

Lecture 2. Analysis of Algorithms. Recursion and its Application

SIT221 Data Structures and Algorithms

Algorithm Analysis

As the size of a problem grows for an algorithm

- Time: How much longer does it run?
- Space: How much memory does it use?

Space Complexity



Here is what moving a 5MB IBM Hard Drive in 1956 was like.

Is memory space still an issue now days?

Experimental study of algorithms

Why not just code the algorithm and time it?

- Hardware: processor(s), memory, and etc.
- Operating System, version of libraries, drivers
- Programs running in the background
- Implementation dependent
- Choice of input
- Number of inputs to test

All these factors may significantly affect the running time.

Experimental study of algorithms: Issues

Timing does not really evaluate the algorithm, but merely evaluates a specific implementation

- Use asymptotic analysis to evaluate an algorithm
 - Examine the algorithm itself, **not** the implementation
 - Reason about performance as a function of n
 - Mathematically prove things about performance
- Use timing to evaluate an implementation

In the real world, we do want to know whether implementation A runs faster than implementation B on data set C

Linear Search: Complexity

```
int LinearSearch( int[] A, int n, int value )
{
    for ( int i = 0 ; i < n; i++ )
    {
        if ( A[i] == value )
            then return i;
    }
    return -1;
}
```

- Worst case: $T(n) = O(n)$ comparisons
- Best case: $T(n) = O(1)$ comparisons
- Average case: $T(n) = O(n)$ comparisons
- Worst-case space complexity: $O(1)$ iterative

Linear Search: Average Case Analysis

- We shall focus on the probable position for the desired element x , rather than the elements of the array A .
- Since for any input A , the element x is equally likely to be present in any location of A . Therefore, $\Pr[A[i] = x] = \frac{1}{n}$ for $1 \leq i \leq n$.
- The cost of accessing the i^{th} location is i and the associated probability is $\frac{1}{n}$. Therefore, the expected cost is

$$1 \times \frac{1}{n} + 2 \times \frac{1}{n} + \dots + n \times \frac{1}{n} = \frac{1}{n} \frac{n(n+1)}{2} = \frac{n+1}{2}.$$

- Finally, $\frac{n+1}{2} = O(n)$ comparisons on average.

Bubble Sort: Complexity

Given is an array A of size n of integer numbers.

```
for ( i = 1 ; i < n ; i++ )  
{  
    int swaps = 0;  
    for ( j = 0 ; j < n - i; j++ )  
    {  
        if ( a[j] > a[j + 1] )  
        {  
            swap( a[j], a[j + 1] );  
            swaps = swaps + 1;  
        }  
    }  
    if ( swaps == 0 ) then break;  
}
```

- Worst case: $T(n) = O(n^2)$ comparisons
- Best case: $T(n) = O(n)$ comparisons
- Average case: $T(n) = O(n^2)$ comparisons
- Worst-case space complexity: $O(1)$ auxiliary

Insertion Sort: Complexity

Given is an array A of size n of integer numbers.

```
for ( i = 1 ; i < n ; i++ )  
{  
    j = i;  
    while ( ( j > 0 ) && ( A[j-1] > A[j] ) )  
    {  
        swap( A[j], A[j-1] );  
        j = j - 1;  
    }  
}
```

- Worst case: $T(n) = O(n^2)$ comparisons
- Best case: $T(n) = O(n)$ comparisons
- Average case: $T(n) = O(n^2)$ comparisons
- Worst-case space complexity: $O(1)$ auxiliary

Selection Sort: Complexity

Given is an array A of size n of integer numbers.

```
for ( int i = 0 ; i < n; i++ )  
{  
    int min = i;  
    for ( int j = i+1; j < n; j++ )  
    {  
        if ( A[j] < A[min] ) then min = j;  
    }  
    if ( min != i ) then swap( A[i], A[min] );  
}
```

- Worst case: $T(n) = O(n^2)$ comparisons
- Best case: $T(n) = O(n^2)$ comparisons
- Average case: $T(n) = O(n^2)$ comparisons
- Worst-case space complexity: $O(1)$ auxiliary

Simple Integer Arithmetics: Complexity Analysis

We want to have algorithms to carry out

- Addition
- Multiplication

of two numbers.

Recall what you have learned in school!

Representation of integer numbers

- Assume that integers are represented as digit strings stored in an array a of size n containing n digits

$$a_{n-1}a_{n-2} \dots a_1a_0$$

- Base B number system, $B > 1$
- Digits $0, 1, \dots, B - 1$

Then $\sum_{i=0}^{n-1} a_i B^i$ represents our integer.

Representation of integer numbers

$$\sum_{i=0}^{n-1} a_i B^i$$

- For $B = 10$, “924” is represented as

$$9 \cdot 10^2 + 2 \cdot 10^1 + 4 \cdot 10^0 = 924$$

- For $B = 2$, “10101” is represented as

$$1 \cdot 2^4 + 0 \cdot 2^3 + 1 \cdot 2^2 + 0 \cdot 2^1 + 1 \cdot 2^0 = 21$$

Choice of primitive operations

Assume that we have access to

- **addition of 3 digits** with a 2 digits result (full adder);
- **multiplication of 2 digits** with 2 digits result.

For example:

Addition:

$$\begin{array}{r} 3 \\ 5 \\ 5 \\ \hline 13 \end{array}$$

Multiplication: $6 \cdot 7 = 42$

School Method for Addition: Example

$$a = 1289, \quad b = 1342, \quad B = 10 \quad \text{base}$$

	a	1289
+	b	1342
		<hr/>
	c	00110
		<hr/> <hr/>
	sum	02631

School Method for Addition: Analysis

Input: Two integers $a = (a_{n-1} \dots a_0)$ and $b = (b_{n-1} \dots b_0)$

Compute: $s = a + b$, where $s = (s_n \dots s_0)$
is an $n + 1$ digit number.

$a_{n-1} \dots a_1 a_0$	first operand
$b_{n-1} \dots b_1 b_0$	second operand
$c_n \ c_{n-1} \dots c_1 \ 0$	carries
<hr style="border: 0.5px solid black;"/>	
$s_n \ s_{n-1} \dots s_1 \ s_0$	sum

$c_n \dots c_0$ is a sequence of carries.

$$c_0 = 0$$

$$c_{i+1} \cdot B + s_i = a_i + b_i + c_i, \ 0 \leq i < n \text{ (invariant holds)}$$

$$s_n = c_n$$

School Method for Addition: Analysis

Pseudo-code:

```
 $c = 0;$   
for ( $i = 0; i < n; c++$ )  
{  
     $s_i = a_i + b_i + c;$   
     $c = 0;$   
    if ( $s_i \geq B$ ) then  
    {  
         $s_i = s_i - B;$   
         $c = 1;$   
    }  
}  
 $s_n = c;$ 
```

Theorem: The addition of two n -digit integers requires exactly n primitive operations. The result is an $n + 1$ integer.

School Method for Multiplication: Example

$$a = 342, \quad b = 26, \quad B = 10 \quad \text{base}$$

1. Compute partial products

$$a \cdot b_0 = 342 \cdot 6 \Rightarrow p_0 = 2052$$

$$a \cdot b_1 = 342 \cdot 2 \Rightarrow p_1 = 684$$

2. Sum up aligned partial products

$$\begin{array}{r} 2052 \\ + 6840 \\ \hline = 8892 \end{array}$$

School Method for Multiplication: Analysis

Input: Two integers $a = (a_{n-1} \dots a_0)$ and $b = (b_{n-1} \dots b_0)$

Compute: $p = a \cdot b$, where $p = (p_{2n-1} \dots p_0)$
is a $2n$ digit number.

Procedure:

1. Multiply n –digit integer a by a one-digit integer b_j to obtain partial product p_j , $0 \leq j \leq n - 1$.
2. Sum up the aligned products $p_j \cdot B^j$.

School Method for Multiplication: Analysis

To compute partial product $p_j = a \cdot b_j$,

1. Compute for each i , $0 \leq i \leq n-1$, c_i and d_i such that

$$a_i \cdot b_j = c_i \cdot B + d_i$$

2. Form two integers

$$c = (c_{n-1} \dots c_0 0) \text{ and } d = (d_{n-1} \dots d_0)$$

3. Add c and d to obtain $p_j = a \cdot b_j$

$$\begin{array}{r}
 c_{n-1} \ c_{n-2} \ \dots \ c_i \quad c_{i-1} \ \dots \ c_0 \ 0 \\
 d_{n-1} \ \dots \ d_{i+1} \ d_i \quad \dots \ d_1 \ d_0 \\
 \hline
 \text{sum of } c \text{ and } d
 \end{array}$$

Number of primitive operations:

n multiplications, $n + 1$ additions, $2n + 1$ in total

School Method for Multiplication: Analysis

Example of $p_j = a \cdot b_j$ calculation:

$$a = 342, b_j = 6, B = 10$$

Computing c's and d's:

$$a_0 \cdot b_j = 2 \cdot 6 = 12$$

$$c_0 = 1, d_0 = 2$$

$$a_1 \cdot b_j = 4 \cdot 6 = 24$$

$$c_1 = 2, d_1 = 4$$

$$a_2 \cdot b_j = 3 \cdot 6 = 18$$

$$c_2 = 1, d_2 = 8$$

Summing up:

$$+ \begin{array}{r} 1210 \\ 842 \end{array}$$

$$= 2052$$


Encoding:

$$(c_2 c_1 c_0 0)$$

$$(d_2 d_1 d_0)$$

School Method for Multiplication

Pseudo-code: $r = 0;$
for ($j = 0; j < n; j++$)
 {
 $r = r + a \cdot b_j \cdot B^j;$ $p_j = a \cdot b_j$
 }



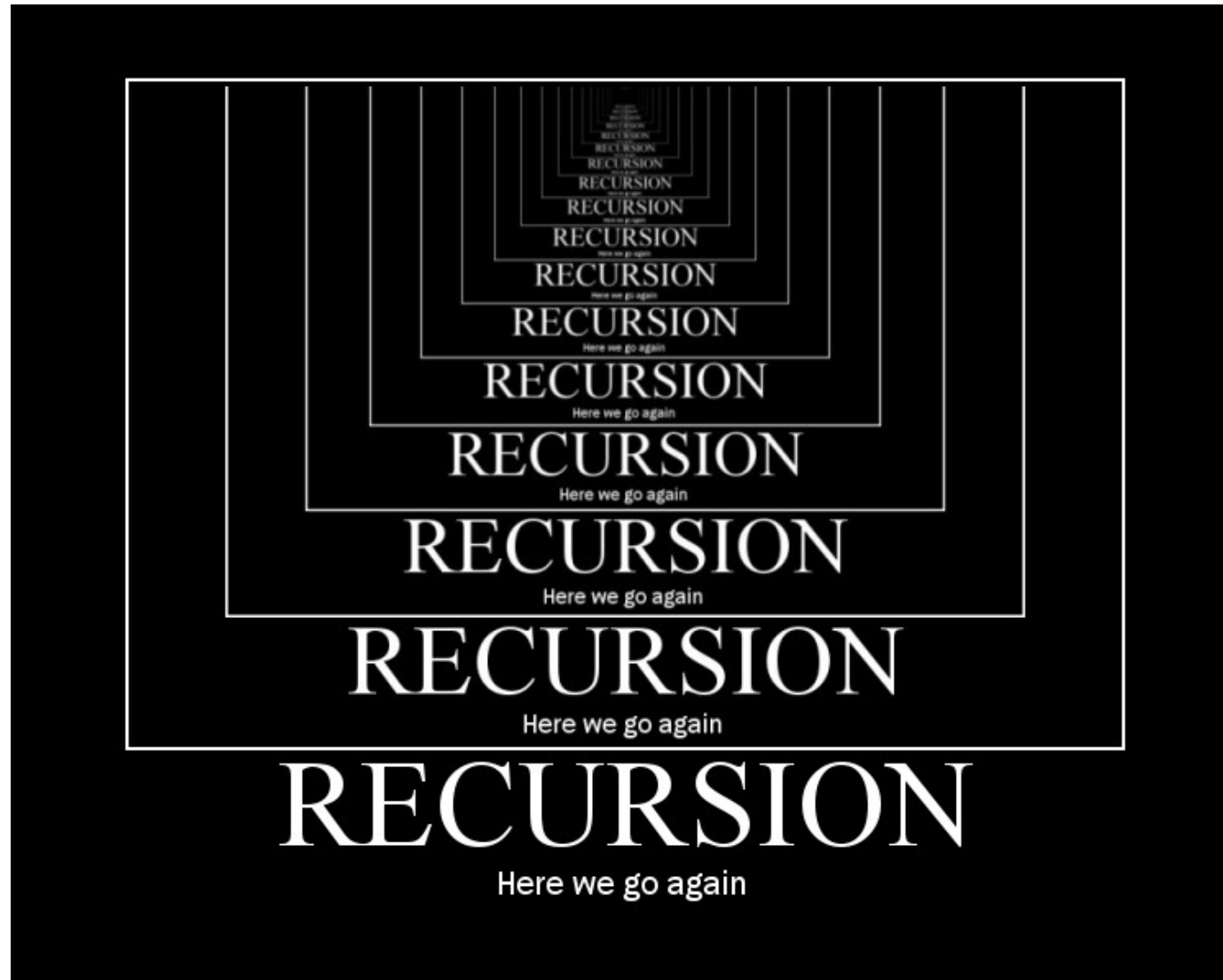
- $2n + 1$ operations for each p_j , $0 \leq j \leq n$,
 $\Rightarrow 2n^2 + n$ operations.
- n summations of numbers having $(n + 1)$ -digits that are nonzero
 $\Rightarrow n^2 + n$ operations.
- In total $3n^2 + 2n$ operations

Theorem: The school method multiplies two n -digit integers with $3n^2 + 2n = \Theta(n^2)$ primitive operations.

Simple Integer Arithmetics: Summary

- Addition can be done using n primitive operations
- School method for multiplication needs $\theta(n^2)$ primitive operations.
- **Question:** Are there faster algorithms for multiplication?

Recursive approach



In order to understand recursion, you must first understand recursion.

Divide and Conquer Paradigm

For a given problem:

- Is it **small enough** to solve trivially?
 - If **YES**, solve it.
 - If **NOT**, break down a problem into sub-problems and see if these can be solved **directly**. If not, divide again.
- Solutions to the sub-problems are then **combined** to give a solution to the original problem.

Examples of problems:

- Sorting data (Quick Sort, Merge Sort)
- Integer multiplication (School method, Karatsuba algorithm)
- Closest pair of points problem

Recursive approach

Recursion – a method of defining a function in terms of its own definition.

Why write a method that calls itself?

- Recursion is a good problem solving approach.
- Recursive solutions are often shorter.
- Solve a problem by reducing the problem to smaller sub-problems; this results in recursive calls.

However...

- Good recursive solutions may be more difficult to design and test.
- Recursive calls can result in an infinite loop of calls

Recursive algorithm: Template

To solve a problem recursively

- break into smaller problems;
- solve sub-problems recursively;
- assemble sub-solutions.

```
recursive-algorithm(input) {  
    // base case  
    if (isSmallEnough(input))  
        compute the solution and return it  
    else  
        // recursive case  
        break input into simpler instances input1, input 2, ...  
        solution1 = recursive-algorithm(input1)  
        solution2 = recursive-algorithm(input2)  
        ...  
        figure out solution to this problem from solution1, solution2, ...  
        return solution  
}
```

Recursion versus iterative approach

- **Emphasis of iteration:**
keep repeating until a task is “done”.
- **Emphasis of recursion:**
break the problem up into smaller parts;
combine the results.

Which is better?

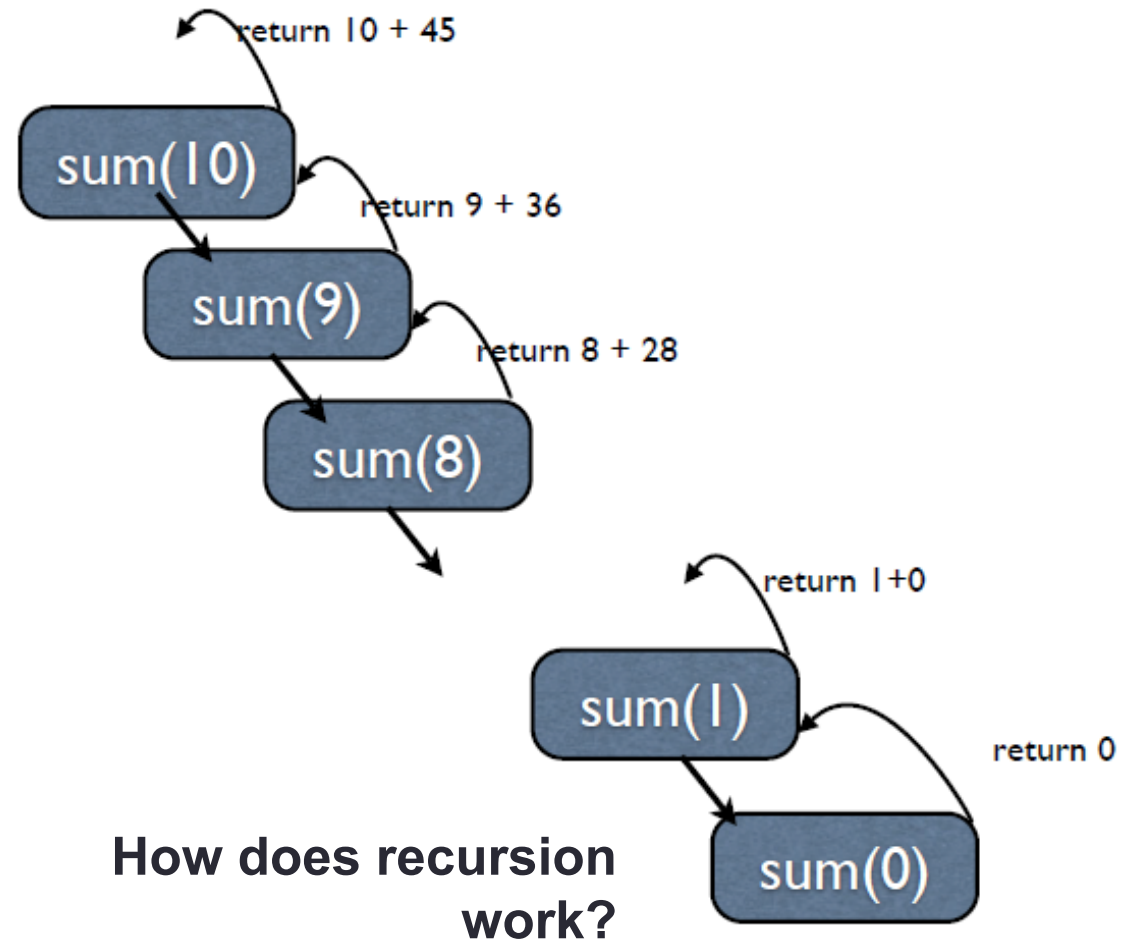
- Iterative solutions keep control local to loop, less “magical”
- Good recursive solutions may be more difficult to design and test.

Recursion versus iterative approach: Example

Write a function that computes the sum of numbers from 0 to n (i) using a loop; (ii) recursively.

```
// with a loop
int sum (int n) {
    int s = 0;
    for (int i=0; i<=n; i++)
        s+= i;
    return s;
}
```

```
// recursively
int sum (int n) {
    // base case
    if (n == 0) return 0;
    // else
    return n + sum(n-1);
}
```



Recursion versus iterative approach: Example

Recursive is not always better!

```
// Fibonacci: recursive version
int Fibonacci_R(int n) {
    if(n<=0) return 0;
    else if(n==1) return 1;
    else return Fibonacci_R(n-1)+Fibonacci_R(n-2);
}
```

This takes $O(2^n)$ steps! Impractical for large n .

```
// Fibonacci: iterative version
int Fibonacci_I(int n) {
    int fib[] = {0,1,1};
    for(int i=2; i<=n; i++) {
        fib[i%3] = fib[(i-1)%3] + fib[(i-2)%3];
    }
    return fib[n%3];
}
```

This iterative approach is “linear”; it takes $O(n)$ steps.

Recursion: Implementation issues

- Recursion is no different than a function call.
- The system keeps track of the sequence of method calls that have been started but not finished yet (active calls). **Order matters!**

Recursion pitfalls:

- **Missed base-case:** infinite recursion, stack overflow.
- **No convergence:** solve recursively a problem that is not simpler than the original one.
- Recursion has an **overhead** (keep track of all active frames). Modern compilers can often optimize the code and eliminate recursion.

Unless you write super-duper optimized code, recursion is good.

Merge Sort: Idea

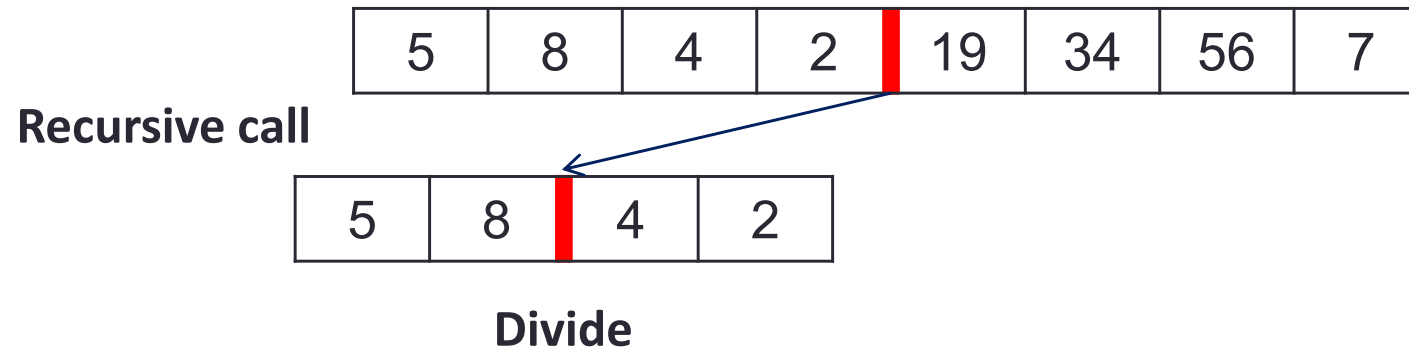
- **Divide:** Divide the unsorted list into two sub-lists of about half the size.
- **Conquer:** Sort each of the two sub-lists recursively until we have list sizes of length 1, in which case the list itself is returned.
- **Merge:** Merge the two sorted sub-lists back into one sorted list.

Merge Sort: Example

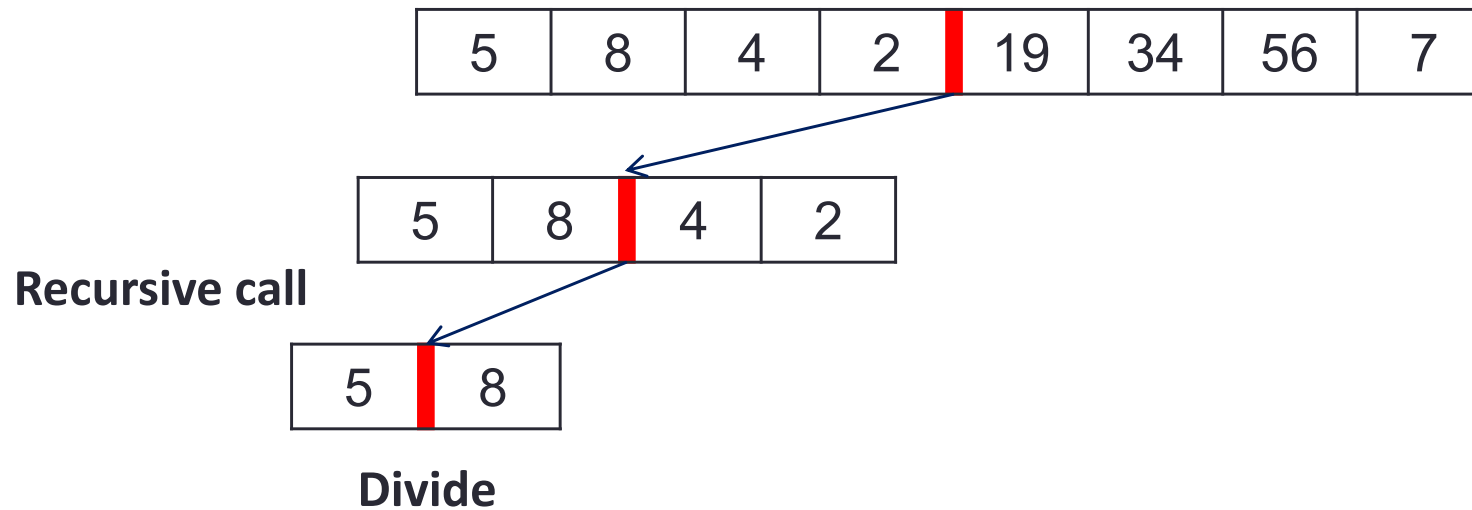
5	8	4	2		19	34	56	7
---	---	---	---	--	----	----	----	---

Divide

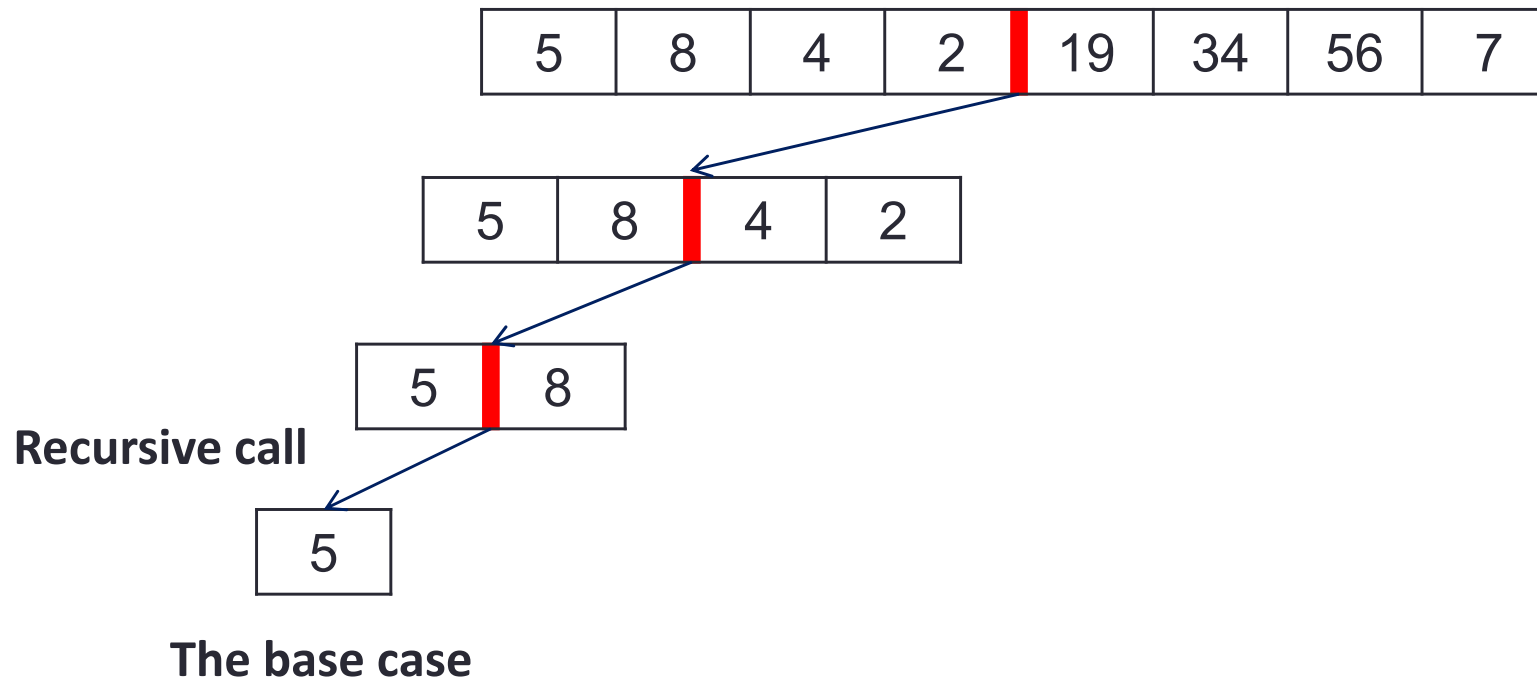
Merge Sort: Example



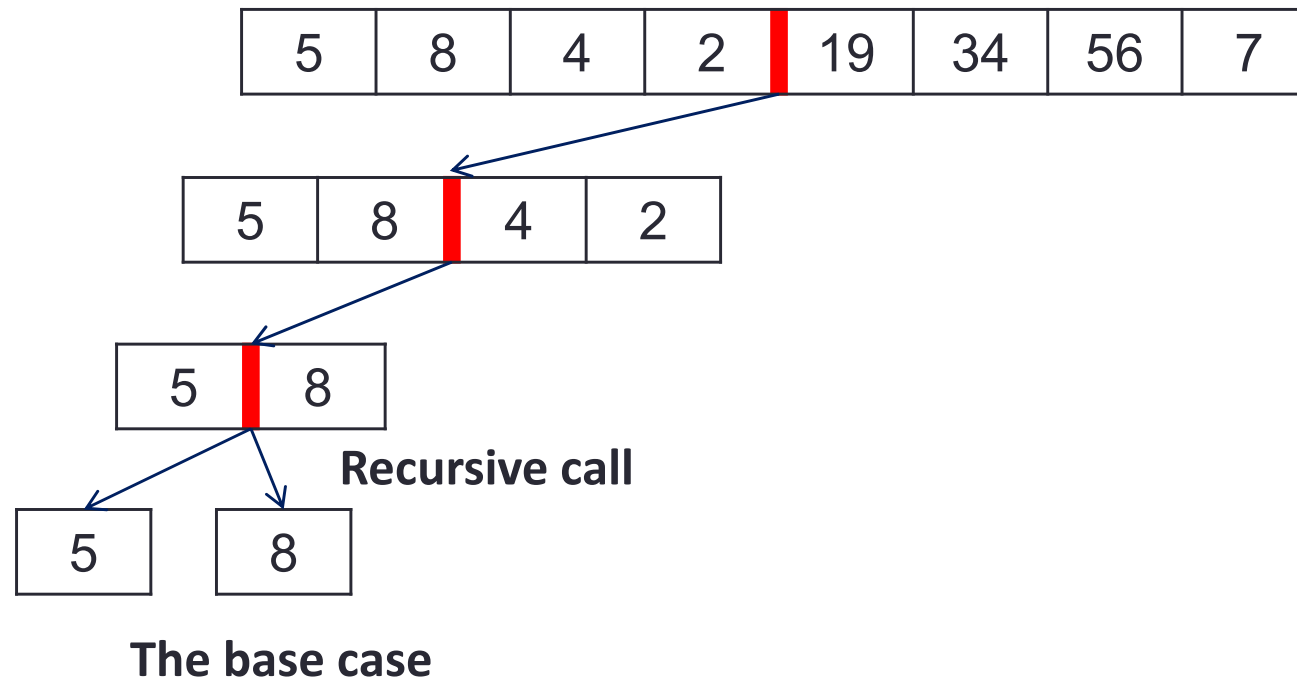
Merge Sort: Example



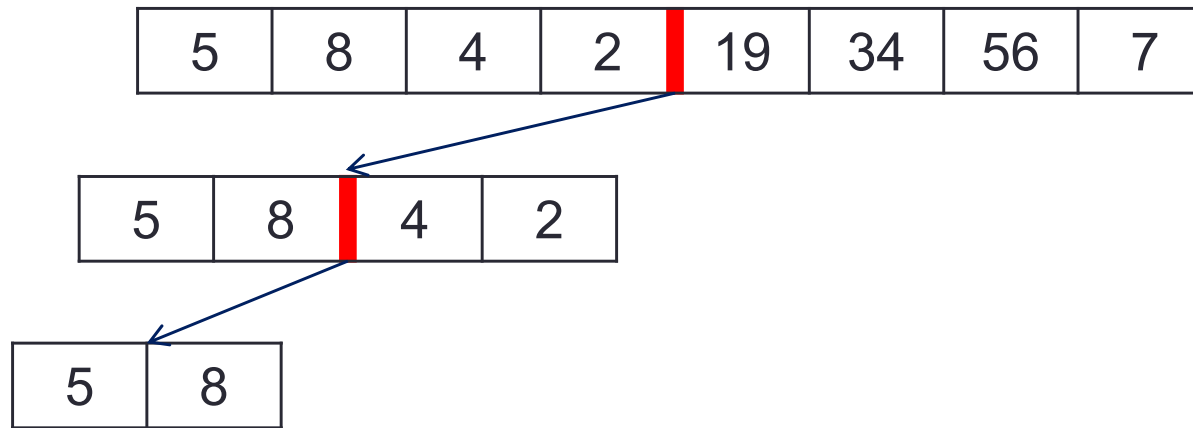
Merge Sort: Example



Merge Sort: Example



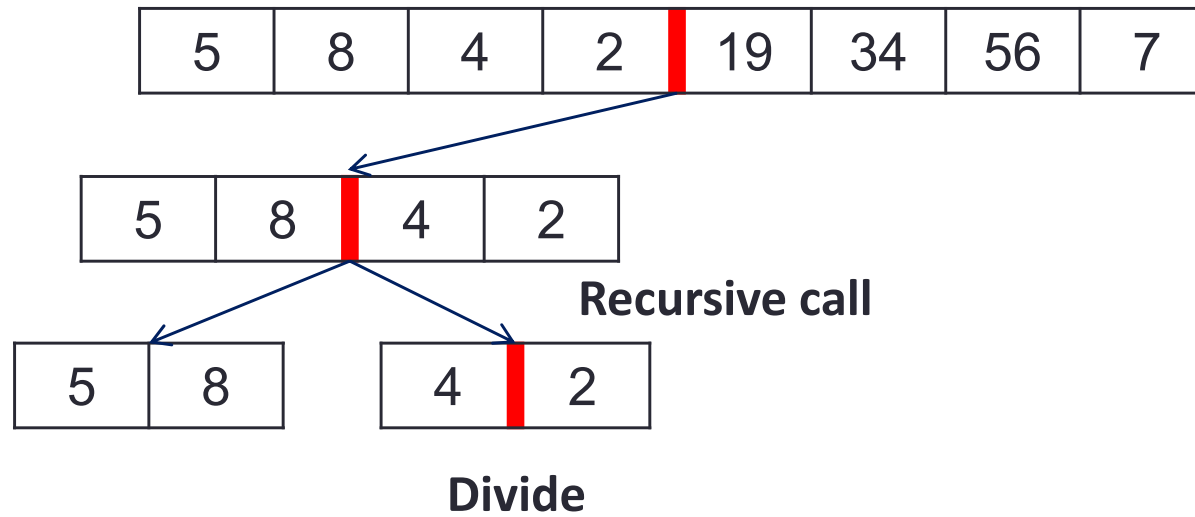
Merge Sort: Example



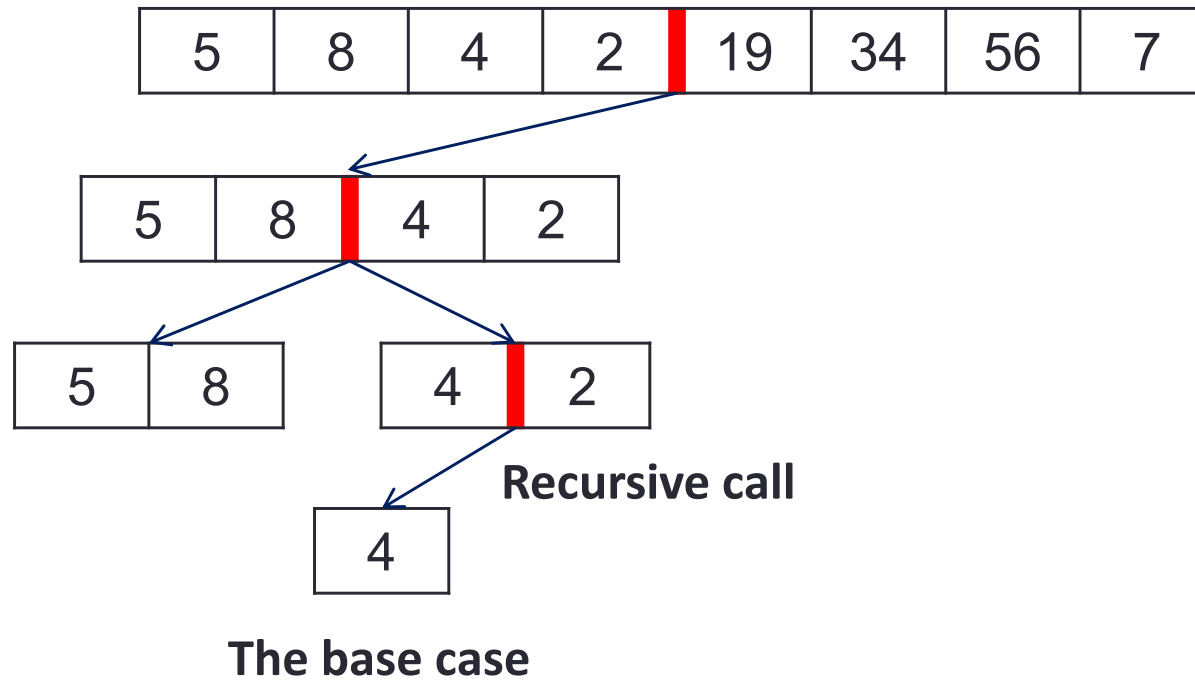
Return from recursive calls.

Merge (sort) the sub-lists

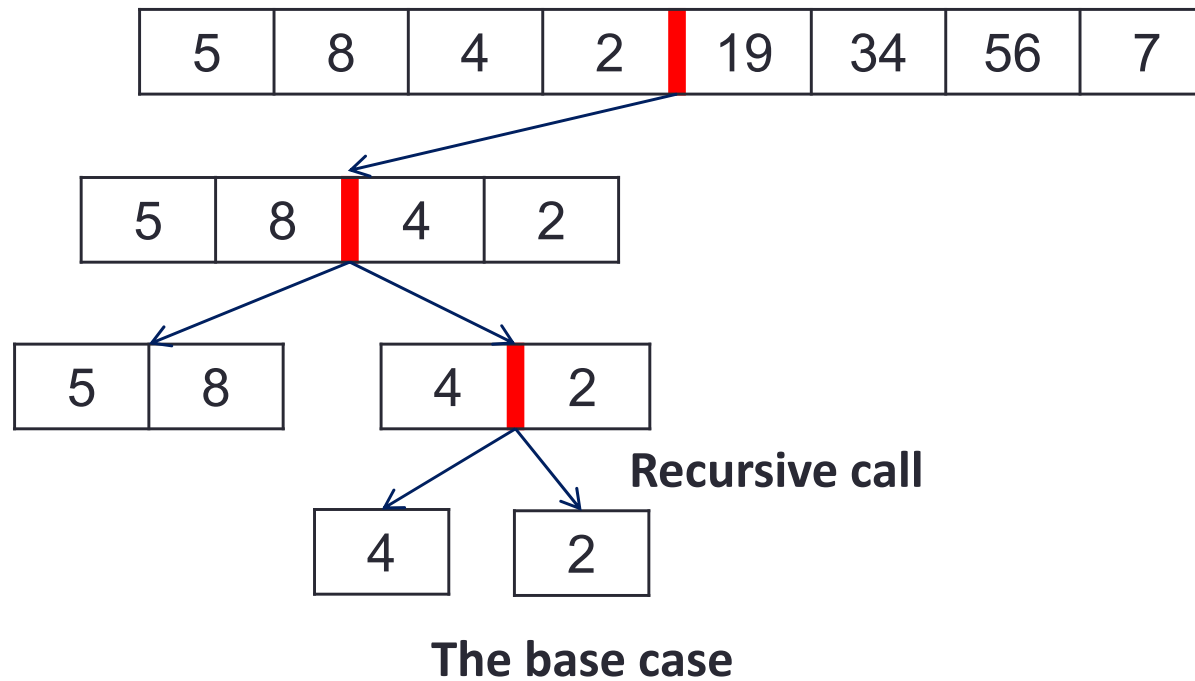
Merge Sort: Example



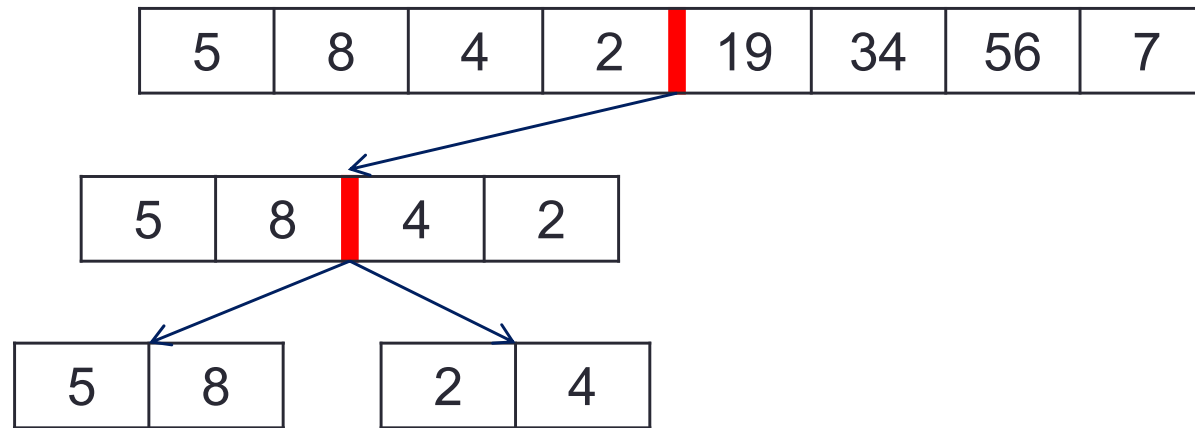
Merge Sort: Example



Merge Sort: Example

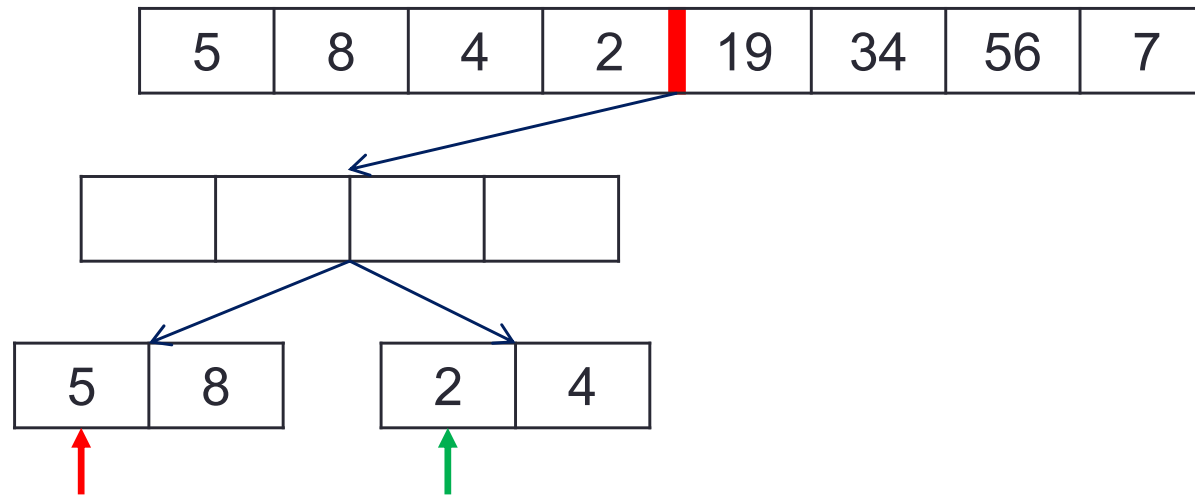


Merge Sort: Example



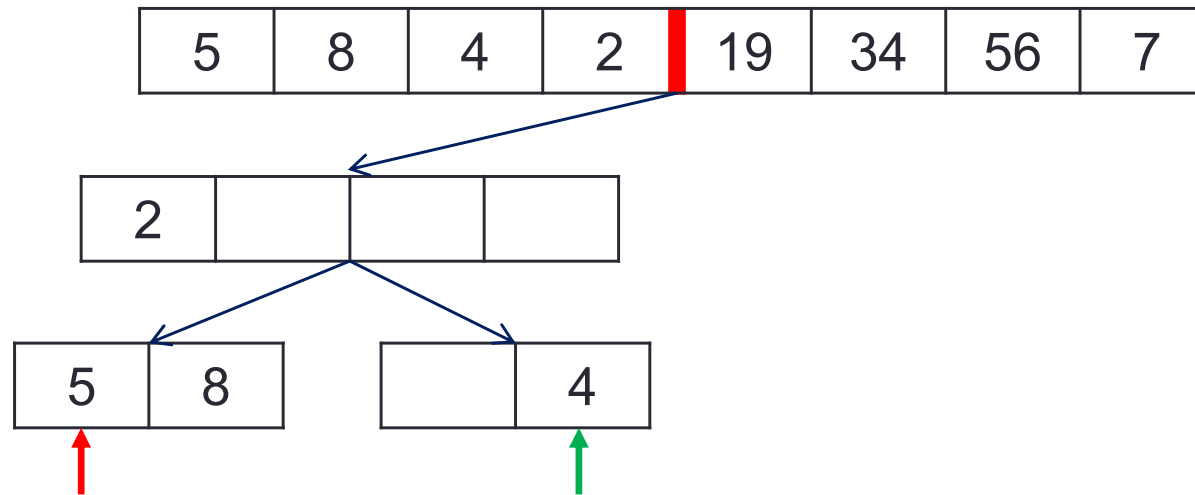
**Return from recursive calls.
Merge (sort) the sub-lists**

Merge Sort: Example

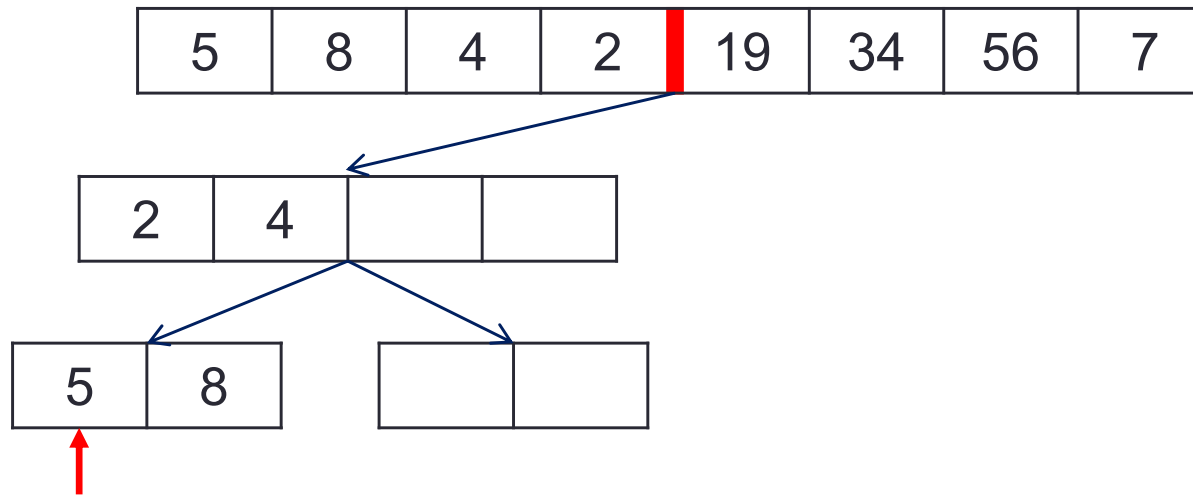


**Return from recursive calls.
Merge (sort) the sub-lists**

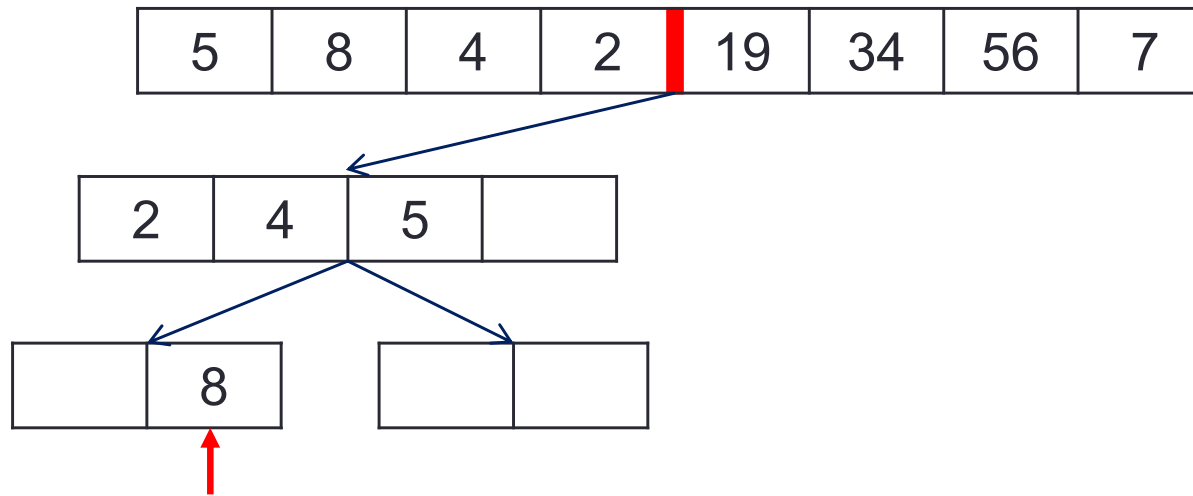
Merge Sort: Example



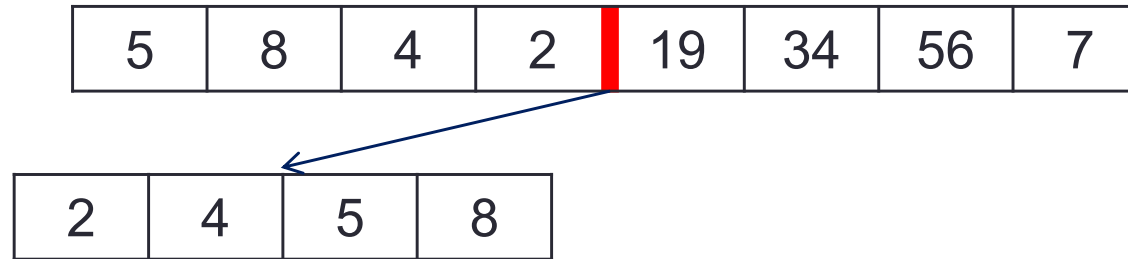
Merge Sort: Example



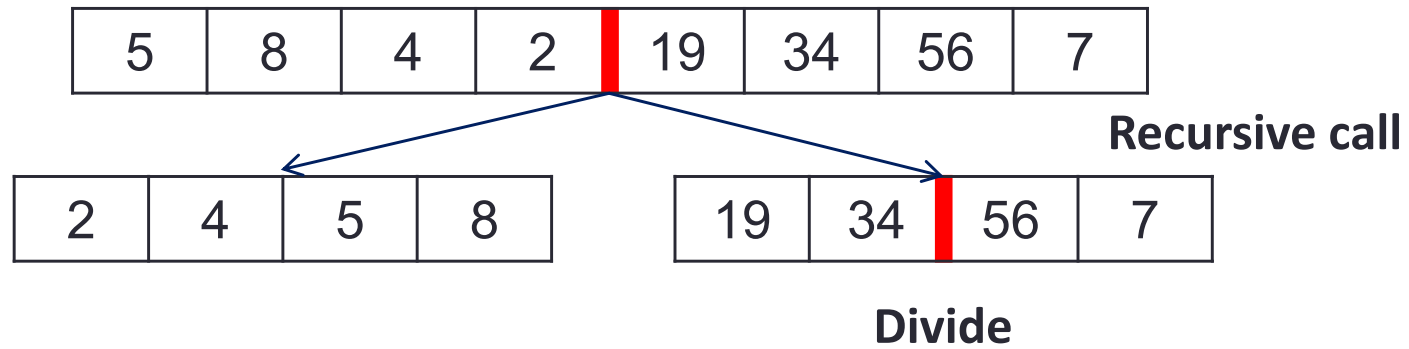
Merge Sort: Example



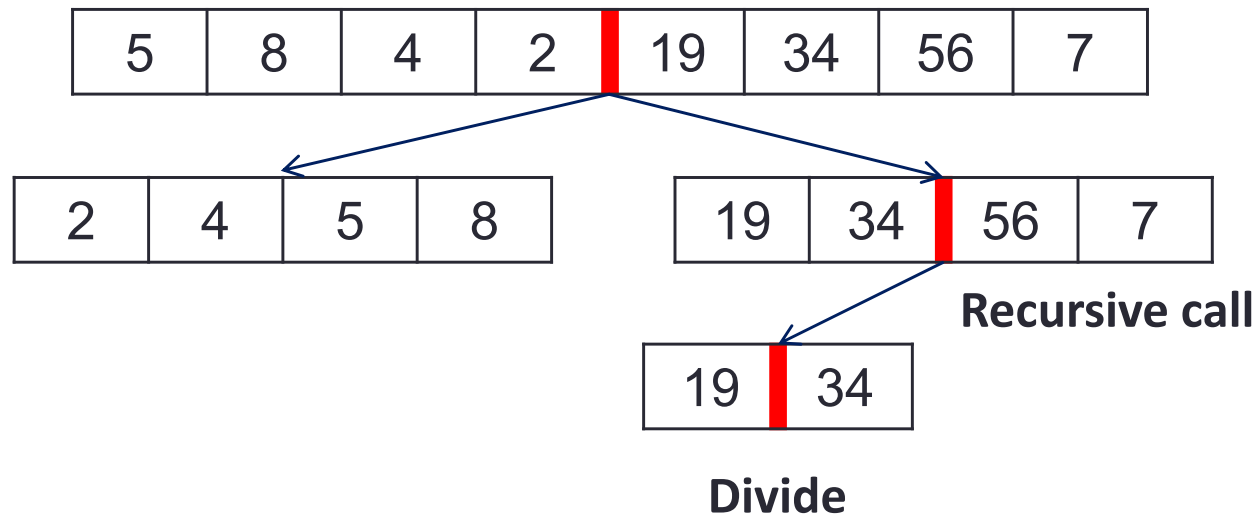
Merge Sort: Example



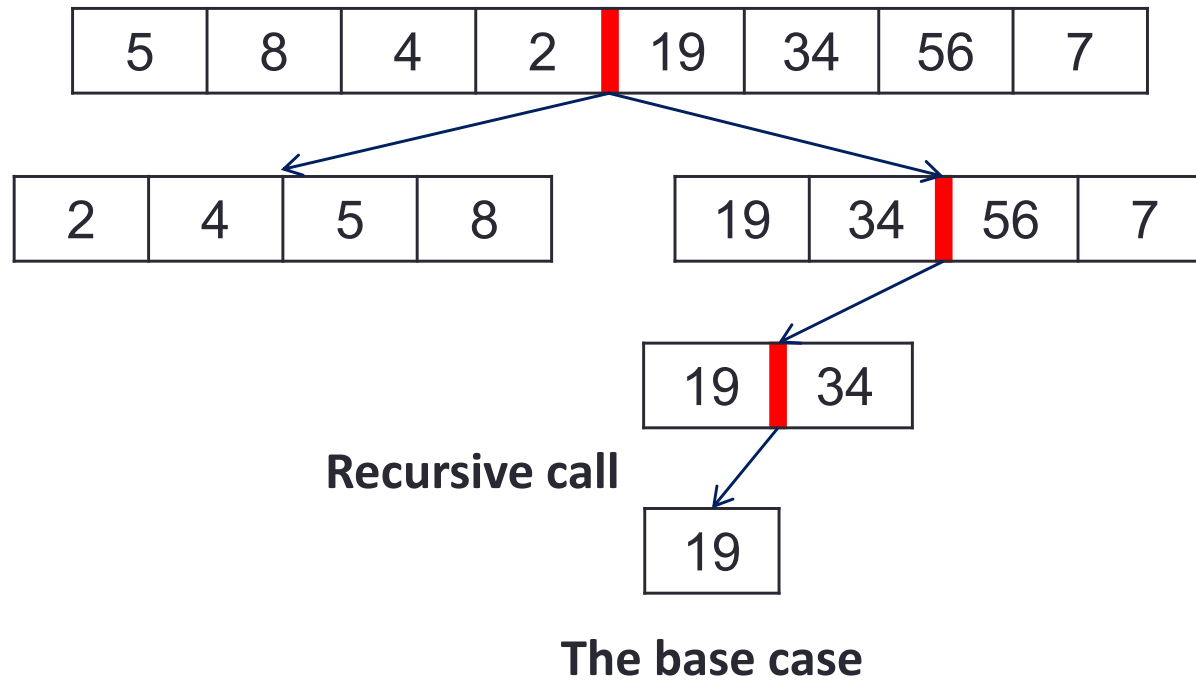
Merge Sort: Example



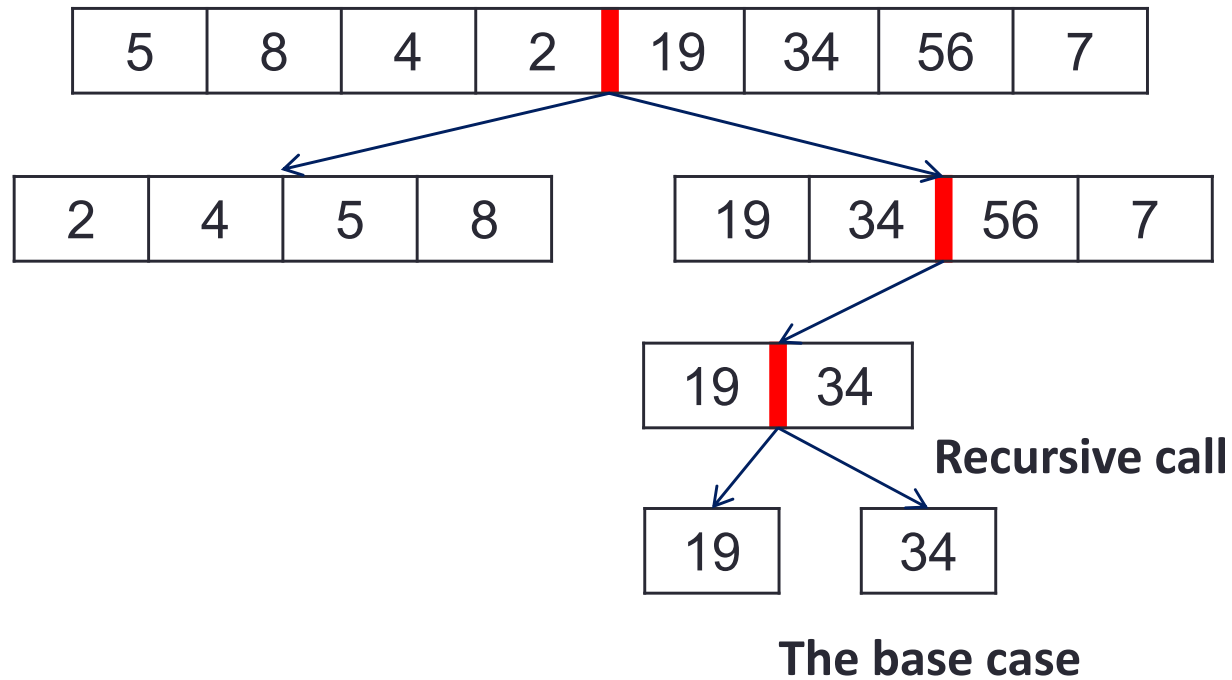
Merge Sort: Example



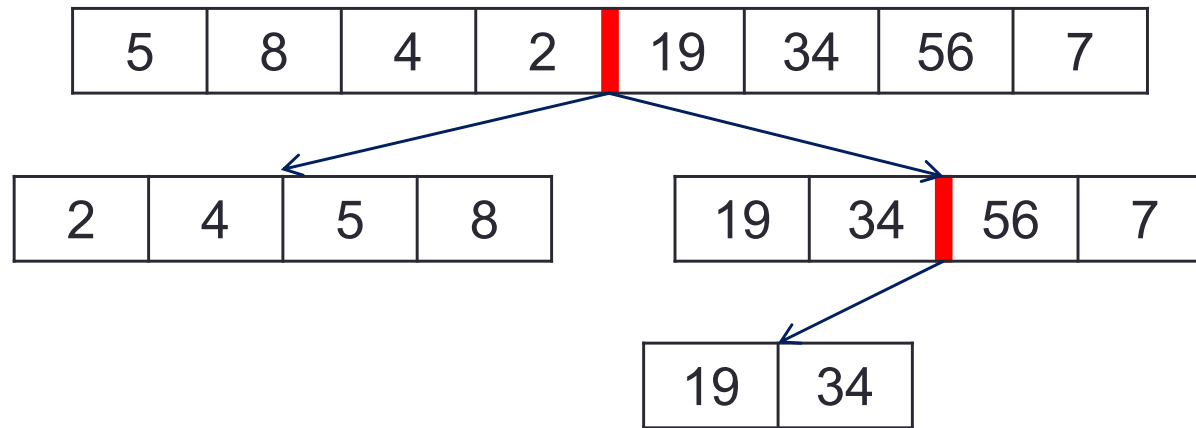
Merge Sort: Example



Merge Sort: Example

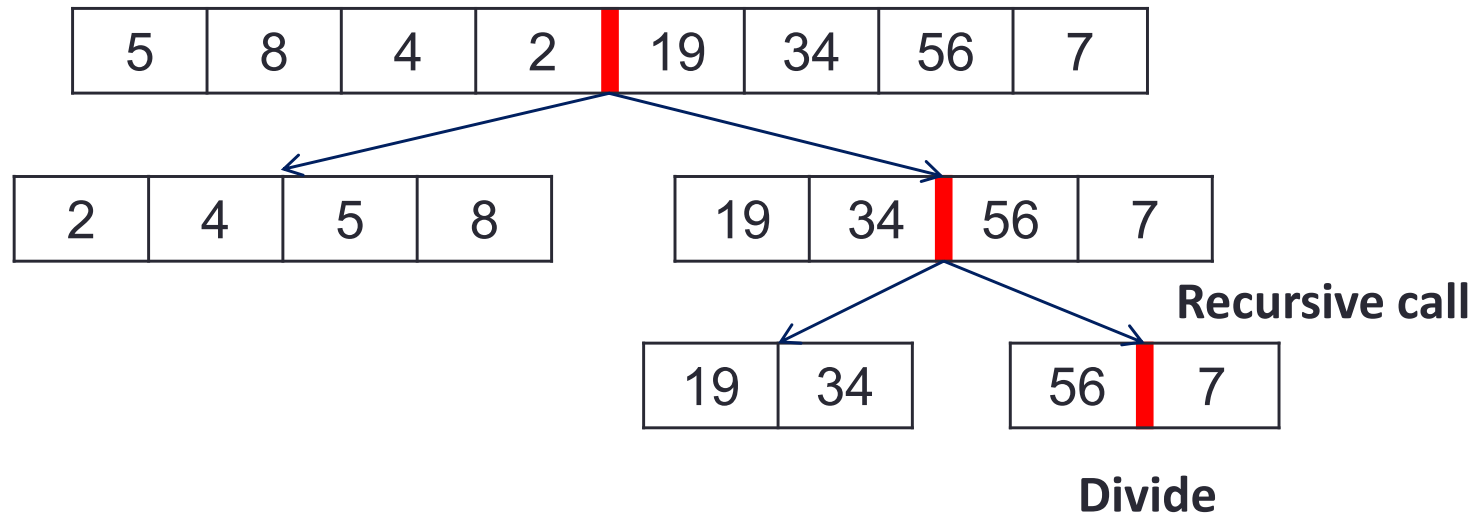


Merge Sort: Example

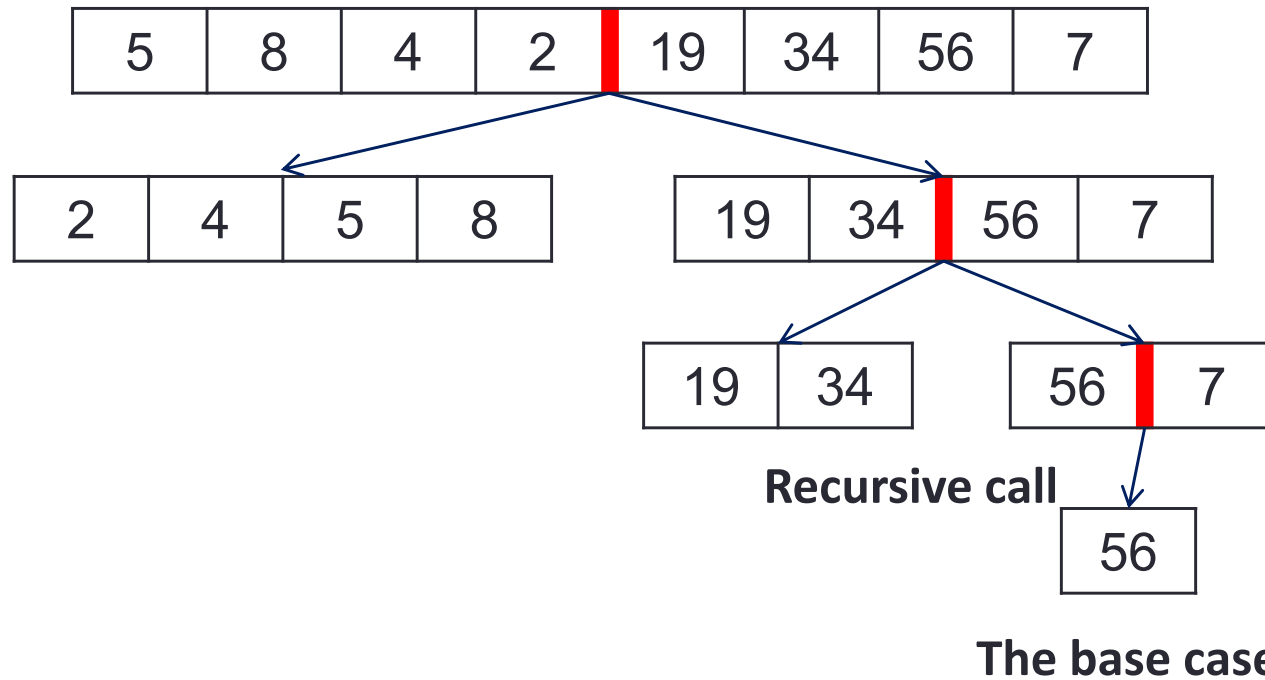


**Return from recursive calls.
Merge (sort) the sub-lists**

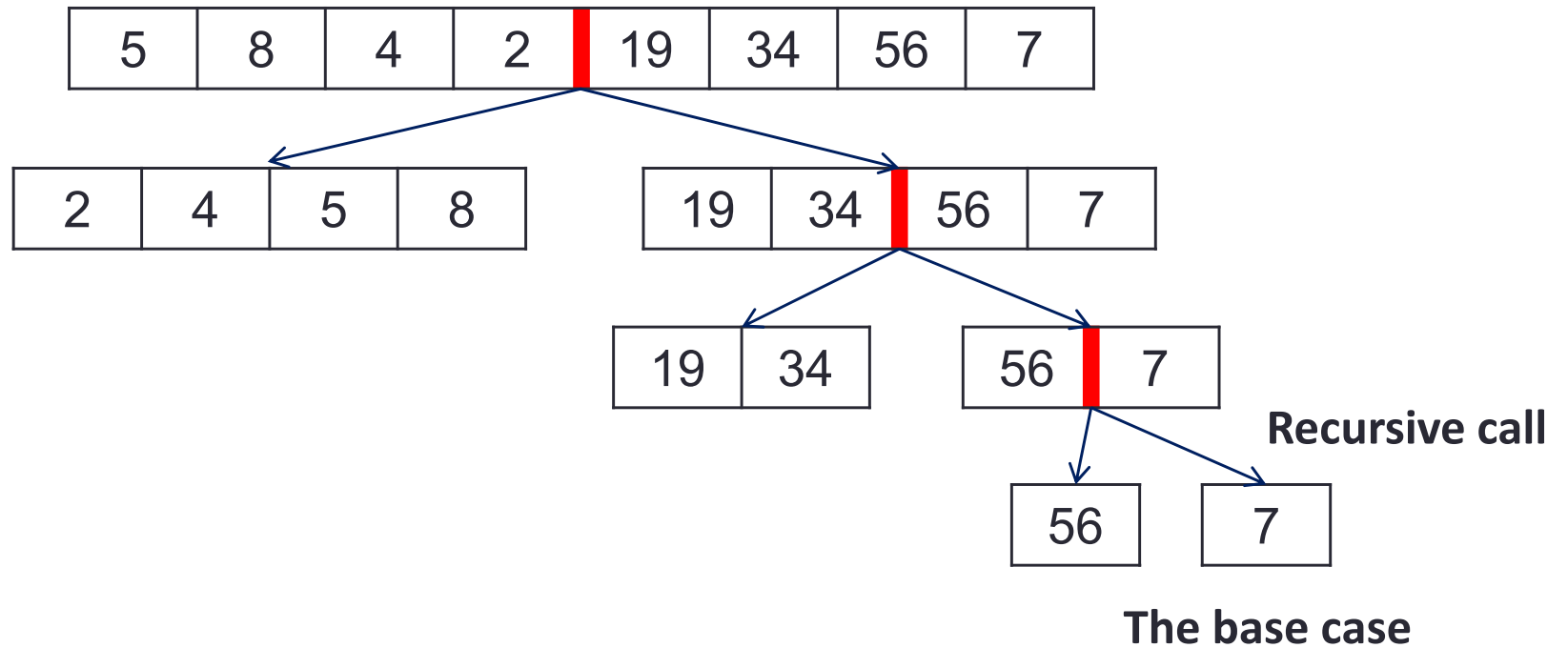
Merge Sort: Example



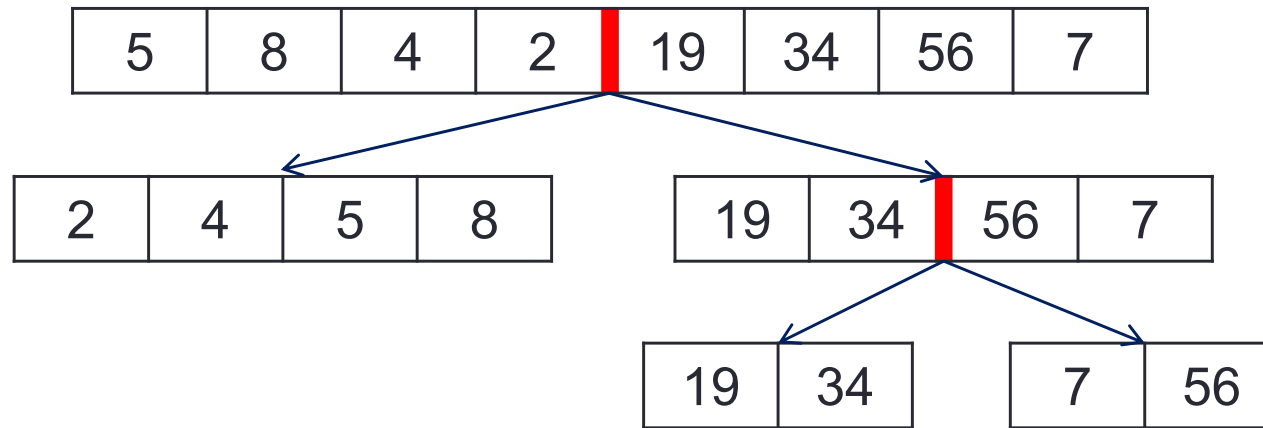
Merge Sort: Example



Merge Sort: Example

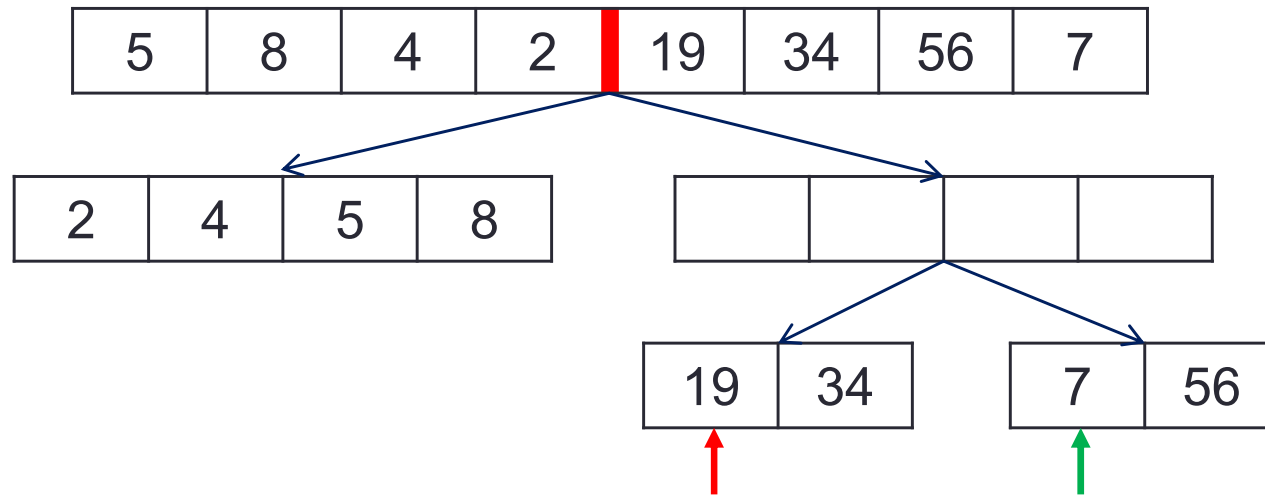


Merge Sort: Example

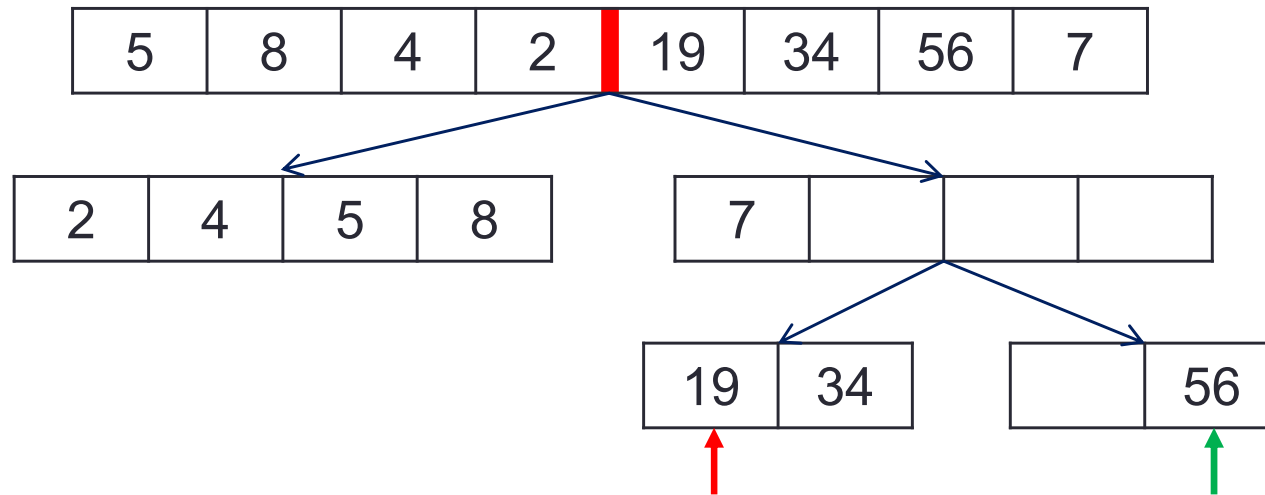


**Return from recursive calls.
Merge (sort) the sub-lists**

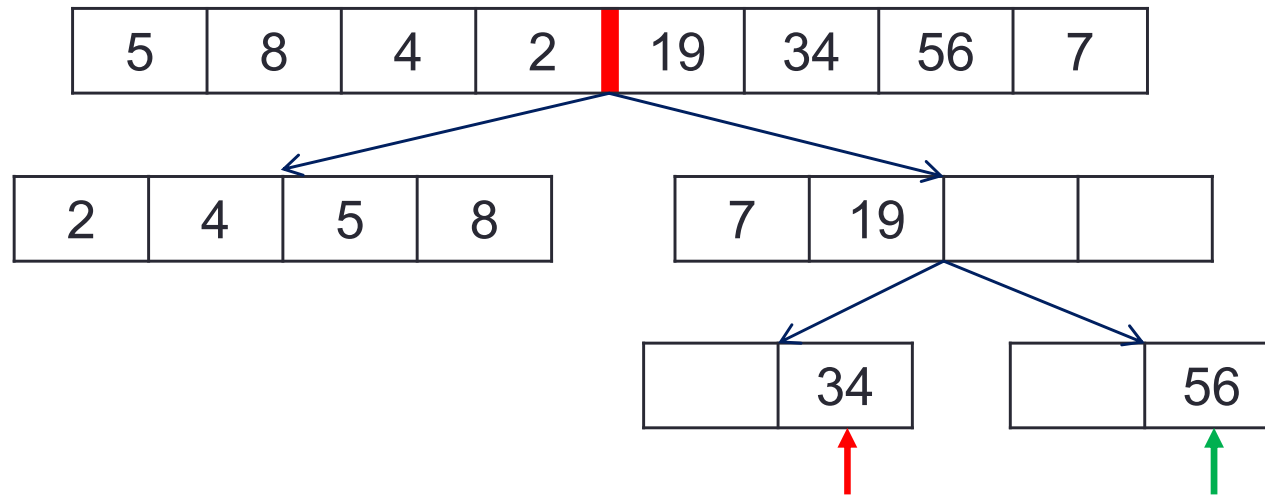
Merge Sort: Example



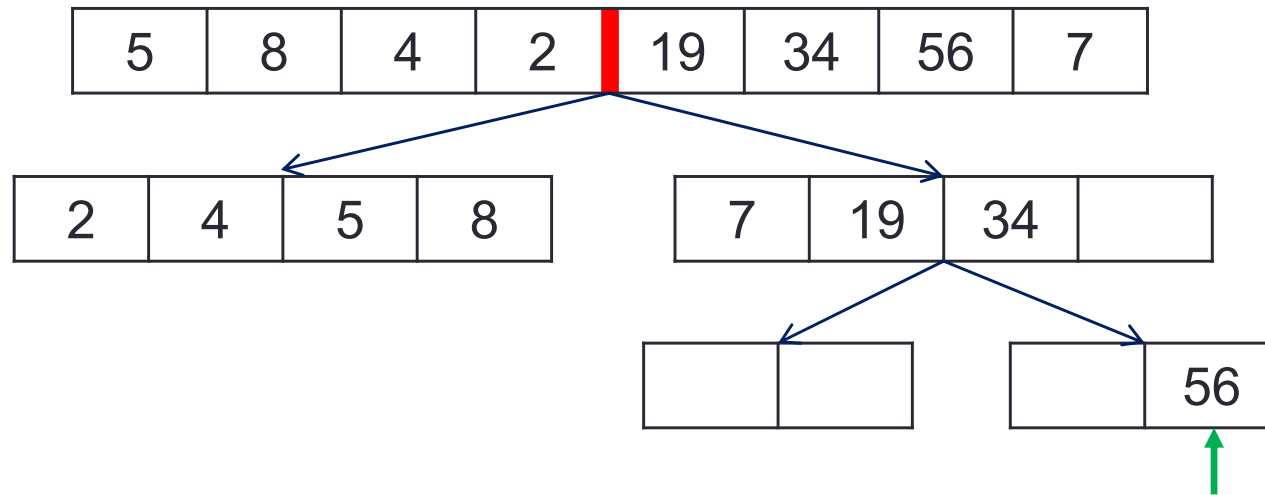
Merge Sort: Example



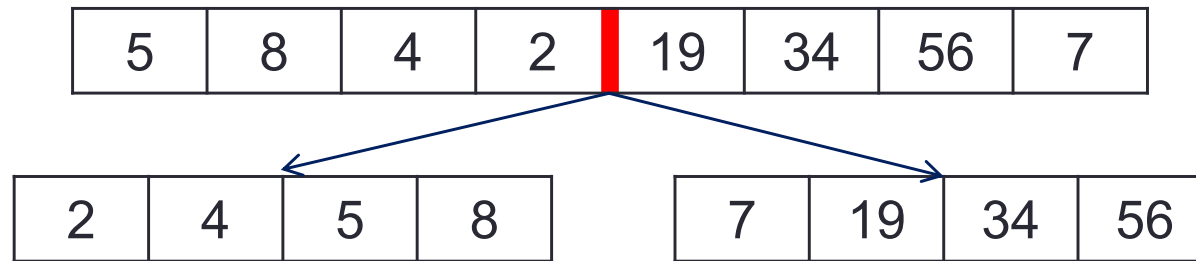
Merge Sort: Example



Merge Sort: Example

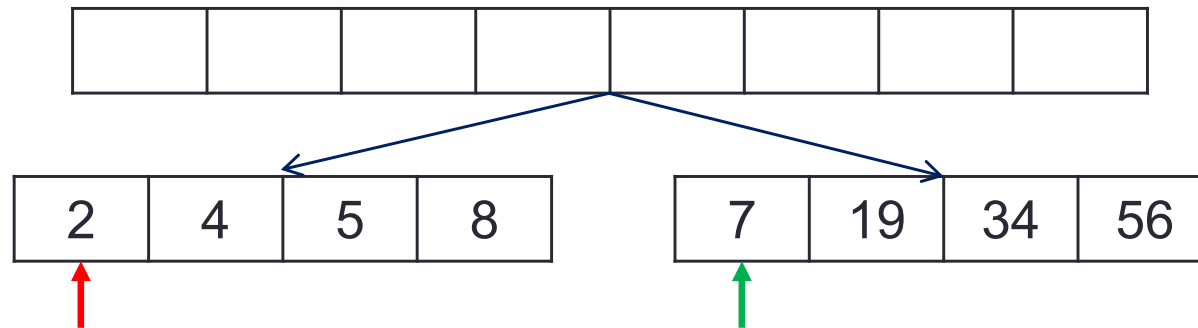


Merge Sort: Example



**Return from recursive calls.
Merge (sort) the sub-lists**

Merge Sort: Example

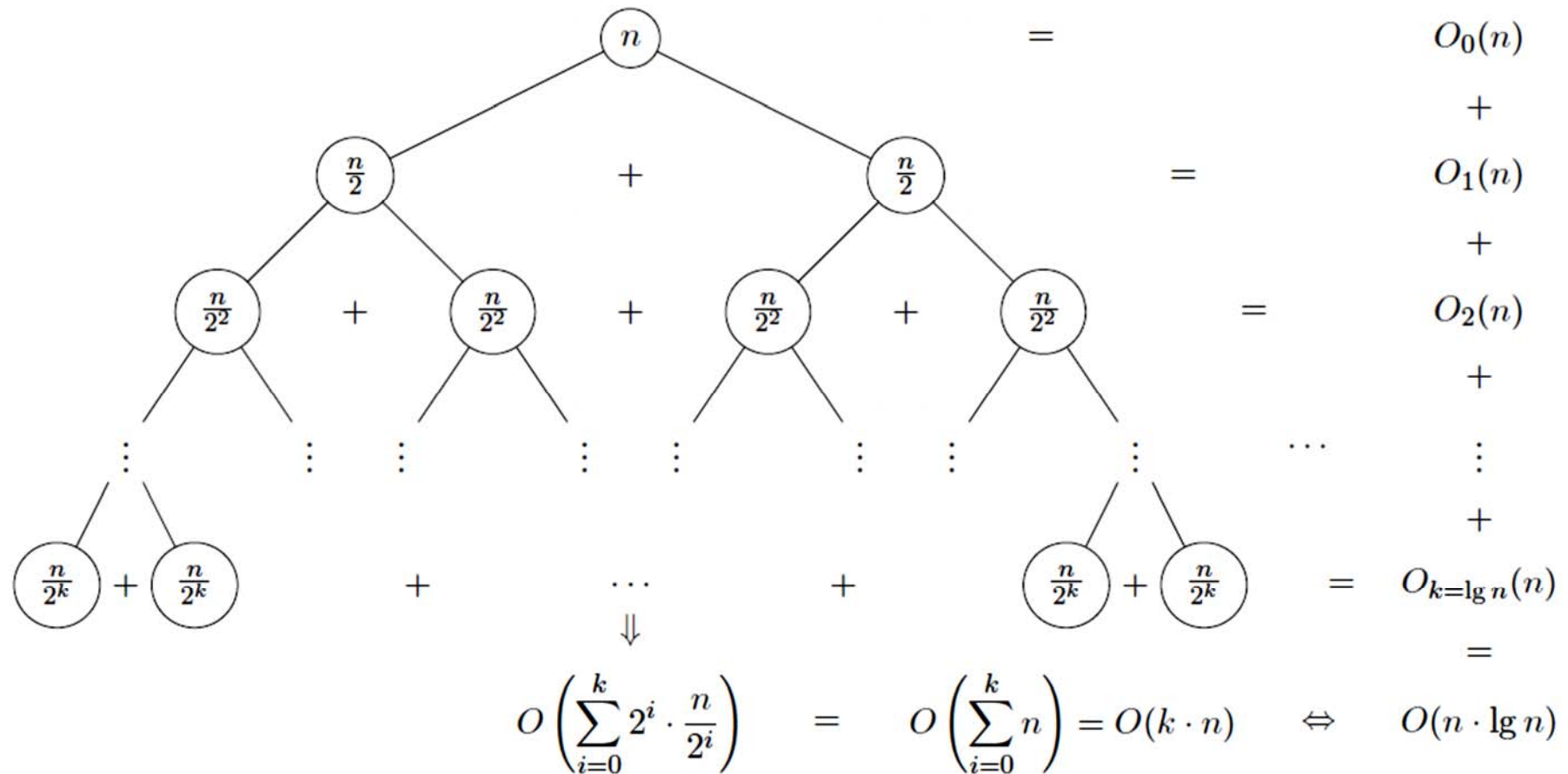


**Proceed with merging the two sub-lists
to obtain the final solution**

Merge Sort: Example

2	4	5	8	7	19	34	56
---	---	---	---	---	----	----	----

Merge Sort: Complexity



Every level i has 2^i sub-lists,
 k levels in total.

Every sub-list has $\frac{n}{2^i}$ elements
 to compare

Merge Sort: Complexity and recurrence relation

The running time of merge sort for a list of length n is

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

—●
apply the algorithm to two lists of
half the size of the original list

●—
and add the n steps taken to
merge the resulting two lists

Merge Sort: Properties and complexity

- Provides **stable sort**, which means that the implementation preserves the input order of equal elements in the sorted output.
- Consistent speed in all type of data sets. Good performance for huge inputs.
- Most common implementation does not sort in place; therefore, requires additional memory space to store the auxiliary arrays.
- Worst case: $T(n) = O(n \log n)$ comparisons
- Best case: $T(n) = O(n \log n)$ comparisons
- Average case: $T(n) = O(n \log n)$ comparisons
- Worst-case space complexity $O(n)$ auxiliary

Quick Sort: Idea

Quick Sort is a randomized sorting algorithm based on the divide-and-conquer paradigm:

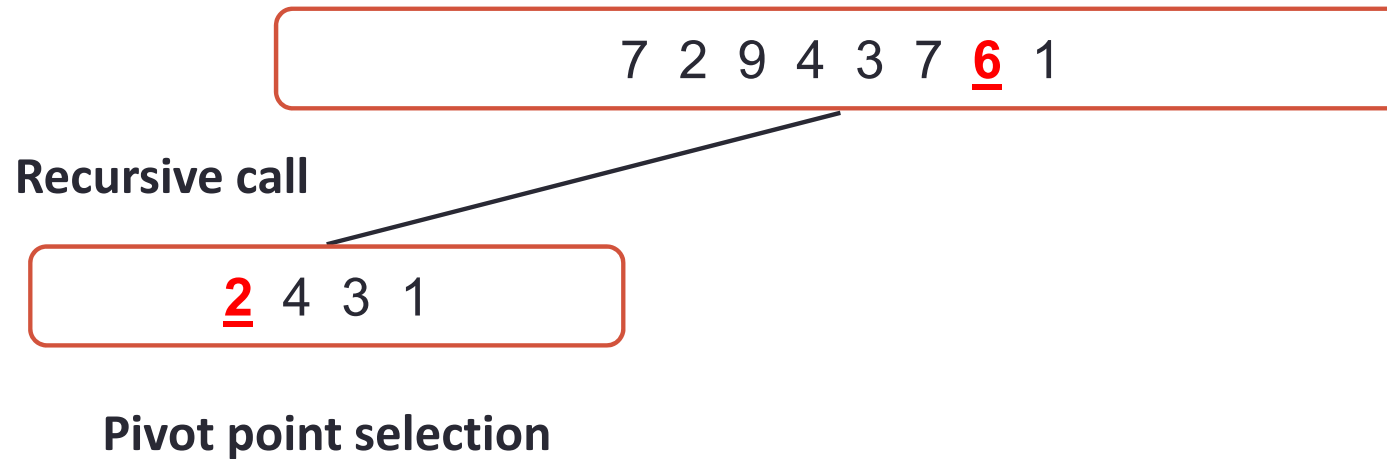
- **Divide**: pick a random element x (called **pivot**) and partition array A into
 - L elements less than x
 - E elements equal x
 - G elements greater than x
- **Recur**: sort L and G
- **Conquer**: join L , E and G

Quick Sort: Example

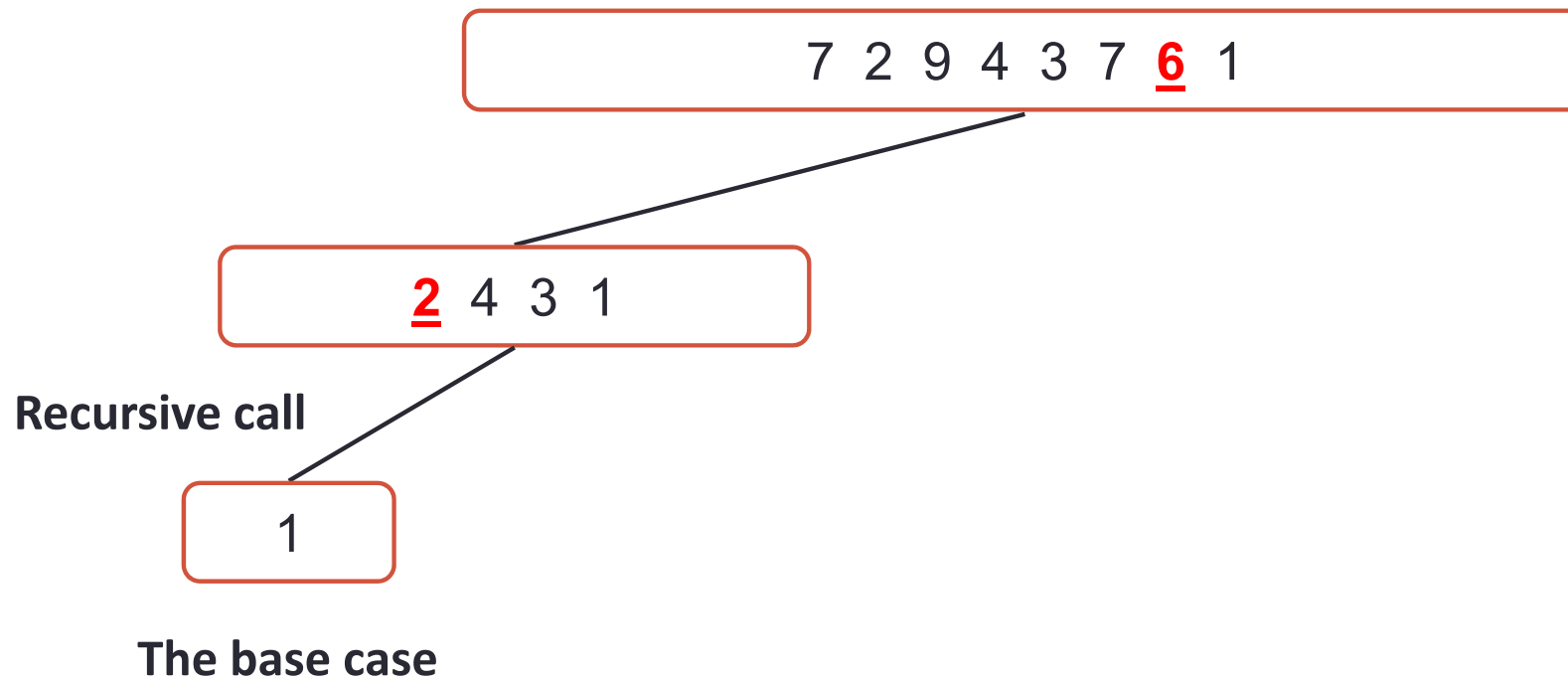
Pivot point selection

7 2 9 4 3 7 6 1

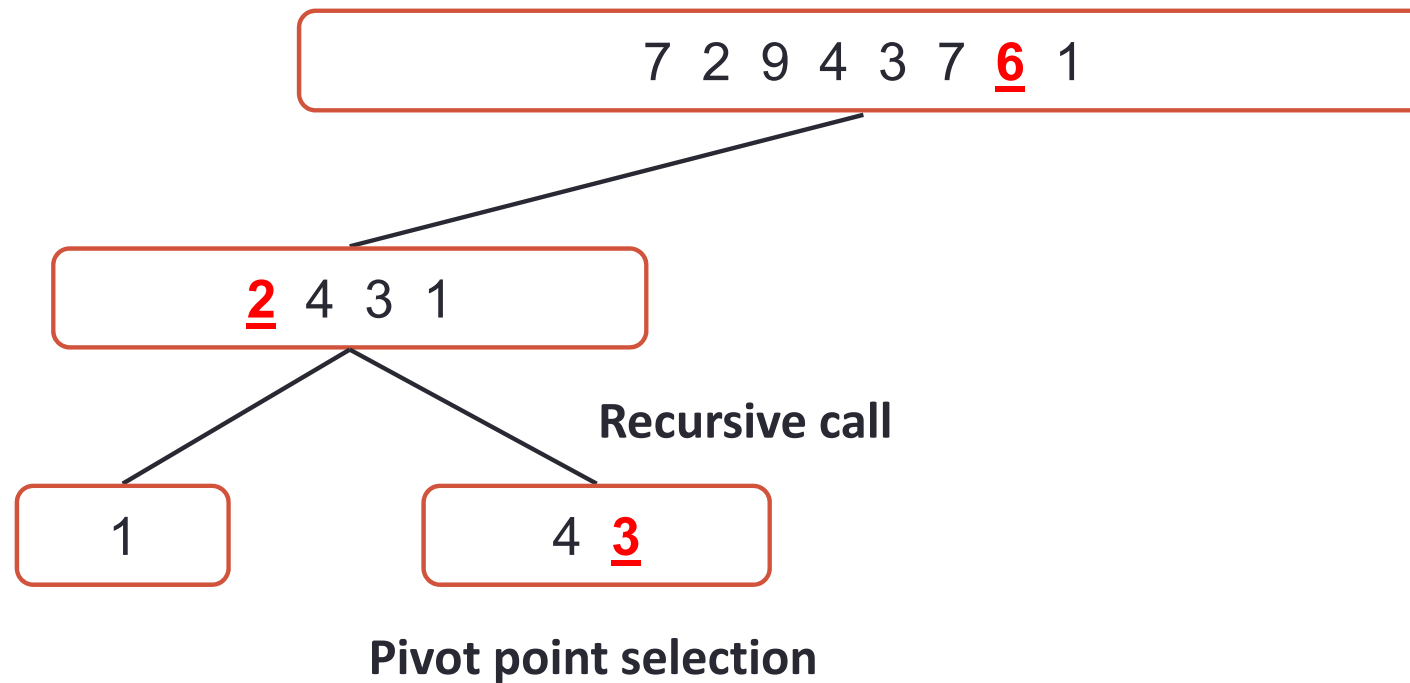
Quick Sort: Example



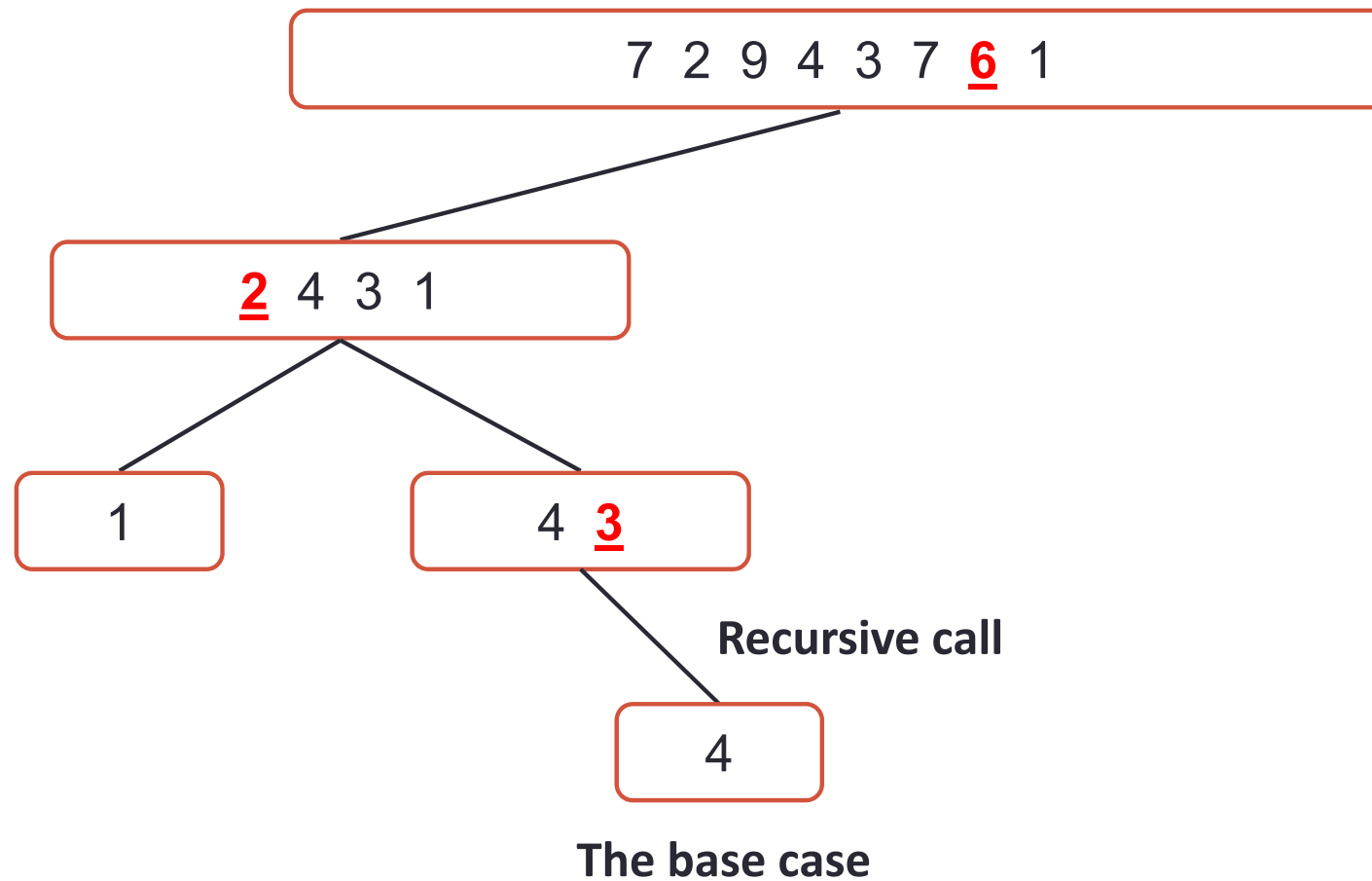
Quick Sort: Example



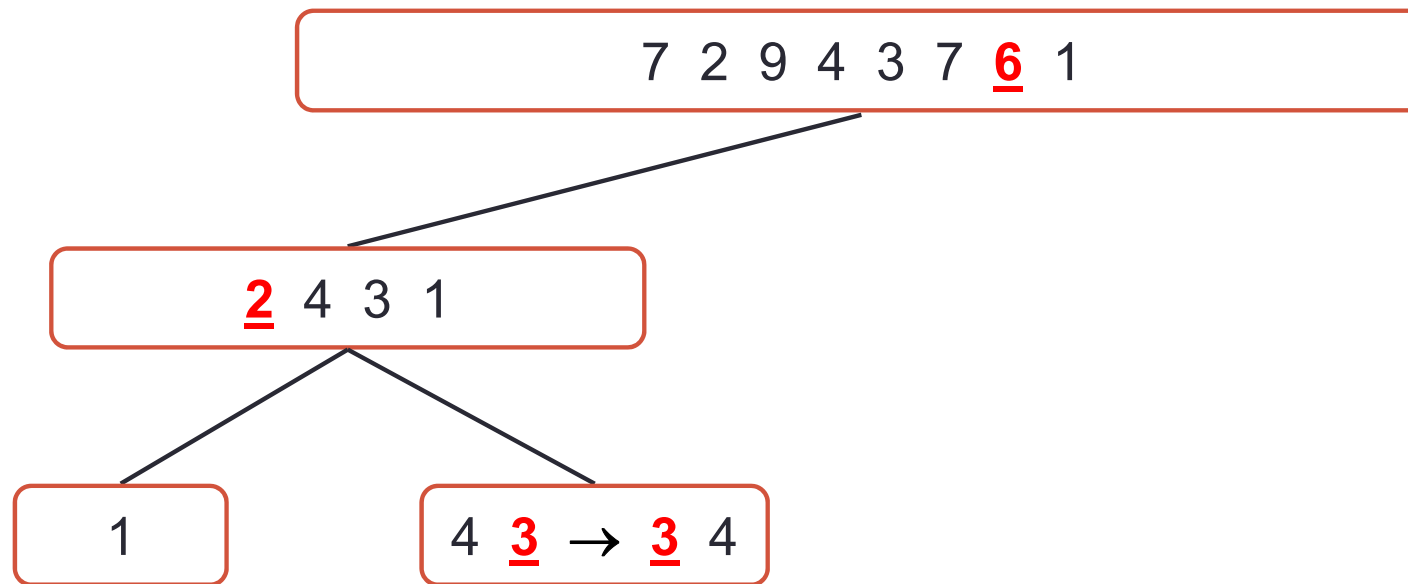
Quick Sort: Example



Quick Sort: Example

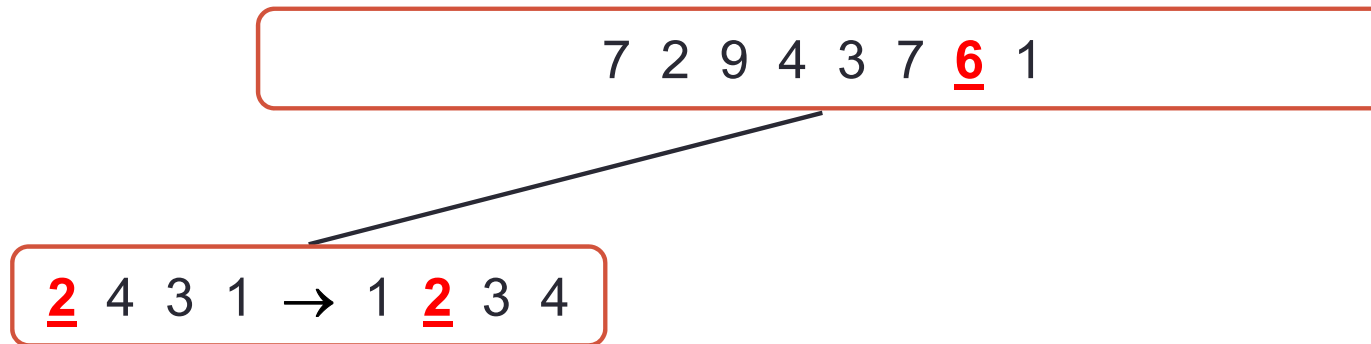


Quick Sort: Example



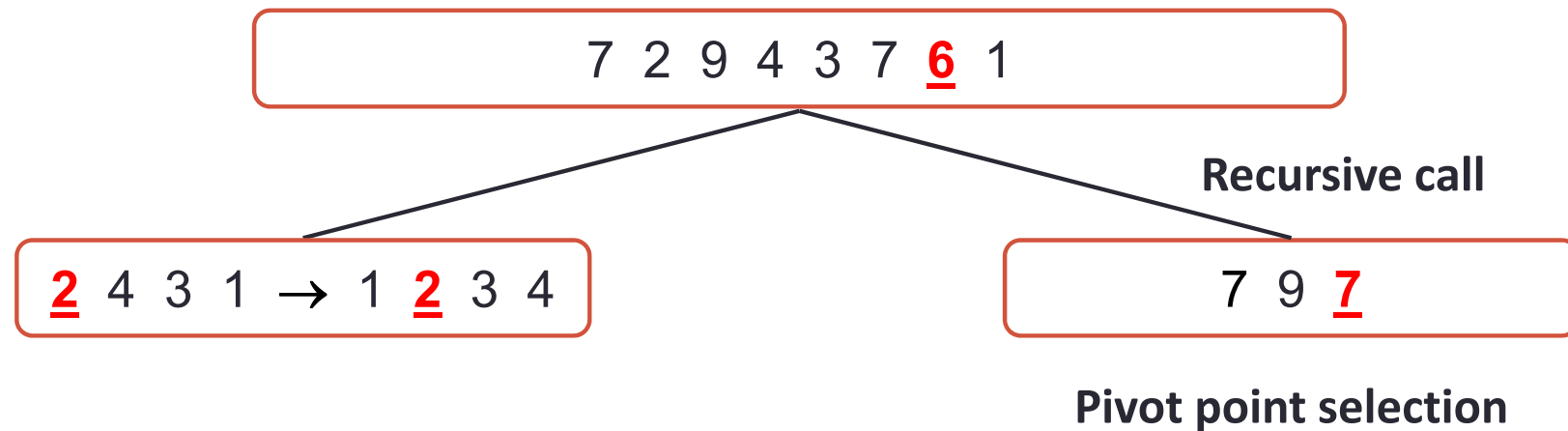
Return from recursive calls.
Combine the sub-lists

Quick Sort: Example

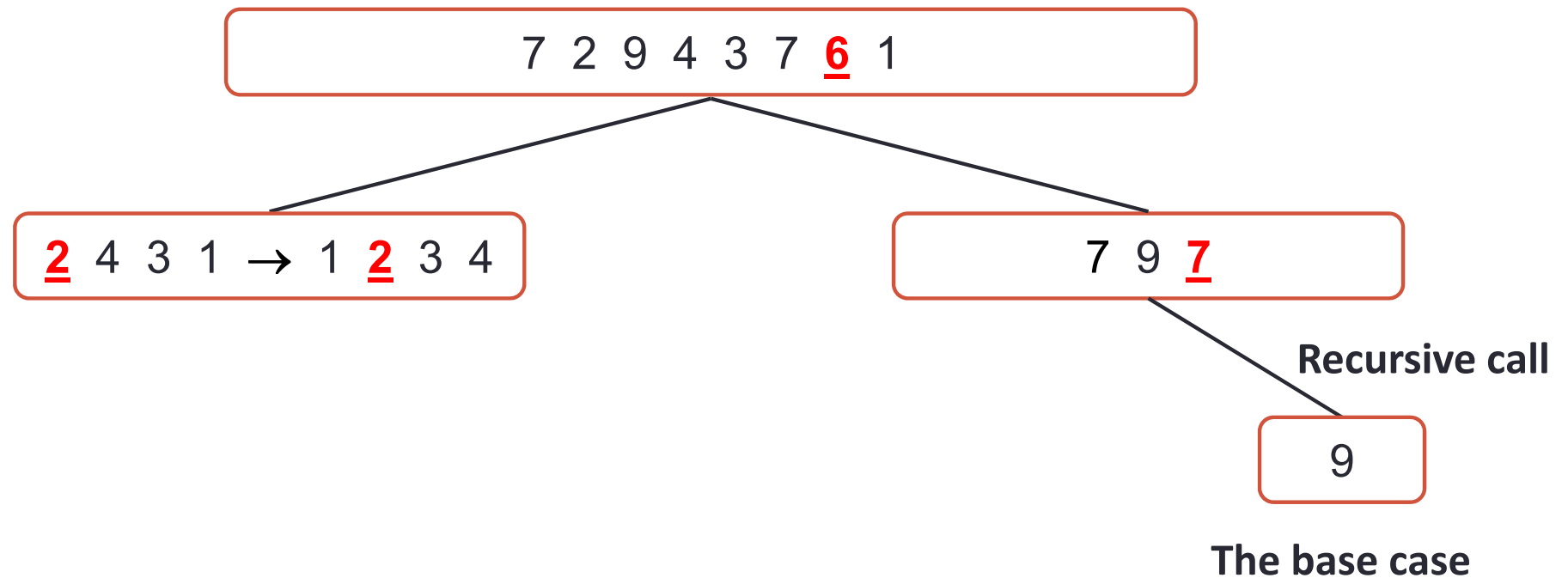


Return from recursive calls.
Combine the sub-lists

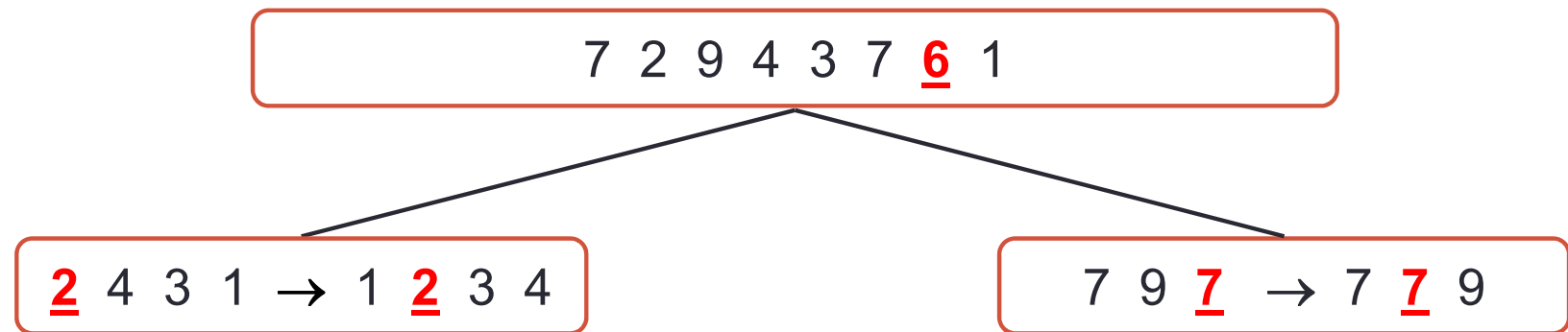
Quick Sort: Example



Quick Sort: Example



Quick Sort: Example



Return from recursive calls.
Combine the sub-lists

Quick Sort: Example

7 2 9 4 3 7 6 1 → 1 2 3 4 6 7 7 9

**Return from recursive calls.
Combine the sub-lists**

Quick Sort: Complexity of partition step

- We partition an input sequence as follows:
 - We remove, in turn, each element y from S and
 - We insert y into L , E or G , depending on the result of the comparison with the pivot x .
- Each insertion and removal is at the beginning or at the end of a sequence, and hence takes $O(1)$ time.
- Thus, the partition step of Quick Sort takes $O(n)$ time.

Quick Sort: Worst case complexity

- The worst case for quick-sort occurs when the pivot is the unique minimum or maximum element.
- One of L and G has size $n - 1$ and the other has size L .
- The running time is proportional to the sum

$$n + (n - 1) + \dots + 2 + 1$$
- Thus, the worst-case running time of Quick Sort is $O(n^2)$.

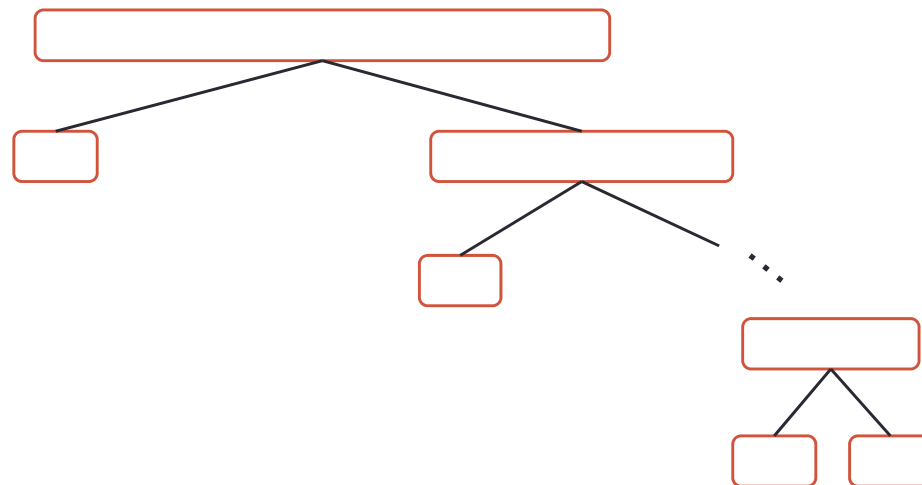
depth time

0 n

1 $n - 1$

... ...

$n - 1$ 1



Quick Sort: Properties and complexity

- Not stable because of long distance swapping.
- High probability of choosing the right pivot
 $O(n^2)$ runtime complexity, but typically $O(n \log n)$ time.
- Requires little space and exhibits good cache locality
Can run **in-place** using only $O(\log n)$ additional storage space to perform sorting.

- Worst case: $T(n) = O(n^2)$ comparisons
- Best case: $T(n) = O(n \log n)$ comparisons
- Average case: $T(n) = O(n \log n)$ comparisons
- Worst-case space complexity $O(n)$ auxiliary
 $O(\log n)$ auxiliary using bounded recursion

Sorting algorithm in C#

List<T>.Sort Method

This method uses the **Introspective Sort** (Introsort) algorithm for an array of n elements as follows:

- If the partition size is fewer than 16 elements, it uses Insertion Sort.
 - If the number of partitions exceeds $2 \log n$, it uses a Heapsort algorithm.
 - Otherwise, it uses a QuickSort algorithm.
-
- This implementation performs an unstable sort; that is, if two elements are equal, their order might not be preserved.
 - On average, this method is an $O(n \log n)$ operation; in the worst case it is an $O(n^2)$ operation.

Other references and things to do

- Have a look at attached references in CloudDeakin.
- Read chapters 5.1.1, 5.2-5.4, 5.6, 12.1, and 12.2 in Data Structures and Algorithms in Java. Michael T. Goodrich, Irvine Roberto Tamassia, and Michael H. Goldwasser, 2014.