

# CMPT 431 Distributed Systems Fall 2019

### Parallel Computing

https://www.cs.sfu.ca/~keval/teaching/cmpt431/fall19/

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## Memory Architectures

#### **Shared Memory Distributed Memory** P1 P2 P0 P0 P1 P2 Memory Memory Memory Memory

### Shared Memory Architectures

- Processors access memory as a global address space
- Memory updates by one processor are visible to others
- Easier to program with global address space
- Typically fast memory access (supported by hardware)
- Difficult to scale
- Adding CPUs (geometrically) increases traffic
- Need to synchronization memory accesses

### Shared Memory: Race Condition

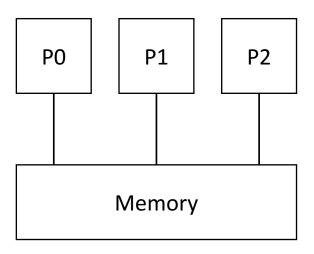
### Distributed Memory Architectures

- Nodes (processors + memories) connected via communication network
- Access to another processor's data via communication protocols (e.g., send-receive calls)
- Scalable (both processor and memory)
- Local access is fast (no coordination required)
- Cost effective
- Difficult to program
- Communication/Synchronization is difficult to manage

### Shared Memory: UMA & NUMA

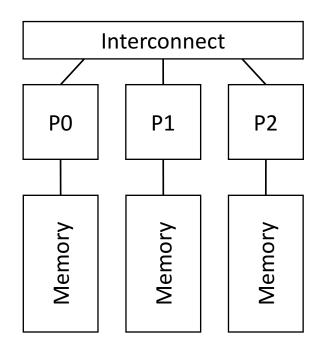
# Uniform Memory Access (UMA)

- Typically Symmetric Multiprocessors (SMP)
- Equal memory access time



# Non-Uniform Memory Access (NUMA)

- Typically multiple SMPs that can access each other's memories
- Memory access times are not equal



#### Communication Models

- Shared Memory
  - Tasks share a common address space they access asynchronously
  - Mutexes/Locks used to control access to shared memory
  - Compiler translates variables into global memory addresses

- Message Passing
  - No shared address space
  - Tasks use their own local memories
  - Data transfer often requires coordination: receive matching send

### Parallel Programming Models

#### Data parallel

- Parallel operations over a collection of data items
- Tasks collectively work on the collection and each task works on a different partition (subset) of the collection
- E.g., increment all elements in an array by 1 (map operation)

#### Task Parallel

- Tasks defined based on the operations to be performed
- Each task performs an operation which is different from that performed by other task
- Operations should be safe to be concurrently executable with other operations
- May or may not operate on the same collection of data items
- E.g., pipelining

### Parallel Programming

- Decompose problem into sub-problems
- Map sub-problems to concurrent tasks
- Ensure dependencies are correctly satisfied
  - E.g., Op1 in thread 1 should happen before op2 in thread 2
  - Coordination via synchronization/communication
- Overall execution is a mix of parallel and sequential executions

### Measuring Performance

- How fast does a job compute?
  - Elapsed time (Latency)
  - compute + communicate + synchronize
- How many jobs complete in a given time?
  - Throughput
- How well does the system scale?
  - Increasing processors (compute nodes)
  - Increasing problem size (constant work per processor)

Weak v/s strong scaling: <a href="https://en.wikipedia.org/wiki/Scalability#Weak\_versus\_strong\_scaling">https://en.wikipedia.org/wiki/Scalability#Weak\_versus\_strong\_scaling</a>

### Performance Metrics

• Speedup, 
$$S_p = \frac{\text{Execution time using 1 processor system } (T_1)}{\text{Execution time using p processor system } (T_p)}$$

• Efficiency = 
$$\frac{S_p}{p}$$

• Cost, 
$$C_p = p \times Tp$$

Optimal if 
$$C_p = T_1$$

### Amdahl's Law

- f = fraction of problem that is sequential
  - (1 f) = fraction of problem that is parallel
- Fastest parallel time,  $T_p = T_1 \times (f + \frac{1-f}{p})$
- Speedup with p processors,  $S_p = \frac{1}{f + \frac{(1-f)}{p}}$

### Amdahl's Law

- Gives an upper bound on speedup
- Only fraction (1 f) is shared by p processors
  - Increasing p cannot speed up fraction f
- Speedup with p processors,  $S_p = \frac{1}{f + \frac{(1-f)}{p}}$
- Upper bound on speedup at  $S_{\infty} = \frac{1}{f}$
- Example: f = 2%,  $S_{\infty} = 1 / 0.02 = 50$

### Amdahl's Law

$$S_{p} = \frac{1}{f + \frac{(1-f)}{p}}$$

