UMD DATA605 - Big Data Systems

10.1: Parallel and Distributed Systems / DBs

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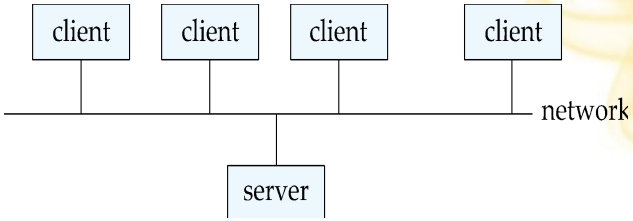
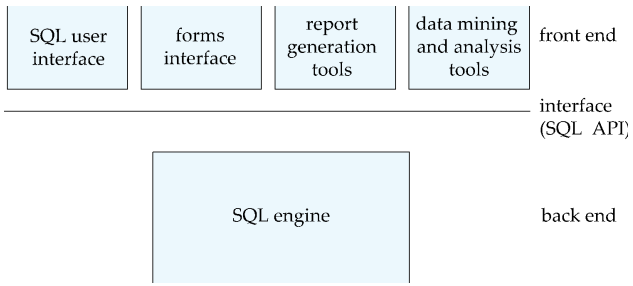
Client-Server Architecture

- **Client-server**: Model for distributed applications partitioning tasks between:
  - *Clients*: Request services (e.g., dashboard, GUI, client applications)
  - *Servers*: Provide resources or services (e.g., database)

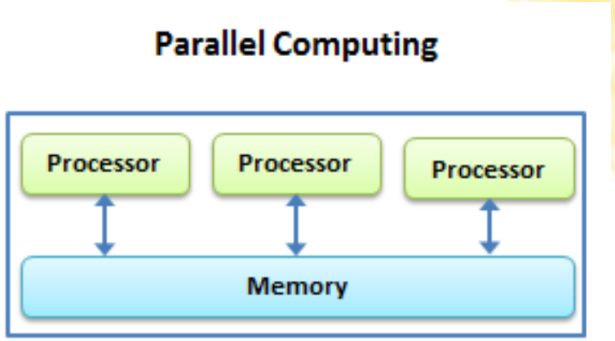


- **Architecture of a database system**:
  - *Back-end* (Server): Manages access, query evaluation, optimization, concurrency control, and recovery
  - *Front-end* (Clients): Tools like forms, report-writers, GUI
- Interface between front-end and back-end:
  - SQL
  - Application programming interface (API)

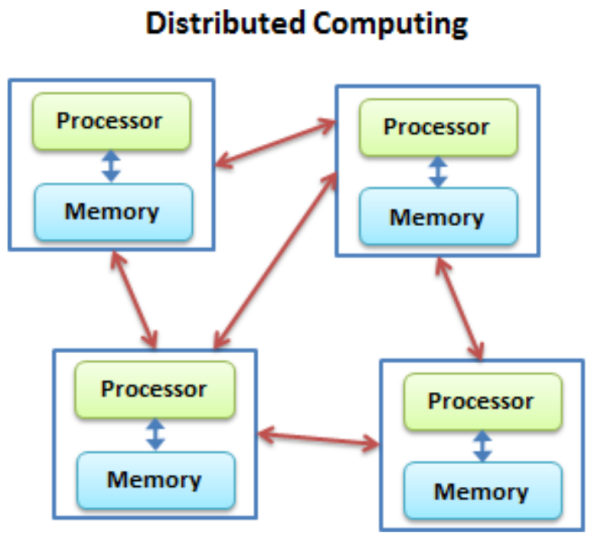


Parallel vs Distributed Computing

- **Parallel computing**
  - One computer, multiple CPUs
  - Cluster: many computers, each with multiple CPUs
  - Homogeneous, geographically close nodes
  - Work on one task simultaneously



- **Distributed computing**
  - Autonomous, geographically separate systems
  - Heterogeneous and distant nodes
  - Perform separate tasks or parts of a larger task



Parallel Systems

- **Parallel systems** consist of:
  - Multiple processors
  - Multiple memories
  - Multiple disks
  - 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
  - Larger degree of parallelism
  - With or without shared memory
  - E.g., GPUs, The Connection Machine

The Connection Machine, MIT, 1980s

Parallel Databases: Introduction

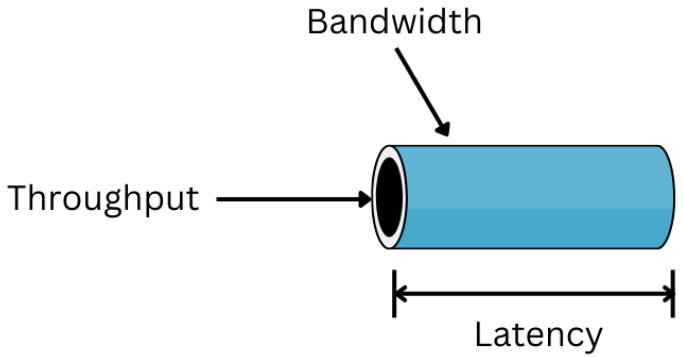
- **Parallel DBs** were the standard approach before MapReduce
- **Parallel machines have become common and affordable**
  - Prices of microprocessors, memory, and disks drop sharply
  - Desktop/laptop computers feature multiple processors
  - Trend will continue
- **DBs are growing increasingly large**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

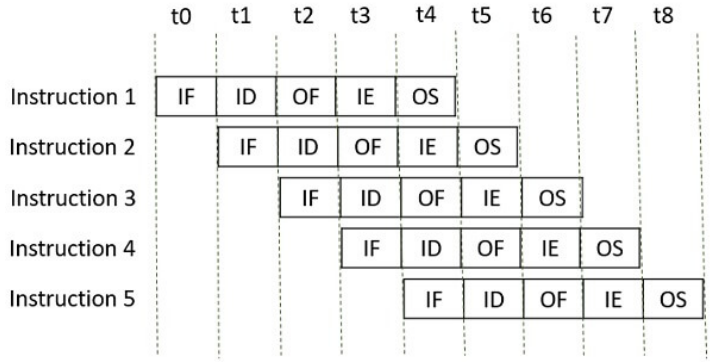
Parallel Databases

- Internet / Big Data created need for large, fast DBs
  - Store petabytes of data
  - Process thousands of transactions per second (e.g., commerce website)
- **Databases can be parallelized**
  - Set-oriented nature of DB queries suits parallelization
  - Some operations are embarrassingly parallel
    - E.g., join between `R` and `S on R.b = S.b` as MapReduce task
- **Parallel DBs**
  - More transactions per second or less time per query
  - Throughput vs response time
  - Speed-up vs scale-up
- **Perfect speedup doesn't happen** due to:
  - Start-up costs
  - Task interference
  - Skew

How to Measure Parallel Performance

- **Throughput**
  - Number of tasks completed in given time
  - Increase by processing tasks in parallel
- **Latency**
  - Time to complete single task from submission
  - Decrease by performing subtasks in parallel
- **Throughput and latency are related but not the same**
  - Increase throughput by reducing latency
  - Increase throughput by pipelining (overlapping task execution)
    - E.g., building a car takes weeks, but one car is completed per hour
    - Pipelining of microprocessor instructions





Pipelining of 5 Instructions

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Speed-Up and Scale-Up: Intuition

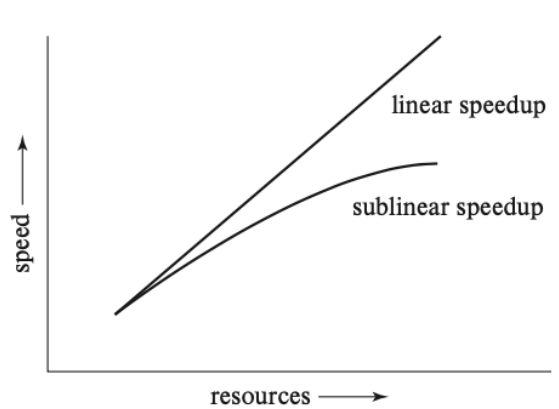
- **You have a workload to execute**
  - Change workload *M*
    - Number of DB transactions
    - Amount of DB data to query
- **You need to execute the workload on a machine**
  - Change computing power *N*
    - Better CPU (scale vertically, scale up)
    - More CPUs (scale horizontally, scale out)
- Two **ways to measure efficiency** when increasing workload and computing power
  - *Speed-up*
    - Keep constant problem size *M*
    - Increase machine power *N*
  - *Scale-up*
    - Increase problem size *M*
    - Increase machine power *N*

Speed-Up vs Scale-Up

- The amount of computing power N can be changed
- The amount of work M can be changed
- **Speed-up**: fixed-sized problem on a small system given to a system N-times larger

$$\text{speed-up} = \frac{\text{small system elapsed time}}{\text{large system elapsed time}}$$

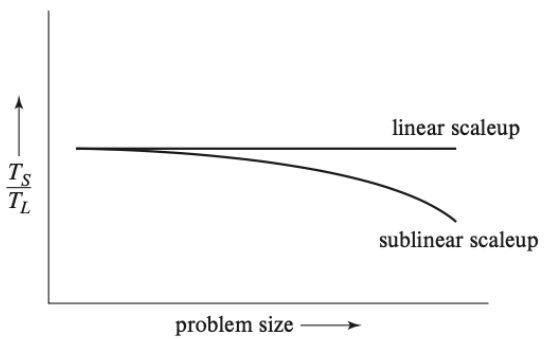
  - Speed-up is linear if equation equals N



- **Scale-up**: increase size of both problem M and system N
  - N-times larger system to perform M-times larger job

$$\text{scale-up} = \frac{\text{small system-problem time}}{\text{big system-problem time}}$$

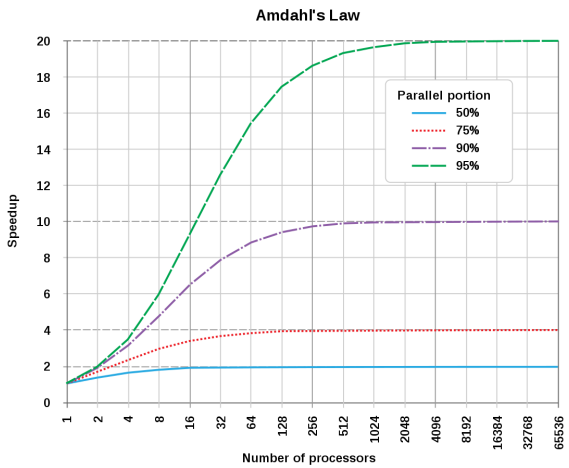
  - Scale-up is linear if equation equals 1



Factors Limiting Speed-up and Scale-up

- **Speed-up and scale-up are typically sub-linear** due to several issues
  - E.g., not all computation is parallelizable
- **Amdahl's Law**
  - p = fraction parallelizable
  - s = number of nodes
  - T = execution time serially
  - $T(p)$ = execution time on s nodes = $(1-p)T + (p/s)T$

$$Speedup(s) = \frac{T}{T(s)} = \frac{1}{(1-p) + \frac{p}{s}}$$



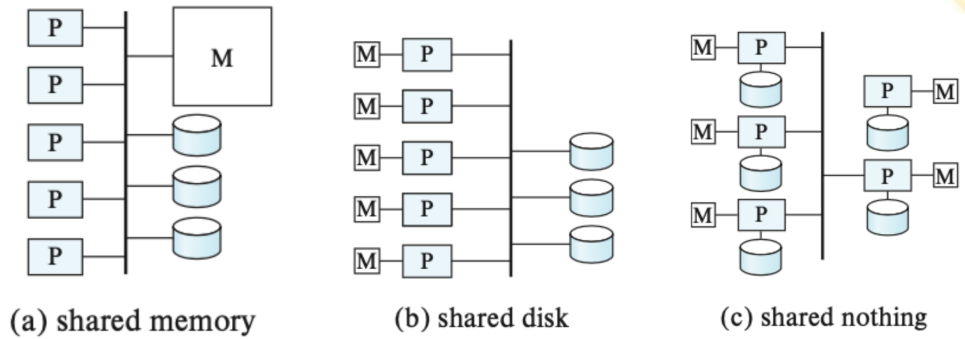
- E.g.,
  - 90% parallelizable → max speed-up 10x
  - 50% parallelizable → max speed-up 2x (even with infinite nodes)

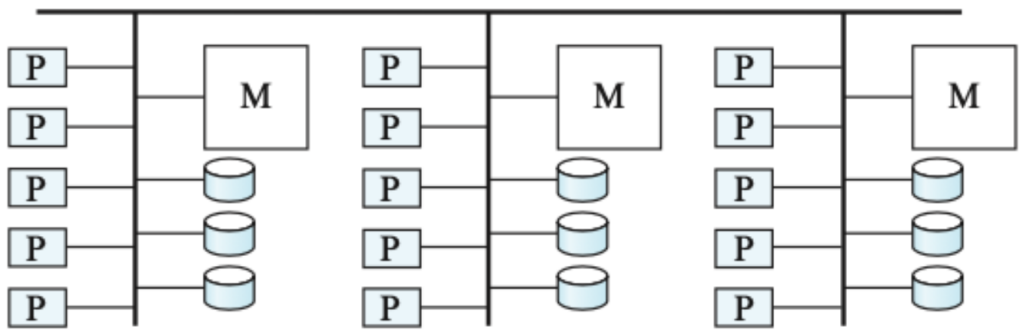
Factors Limiting Speed-up and Scale-up

- **Startup costs**
  - Starting processes may dominate computation time
  - E.g., dBs create thread pool at startup
- **Interference**
  - Processes compete for shared resources (e.g., system bus, disks, locks)
  - Time spent waiting on other processes
  - E.g., devs touching same code create merge conflicts
- **Cost of synchronization**
  - Smaller work pieces increase synchronization complexity
  - E.g., hiring many developers in a company
- **Skew**
  - Splitting work increases variance in task response time
  - Difficult to split tasks equally
  - Execution time determined by slowest task

Topology of Parallel Systems

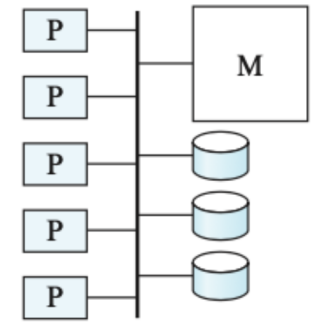
- Many ways to organize computation and storage
  - M = memory
  - P = processors
  - D = disks
- **Topology**
  - Shared memory
  - Shared disk
  - Shared nothing
  - Hierarchical
- **Problems**
  - Cache coherency
  - Data communication
  - Fault tolerance
  - Resource congestion



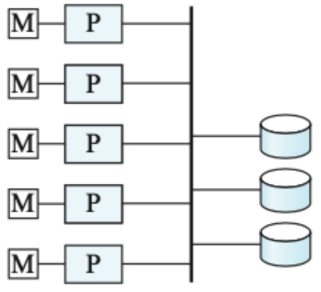


Topology of Parallel Systems: Comparison

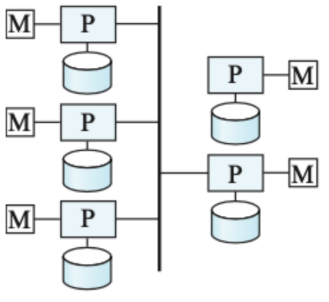
	Shared Memory	Shared Disk	Shared Nothing
Communication between processors	Extremely fast	Disk interconnect is very fast	Over a LAN, so slowest
Scalability?	Not beyond 32 or 64 or so (memory bus is the bottleneck)	Not very scalable (disk interconnect is the bottleneck)	Very very scalable
Notes	Cache-coherency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



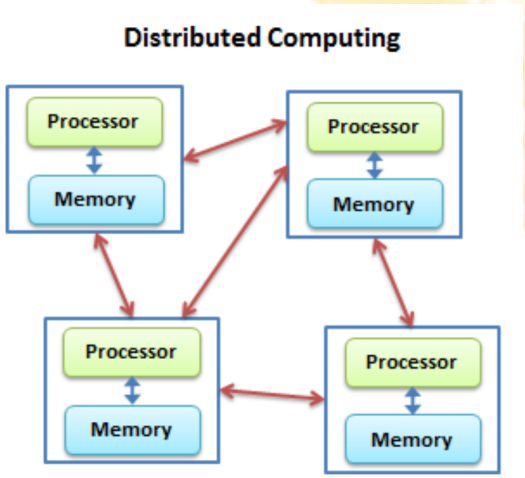
(b) shared disk



(c) shared nothing

Distributed Databases

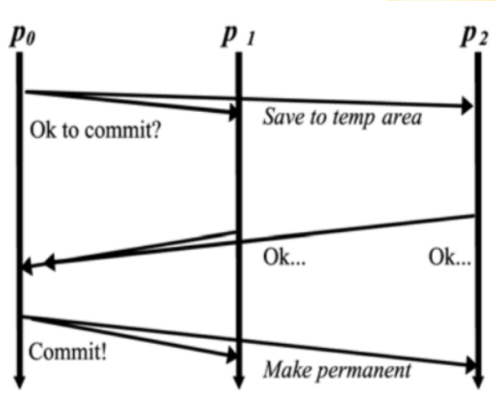
- **Distributed DBs**
  - DB stored on nodes at geographically separated sites
  - Communicate through high-speed private networks or Internet
- **Why needed?**
  - Large corporation with global offices
  - Redundancy and disaster recovery
  - Natural disasters, power outage, hacker attacks
  - Achieve high-availability despite failures
  - Typically not for performance
    - Use parallel DB for high performance



- **Wide-area networks (WAN) vs Local-area networks (LAN)**
  - Lower bandwidth
  - Higher latency
  - Greater probability of failures and network partition
  - No sharing of memory or disks
    - Communication delay is dominant
  - Nodes can differ in size and functions
    - Parallel DBs have similar nodes

Consistency Issues in Distributed DB Systems

- **Parallel and distributed DBs**
  - Efficient for query processing (read-only)
  - Requires consistency enforcement
- **Atomicity issues**
  - *Problem*: Transaction is all-or-nothing across nodes
  - Two-phase commit (2PC) is centralized
    - Commit decision by a single coordinator node
    - Each node executes transaction, reaching "ready state"
    - If all nodes reach ready state, coordinator commits
    - If a node fails in ready state, it can recover (e.g., write-ahead logs)
    - If a node aborts, coordinator aborts transaction
  - Distributed consensus, e.g.,
    - Paxos
    - Blockchain



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

Consistency Issues in Distributed DB Systems

- **Concurrency issues**
  - *Problem*: Multiple processes writing and reading simultaneously
  - Locks / deadlock management
- **Autonomy issues**
  - *Problem*: Units/departments protective of their systems
  - E.g., administering systems, patching, updating