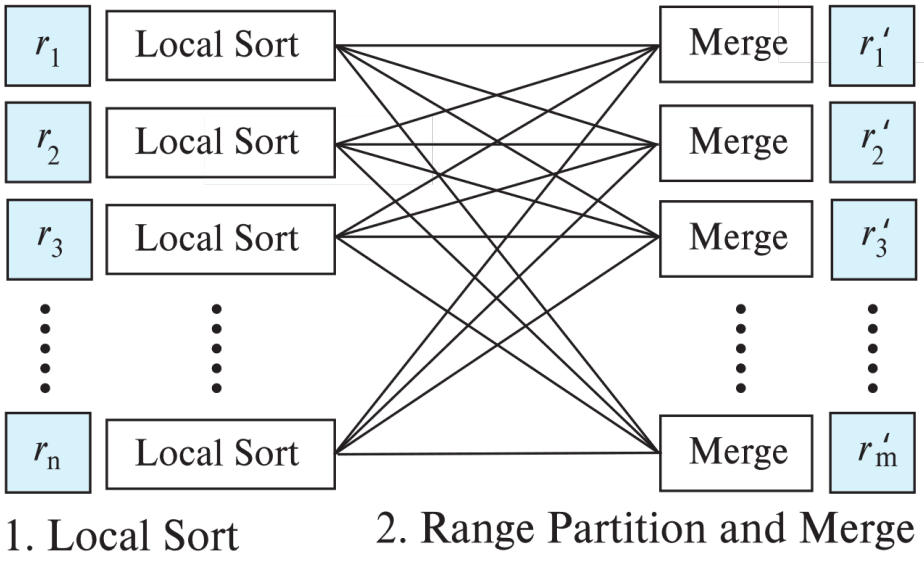


2) (External) sort locally at each node
3) Merge if output required at one node

Parallel Sort



(a) Range Partitioning Sort



(b) Parallel External Sort-Merge

Parallel Sort

Range-Partitioning Sort

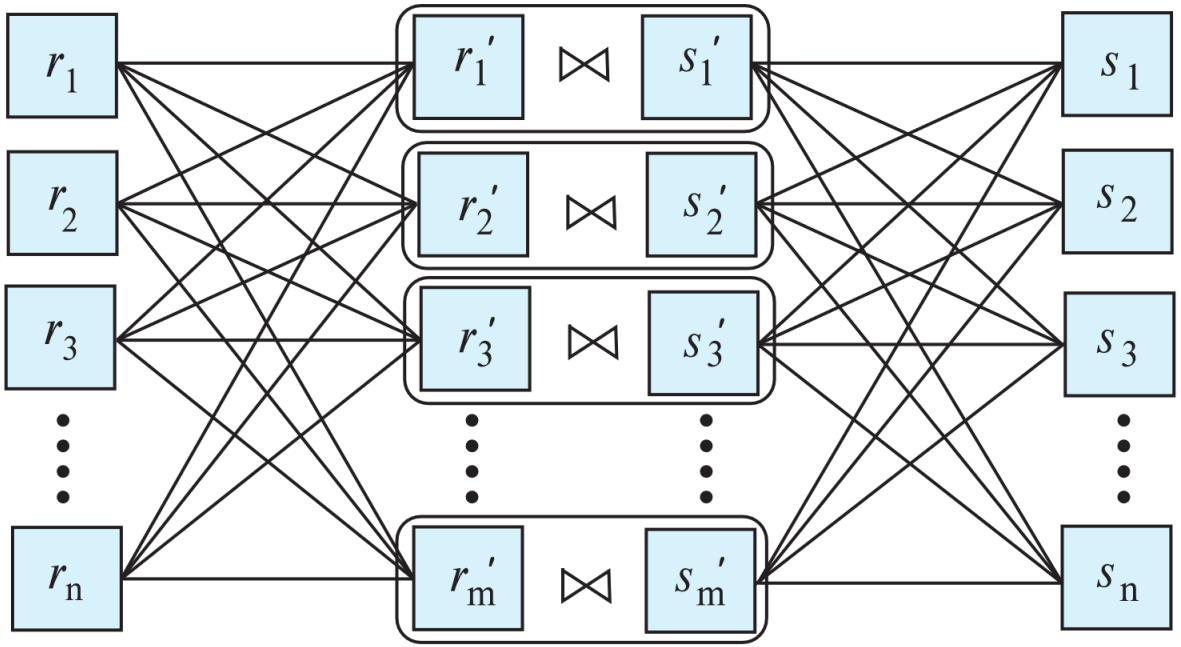
- Choose nodes N_1, ..., N_m, where $m \leq n$ -1 to do sorting.
- Create range-partition vector with m-1 entries, on the sorting attributes
- Redistribute the relation using range partitioning
- Each node N_i sorts its partition of the relation locally.
  - Example of **data parallelism: e**ach node executes same operation in parallel with other nodes, without any interaction with the others.
- Final merge operation is trivial: range-partitioning ensures that, if i < j, all key values in node N_i are all less than all key values in N_j.

Parallel Sort (Cont.)

Parallel External Sort-Merge

- Assume the relation has already been partitioned among nodes N1, ..., Nn (in whatever manner).
- Each node Ni locally sorts the data (using local disk as required)
- The sorted runs on each node are then merged in parallel:
  - The sorted partitions at each node Ni are range-partitioned across the processors N1, ..., Nm.
  - Each node Ni performs a merge on the streams as they are received, to get a single sorted run.
  - The sorted runs on nodes N1,..., Nm are concatenated to get the final result.
- Algorithm as described vulnerable to execution skew
  - all nodes send to node 1, then all nodes send data to node 2, …
  - Can be modified so each node sends data to all other nodes in parallel (block at a time)

Partitioned Parallel Join



Step 1: Partition r Step 2: Partition s

Step 3: Each node N_i computes $r_i' \bowtie s_i'$

Partition using range or hash partitioning, on join attributes

Partitioned Parallel Join (Cont.)

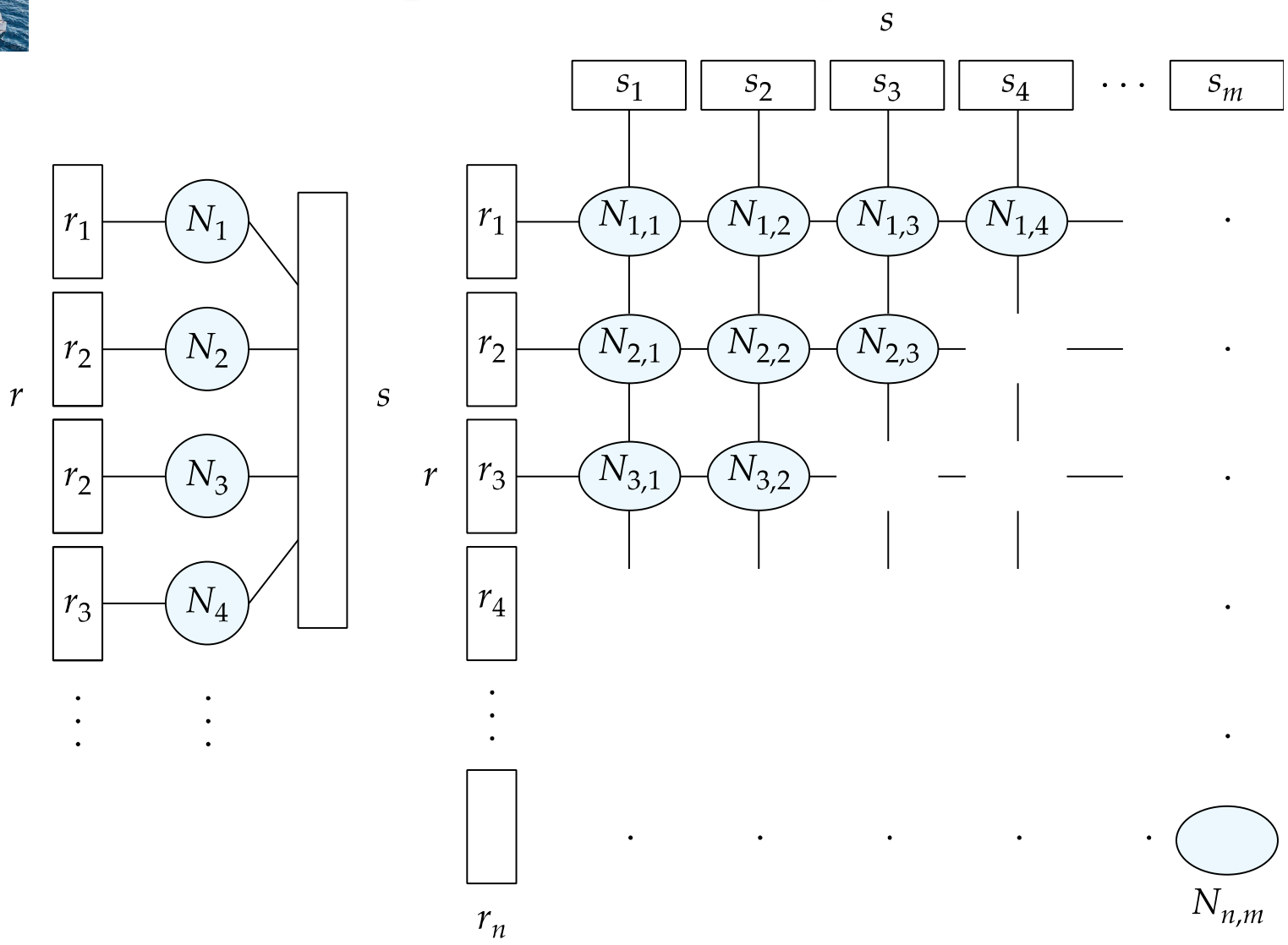
- For equi-joins and natural joins, it is possible to *partition* the two input relations across the processors, and compute the join locally at each processor.
- Can use either *range partitioning* or *hash partitioning*.
- *r* and *s* must be partitioned on their join attributes *r*.A and *s*.B), using the same range-partitioning vector or hash function.
- Join can be computed at each site using any of
  - Hash join, leading to **partitioned parallel hash join**
  - Merge join, leading to **partitioned parallel merge join**
  - Nested loops join, leading to **partitioned parallel nested-loops join** or **partitioned parallel index nested-loops join**

Partitioned Parallel Hash-Join

Parallelizing partitioned hash join:

- A hash function h_1 takes the join attribute value of each tuple in s and maps this tuple to one of the n nodes.
- As tuples of relation s are received at the destination nodes, they are partitioned further using another hash function, h_2, which is used to compute the hash-join locally.
- Repeat above for each tupe in r.
- Each node N_i executes the build and probe phases of the hash-join algorithm on the local partitions r_i and s_i of r and s to produce a partition of the final result of the hash-join.
- Note: Hash-join optimizations can be applied to the parallel case
  - e.g., the hybrid hash-join algorithm can be used to cache some of the incoming tuples in memory and avoid the cost of writing them and reading them back in.

Fragment-and-Replicate Joins



Asymmetric and Symmetric Fragment-and-Replicate Joins

Fragment-and-Replicate Join

- Partitioning not possible for some join conditions
  - e.g., non-equijoin conditions, such as r.A > s.B.
- For joins were partitioning is not applicable, parallelization can be accomplished by **fragment and replicate technique**
- Special case – **asymmetric fragment-and-replicate**:
  - One of the relations, say r, is partitioned; any partitioning technique can be used.
  - The other relation, s, is replicated across all the processors.
  - Node Ni then locally computes the join of ri with all of s using any join technique.
  - Also referred to as **broadcast join**

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., if *s* is small and *r* is large, and *r* is already partitioned, it may be cheaper to replicate *s* across all nodes, rather than repartition *r* and *s* on the join attributes.
- Question: how do you implement left outer join using above join techniques?

Handling Skew

- Skew can significantly slow down parallel join
- **Join skew avoidance**
  - Balanced partitioning vector
  - Virtual node partitioning
- **Dynamic handling of join skew**
  - Detect overloaded physical nodes
  - If a physical node has no remaining work, take on a waiting task (virtual node) currently assigned to a different physical node that is overloaded
  - Example of **work stealing**
    - Cheaper to implement in shared memory system, but can be used even in shared nothing/shared disk system

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 node.
- 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 node whose partition overlaps with the specified range of values.
- In all other cases: the selection is performed in parallel at all the nodes.

Other Relational Operations (Cont.)

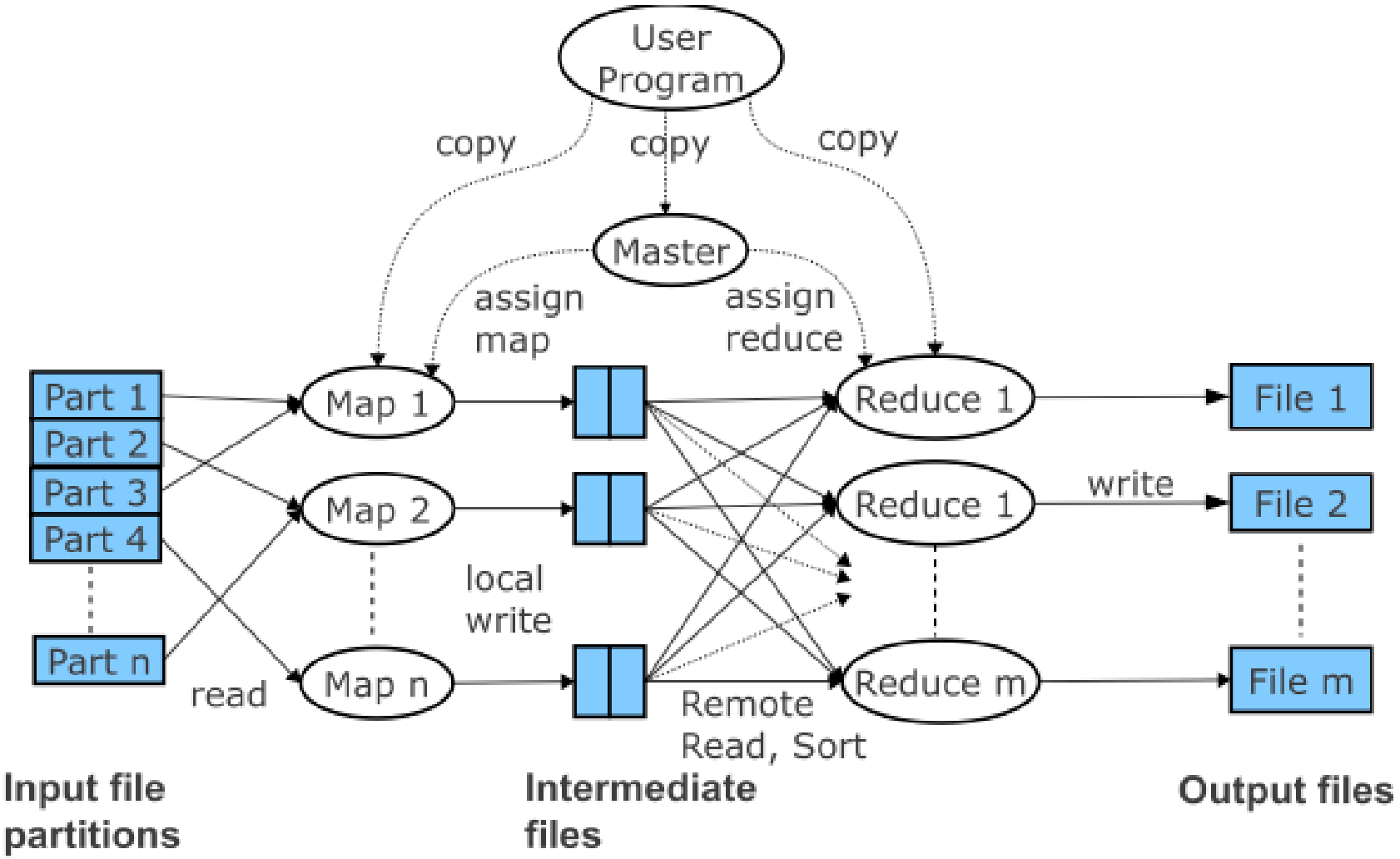
- **Duplicate elimination**
  - Perform by using either of the parallel sort techniques
    - eliminate duplicates as soon as they are found during sorting.
  - Can also partition the tuples (using either range- or hash-partitioning) and perform duplicate elimination locally at each node.

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

Grouping/Aggregation

- **Step 1**: Partition the relation on the grouping attributes
- **Step 2**: Compute the aggregate values locally at each node.
- **Optimization:** Can reduce cost of transferring tuples during partitioning by **partial aggregation** before partitioning
  - For distributive aggregate
  - Can be done as part of run generation
  - Consider the **sum** aggregation operation:
    - Perform aggregation operation at each node N_i on those tuples stored its local disk
      - results in tuples with partial sums at each node.
    - Result of the local aggregation is partitioned on the grouping attributes, and the aggregation performed again at each node N_i to get the final result.
  - Fewer tuples need to be sent to other nodes during partitioning.

Map and Reduce Operations



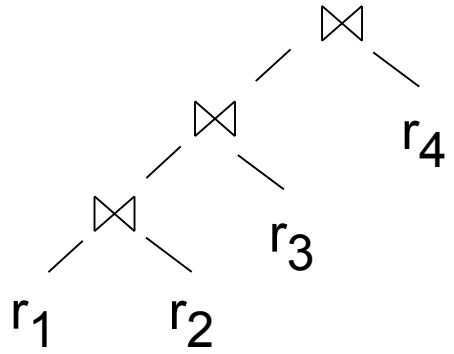
Map and Reduce Operations

- Map and reduce **workers**
  - Threads/processes that execute map and reduce functions
- Map and reduce **tasks**
  - Units of map and reduce work
  - Many more tasks than workers
    - Similar to virtual node partitioning
- Skew handling
  - **Straggler tasks**
    - Can be handled by initiating an extra copy of the task at another node
  - Partial aggregation (combiners) helps reduce skew at reduce nodes

PARALLEL EVALUATION OF QUERY PLANS

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

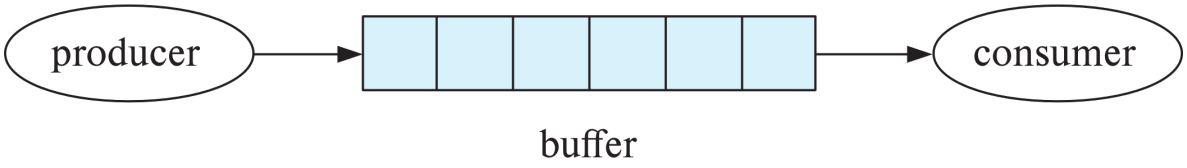


Each of these operations can execute in parallel, sending result tuples it computes to the next operation even as it is computing further results

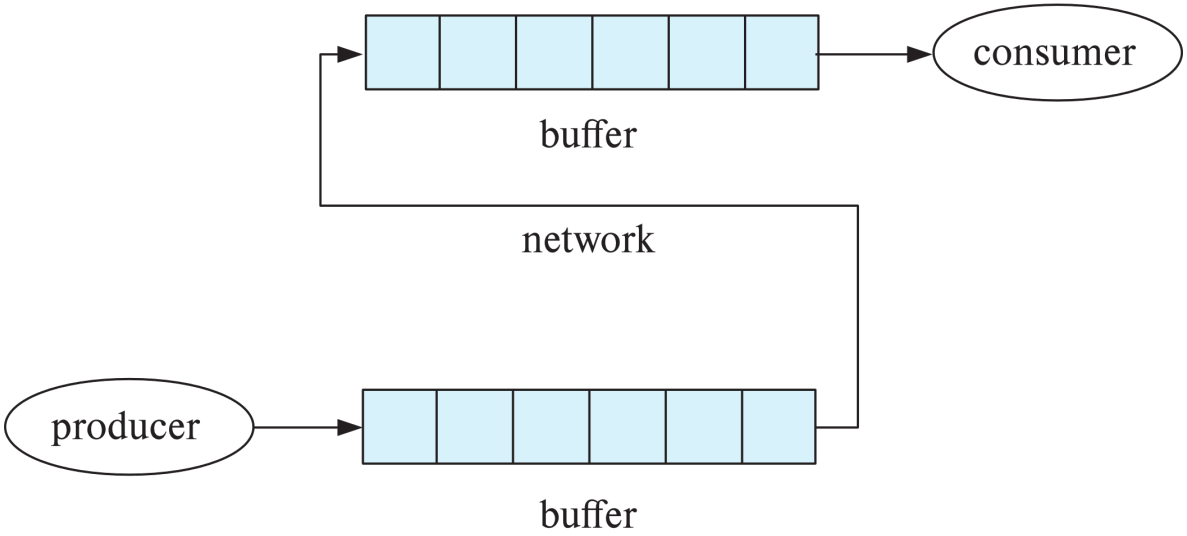
- Provided a pipelineable join evaluation algorithm (e.g. indexed nested loops join) is used

Pipelined Parallelism

- Push model of computation appropriate for pipelining in parallel databases
- Buffer between consumer and producer
- Can batch tuples before sending to next operator
  - Reduce number of messages,
  - reduce contention on shared buffers



(a) Producer-consumer in shared memory



(b) Producer-consumer across a network

Utility of Pipeline Parallelism

- Limitations
  - Does not provide a high degree of parallelism since pipeline chains are not very long
  - 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.
- But pipeline parallelism is still very useful since it avoids writing intermediate results to disk

Independent Parallelism

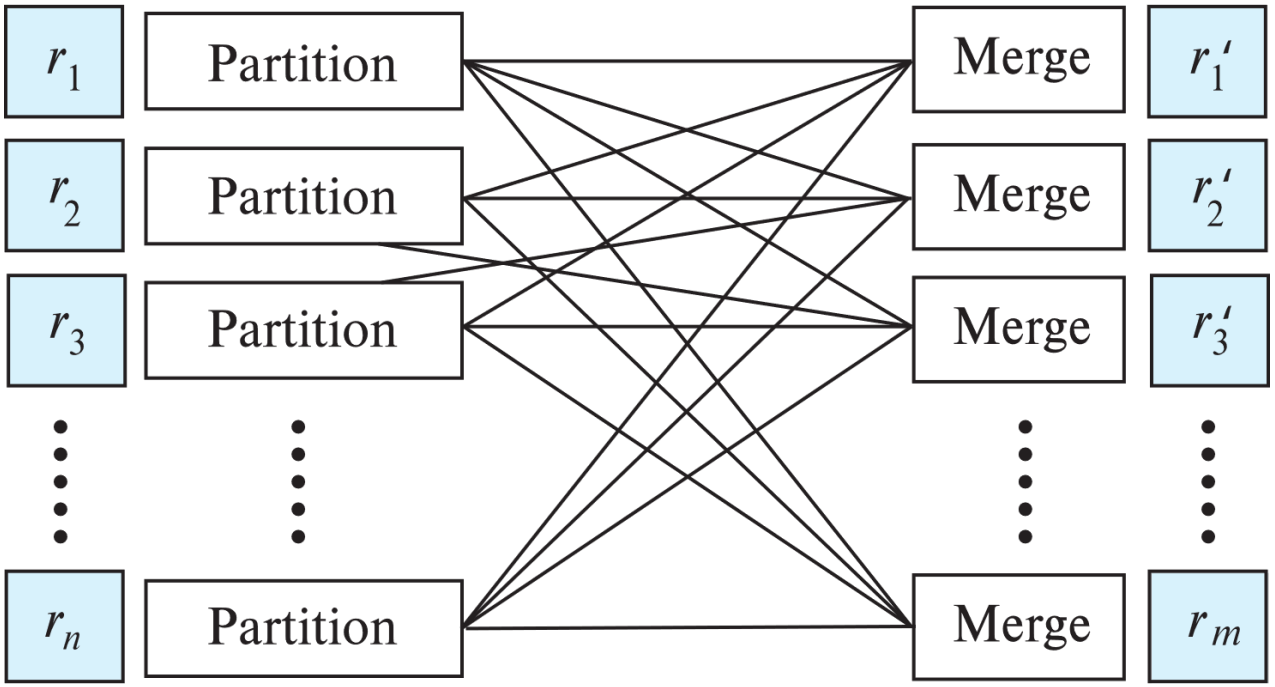
- **Independent parallelism**
  - Consider a join of four relations

    $r_1 \bowtie r_2 \bowtie r_3 \bowtie r_4$

    - Let N_1 be assigned the computation of temp1 = $r_1 \bowtie r_2$
    - And N_2 be assigned the computation of temp2 = $r_3 \bowtie r_4$
    - And N_3 be assigned the computation of temp1 $\bowtie$ $temp_2$
    - N_1 and N_2 can work **independently in parallel**
    - N_3 has to wait for input from N_1 and N_2
      - Can pipeline output of N_1 and N_2 to N_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,

Exchange Operator

- Repartitioning implemented using the **exchange operator**
  - **Partition** and **merge** steps



Exchange Operator Model

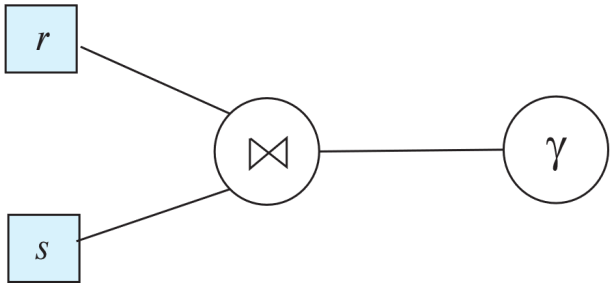
- Movement of data encapsulated in **exchange operator**
- Partitioning of data can be done by
  - Hash partitioning
  - Range partitioning
  - Replicating data to all nodes (called **broadcasting**)
  - Sending all data to a single node
- Destination nodes can receive data from multiple source nodes. Incoming data can be merged by:
  - **Random merge**
  - **Ordered merge**
- Other operators in a plan can be unaware of parallelism
  - **Data parallelism**: each operator works purely on local data
  - Not always best way, but works well in most cases

Parallel Plans Using Exchange Operator

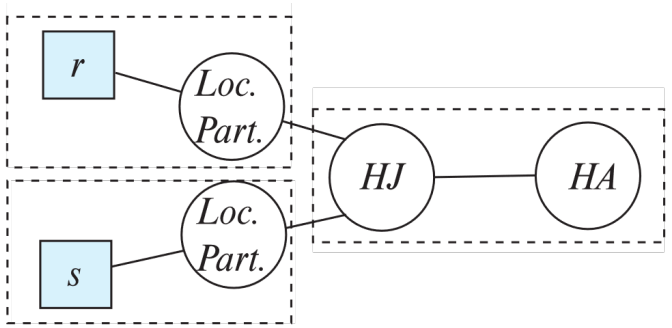
- Range partitioning sort:
  1. Exchange operator using range partitioning, followed by
  2. Local sort
- Parallel external sort merge
  1. Local sort followed by
  2. Exchange operator with ordered merge
- Partitioned join
  1. Exchange operator with hash or range partitioning, followed by
  2. Local join
- Asymmetric fragment and replicate
  1. Exchange operator using broadcast replication, followed by
  2. Local join
- Exchange operator can also implement push model, with batching

Parallel Plans

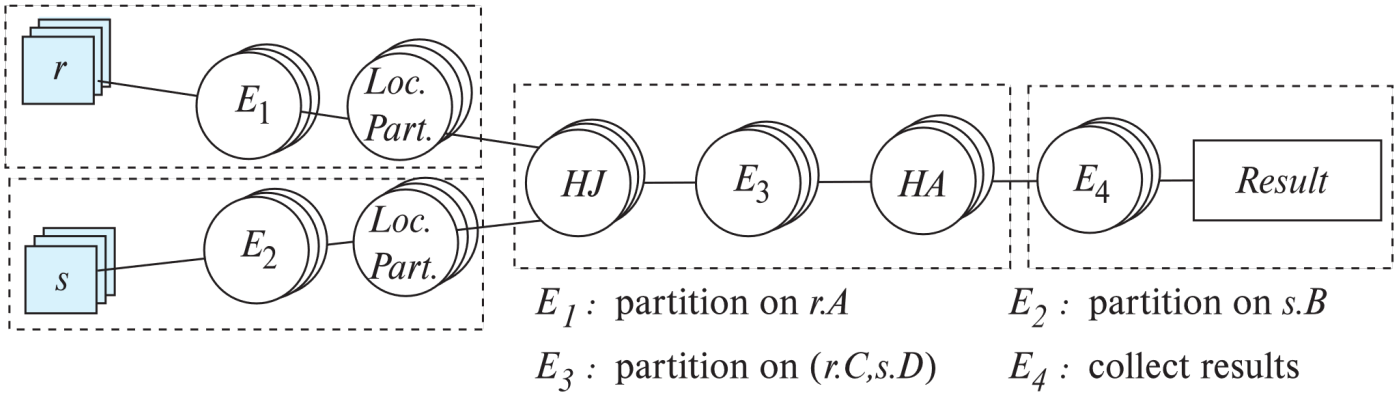
Dashed boxes denote pipelined segment



(a) Logical Query

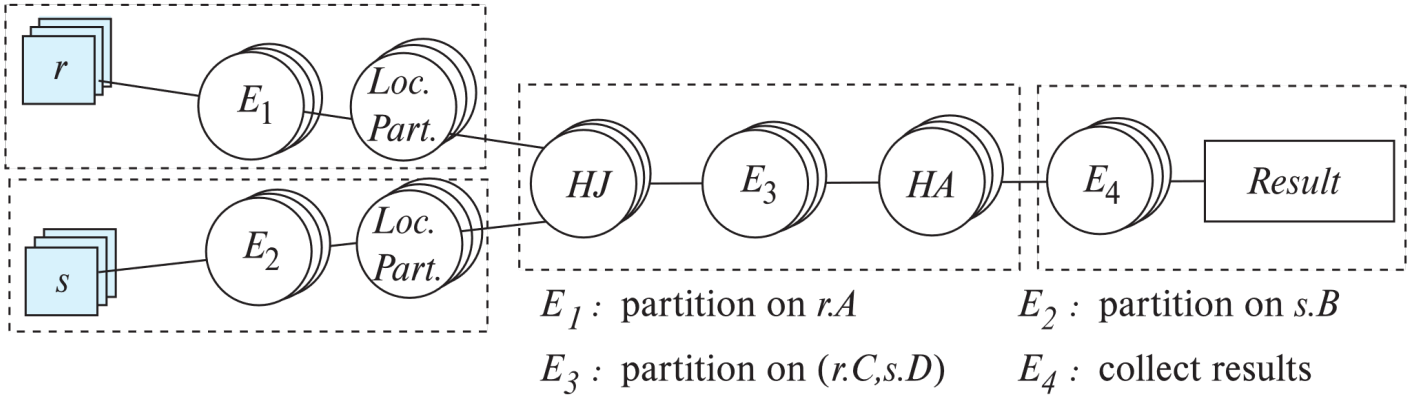


(b) Sequential Plan

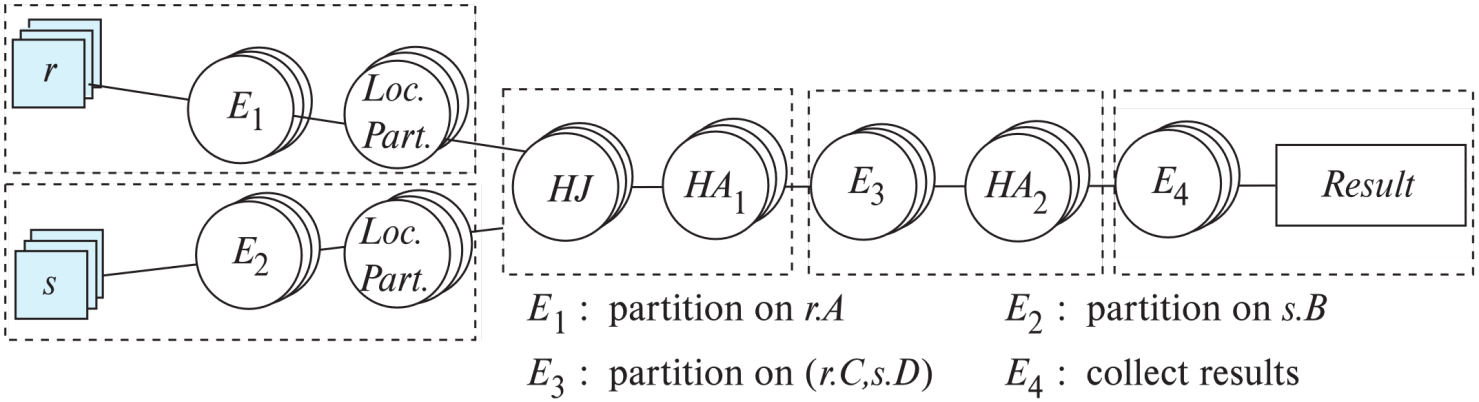


(c) Parallel Plan

Parallel Plans (Cont.)



(c) Parallel Plan



(c) Parallel Plan with Partial Aggregation

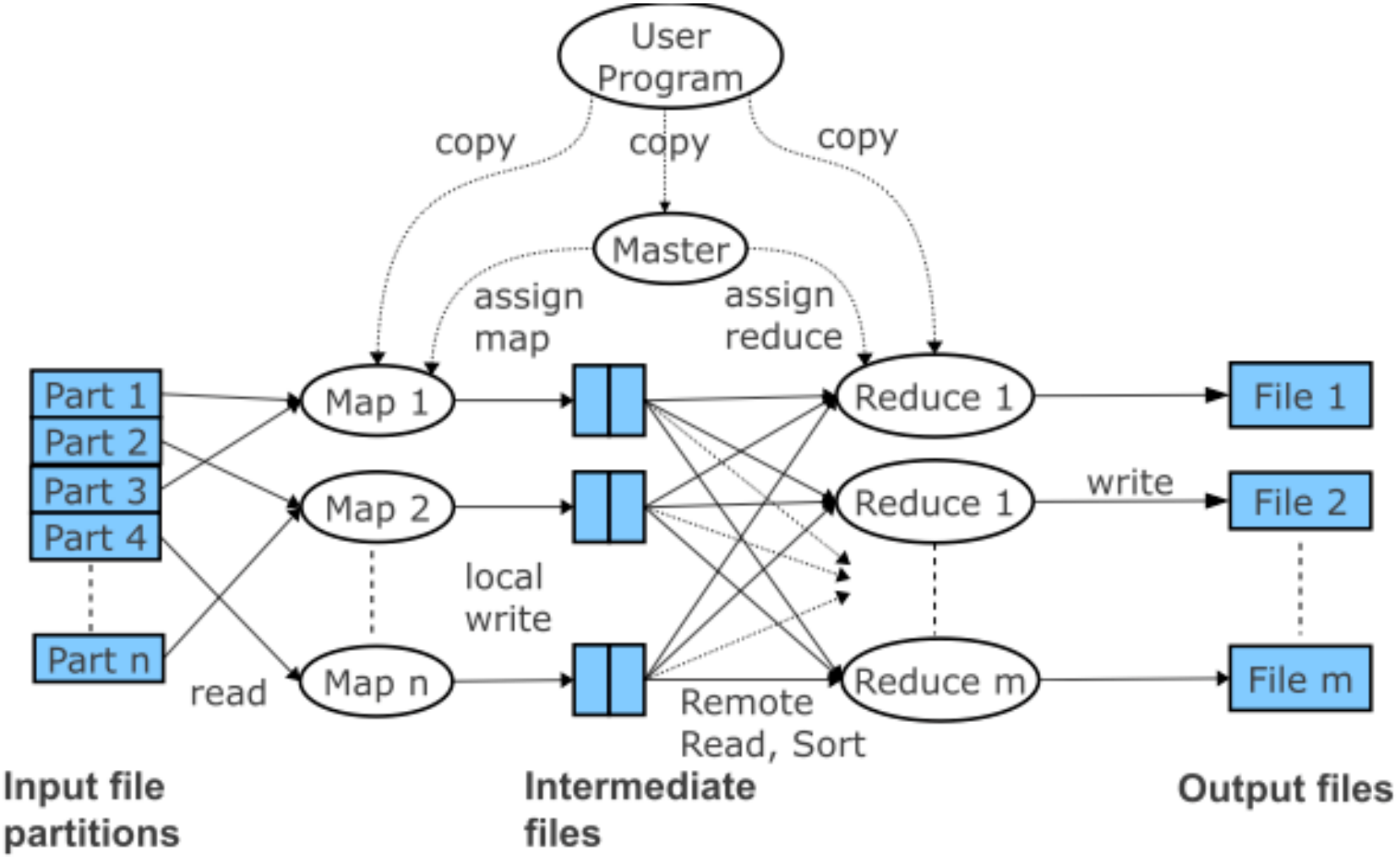
Fault Tolerance in Query Plans

- **Alternative 1: Re-execute the query on failure**
  - Works well if mean time to failure >> query execution time
    - Good for medium scale parallelism with 100's of machines
  - Works badly on massively parallel execution of long queries
    - Where probability of some node failing during execution of a single query is high

Fault Tolerance in Query Plans

- **Alternative 2: Re-execute work of only failed nodes**
  - Works well if consumers process data only after it is completely generated
    - Just discard partial data
    - Used in map-reduce implementations
  - Problems arise if consumers process data as it is generated (pipelined execution)
    - Only new tuples must be consumed from re-execution
    - Re-execution must generate tuples in exactly same order to efficiently determine which tuples are new
- **Straggler nodes** (nodes that are running slow) can be treated similar to failed nodes

Fault Tolerance in Map-Reduce



Fault Tolerance in Map Reduce Implementation

- Map workers writes data to local disk
  - Cheaper than writing to distributed file system
- When task is complete, data is sent to reducers
- Reducers use data only after it is fully received
- On map worker failure:
  - Reexecute map tasks on a new node
  - Reducers get data from new node, discarding partially received data (if any) from failed node
- On reduce worker failure
  - Reexecute reduce task on new node
  - Re-fetch data from map nodes
- On completion of a map-reduce phase, result is written to distributed file system
  - Replication ensures result is safe from failures

Fault Tolerant Query Execution

- Overheads of fault-tolerant query execution
  - Materialization cost
  - Each step has to wait till the previous step finishes
    - Stragglers can cause significant delays
- Pipelined execution can avoid these costs
  - But harder to make pipelined execution fault-tolerant
    - E.g. duplication of tuples when failed task is reexecuted
- Apache Spark uses concept of Resilient Distributed Datasets (RDDs)
  - Data can be replicated in memory/on disk
  - But intermediate results are not materialized
    - Query nodes can be reexecuted to regenerate results

Query Processing in Shared Memory Systems

- Parallel query processing techniques discussed so far can be optimized if data is in shared memory
- Shared memory parallel processing usually based on **threads**, instead of processes
  - Usually number of threads = number of cores * number off hardware threads per core

Query Processing in Shared Memory Systems

Optimized algorithms for shared memory

- With asymmetric fragment-and-replicate join, the smaller relation can be in shared memory, instead of being replicated for each thread
- Hash join can be done by
  - Partitioning build relation to each thread, OR
  - **Shared build relation** with singe index, in shared memory
    - Probe relation can be partitioned into small pieces (a.k.a. morsels)
    - Each thread processes one piece of the probe at a time, in parallel with other threads
    - Shared index construction can be parallelized, but carefully
      - Multiple threads may try to write to same location in shared memory
      - Atomic instruction (test-and-set/compare-and-swap) can be used to add entries to hash table list

Query Processing in Shared Memory Systems

- Skew can be handled by **work stealing**
  - Idle processors can take up tasks allocated to other processors
  - Virtual node partitioning allows tasks to be broken into small pieces
    - Cost of reallocating a partition is low in shared memory
    - Even simpler if shared build relation is used
      - only probe relation partitioned need to be reassigned
- Query processing algorithms should be are of NUMA: Non-uniform memory access
  - Each thread scheduled as far as possible on same core every time it runs
  - Data structures used by only 1 thread allocated in memory local to the core on which the thread is running

Query Processing in Shared Memory Systems

- Cache-conscious algorithms used in main-memory centralized query processing should also be used in shared-memory systems
- **Single Instruction Multiple Data** (**SIMD**) parallelism is increasingly used
  - In GPUs as well as Intel Xeon Phi co-processors
  - *Vector processing*
- Vector processing can be used for relational operations

QUERY OPTIMIZATION FOR PARALLEL QUERY EXECUTION

Query Optimization For Parallel Execution

- Query optimization in parallel databases is significantly more complex than query optimization in sequential databases.
  - Different options for partitioning inputs and intermediate results
  - Cost models are more complicated, since we must take into account partitioning costs and issues such as skew and resource contention.

Parallel Query Plan Space

A parallel query plan must specify

- How to parallelize each operation, including which algorithm to use, and how to partition inputs and intermediate results (using exchange operators)
- How the plan is to be **scheduled**
  - How many nodes to use for each operation
  - What operations to pipeline within same node or different nodes
  - What operations to execute independently in parallel, and
  - What operations to execute sequentially, one after the other.
- E.g. In query ${}_{r.A}\gamma_{\text{sum}(s.C)}(r \bowtie_{r.A=s.A \ r.B=s.B} s)$
  - Partitioning r and s on (A,B) for join will require repartitioning for aggregation
  - But partitioning r and s on (A) for join will allow aggregation with no further repartitioning
- Query optimizer has to choose best plan taking above issues into account

Cost of Parallel Query Execution

- **Resource consumption cost model**
  - used for centralized databases
- **Response time cost model**
  - attempts to better estimate the time to completion of a query
  - E.g. If an operation performs I/O operations in parallel with CPU execution, the response time
    $T = max$(CPU cost, I/O cost)
    - Resource consumption cost model uses (CPU cost + I/O cost).
  - E.g., if two operations o_1 and o_2 are in a pipeline, with CPU and I/O costs c_1; io_1 and c_2; io_2 respectively, then response time
    $T = max(c_1 + c_2, io_1 + io_2)$.
  - Operators in parallel: $T = max\ (T_1, T_1, \ldots, T_n)$
    - Skew is an issue

Cost of Parallel Query Execution (Cont.)

- Response time cost model would have to take into account
  - **Start-up costs** for initiating an operation on multiple nodes
  - **Skew** in distribution of work
- Response time cost model better suited for parallel databases
  - But not used much since it increases cost of query optimization

Choosing Query Plans

- The number of parallel evaluation plans from which to choose from is much larger than the number of sequential evaluation plans
  - Many alternative partitioning options
  - Choosing a good physical organization (partitioning technique) is important to speed up queries.
- Two alternatives often used for choosing parallel plans:
  - First choose most efficient sequential plan and then choose how best to parallelize the operations in that plan
    - Heuristic, since best sequential plan may not lead to best parallel plan
  - Parallelize every operation across all nodes
    - Use exchange operator to perform (re)partitioning
    - Use standard query optimizer with extended cost model

Physical Schema

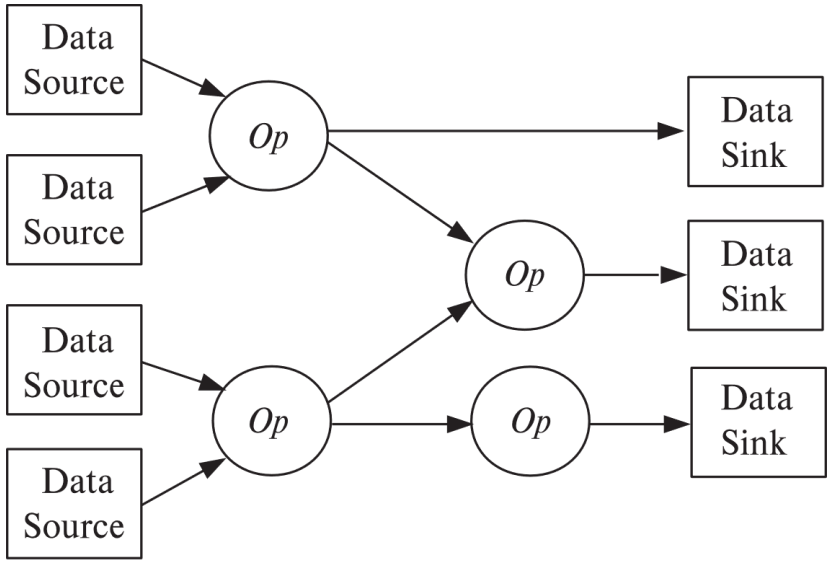
- Partitioning scheme important for queries
- **Colocate data** that is accessed together
  - E.g., all records for a particular user
  - E.g., *student* record with all *takes* records of the student
- Store multiple copies of a relation, partitioned on different attributes
  - E.g., extra copy of *takes* partitioned on *(course id, year, semester, sec id)* for colocation with *section* record
- Materialized views to avoid joins at query time
  - Materialized view itself is stored partitioned across nodes
  - Speeds up queries, but extra cost for updates
  - Extra copy of materialized view may be stored partitioned on different attributes
- *See book for details of parallel maintenance of materialized views*

STREAMING DATA

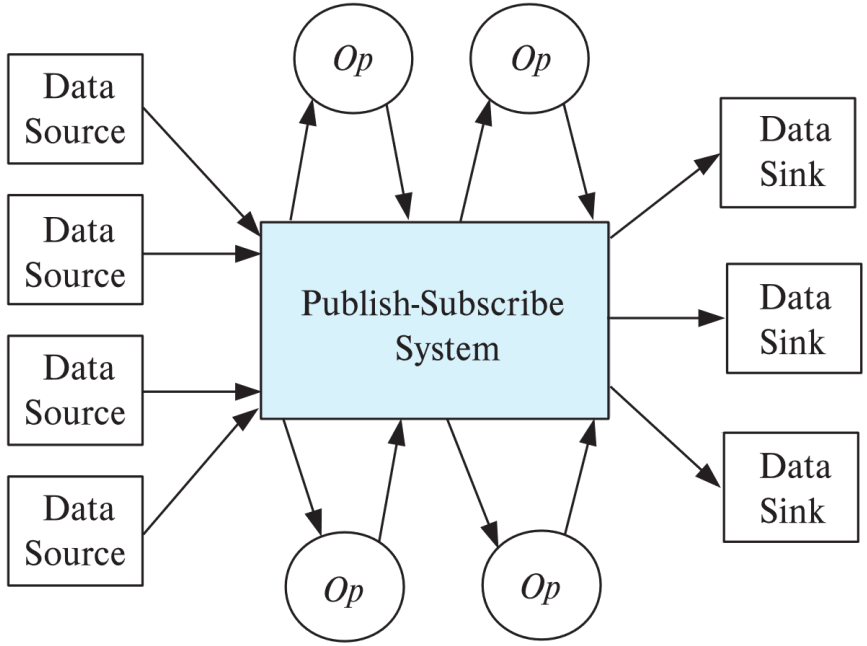
Streaming Data

- Real-time analytics is increasingly important
- Online processing of incoming data
- But data must also be stored for later processing
- Architecture alternatives:
  - **Lambda architecture**: sends a copy of data to real time stream analytics system, and another copy to data storage system
  - Increasingly, same system provides storage and real time stream analytics

Logical Routing of Streams



(a) DAG representation of streaming data flow



(b) Publish-subscribe representation of streaming data flow

Parallel Processing of Streaming Data

- Logical routing of tuples is done by creating a Directed Acyclic Graph (DAG)
  - Can be done by creating a configuration file
    - Called a *topology* in the Apache Storm system
  - OR, can be done dynamically by using publish-subscribe system
    - E.g., Apache Kafka
    - Producers ***publish*** to **topic/stream**, consumers ***subscribe*** to topic/streams

Parallel Processing of Streaming Data

- Physical DAG reflects parallel execution of operator instances
- Parallel implementation of publish-subscribe system
  - Each topic/stream is partitioned (**topic-partition**)
- Multiple instances of each operator, running in parallel
  - Each subscribes to one or more partitions of a topic
- In Kafka, multiple instances of an operator register with an associated **consumer group**
  - Each topic-partition sent to a single consumer from the consumer group
- Streaming operators often need to store state
  - Can be stored locally (cheaper) or in a parallel data-store (better for fault tolerance)

Fault Tolerance

- Possible semantics when dealing with failures
  - **At-least once**
  - **At-most once**
  - **Exactly once**
- Can be implemented in the publish-subscribe/routing system
  - Need to store tuples, including intermediate results, persistently
  - Can lower overhead by **checkpointing** operator state, and replaying operator from checkpoint, instead of persisting operator output
    - But need to ensure duplicates are removed
- Replication of operators: Copy of operator running concurrently with original
  - Similar to hot-spare
  - Allows instant recovery from failure

Distributed Query Processing

Database System Concepts, 7th Ed.

Data Integration From Multiple Sources

- Many database applications require data from multiple databases
- A **federated database system** is a software layer on top of existing database systems, which is designed to manipulate information in heterogeneous databases
  - Creates an illusion of logical database integration without any physical database integration
  - Each database has its **local schema**
  - **Global schema** integrates all the local schema
    - **Schema integration**
  - Queries can be issued against global schema, and translated to queries on local schemas
    - Databases that support common schema and queries, but not updates, are referred to as **mediator** systems

Data Integration From Multiple Sources

- **Data virtualization**
  - Allows data access from multiple databases, but without a common schema
- **External data** approach: allows database to treat external data as a database relation (**foreign tables**)
  - Many databases today allow a local table to be defined as a view on external data
  - SQL Management of External Data (SQL MED) standard
- **Wrapper** for a data source is a view that translates data from local to a global schema
  - Wrappers must also translate updates on global schema to updates on local schema

Data Warehouses and Data Lakes

- **Data warehouse** is an alternative to data integration
  - Migrates data to a common schema, avoiding run-time overhead
  - Cost of translating schema/data to a common warehouse schema can be significant
- **Data lake**: architecture where data is stored in multiple data storage systems, in different storage formats, but which can be queried from a single system.

Schema and Data Integration

- **Schema integration**: creating a unified conceptual schema
  - Requires creation of **global schema**, integrating a number of **local schema**
- **Global-as-view approach**
  - At each site, create a view of local data, mapping it to the global schema
  - Union of local views is the global view
  - Good for queries, but not for updates
    - E.g., which local database should an insert go to?
- **Local-as-view approach**
  - Create a view defining contents of local data as a view of global data
    - Site stores local data as before, the view is for update processing
  - Updates on global schema are mapped to updates to the local views
- *See book for more details with an example*

Unified View of Data

- Agreement on a common data model
  - Typically the relational model
- Agreement on a common conceptual schema
  - Different names for same relation/attribute
  - Same relation/attribute name means different things
- Agreement on a single representation of shared data
  - E.g., data types, precision,
  - Character sets
    - ASCII vs EBCDIC
    - Sort order variations
- Agreement on units of measure

Unified View of Data (Cont.)

- Variations in names
  - E.g., Köln vs Cologne, Mumbai vs Bombay
- One approach: globally unique naming system
  - E.g. GeoNames database (www.geonames.org)
- Another approach: specification of name equivalences
  - E.g. used in the Linked Data project supporting integration of a large number of databases storing data in RDF data

Query Processing Across Data Sources

- Several issues in query processing across multiple sources
- Limited query capabilities
  - Some data sources allow only restricted forms of selections
    - E.g., web forms, flat file data sources
  - Queries have to be broken up and processed partly at the source and partly at a different site
- Removal of duplicate information when sites have overlapping information
  - Decide which sites to execute query
- Global query optimization

Join Locations and Join Ordering

- Consider the following relational algebra expression in which the three relations are neither replicated nor fragmented

  $r1 \bowtie r2 \bowtie$ r3
- *r1* is stored at site S_1
- *r2* at S_2
- *r3* at S_3
- For a query issued at site S_I, the system needs to produce the result at site S_I

Possible Query Processing Strategies

- Ship copies of all three relations to site S_I and choose a strategy for processing the entire locally at site S_I.
  - Ship a copy of the *r1* relation to site S_2 and compute
    $temp_1 = r1 \bowtie r2$ *at* S_2.
  - Ship $temp_1$ from S_2 to S_3, and compute
    $temp_2 = temp_1 \bowtie r3$ at S_3
  - Ship the result $temp_2$ to S_I.
- Devise similar strategies, exchanging the roles S_1, S_2, S_3
- Must consider following factors:
  - amount of data being shipped
  - cost of transmitting a data block between sites
  - relative processing speed at each site

Semijoin Strategy

- Let r_1 be a relation with schema R_1 stores at site S_1

  Let r_2 be a relation with schema R_2 stores at site S_2
- Evaluate the expression $r_1 \bowtie r_2$ and obtain the result at S_1.
  1. Compute $temp_1 \leftarrow \prod_{R1 \cap R2}$ (r1) at $S1$.
  2. Ship $temp_1$ from S_1 to S_2.
  3. Compute $temp_2 \leftarrow r_2 \bowtie$ temp1 at S_2
  4. Ship $temp_2$ from S_2 to S_1.
  5. Compute $r_1 \bowtie temp_2$ at S_1. This is the same as $r_1 \bowtie r_2$.

Semijoin Reduction

- The **semijoin** of r_1 with r_2, is denoted by:

$$r_1 \ltimes r_2 \qquad \Pi_{R1}\,(r_1 \bowtie r_2)$$

- Thus, $r_1 \ltimes r_2$ selects those tuples of r_1 that contributed to $r_1 \bowtie r_2$.
- In step 3 above, $temp_2 = r_2 \ltimes r_1$.
- For joins of several relations, the above strategy can be extended to a series of semijoin steps.
- Semijoin can be computed approximately by using a Bloom filter
  - For each tuple of r_2 compute hash value on join attribute; if hash value is i, and set bit i of the bitmap
  - Send bitmap to site containing r_1
  - Fetch only tuples of r_1 whose join attribute value hashes to a bit that is set to 1 in the bitmap
  - Bloom filter is an optimized bitmap filter structure (Section 24.1)

Distributed Query Optimization

- New physical property for each relation: location of data
- Operators also need to be annotated with the site where they are executed
  - Operators typically operate only on local data
  - Remote data is typically fetched locally before operator is executed
- Optimizer needs to find best plan taking data location and operator execution location into account.

Distributed Directory Systems

- Distributed directory systems are widely used
  - Internet Domain Name Service (**DNS**)
  - **Lightweight Directory Access Protocol** (**LDAP**)
    - Widely used to store organizational data, especially user profiles
- Data in a distributed directory system are stored and controlled in a distributed hierarchical manner
  - E.g. data about yale.edu is provided by a Yale, and about IIT Bombay by an IIT Bombay server
  - Data can be queries in a uniform manner regardless of where it is stored
    - Queries get forwarded to the site where the information is stored

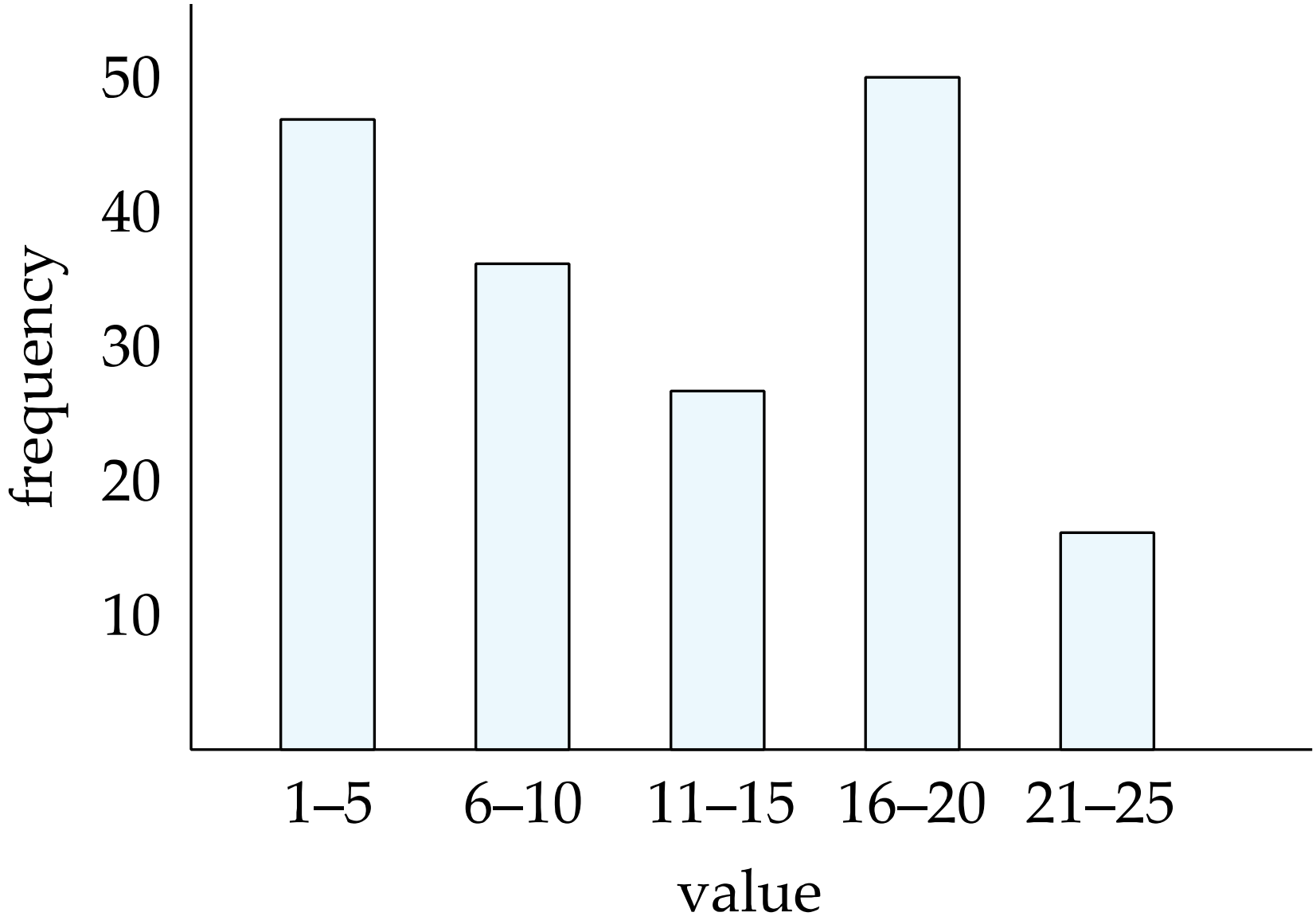
End of Chapter

Join Strategies that Exploit Parallelism

- Consider $r_1 \bowtie r_2 \bowtie r_3 \bowtie r_4$ where relation ri is stored at site S_i. The result must be presented at site S_1.
- r_1 is shipped to S_2 and $r_1 \bowtie r_2$ is computed at S_2: simultaneously r_3 is shipped to S_4 and $r_3 \bowtie r_4$ is computed at S_4
- S_2 ships tuples of $(r_1 \bowtie r_2)$ to S_1 as they produced;
  S_4 ships tuples of $(r_3 \bowtie r_4)$ to S_1
- Once tuples of $(r_1 \bowtie r_2)$ and $(r_3 \bowtie r_4)$ arrive at S_1 $(r_1 \bowtie r_2) \bowtie (r_3 \quad r_4)$ is computed in parallel with the computation of $(r_1 \bowtie r_2)$ at S_2 and the computation of $(r_3 \bowtie r_4)$ at S_4.

Mediator Systems

- **Mediator** systems are systems that integrate multiple heterogeneous data sources by providing an integrated global view, and providing query facilities on global view
  - Unlike full fledged multidatabase systems, mediators generally do not bother about transaction processing
  - But the terms mediator and multidatabase are sometimes used interchangeably
  - The term **virtual database** is also used to refer to mediator/multidatabase systems


frequency
50
40
30
20
10
1–5
6–10
11–15
16–20
21–25
value

Distributed Query Processing

- For centralized systems, the primary criterion for measuring the cost of a particular strategy is the number of disk accesses.
- In a distributed system, other issues must be taken into account:
  - The cost of a data transmission over the network.
  - The potential gain in performance from having several sites process parts of the query in parallel.

Query Transformation

- Translating algebraic queries on fragments.
  - It must be possible to construct relation *r* from its fragments
  - Replace relation *r* by the expression to construct relation *r* from its fragments
- Consider the horizontal fragmentation of the *account* relation into

  $account_1 = \sigma_{branch\_name = \text{“Hillside”}} (account)$

  $account_2 = \sigma_{branch\_name = \text{“Valleyview”}} (account)$
- The query $\sigma_{branch\_name = \text{“Hillside”}} (account)$ becomes

  $\sigma_{branch\_name = \text{“Hillside”}} (account_1 \cup account_2)$

  which is optimized into

  $\sigma_{branch\_name = \text{“Hillside”}} (account_1) \cup \sigma_{branch\_name = \text{“Hillside”}} (account_2)$

Example Query (Cont.)

- Since $account_1$ has only tuples pertaining to the Hillside branch, we can eliminate the selection operation.
- Apply the definition of $account_2$ to obtain

  $\sigma_{branch\_name = \text{“Hillside”}} (\sigma_{branch\_name = \text{“Valleyview”}} (account))$

- This expression is the empty set regardless of the contents of the *account* relation.
- Final strategy is for the Hillside site to return $account_1$ as the result of the query.

Advantages

- Preservation of investment in existing
  - hardware
  - system software
  - Applications
- Local autonomy and administrative control
- Allows use of special-purpose DBMSs
- Step towards a unified homogeneous DBMS
  - Full integration into a homogeneous DBMS faces
    - Technical difficulties and cost of conversion
    - Organizational/political difficulties
      - Organizations do not want to give up control on their data
      - Local databases wish to retain a great deal of **autonomy**

End of Chapter 22

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

$$T_{part} + T_{asm} + \max(T_1, T_1, \ldots, T_n)$$

  - 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 node N_i
    - this needs to be estimated taking into account the skew, and the time wasted in contention.