

# PARALLEL PROCESSING

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# PARALLEL ALGORITHM COMPLEXITY

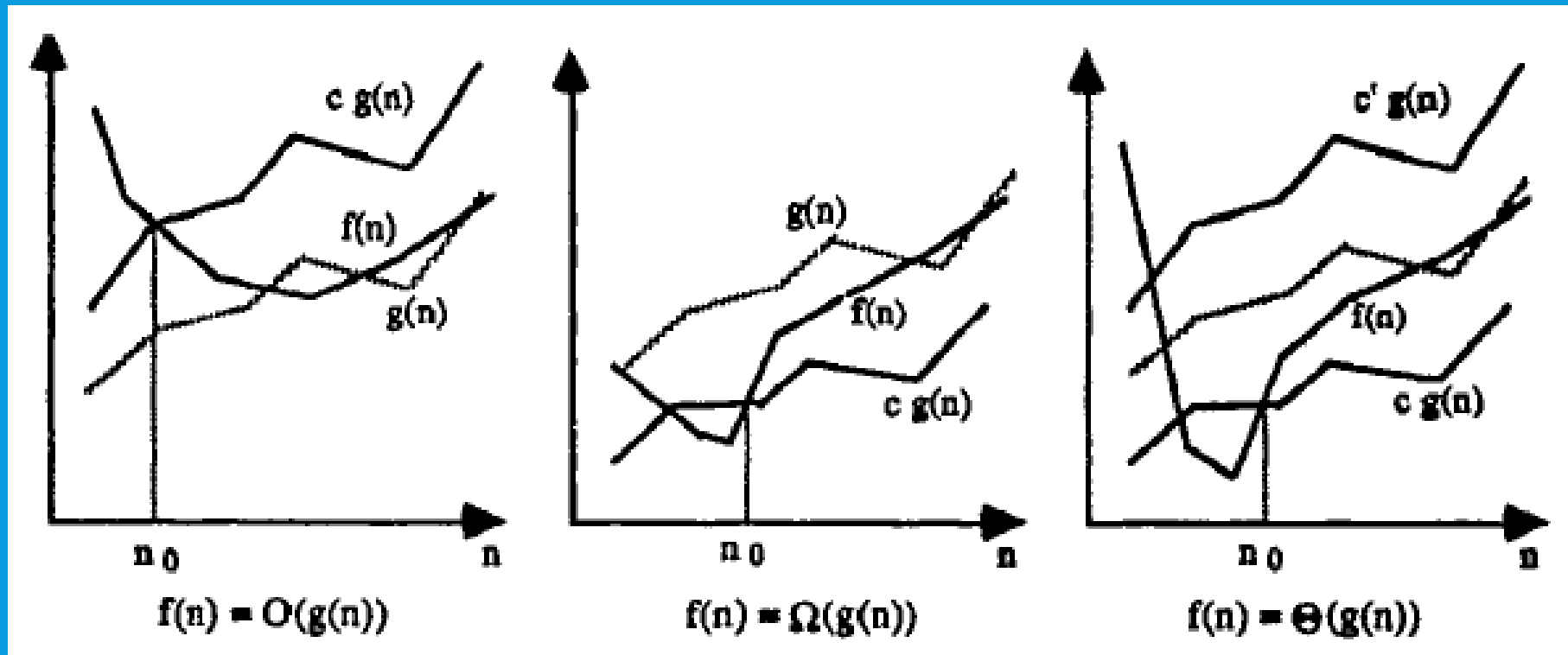
- For large problem size  $n$  we use asymptotic complexity to analyze and compare parallel algorithms.
- An algorithm of complexity  $(\log_2 n)^2$  and another algorithm of complexity  $500 \log_2 n$  the later is taking on the order of  $\log_2 n$ .

$f(n) = O(g(n))$  if  $\exists c, n_0$  such that  $\forall n > n_0$  we have  $f(n) < c g(n)$

$f(n) = \Omega(g(n))$  if  $\exists c, n_0$  such that  $\forall n > n_0$  we have  $f(n) > c g(n)$

$f(n) = \Theta(g(n))$  if  $\exists c, c', n_0$  such that  $\forall n > n_0$  we have  $c g(n) < f(n) < c' g(n)$

# PARALLEL ALGORITHM COMPLEXITY



# PARALLEL ALGORITHM COMPLEXITY

- Some methods used in devising parallel algorithms
  - Divide and Conquer.
  - Randomization.
  - Approximation

# PARALLEL ALGORITHM COMPLEXITY

- **Divide and Conquer.**

- Some problems in P can be solved in parallel by decomposing the problem of size  $n$  into two or more “smaller” sub-problems.
- For a problem of size  $n$  ,
  - $T_d(n)$  is decomposing time.
  - $T_s$  is the time to solve sub-problem.
  - $T_c(n)$  the time to combine.
  - The total time  $T(n) = T_d(n) + T_s + T_c(n)$

# PARALLEL ALGORITHM COMPLEXITY

- **Divide and Conquer example**

- sorting a list of  $n$  keys, we can decompose the list into two halves each of  $n/2$  elements.
- Time to sort is  $T\left(\frac{n}{2}\right)$  each sub list will be sorted in the same manner (decomposed, sorted, and merged).
- Time to decompose and combine is  $2 \log(n)$
- $T(n) = T(n/2) + 2 \log n$ .

# PARALLEL ALGORITHM COMPLEXITY

- **Randomization**

- Sometimes it is impossible, or computationally difficult, to decompose a large problem into smaller problems in such a way that the solution times of the sub-problems are roughly equal.
- Large decomposition and combining overheads, or wide variations in the solution times of the sub-problems, may reduce the effective speed-up achievable by the divide-and-conquer method.
- it might be possible to use random decisions that lead to good results with very high probability.

# PARALLEL ALGORITHM COMPLEXITY

- Randomization
  - Sorting Algorithm Example:
    - Suppose that each of  $p$  processors begins with a sub-list of size  $n/p$ .
    - First each processor selects a random sample of size  $k$  from its local sub-list.
    - The  $kp$  samples from all processors form a smaller list that can be readily sorted.
    - This sorted list of samples is now divided into  $p$  equal segments.
    - The beginning values in the  $p$  segments used as thresholds to divide the original list of  $n$  keys into  $p$  sub-lists.
    - The lengths of these latter sub-lists will be approximately balanced.
    - The sub-lists are sorted within each processor.
    - Depending on the threshold permutation between processors.
    - Local sorting at each processor needed to sort the  $n$  keys.



# PARALLEL ALGORITHM COMPLEXITY

- **Randomization Practices**
- Other useful practices of randomization:
  - **Random Search:** When searching large space for an element that exist, random search can lead to very good average-case performance.
  - **Control randomization:** To avoid consistently experiencing close to worst-case because unfortunate distribution of inputs, the inputs can be chosen at random.
  - **Symmetry breaking:** Interacting deterministic processes may exhibit a cyclic behavior that leads to deadlock. Randomization can be used to break the symmetry and thus the deadlock.

# PARALLEL ALGORITHM COMPLEXITY

- **Approximation**

- Iterative numerical methods often use approximation to arrive at the solution(s).
- For example, to solve a system of  $n$  linear equations, one can begin with some rough estimates for the answers and then successively refine these estimates using parallel numerical calculations.
- Jacobi relaxation is an example. The analysis of complexity is somewhat more difficult here as the number of iterations required often cannot be expressed as a simple function of the desired accuracy and/or the problem size.

# PARALLEL ALGORITHM COMPLEXITY

- **Approximation example**
- Suppose we are given the following linear system:

$$\begin{aligned}10x_1 - x_2 + 2x_3 &= 6, \\ -x_1 + 11x_2 - x_3 + 3x_4 &= 25, \\ 2x_1 - x_2 + 10x_3 - x_4 &= -11, \\ 3x_2 - x_3 + 8x_4 &= 15.\end{aligned}$$

# PARALLEL ALGORITHM COMPLEXITY

- **Approximation example**

If we choose  $(0, 0, 0, 0)$  as the initial approximation, then the first approximate solution is:

$$x_1 = (6 + 0 - (2 * 0))/10 = 0.6,$$

$$x_2 = (25 + 0 + 0 - (3 * 0))/11 = 25/11 = 2.2727,$$

$$x_3 = (-11 - (2 * 0) + 0 + 0)/10 = -1.1,$$

$$x_4 = (15 - (3 * 0) + 0)/8 = 1.875.$$

# PARALLEL ALGORITHM COMPLEXITY

- **Approximation example**

Using the approximations obtained, the iterative procedure is repeated until the desired accuracy has been reached.

$x_1$	$x_2$	$x_3$	$x_4$
0.6	2.27272	-1.1	1.875
1.04727	1.7159	-0.80522	0.88522
0.93263	2.05330	-1.0493	1.13088
1.01519	1.95369	-0.9681	0.97384
0.98899	2.0114	-1.0102	1.02135

The exact solution is (1,2,-1,1)



# PARALLEL ALGORITHM COMPLEXITY

- SOLVING RECURRENCES

- *We may solve recurrence by unrolling:*

$$\begin{aligned} f(n) &= f(n-1) + n \quad \{\text{rewrite } f(n-1) \text{ as } f((n-1)-1) + n-1\} \\ &= f(n-2) + n-1 + n \\ &= f(n-3) + n-2 + n-1 + n \\ &\dots \\ &= f(1) + 2 + 3 + \dots + n-1 + n \\ &= n(n+1)/2 - 1 \\ &= \Theta(n^2) \end{aligned}$$