Architecture and Implementation of Database Systems (Winter 2013/14)

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Part IX

Parallel Databases

Motivation

It is increasingly attractive to leverage **parallelism** available in hardware.

Reduced Cost:

- Large monolithic systems are extremely complex to build.
- Smaller systems sell at much higher volumes, with much better price/performance ratio.

Reduced Energy Consumption:

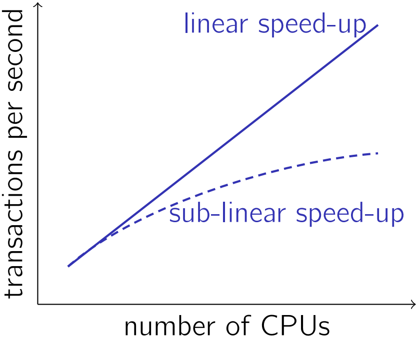
- Performance scales linearly with clock frequency; energy consumption scales quadratically.
- Additional **cooling cost** makes this even worse.
- Modern chip designs are **power-limited** ($\leadsto$ multi-core)

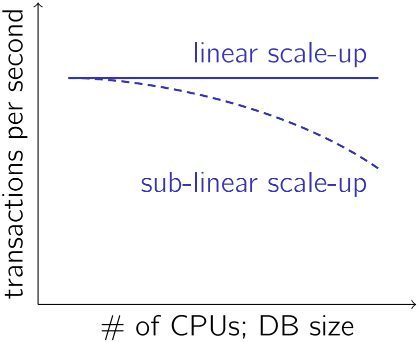
Prepare for Hardware Failures?

- A spare COTS system is cheaper than a spare mainframe.

Scaling with Parallelism

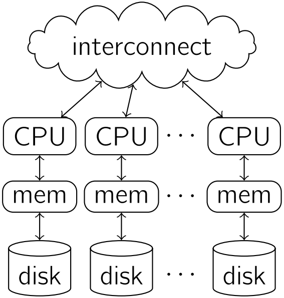
Desirable: **speed-up** and **scale-up**



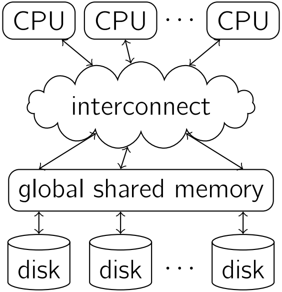


Parallel Database Architectures

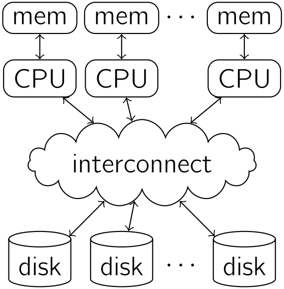
Different architectures have been proposed for **parallel databases**.



shared nothing



shared memory



shared disk

Shared Memory

Advantages of shared memory architectures:

- Porting to shared memory architecture (relatively) easy.

Problems of shared memory architectures:

- **Contention** in interconnect
  - → Here: **memory contention**
  - → Hard to build scalable and fast interconnect.
- **Interference**:
  - → Addl. CPUs **slow down** existing ones (*e.g.*, due to contention).

→ Suitable for **low degrees of parallelism** (up to few tens).

Shared Disk, Shared Memory

Shared disk architectures have similar problems.

→ **contention** and **interference** problems

Further:

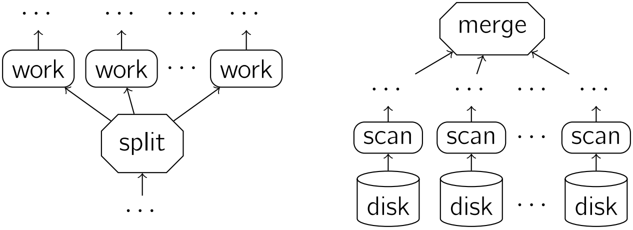
- For **read/write** access, **coherence** tricky to get right.

→ **Shared nothing** seems to be the method of choice.

Parallel Query Evaluation

Intra-query parallelism:

- **Pipeline parallelism:**
  - → Assign plan operators to CPUs; send tuples from CPU to CPU.
  - → Only works for **non-blocking operators**.
  - → **Limited scalability**: few operators per plan; load balancing?
- **Data parallelism:**



Data Parallelism

Data parallelism goes particularly well with **data partitioning**.

$\rightarrow$ **Distribute** tuples over nodes ($\rightarrow$ **horizontal partitioning**)

$\rightsquigarrow$ **Parallel scan**; high I/O bandwidth

Round-Robin Partitioning:

- Easy, trivial **load balancing**

Range Partitioning:

- Need to access only those nodes that hold relevant data.
- **Data skew** may lead to trouble.
- May be beneficial for **sorting**, **joining**, etc.
- Range boundaries?

Data Parallelism

Hash Partitioning:

- **Data skew** less of a problem
- May also help certain operations (*e.g.*, **joins**)
- **No knowledge** about data or types required

Parallelizing Operator Evaluation

Scan: Easy

→ Scan-heavy queries benefit easily from data parallelism.

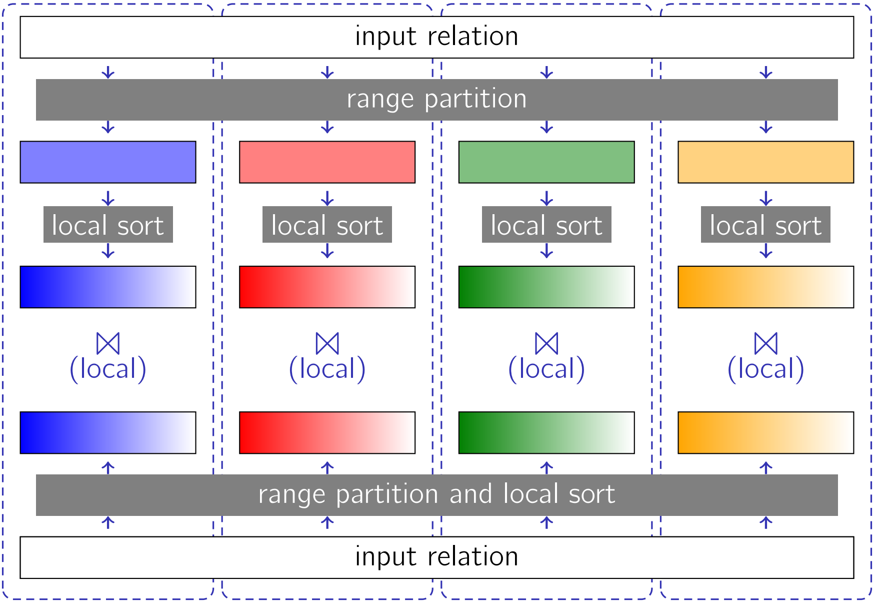
Sort:

- Merge sort/external sort: run early stages in parallel, then merge
- With **range partitioning**, merging becomes trivial.
  → Thus, first range-partition (re-distribute) data, then sort.
  → Determine range boundaries with help of **sampling**.

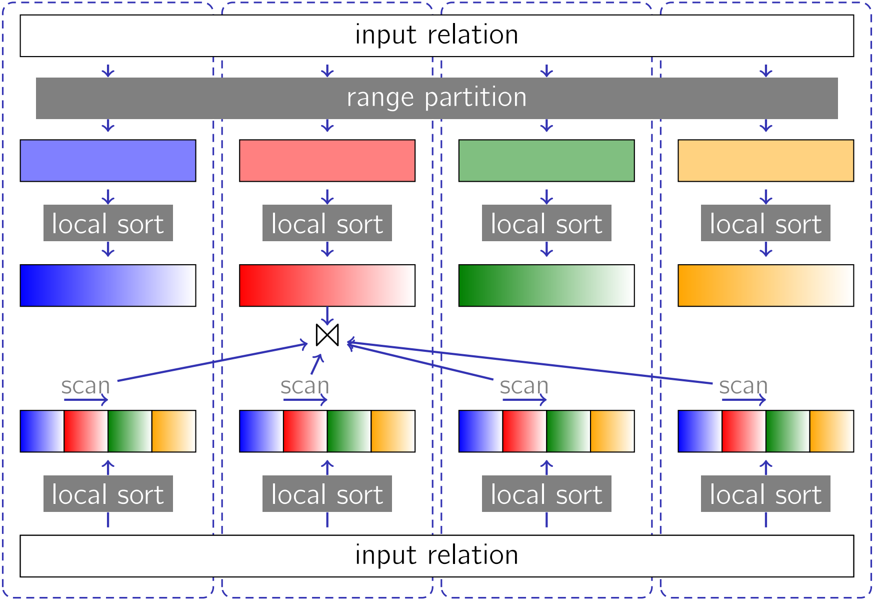
Join:

- **Partition** (re-distribute) tuples (hash or range partitioning)
- $R_i \bowtie S_i$ joins can now be computed locally.

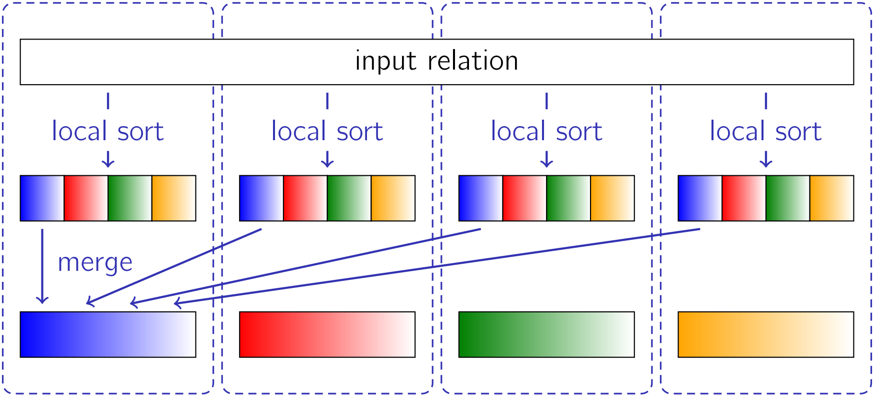
Parallel Joins (Using Merge Sort Locally)



Parallel Joins (here: MPSM)



Instead: Sort, then Merge/Partition



- Re-distributes ("shuffles") likely limited by interconnect bandwidth.
- Perform merge/join during shuffle
  - $\rightarrow$ Leverage available CPU capacity while I/O-limited.

Reduce Communication for Joins

Bloom filters can help reduce communication cost.

1. Partition and distribute outer join relation R.
2. On each node H_i, compute Bloom filter vector for R_i.
3. Broadcast all Bloom filters to all nodes.
4. Partition and distribute S, but filter tuples before sending.
5. Compute $R_i \bowtie S_i$ locally on all H_i.