Parallel DBMSs

Instructor: Peter Baumann

email: pbaumann@constructor.university
tel: -3178
office: room 88, Research 1

Overview

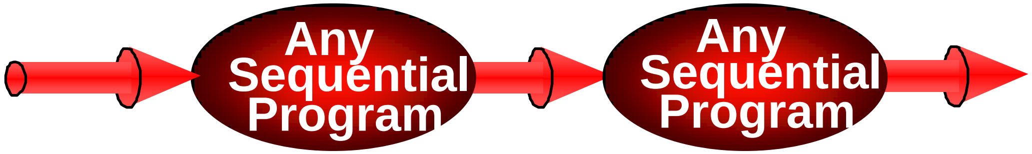
- Motivation
- Data partitioning
- Query operator parallelization
- Skew
- Optimization

Parallelization: Principle

- Goal
  - Improve performance by executing multiple operations in parallel
  - More processors →
    each query faster / same speed on more data / more transactions per second / ...
- In LAN: cost(network) << cost(disk IO)
- Key challenge
  - overhead & contention can kill performance

Parallelization Variants

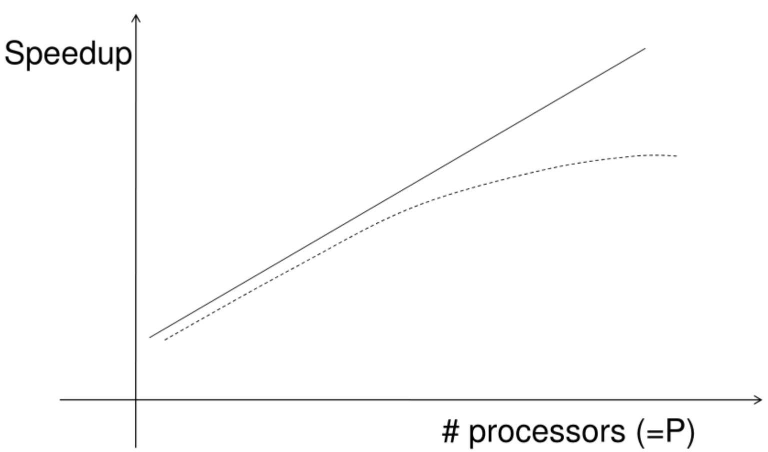
- Pipeline parallelism
  - many machines each doing one step in a multi-step process

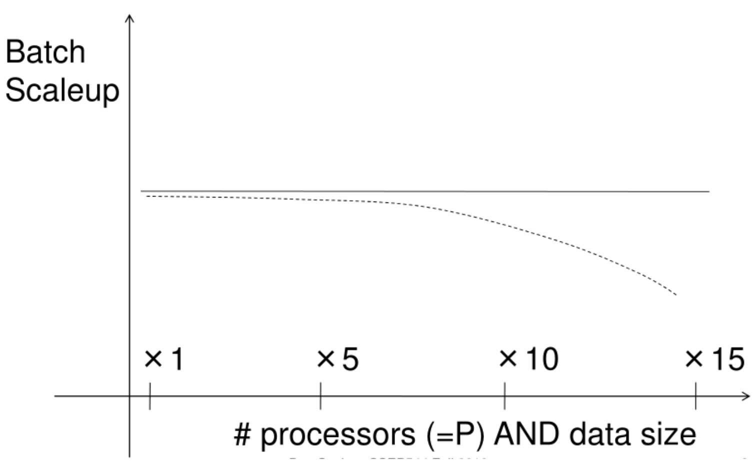


- Partition parallelism
  - many machines doing the same thing to different pieces of data

Speedup & Scaleup

- Speedup: faster
- Scaleup: do more
- Linear vs non-linear (sub-linear)





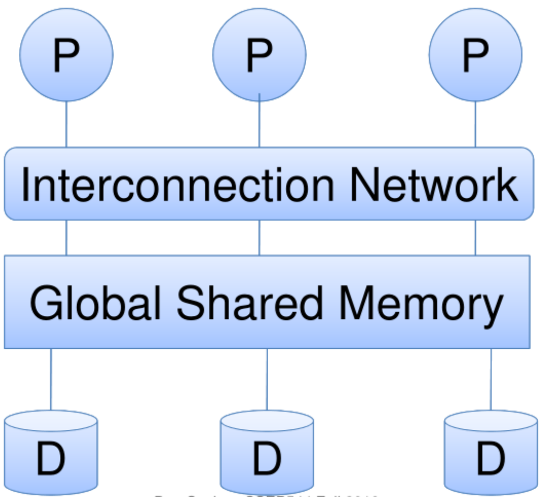
Challenges to Linear Speedup & Scaleup

- Startup cost
  - Cost of starting an operation on many processors
- Interference
  - Contention for resources between processors
- Skew
  - Slowest processor becomes the bottleneck
- Blocking operations
  - Can continue only once all results are seen: sort, top-k, aggregation, ...

Architectures for Parallel Databases

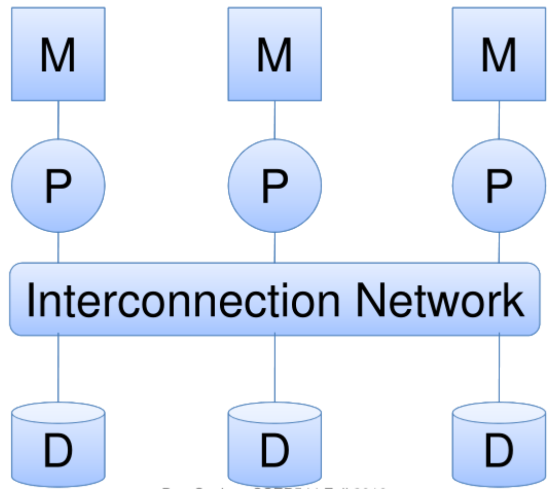
Shared memory

Sequent, SGI, Sun, NEC



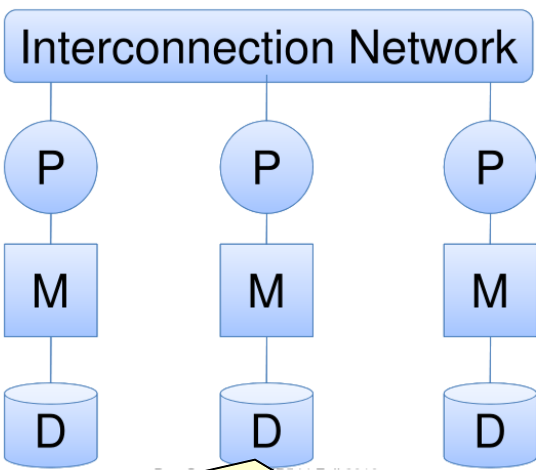
Shared disk

VMScluster, Sysplex



Shared nothing

Tandem, Teradata, SP2



most scalable
- minimizes interference by minimizing resource sharing
- commodity hardware
most difficult

Architectures for Parallel Databases

Shared memory | Shared disk | Shared nothing

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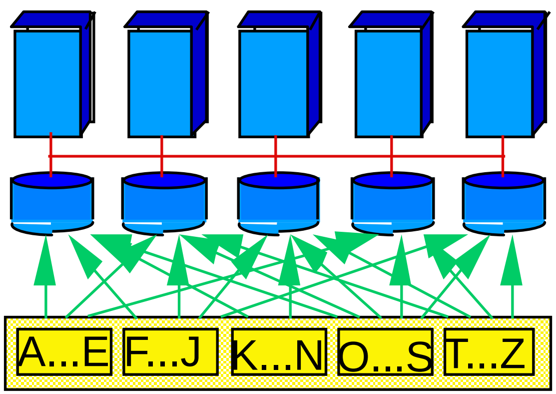
Data Placement: How to Partition?

- Partitioning always necessary: tuples assigned to set of disks / processors
  - Static or during query

Round Robin

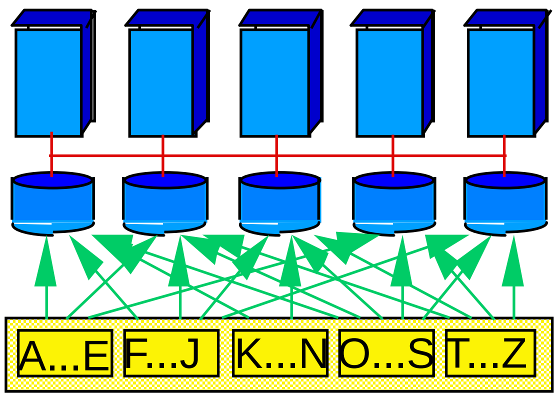
tuple t_i → chunk (i mod P)



☺ balance load, full scan
☹ range queries

Hash partitioning

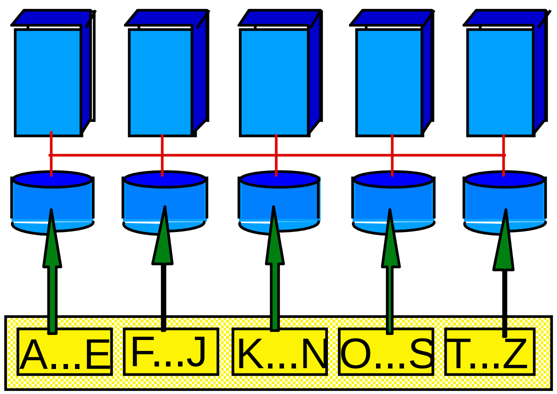
tuple t → chunk h(t.A) mod P



☺ equijoins, point queries, full scan; ☹ range queries

Range partitioning

tuple t → chunk i if v_{i-1} < t.A < v_i



☺ equijoins, range queries, group-by

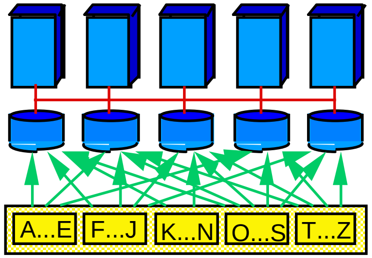
Partition vector = list of switch points [v_1; …; v_p]

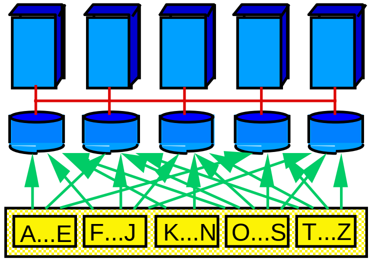
|| of Query Operators

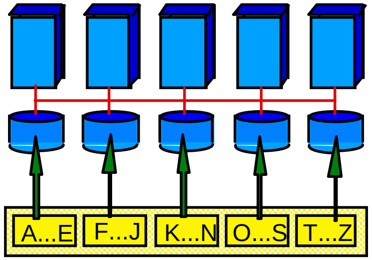
- Discussion assumes:
  - read-only queries
  - shared-nothing architecture
  - n processors, $P_0, \ldots, P_{n-1}$, and n disks $D_0, \ldots, D_{n-1}$, where disk D_i is associated with processor P_i
- Will look at filter, sort, join
- PS: Shared-nothing architectures can be efficiently simulated on shared-memory and shared-disk systems

|| Filter

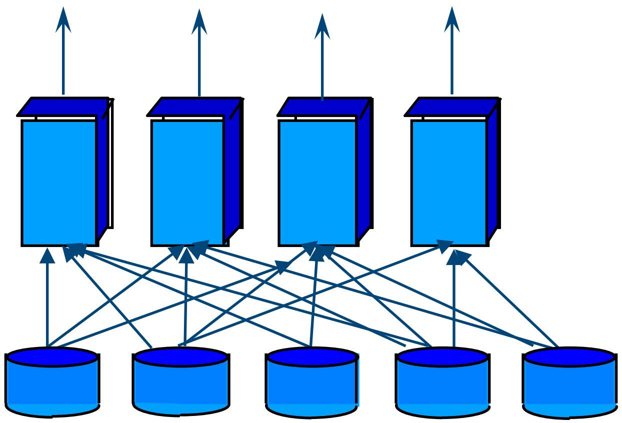
- How is work distribution among processors?
  - Point query $\sigma_{A=v}(R)$, range query $\sigma_{v1<A<v2}(R)$
  - Load balancing
- Round robin: all servers do the work
- Hash partition:
  - One server for $\sigma_{A=v}(R)$
  - All servers for $\sigma_{v1<A<v2}(R)$
- Range partition: one server does the work



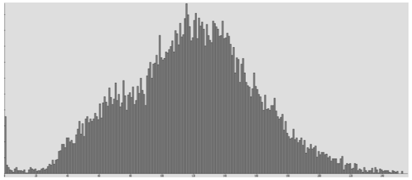




|| Sort-Merge with Range-Partitioning

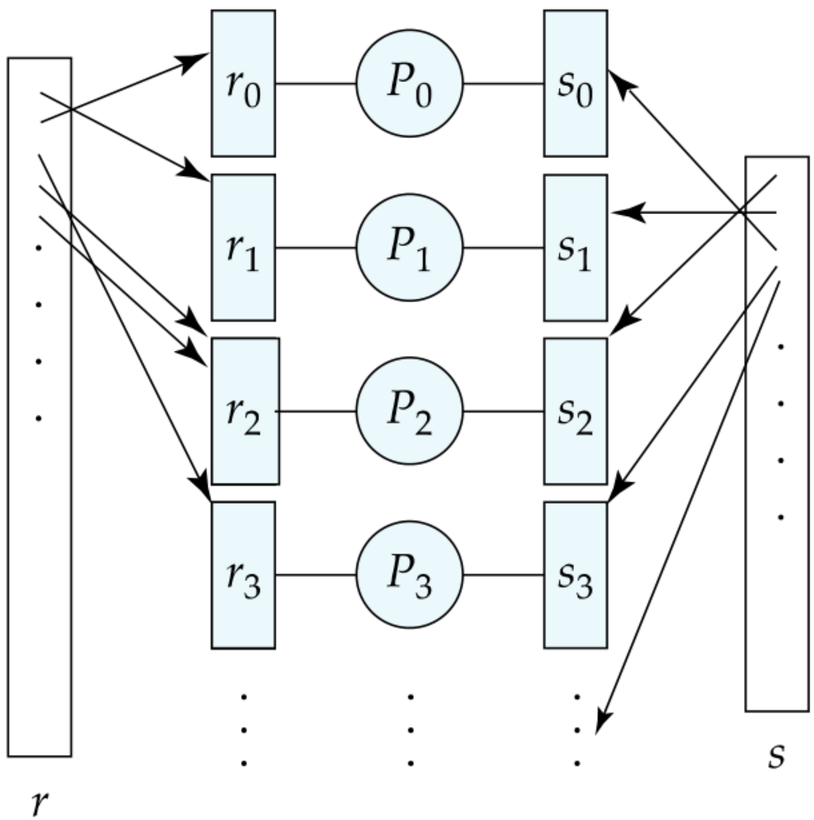


- Choose partitioning vector
- Scan table in parallel, range-partition as you go
- Each processor: sort partition locally
  - All execute same operation in parallel, no interaction
  - Can create local index
- Final merge operation (trivial: concatenation of sorted partial results)
  - range-partitioning ensures global sortedness
- Problem: skew – more later



Partitioned Join

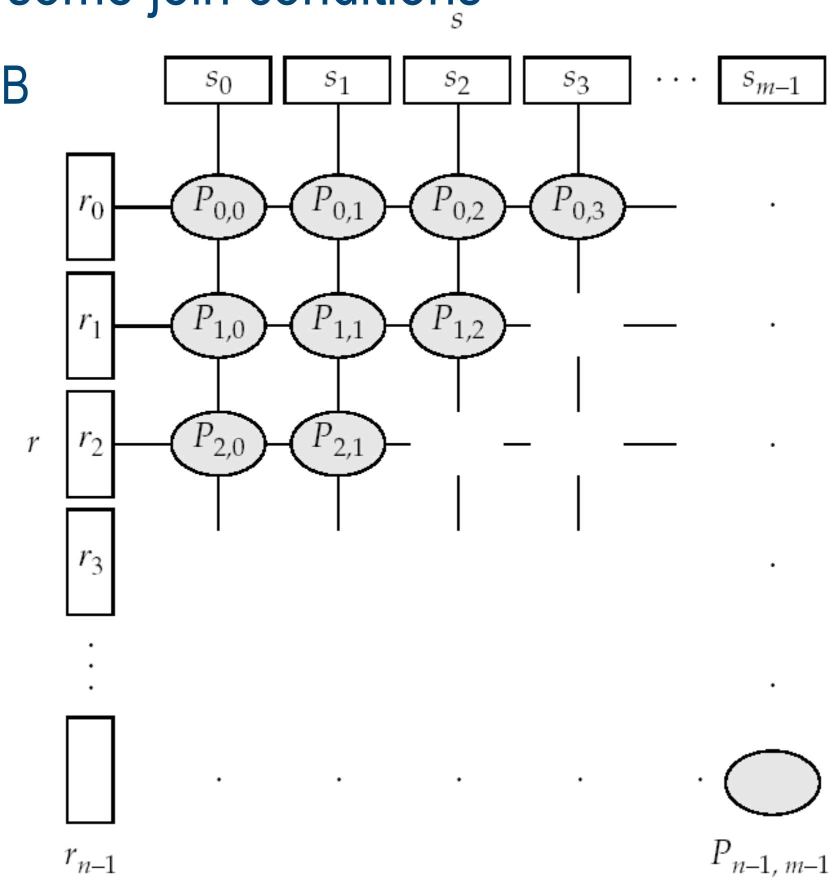
- For Equi-Join R $\rhd\lhd_{R.A=S.B}$ S :
  - partition input relations, distribute
  - compute join partitions
  - recollect
- Partition R, S on join attrs R.A & S.B
  - No need to sort
  - Range, hash partitioning all fine



- Corresponding partitions R_i & S_i → processor P_i,
- P_i locally computes $R_i \rhd\lhd_{Ri.A=Si.B} S_i$
  - Any standard join method

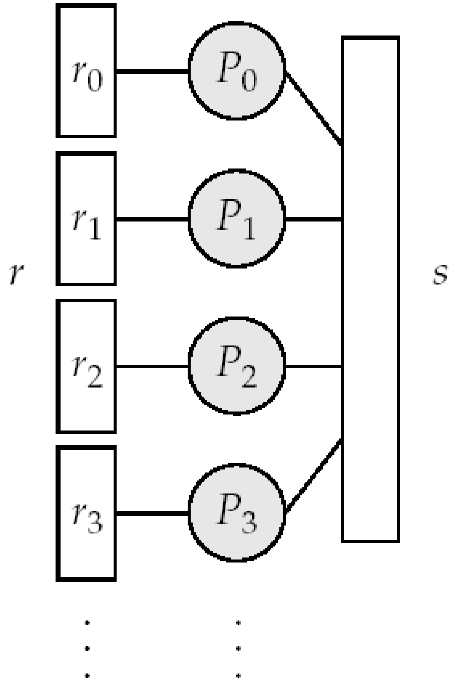
Fragment-and-Replicate Join

- Observation: Partitioning not possible for some join conditions
  - Ex: non-equijoin conditions, such as R.A > S.B
- fragment & replicate



Fragment-and-Replicate Join

- Observation: Partitioning not possible for some join conditions
  - Ex: non-equijoin conditions, such as R.A > S.B
- fragment & replicate
- Special case: asymmetric fragment-and-replicate
  - R partitioned; any partitioning technique can be used
  - small S replicated across all processors



Cost of || Evaluation

- no skew in partitioning, no || overhead: expected speed-up is 1/n
- skew & overheads taken into account, || time estimate:

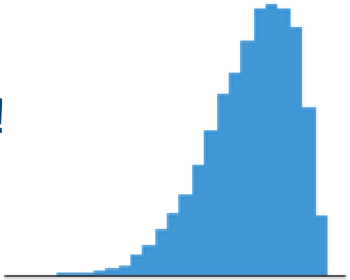
  $$T_{part} + \max(T_0,\ldots,T_{n-1}) + T_{asm}$$

  where:
  - T_{part} time for partitioning the relations
  - T_{asm} time for assembling the results
  - T_i time taken for operation at processor P_i
    (needs to be estimated taking into account skew and time wasted in contentions)


SKEW
Designed by Nightfly 2004

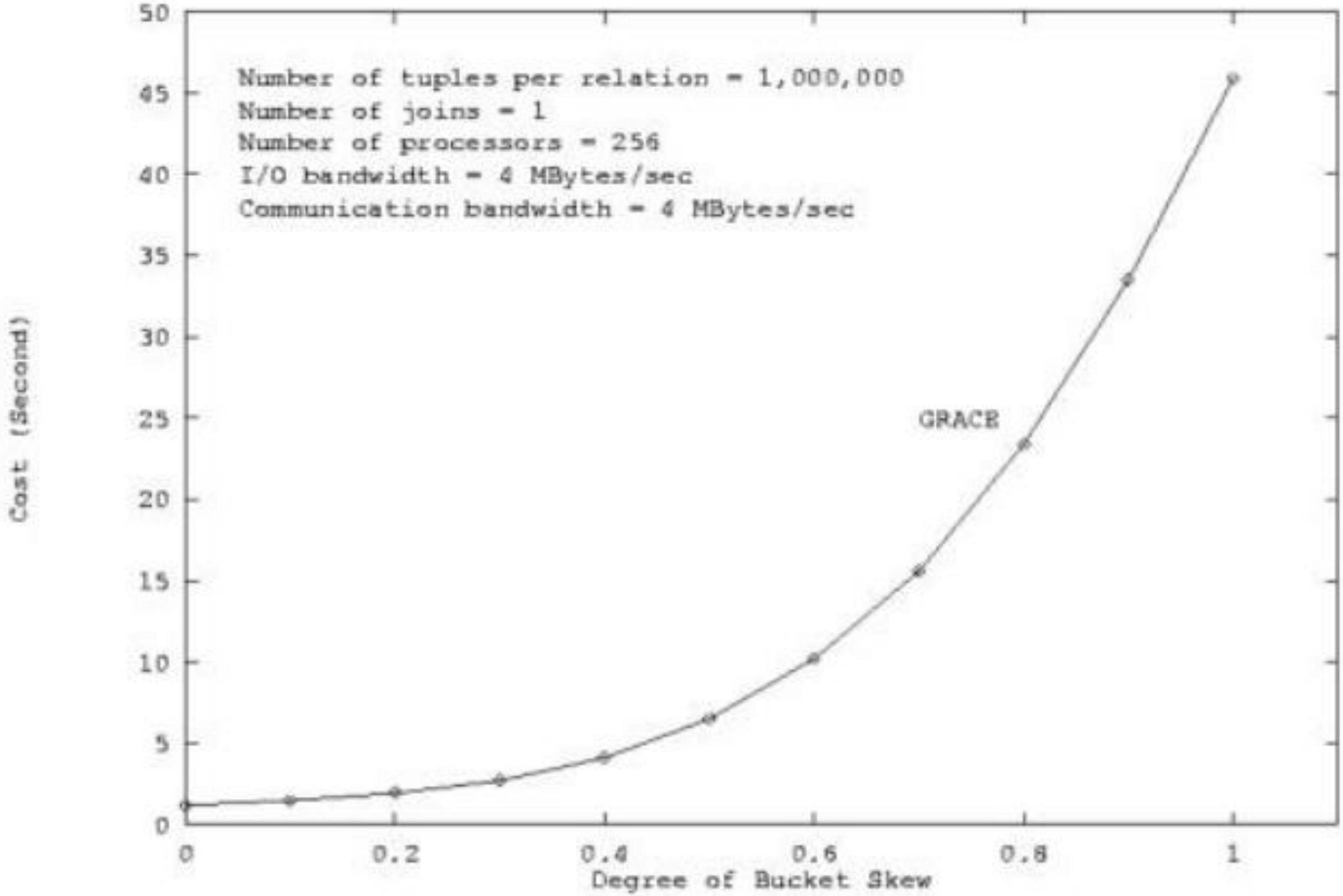
Skew

- distribution of tuples to disks may be skewed
  = some disks have many tuples, while others may have fewer tuples
- Attribute-value skew
  - Many tuples share same values, few distinct values;
    all tuples with same value for partitioning attribute end up in same partition!
  - Affects hash-partitioning, range-partitioning



- Consequence: Partition skew
  - Range-partitioning: bad partition vector → too many tuples to some partitions, too few to others
  - Less likely with hash-partitioning if hash-function good

Skew Kills || Performance

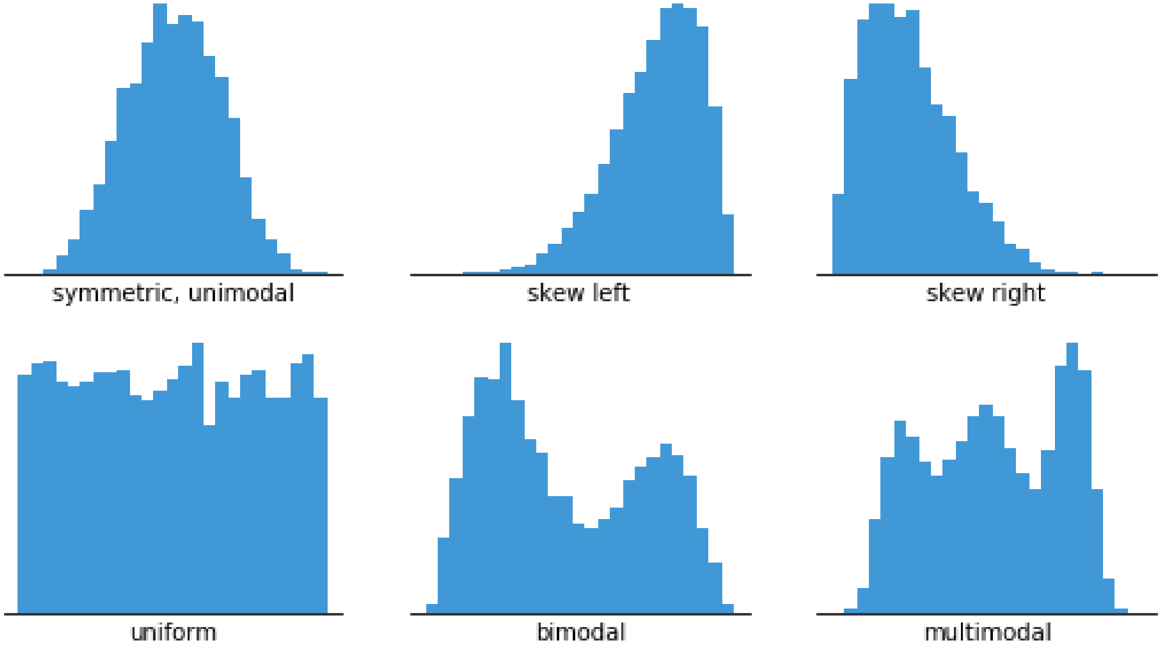


Handling Skew in Range-Partitioning

- Method for a balanced partitioning vector
  - Sort relation on partitioning attribute
  - Scan relation in sort order
  - After every $1/n^{th}$ of relation: add attribute value of next tuple to partition vector
- Drawbacks:
  - Imbalance possible if duplicates in partitioning attributes
  - Best for initial table load; frequent updates may change=disturb distribution
  - Table scan expensive
- Alternative: histograms ⇘

Histograms

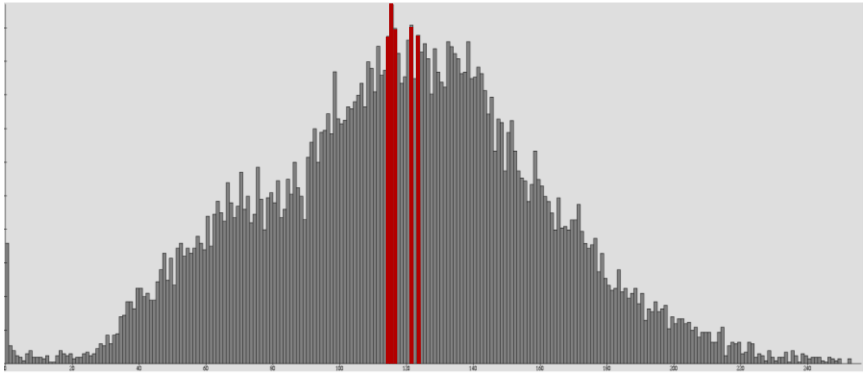
- Helps finding balanced partitioning vector
- Histogram can be constructed by
  - scanning complete relation
    - *expensive*
  - sampling
    - *Accuracy?*
    - *Over time, with updates?*



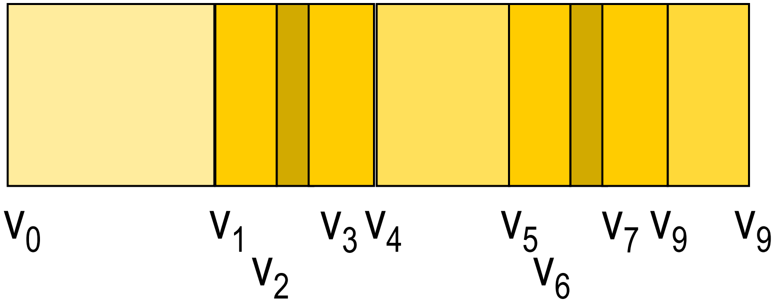
[Atlassian]

Histograms Types

- Two main types of histograms:
- frequency histogram
  - (attribute value, frequency) pairs for N most frequent attribute values
  - optimizer estimates selectivity of equality predicates



- quantile histogram
  - = equidepth range histogram
  - optimizer estimates selectivity of range predicates



Histograms in Practice: Oracle

- single histogram, can act as either frequency histogram or equidepth histogram
  - frequency version used when number of unique values of attribute is low
  - switches to equidepth histogram if domain is large and number of unique values crosses a threshold
- Default threshold value is 75
  - will be number of buckets in equidepth histogram
- Oracle provides view, *all_tab_histogram*, to read histogram information

Histograms in Practice: DB2

- quantile histogram
  - 20 buckets by default to approximate data distribution
  - stored in system table *SYSIBM.SYSCOLDIST*
- frequency histogram
  - Top 10 by default, can be specified by DBA
  - used to estimate selectivity of equality predicates

Histograms in Practice: MS SQL Server

- mix of frequency and equidepth histogram
  - frequency of bucket boundaries + number of tuples in bucket
  - number of buckets can go up to 200
- Histograms by default generated with sampling
- stored procedure *DBCC SHOW STATISTICS* extracts histogram information

Histograms in Practice: PostgreSQL

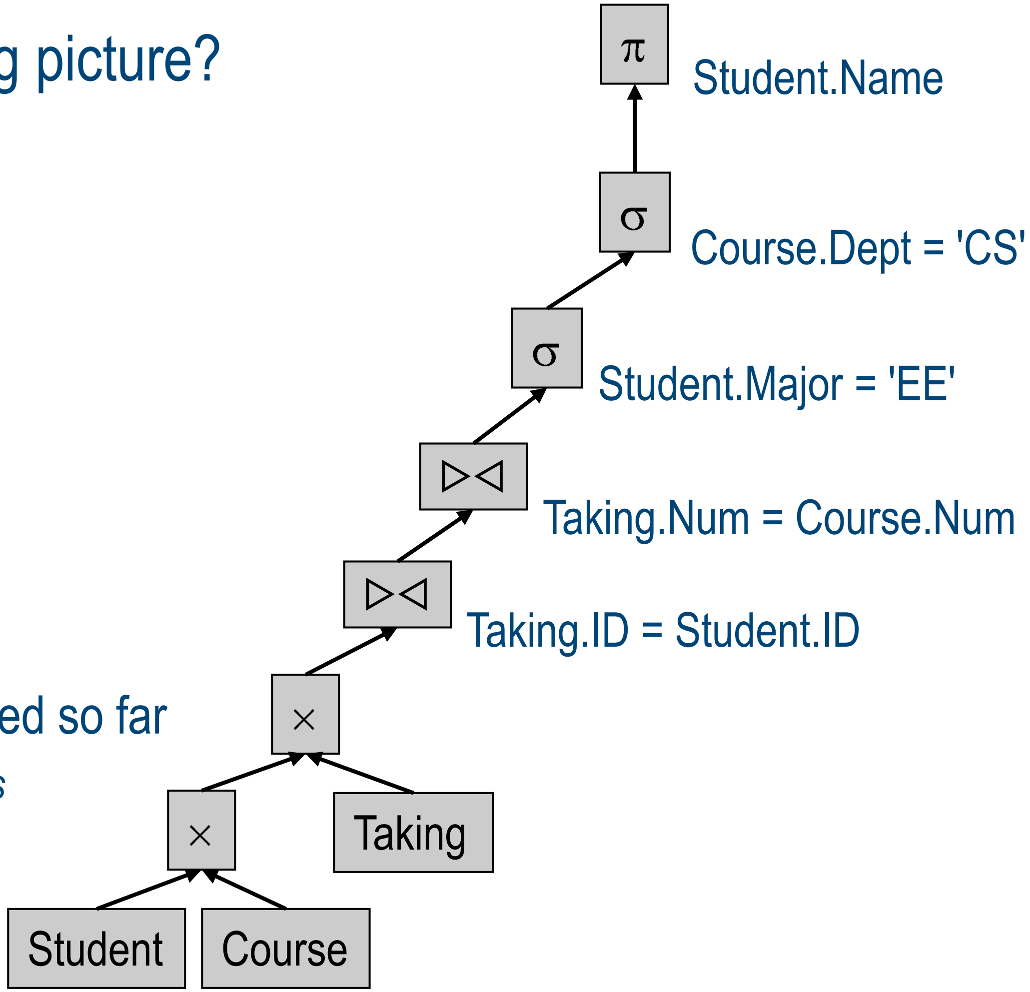
- mixture of end biased and equidepth histograms
- Histograms stored in relation *pg_stats* catalog table
  - most frequent values stored as an array in the *most_common_vals* column
  - equi-depth histogram stored as two arrays:
    - *frequency of corresponding buckets*
    - *bounds of the buckets*
- 10 buckets by default

Different Approach: Virtual Partitioning

- create large number of partitions
  - say, 10x to 20x number of disks / processors
- Assign virtual processors to partitions
  - round-robin or based on cost estimate
- Basic idea:
  - If any normal partition skewed, this skew spread over several virtual partitions
  - Skewed virtual partitions spread across several processors, so work distributed evenly

Taxonomy for Parallel Query Evaluation

- So far: looked at operators – big picture?
- Inter-query ||
  - 1 query → 1 processor
- Intra-query ||:
  - Inter-operator ||
    - *query runs on multiple processors*
    - *operator runs on one processor*
  - Intra-operator || ← inspected so far
    - *operator runs on multiple processors*
    - *most scalable*



Interquery Parallelism

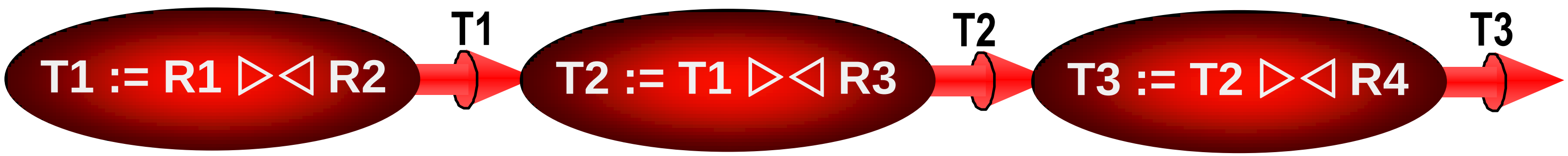
- Queries/transactions execute in parallel with one another
  - Increases transaction throughput; used primarily for larger #TAs per second
- Easiest ||
- Locking & logging coordinated by passing messages between processors
  - Data in local buffer may have been updated at another processor
- Cache-coherency challenging: buffer reads and writes need latest version
  - Simple cache coherency protocol for shared disk systems:
    Lock page; read page from disk; write page if modified; unlock page
  - Each page has home processor, all page requests sent to home processor

Intra-Query Parallelism

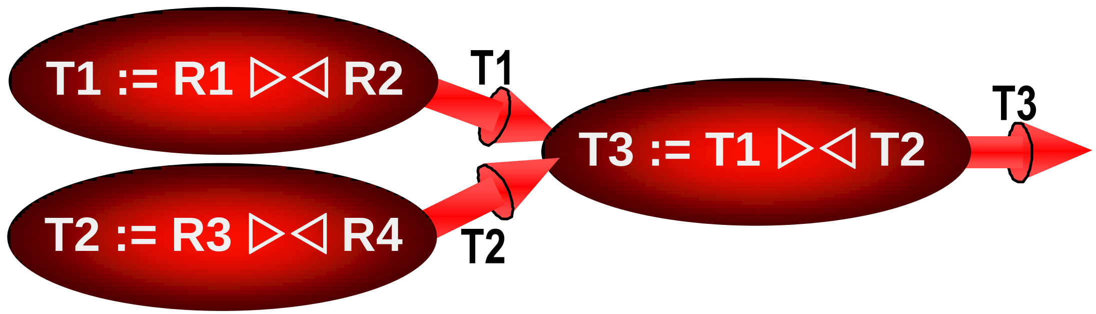
- 1 query → n processors/disks;
  - important for long-running queries
- Two complementary forms:
- Inter-operator || – execute query operations in parallel, aka “pipelining”
- Intra-operator || – parallelize execution of each individual operation in query

Inter-Operator Parallelism

- Execute query operations in parallel
  - Ex: pipelining of R1▷◁ R2 ▷◁ R3 ▷◁ R4



  - Even better:



- Tuple streams
  → avoid (disk) storage of large intermediate tables

- Drawbacks:
  - Useful with small #processors, not for #procs >> #ops
  - Not possible to parallelize blocking operations (e.g., aggregate, sort)
  - Skew: cost of operators can vary significantly

Intra-Operator Parallelism

- parallelize execution of each individual operation in query
  - See earlier examples

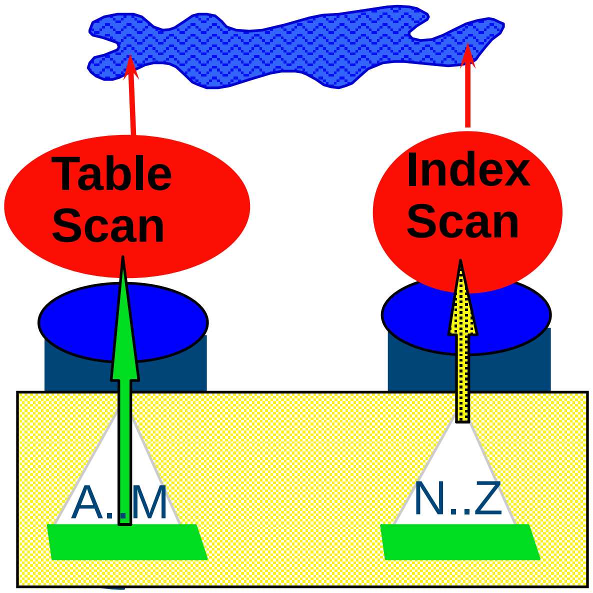
- Scales better with increasing parallelism
  - #tuples processed by operation typically >> #operations in query

|| Query Optimization

- Query optimization in || databases significantly more complex than in sequential databases; *ongoing research!*
  - | parallel evaluation plans | >> | sequential evaluation plans |
- Cost models more complicated
  - How to parallelize each operation, how many processors to use? What operations to pipeline? what operations to execute independently in parallel? what operations to execute sequentially? …etc.
- Heuristic I: parallelize every operation across all processors (MapReduce!)
- Heuristic II: choose most efficient sequential plan, parallelize that plan
- Critical:
  - good physical organization (partitioning technique)
  - Good resource need estimate

What's Wrong With That?

- Best serial plan != Best || plan! …why?
- Trivial counter example:
  - This query:
    ```
    SELECT *
    FROM telephone_book
    WHERE name < "NoGood"
    ```
  - Table partitioned with local index at two nodes
  - Range query addresses all of node 1 and 1% of node 2
- Assessment:
  - Node 1 should best do a scan of its partition, Node 2 should best use index



Distributed Databases

- Parallel database system:
  - One DB server environment (cloud, data center), stores all data
  - Typically: processing nodes + Storage-Area Network (SAN) + fast network
- Distributed database system:
  - Data stored across several geographically remote sites → slow, failing network
  - each site managed by independent DB server
  - Distributed transactions
- Failures to be expected always
  - More hardware → more failure probability
  - Replication

Summary

- Parallel processing boosts performance
  - Massive research done, continuing
- Challenges:
  - Data placement, data skew
  - Parallel bulk load, data maintenance (updates, index), online repartitioning, ...
  - Complex optimization
- Even more challenging: distributed query processing
  - Independent nodes; failures; ...