Chap.2 Getting Started

- Here we study two sorting algorithms
- Insertion sort sorts by inserting into a sorted list the elements of the input array one after the other
- Merge sort sorts by recursively the input array into halves, sorting the halves separately, and then merging them into a full sorted list

The problem of sorting

Input: sequence $\langle a_1, a_2, ..., a_n \rangle$ of numbers.

Output: permutation $\langle a'_1, a'_2, ..., a'_n \rangle$ such that $a'_1 \le a'_2 \le \cdots \le a'_n$.

Example:

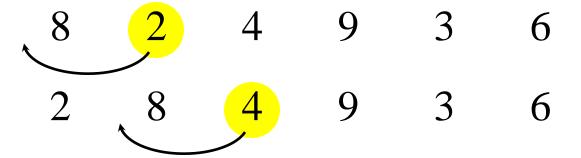
Input: 8 2 4 9 3 6

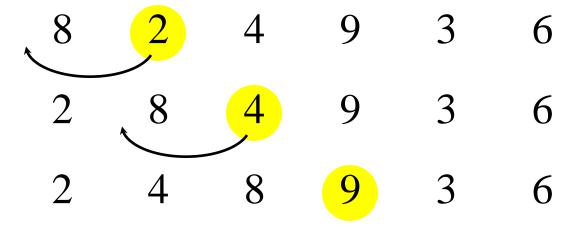
Output: 2 3 4 6 8 9

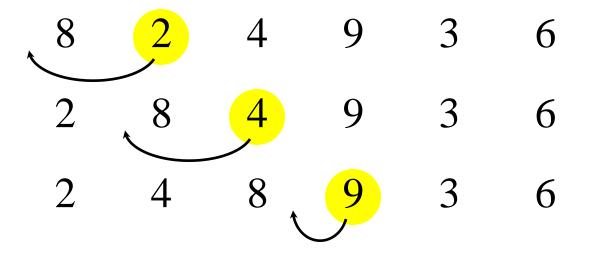
8 2 4 9 3 6

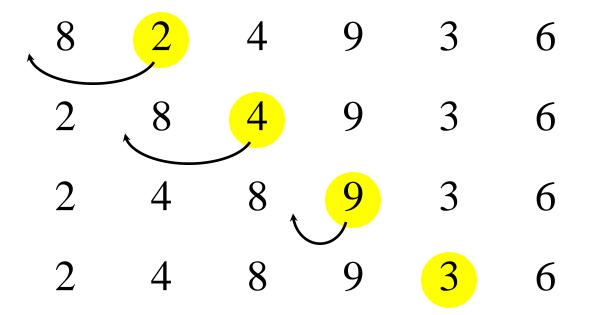
8 2 4 9 3 6

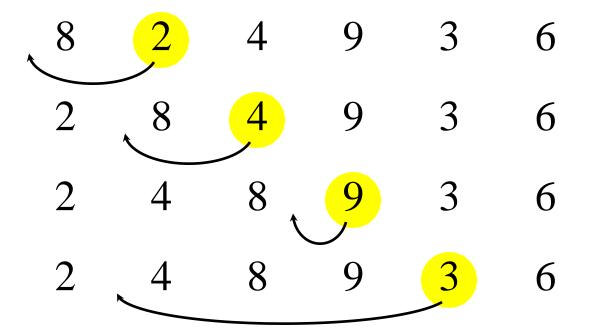


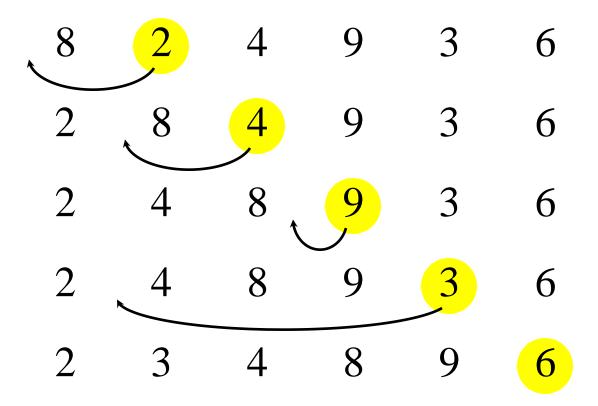


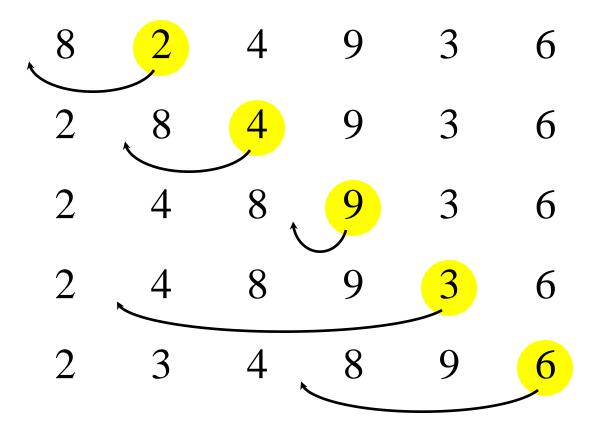


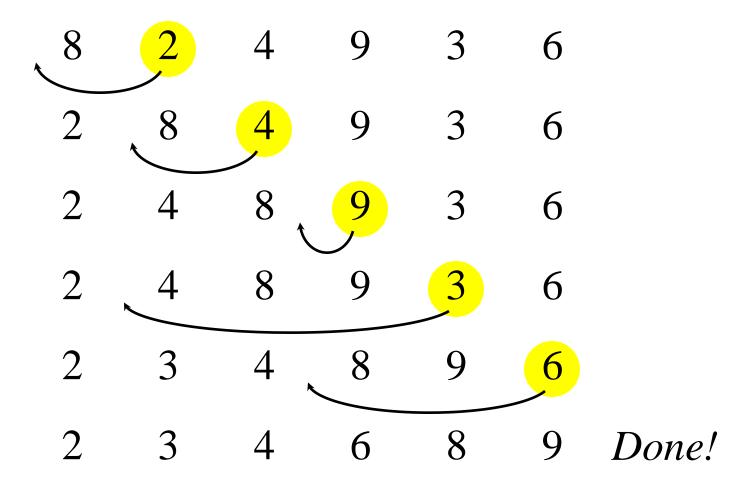


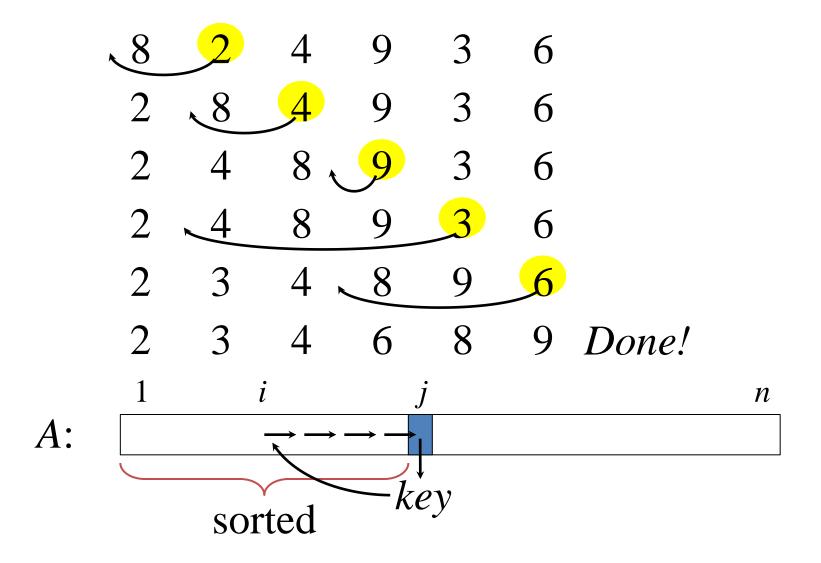












Insertion Sort

```
INSERTION-SORT(A)
1. for j = 2 to length[A]
       do key \leftarrow A[j]
3.
            //insert A[/] to sorted sequence A[1../-1]
             i \leftarrow j-1
4.
            while i > 0 and A[i] > key
5.
6.
                    do A[i+1] \leftarrow A[i] //move A[i] one
     position right
                         i \leftarrow i - 1
7.
8.
           A[i+1] \leftarrow key
```

Running time

- The running time depends on the input: an already sorted sequence is easier to sort.
- <u>Major Simplifying Convention</u>: Parameterize the running time by the size of the input, since short sequences are easier to sort than long ones.
 - $T_A(n) = \text{time of A on length n inputs}$
- Generally, we seek upper bounds on the running time, to have a guarantee of performance.

Kinds of analysis

Worst-case:

T(n) = maximum time of algorithm on any input of size n.

Average-case:

T(n) = expected time of algorithm over all inputs of size n.

Need assumption of statistical distribution of inputs.

Best-case:

works fast on some input.

Analysis of Algorithm

- When we analyze an algorithm, we are often primarily interested in its <u>worst-case</u> performance.
- Why?
 - The worst-case is an *upper bound on the* running time of an algorithm. (We know its performance can't be any worse than that.)
 - For some algorithms, the worse case occurs fairly often.

Machine-independent time

What is insertion sort's worst-case time?

Basic Idea:

Ignore machine dependent constants, otherwise impossible to verify and to compare algorithms

Look at *growth* of T(n) as $n \to \infty$.

Asymptotic Analysis

Insertion sort analysis

- Worst case
 - Reverse sorted list
 - $-O(n^2)$
- Best Case
 - Sorted input
 - -O(n)
- Is insertion sort a fast sorting algorithm?
 - Moderately so, for small n.
 - Not at all, for large n.

Merge Sort

- Insertion sort used an *incremental approach* to sorting: sort the smallest subarray (1 item), add one more item to the subarray, sort it, add one more item, sort it, etc.
- Merge sort uses a divide-and-conquer
 approach, based on the concept of recursion.

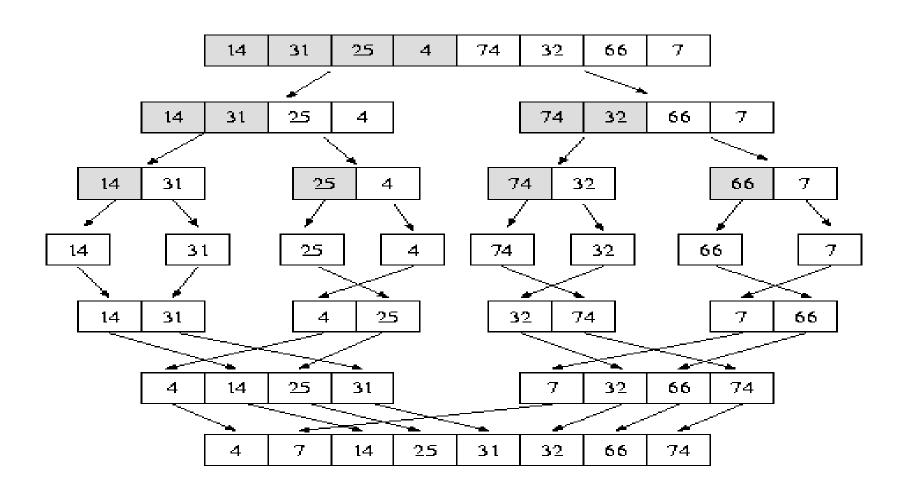
Merge Sort

- Divide-and-conquer:
 - Divide the problem into several subproblems.
 - Conquer the subproblems by solving them recursively. If the subproblems are small enough, solve them directly.
 - Combine the solutions to the subproblems to get the solution for the original problem.

Merge Sort (divide & conquer)

- Divide the n-element sequence to be sorted into two subsequences of n/2 each.
- Conquer by sorting the subsequences recursively by calling merge sort again. If the subsequences are small enough (of length 1), solve them directly.(Arrays of length 1 are already sorted.)
- Combine the two sorted subsequences by merging them to get a sorted sequence.

Merge Sort Example



Merge sort

- Merge sort basically consists of recursive calls to itself.
- The base case (which stops the recursion)
 occurs when a subsequence has a size of 1.
- The combine step is accomplished by a call to an algorithm called Merge.

Merge Sort(A,p,r)

```
1. if p < r

2. then q \leftarrow \lfloor (p+r)/2 \rfloor

3. MERGE-SORT(A, p, q)

4. MERGE-SORT(A, q+1, r)

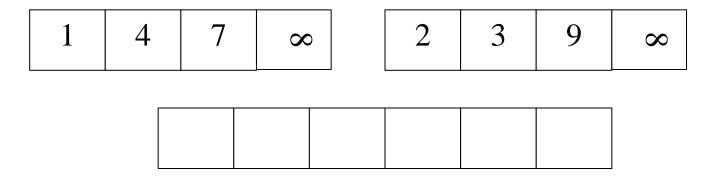
5. MERGE(A, p, q, r)

Call to MERGE-SORT(A,1,n) (suppose n=length(A))
```

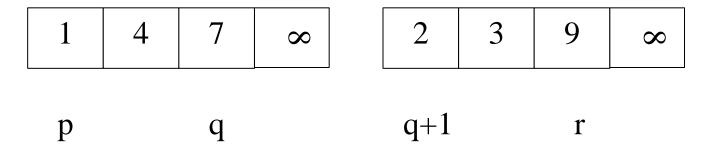
 Merge works by assuming you have two already sorted sublists and an empty array

1	4	7
2	3	9

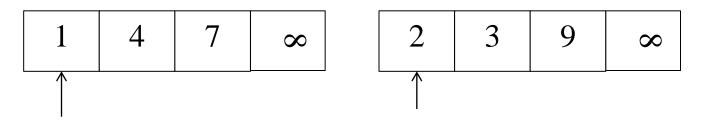




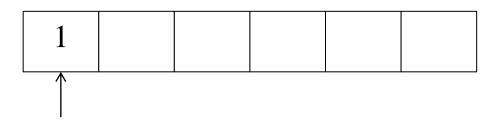
• Let's assume we have an *infinity, which* is guaranteed to be larger than the last item at the end of each sublist which lets us know when we have hit the end of the sublist.

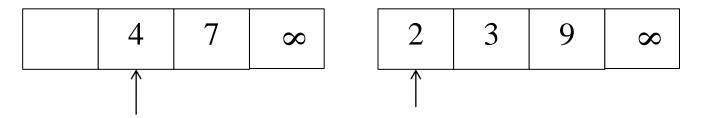


 The two sublists are indexed from p to q (for the first sublist) and from q+1 to r for the second sublist. There are (r – p) + 1 items in the two sublists combined, so we will need an output array of that size.

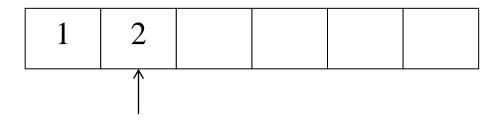


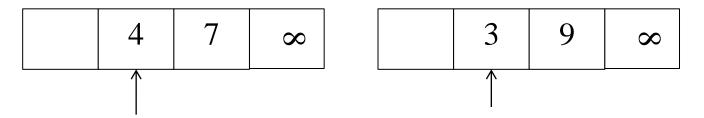
- Look at the first item in each subarray.
 Choose the smallest item.
- Move the chosen item to the output array



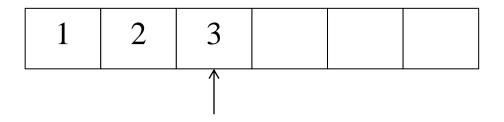


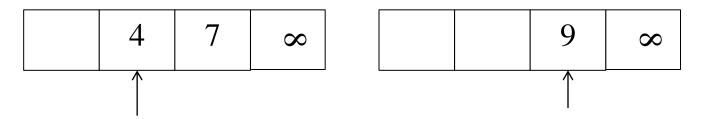
- Look at the first item in each subarray.
 Choose the smallest item.
- Move the chosen item to the output array



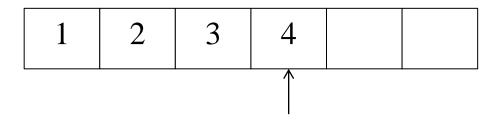


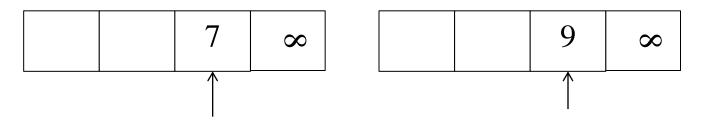
- Look at the first item in each subarray.
 Choose the smallest item.
- Move the chosen item to the output array



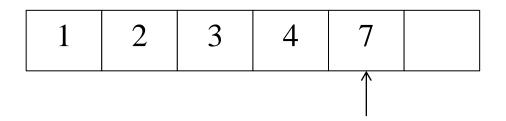


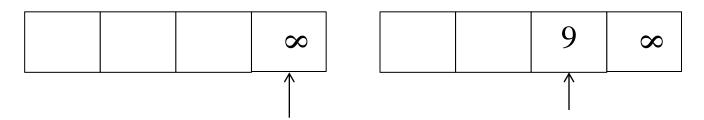
- Look at the first item in each subarray.
 Choose the smallest item.
- Move the chosen item to the output array



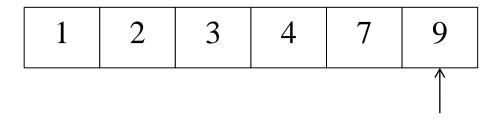


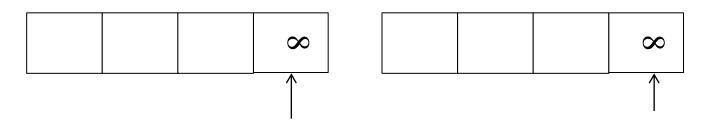
- Look at the first item in each subarray.
 Choose the smallest item.
- Move the chosen item to the output array





- Look at the first item in each subarray.
 Choose the smallest item.
- Move the chosen item to the output array





- We know that we have only n = (r p) + 1 items. So, we will make only (r p) + 1 moves.
- Here r = 1 and p = 6, and (6 1) + 1 = 6, so when we have made our 6th move we're through.

1	2	3	4	7	9

Merge(A,p,q,r)

```
MERGE(A, p, q, r)
 1 \quad n_1 \leftarrow q - p + 1
 2 \quad n_2 \leftarrow r - q
 3 create arrays L[1..n_1+1] and R[1..n_2+1]
 4 for i \leftarrow 1 to n_1
           do L[i] \leftarrow A[p+i-1]
 6 for j \leftarrow 1 to n_2
 7 do R[j] \leftarrow A[q+j]
 8 L[n_1+1] \leftarrow \infty
 9 R[n_2+1] \leftarrow \infty
10 \quad i \leftarrow 1
11 i \leftarrow 1
12 for k \leftarrow p to r
13
            do if L[i] \leq R[j]
14
                   then A[k] \leftarrow L[i]
15
                         i \leftarrow i + 1
                   else A[k] \leftarrow R[j]
16
17
                         j \leftarrow j + 1
```

Analysis of Divide-and-Conquer

- The Merge-Sort algorithm contains a recursive call to itself. When an algorithm contains a recursive call to itself, its running time often can be described by a *recurrence equation, or recurrence*.
- The recurrence equation describes the running time on a problem of size n in terms of the running time on smaller inputs.
- We can use mathematical tools to solve the recurrence and provide bounds on the performance of the algorithm.

Analysis of Divide-and-Conquer

- A recurrence of a divide-and-conquer algorithm is based on its 3 parts: divide, conquer, and combine.
- Let T(n) be the running time on a problem of size n.
- If the problem is small enough, say n <= c, we can solve it in a straightforward manner, which takes constant time, which we write as $\Theta(1)$.
- If the problem is bigger, we solve it by dividing the problem to get **a** subproblems, each of which is 1/**b** the size of the original. For Merge-Sort, both a and b are 2.

Analysis of Divide-and-Conquer

- Described by recursive equation
- Suppose T(n) is the running time on a problem of size n.

```
• \pi(n) = \Theta(1) if n \le c
a\pi(n/b) + D(n) + C(n) \text{ otherwise}
Where a: number of subproblems
n/b: size of each subproblem
D(n): cost of divide operation
C(n): cost of combination operation
```

- Base case: n = 1. Merge sort on an array of size 1 takes constant time, $\Theta(1)$.
- **Divide:** The Divide step of Merge-Sort just calculates the middle of the subarray. This takes constant time. So $D(n) = \Theta(1)$.
- **Conquer:** We make 2 calls to Merge-Sort. Each call handles 1/2 of the subarray that we pass as a parameter to the call. The total time required is 2T(n/2).
- Combine: Running Merge on an n-element subarray takes $\Theta(n)$, so $C(n) = \Theta(n)$.

Here is what we get:

$$\mathcal{T}(n) = \begin{cases} \Theta(1) & \text{if } n=1 \\ 2\mathcal{T}(n/2) + \Theta(1) + \Theta(n) & \text{if } n > 1 \end{cases}$$

• By inspection, we can see that we can ignore the $\Theta(1)$ factor, as it is irrelevant compared to $\Theta(n)$. We can rewrite this recurrence as:

$$7(n) =$$
 c if $n=1$
 $27(n/2) + c(n)$ if $n>1$

- How many Divide steps?
- Let's assume that n is some power of 2.
- Then for an array of size n, it will take us log₂n steps to recursively subdivide the array into subarrays of size 1.

Example: $8 = 2^3$

Step 0



Step 1





Step 2





Step 3















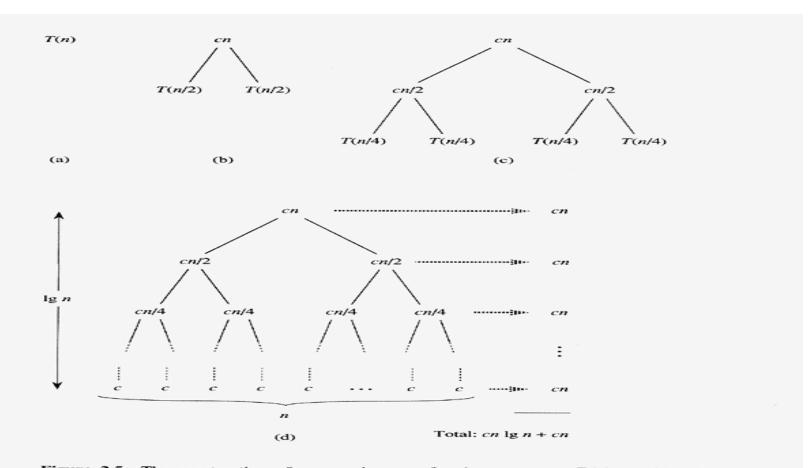


Figure 2.5 The construction of a recursion tree for the recurrence T(n) = 2T(n/2) + cn. Part (a) shows T(n), which is progressively expanded in (b)-(d) to form the recursion tree. The fully expanded tree in part (d) has $\lg n + 1$ levels (i.e., it has height $\lg n$, as indicated), and each level contributes a total cost of cn. The total cost, therefore, is $cn \lg n + cn$, which is $\Theta(n \lg n)$.

- So, it took us log₂n steps to divide the array all the way down into subarrays of size 1.
- As a result, we will have log₂n + 1 layers in the recurrence tree.
- Every layer of the recurrence tree it takes us n steps, since we have to put each array item into its proper position within each array.

- Consequently, the total cost can be expressed as: cn(log₂n + 1)
 = cn(log₂n) + cn
- Ignoring the low-order term and the constant c gives:

 $\Theta(n \log_2 n)$