

Algorithms and Data Structures

Module 2

Lecture 11

**'Divide-and-Conquer' strategy.
MergeSort.**

Greedy algorithms (reminder)

Key characteristics of a greedy algorithm:

- Can solve an optimization problem.
- Builds solution iteratively, adding one element after another.
- At each step, adds the element which is the best at the current situation.
- Does not revise the decisions (one-pass algorithm).

Divide-and-Conquer strategy

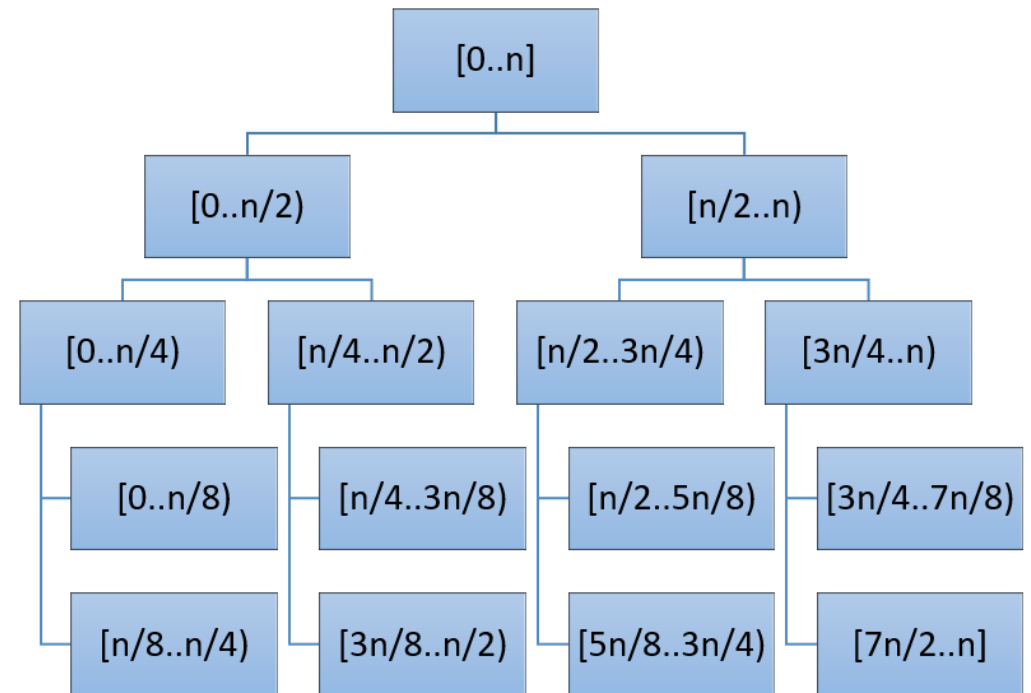
A 'Divide-and-Conquer' strategy:

- 1. Divide** the given instance of the problem into several *independent smaller* instances of the *same* problem. Division does not necessarily mean dividing the dataset into disjoint datasets; it can mean a more general sort of *reduction*.
- 2. Solve** all smaller instances. Usually we *recursively* use the same algorithm for solving smaller instances.
- 3. Combine** the solutions of the smaller instances into the solution of the initial problem instance.

Divide-and-Conquer strategy

A 'Divide-and-Conquer' algorithm is usually implemented as a recursive function.

The run of a recursive algorithm can be represented as a *recursion tree*.



MergeSort

Task: given an array $A[0..n - 1]$, sort it in ascending order.

MergeSort:

1. [**Divide**] Divide the array into two subarrays each of size approximately $n/2$.
2. [**Solve**] Recursively sort both subarrays, using MergeSort.
3. [**Combine**] Merge the sorted subarrays into the resulting sorted array.

MergeSort: steps' implementation

Divide:

Just divide the array $A[0..n - 1]$ into two subarrays.

This can be made in an 'in-place' manner if we let the subarrays to be the segments $A\left[0..\frac{n}{2} - 1\right]$ and $A\left[\frac{n}{2}..n - 1\right]$.

Time complexity: $O(1)$.

MergeSort: steps' implementation

Solve:

Recursive call the MergeSort procedure.

!! For any recursive procedure we must provide a non-recursive branch. For MergeSort, we process short arrays non-recursively. Options:

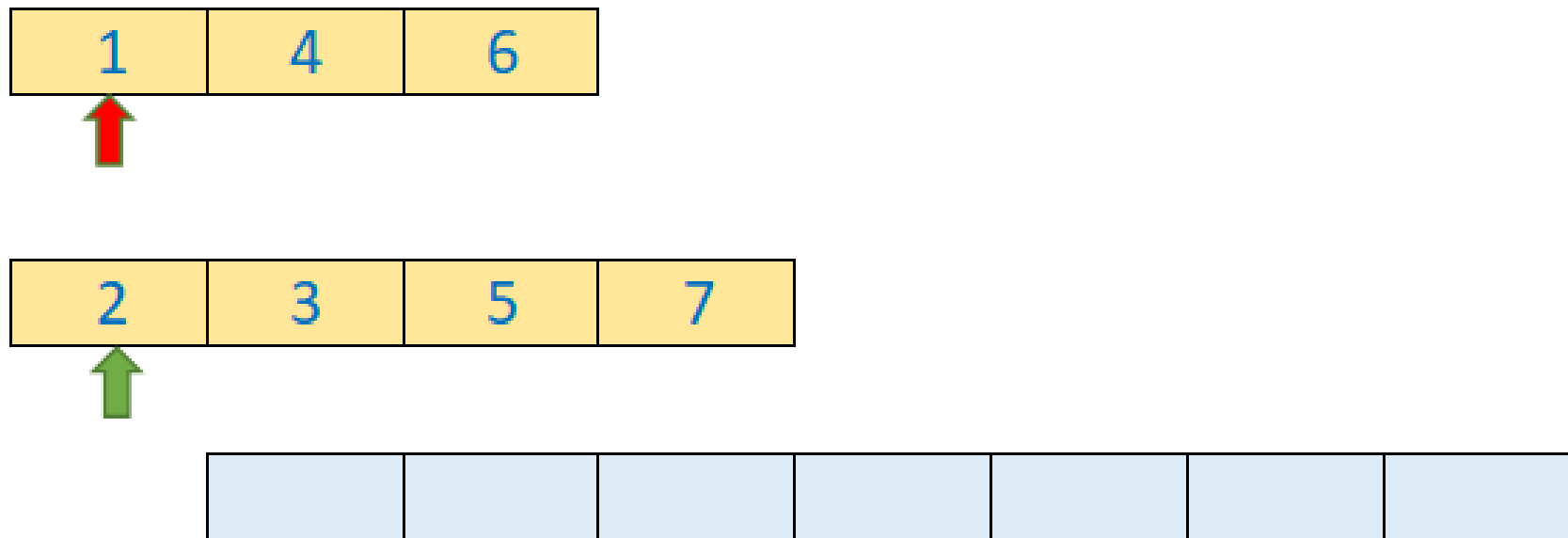
- For cases $n = 0$ and $n = 1$ no sorting needed.
- For small arrays (say, $n \leq 100$) running non-recursive sorting procedure (e.g. bubble sort) is more efficient.

Time complexity: depends on complexity of the 'Combine' step.

MergeSort: steps' implementation

Combine:

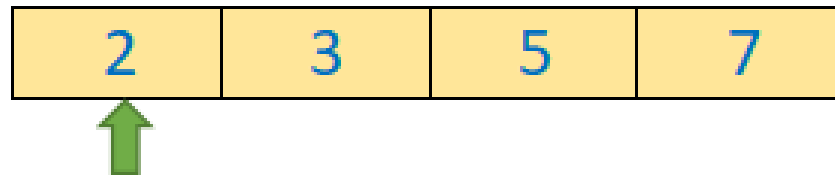
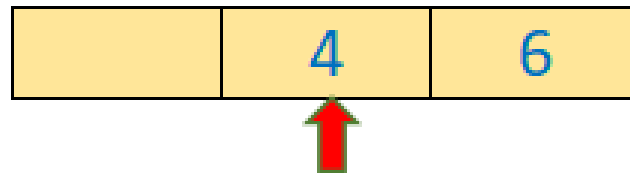
Given two sorted subarrays, how can we get one single sorted array? We compare the first items of subarrays.



MergeSort: steps' implementation

Combine:

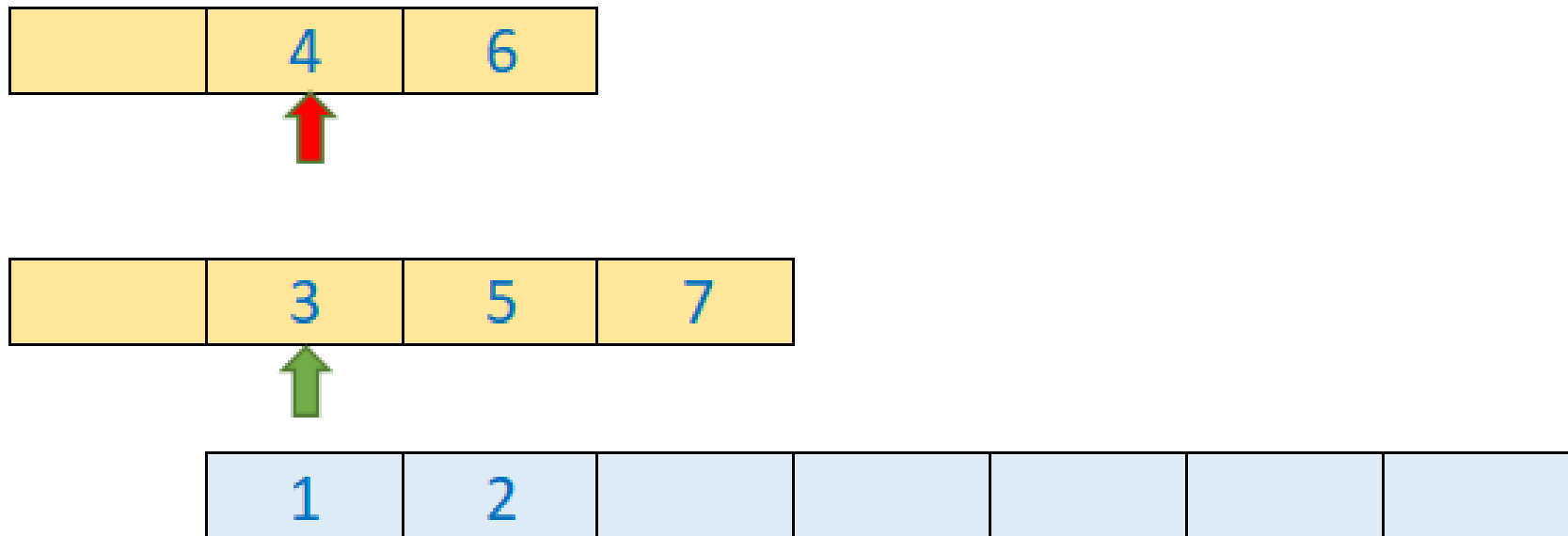
We put the least item to the target array and move the pointer in it's subarray to the next position.



MergeSort: steps' implementation

Combine:

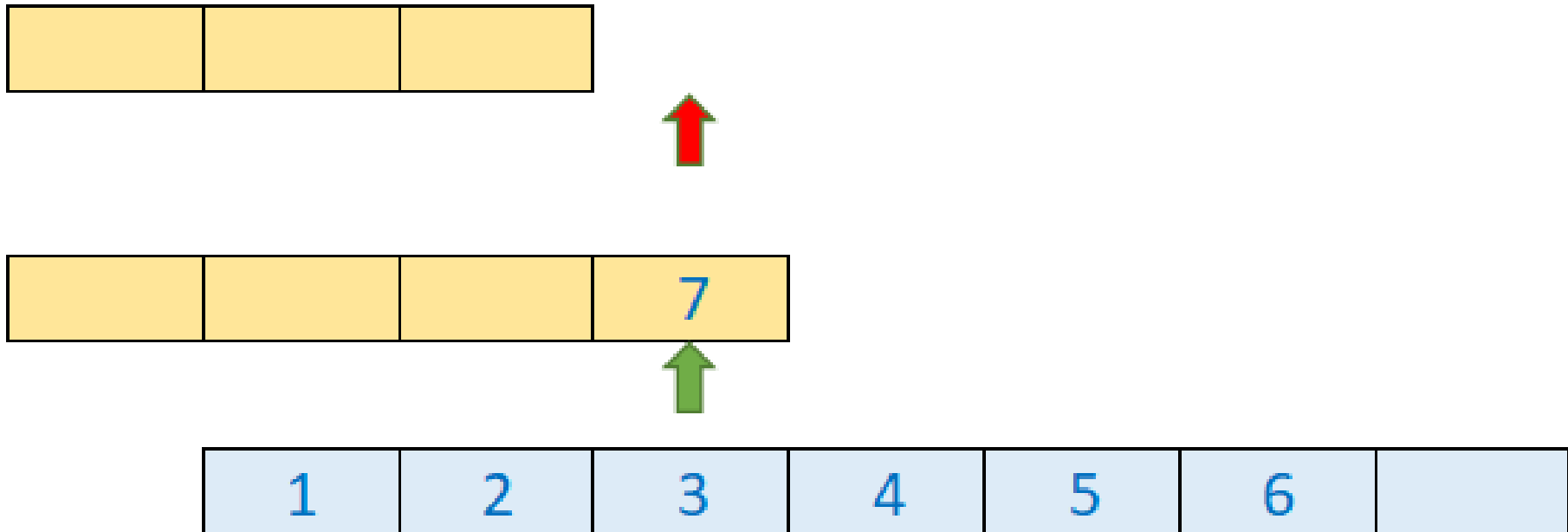
Then we repeat this procedure...



MergeSort: steps' implementation

Combine:

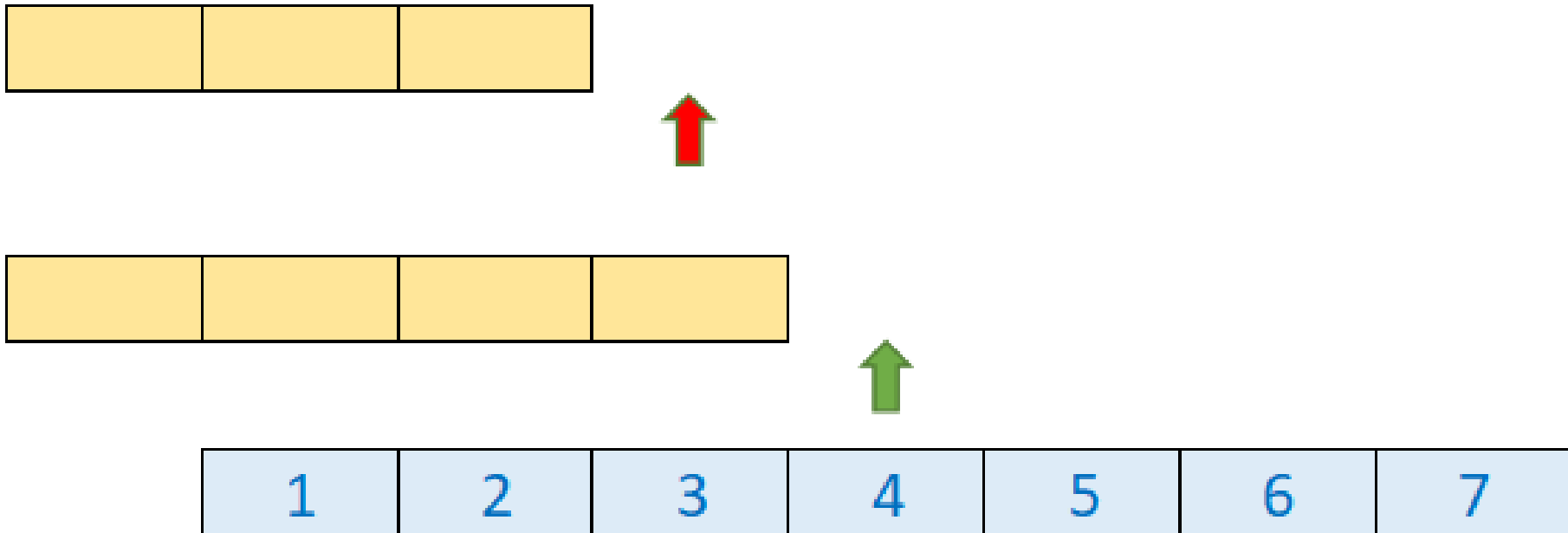
... until one of the subarrays becomes empty.



MergeSort: steps' implementation

Combine:

As a result we get the sorted array!



MergeSort: time complexity

Let's evaluate the total time complexity of the MergeSort procedure.

Divide: takes $O(1)$ time.

Solve: ???

Combine: takes $O(n)$ comparisons and assignments.

Let $T(n)$ be the time complexity of merge sorting for an array of size n .

MergeSort: time complexity

Let $T(n)$ be the time complexity of merge sorting for an array of size n .

$$T(n) = \begin{cases} c, & \text{for } n = 1 \\ 2T\left(\frac{n}{2}\right) + dn, & \text{for } n > 1 \end{cases}$$

After solving this *recurrence*, we get $T(n) = O(n \cdot \log_2 n)$.

Divide-and-Conquer: Master theorem

Consider a recursive algorithm of this form:

```
procedure p(input x of size n):  
    if n < some constant k:  
        Solve x directly without recursion  
    else:  
        Create a subproblems of x, each having size n/b  
        Call procedure p recursively on each subproblem  
        Combine the results from the subproblems
```

f(n)

[https://en.wikipedia.org/wiki/Master_theorem_\(analysis_of_algorithms\)](https://en.wikipedia.org/wiki/Master_theorem_(analysis_of_algorithms))

Divide-and-Conquer: Master Theorem

Time complexity of this procedure is

$$T(n) = aT\left(\frac{n}{b}\right) + f(n)$$

The **Master Theorem**: there are 3 cases:

- 1) If $f(n) = \Omega(n^{\log_b a + \varepsilon})$ for some constant $\varepsilon > 0$, and $f(n)$ satisfies the regularity condition, then $T(n) = \Theta(f(n))$.
- 2) If $f(n) = \Omega(n^{\log_b a} (\log n)^k)$ for $k \geq 0$, then $T(n) = \Theta(n^{\log_b a} (\log n)^{k+1})$.
- 3) If $f(n) = \Omega(n^{\log_b a - \varepsilon})$ for some constant $\varepsilon > 0$, then $T(n) = \Theta(n^{\log_b a})$.

The regularity condition: $a \cdot f\left(\frac{n}{b}\right) \leq c \cdot f(n)$ for some constant $c < 1$ and all sufficiently large n .

Divide-and-Conquer: Master Theorem

There is a simplified version of the Master Theorem for the case $f(n) = O(n)$.

The **Master Theorem (simplified version)**: there are 3 cases:

- 1) If $a < b$, then $T(n) = \Theta(n)$.
- 2) If $a = b$, then $T(n) = \Theta(n \log n)$.
- 3) If $a > b$, then $T(n) = \Theta(n^{\log_b a})$.

Divide-and-Conquer: Master Theorem

Let's consider the simplified case. For simplicity let $n = b^k$.

$$T(n) = \begin{cases} c, & \text{for } n = 1 \\ aT\left(\frac{n}{b}\right) + dn, & \text{for } n > 1 \end{cases}$$

Hence, $T(n) = aT\left(\frac{n}{b}\right) + dn = a\left[aT\left(\frac{n}{b^2}\right) + d \cdot \frac{n}{b}\right] + dn = a^2 \cdot T\left(\frac{n}{b^2}\right) + dn \cdot$

$$\left(\frac{a}{b} + 1\right) = \dots = a^k \cdot T\left(\frac{n}{b^k}\right) + dn \cdot \sum_{i=0}^{k-1} \left(\frac{a}{b}\right)^i = a^k c + dn \cdot \sum_{i=0}^{k-1} \left(\frac{a}{b}\right)^i.$$

Divide-and-Conquer: Master Theorem

$$T(n) = \dots = a^k c + dn \cdot \sum_{i=0}^{k-1} \left(\frac{a}{b}\right)^i.$$

Case 1: $a < b$

In this case $\sum_{i=0}^{k-1} \left(\frac{a}{b}\right)^i \rightarrow \text{const}$, hence $T(n) = \Theta(a^k) + \Theta(n) =$

$$\Theta(b^k) + \Theta(n) = \Theta(n).$$

Divide-and-Conquer: Master Theorem

$$T(n) = \dots = a^k c + dn \cdot \sum_{i=0}^{k-1} \left(\frac{a}{b}\right)^i.$$

Case 2: $a = b$

In this case $\frac{a}{b} = 1$ and $\sum_{i=0}^{k-1} \left(\frac{a}{b}\right)^i = k$, hence $T(n) = \Theta(a^k) +$

$$\Theta(n \cdot k) = \Theta(n) + \Theta(n \cdot \log n) = \Theta(n \log n).$$

Divide-and-Conquer: Master Theorem

$$T(n) = \dots = a^k c + dn \cdot \sum_{i=0}^{k-1} \left(\frac{a}{b}\right)^i.$$

Case 3: $a > b$

Treat $\sum_{i=0}^{k-1} \left(\frac{a}{b}\right)^i$ as the partial sum of the geometric sequence: $\sum_{i=0}^{k-1} \left(\frac{a}{b}\right)^i = \frac{\left(\frac{a}{b}\right)^k - 1}{\frac{a}{b} - 1} =$

$\frac{a^k - b^k}{a - b} \frac{1}{b^k} = \Theta\left(\frac{a^k}{b^k}\right)$. Recall that $b^k = n$, hence $T(n) = a^k c + dn \cdot \sum_{i=0}^{k-1} \left(\frac{a}{b}\right)^i = a^k c + dn \cdot$

$$\Theta\left(\frac{a^k}{n}\right) = a^k c + \Theta(a^k) = \Theta(a^k) = \Theta(a^{\log_b n}) = \Theta(n^{\log_b a}).$$

Divide-and-Conquer: Master Theorem

Algorithm	Recurrence relationship	Run time
Binary search	$T(n) = T\left(\frac{n}{2}\right) + O(1)$	$O(\log n)$
Merge sort	$T(n) = 2T\left(\frac{n}{2}\right) + O(n)$	$O(n \log n)$