



## Algorithm Design IV

Divide and Conquer I

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The **divide-and-conquer** strategy solves a problem by:

- 1 Breaking it into **subproblems** that are themselves smaller instances of the same type of problem.
- 2 **Recursively** solving these subproblems.
- 3 **Appropriately** combining their answers.

## Multiplication

# Product of Complex Numbers

Carl Friedrich Gauss(1777-1855) noticed that although the product of two complex numbers

$$(a + bi)(c + di) = ac - bd + (bc + ad)i$$

seems to involve **four** real-number multiplications, it can in fact be done with just **three**:  $ac$ ,  $bd$ , and  $(a + b)(c + d)$ , since

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- In big  $O$  way of thinking, reducing the number of multiplications from **four** to **three** seems wasted ingenuity.
- But this modest improvement becomes very significant when applied **recursively**.

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As a first step toward multiplying  $x$  and  $y$ , we split each of them into their left and right halves, which are  $n/2$  bits long

$$x = \boxed{x_L} \boxed{x_R} = 2^{n/2}x_L + x_R$$

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By **Gauss's** trick, three multiplications  $x_L y_L$ ,  $x_R y_R$ , and  $(x_L + x_R)(y_L + y_R)$  suffice.

## Algorithm for Integer Multiplication

MULTIPLY ( $x, y$ )

*Two positive integers  $x$  and  $y$ , in binary;*

$n = \max(\text{size of } x, \text{size of } y)$  rounded as a power of 2;

**if**  $n = 1$  **then** return ( $xy$ );

$x_L, x_R =$  leftmost  $n/2$ , rightmost  $n/2$  bits of  $x$ ;

$y_L, y_R =$  leftmost  $n/2$ , rightmost  $n/2$  bits of  $y$ ;

$P_1 = \text{MULTIPLY}(x_L, y_L)$ ;

$P_2 = \text{MULTIPLY}(x_R, y_R)$ ;

$P_3 = \text{MULTIPLY}(x_L + x_R, y_L + y_R)$ ;

return ( $P_1 \times 2^n + (P_3 - P_1 - P_2) \times 2^{n/2} + P_2$ )



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The **branch factor** is **3**: each problem produces three smaller ones, with the result that at depth  $k$  there are  $3^k$  subproblems, each of **size**  $n/2^k$ .

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For each subproblem, a **linear** amount of work is done in combining their answers.

## Time Analysis

The total time spent at depth  $k$  in the tree is

$$3^k \times O\left(\frac{n}{2^k}\right) = \left(\frac{3}{2}\right)^k \times O(n)$$



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Therefore, the overall running time is

$$O(n^{\log_2 3}) \approx O(n^{1.59})$$

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- Yes!

## Recurrence Relations



## Master Theorem

If  $T(n) = aT(\lceil n/b \rceil) + O(n^d)$  for some constants  $a > 0$ ,  $b > 1$  and  $d \geq 0$ , then

$$T(n) = \begin{cases} O(n^d) & \text{if } d > \log_b a \\ O(n^d \log n) & \text{if } d = \log_b a \\ O(n^{\log_b a}) & \text{if } d < \log_b a \end{cases}$$

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Its branching factor is  $a$ , so the  $k$ -th level of the tree is made up of  $a^k$  subproblems, each of size  $n/b^k$ .

$$a^k \times O\left(\frac{n}{b^k}\right)^d = O(n^d) \times \left(\frac{a}{b^d}\right)^k$$

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$k$  goes from 0 to  $\log_b n$ , these numbers form a geometric series with ratio  $a/b^d$ , comes down to three cases.

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The series is increasing and its sum is given by its last term,  $O(n^{\log_b a})$

The ratio is exactly 1.

In this case all  $O(\log n)$  terms of the series are equal to  $O(n^d)$ .

## Merge Sort

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## The Algorithm

```
MERGESORT ( $a[1 \dots n]$ )  
An array of numbers  $a[1 \dots n]$ ;  
if  $n > 1$  then  
|   return (MERGE (MERGESORT ( $a[1 \dots \lfloor n/2 \rfloor]$ ),  
|       MERGESORT ( $a[\lfloor n/2 \rfloor + 1 \dots n]$ ))));  
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```
MERGE ( $x[1 \dots k], y[1 \dots l]$ )  
if  $k = 0$  then return  $y[1 \dots l]$ ;  
if  $l = 0$  then return  $x[1 \dots k]$ ;  
if  $x[1] \leq y[1]$  then return ( $x[1] \circ$  MERGE ( $x[2 \dots k], y[1 \dots l]$ ));  
else return ( $y[1] \circ$  MERGE ( $x[1 \dots k], y[2 \dots l]$ ));
```

## An Iterative Version

```
ITERATIVE-MERGESORT ( $a[1 \dots n]$ )  
An array of numbers  $a[1 \dots n]$ ;  
 $Q = [ ]$  empty queue;  
for  $i = 1$  to  $n$  do  
  | Inject ( $Q, [a[i]]$ );  
end  
while  $|Q| > 1$  do  
  | Inject ( $Q, \text{MERGE}(\text{Eject}(Q), \text{Eject}(Q))$ );  
end  
return ( $\text{Eject}(Q)$ );
```

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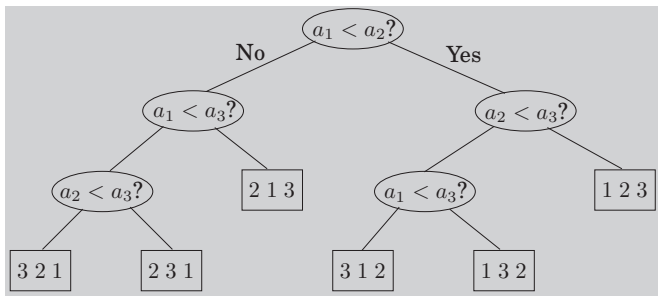
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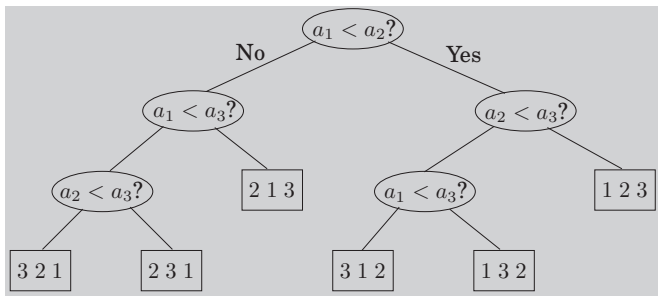
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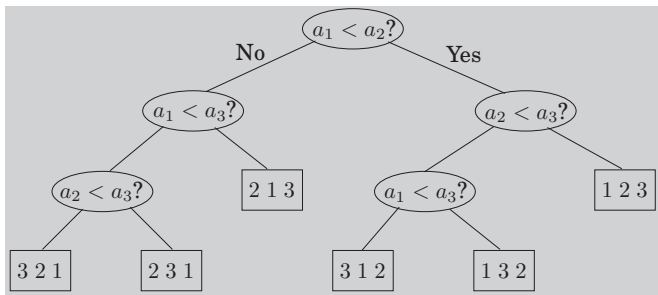
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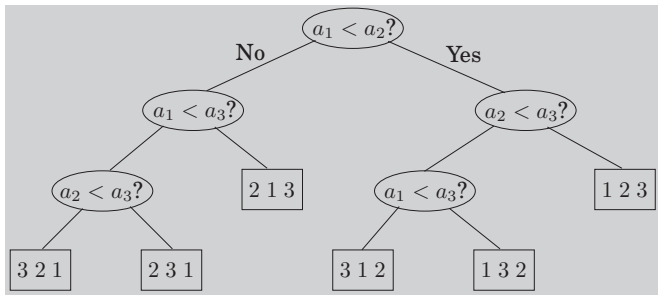


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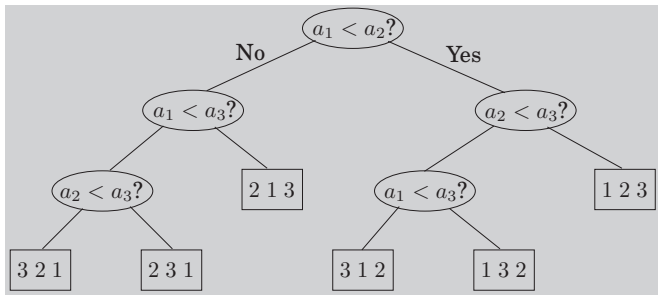
Assume  $n$  elements. Each of its leaves is labeled by a **permutation** of  $\{1, 2, \dots, n\}$ .

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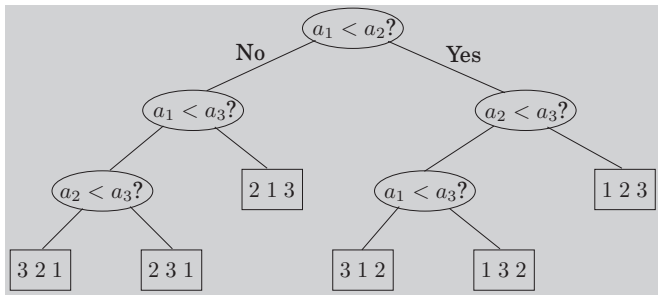
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So, the depth of the tree - and the complexity of the algorithm - must be at least

$$\log(n!) \approx \log(\sqrt{\pi(2n+1/3)} \cdot n^n \cdot e^{-n}) = \Omega(n \log n)$$

**Median**



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# Selection

**Input:** A list of number  $S$ ; an integer  $k$ .

**Output:** The  $k$ th smallest element of  $S$ .

## A Randomized Selection

For any number  $v$ , imagine splitting list  $S$  into three categories:

- elements smaller than  $v$ , i.e.,  $S_L$ ;
- those equal to  $v$ , i.e.,  $S_v$  (there might be duplicates);
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$$selection(S, k) = \begin{cases} selection(S_L, k) & \text{if } k \leq |S_L| \\ v & \text{if } |S_L| < k \leq |S_L| + |S_v| \\ selection(S_R, k - |S_L| - |S_v|) & \text{if } k > |S_L| + |S_v| \end{cases}$$



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Instead, we pick  $v$  randomly from  $S$ !

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**Best-case** scenario  $O(n)$

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*Proof:*

Let  $E$  be the expected number of tosses before heads is seen.

$$E = 1 + \frac{1}{2}E$$

Therefore,  $E = 2$ .

# The Efficiency Analysis

Let  $T(n)$  be the **expected running time** on the array of size  $n$ , we get

$$T(n) \leq T(3n/4) + O(n) = O(n)$$

## Matrix Multiplication

The product of two  $n \times n$  matrices  $X$  and  $Y$  is a  $n \times n$  matrix  $Z = XY$ , with which  $(i, j)$ th entry

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In general, matrix multiplication is not commutative, say,  $XY \neq YX$



The product of two  $n \times n$  matrices  $X$  and  $Y$  is a  $n \times n$  matrix  $Z = XY$ , with which  $(i, j)$ th entry

$$Z_{ij} = \sum_{k=1}^n X_{ik} Y_{kj}$$

In general, matrix multiplication is not commutative, say,  $XY \neq YX$

The running time for matrix multiplication is  $O(n^3)$

- There are  $n^2$  entries to be computed, and each takes  $O(n)$  time.

Matrix multiplication can be performed **blockwise**.

$$X = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \quad Y = \begin{bmatrix} E & F \\ G & H \end{bmatrix}$$

$$XY = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{bmatrix} E & F \\ G & H \end{bmatrix} = \begin{bmatrix} AE + BG & AF + BH \\ CE + DG & CF + DH \end{bmatrix}$$

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$$T(n) = 8T(n/2) + O(n^2)$$

$$T(n) = O(n^3)$$

## Strassen Algorithm

$$X = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \quad Y = \begin{bmatrix} E & F \\ G & H \end{bmatrix}$$
$$XY = \begin{bmatrix} P_5 + P_4 - P_2 + P_6 & P_1 + P_2 \\ P_3 + P_4 & P_1 + P_5 - P_3 - P_7 \end{bmatrix}$$

# Strassen Algorithm

$$X = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \quad Y = \begin{bmatrix} E & F \\ G & H \end{bmatrix}$$

$$XY = \begin{bmatrix} P_5 + P_4 - P_2 + P_6 & P_1 + P_2 \\ P_3 + P_4 & P_1 + P_5 - P_3 - P_7 \end{bmatrix}$$

$$P_1 = A(F - H) \quad P_5 = (A + D)(E + H)$$

$$P_2 = (A + B)H \quad P_6 = (B - D)(G + H)$$

$$P_3 = (C + D)E \quad P_7 = (A - C)(E + F)$$

$$P_4 = D(G - E)$$

# Strassen Algorithm

$$X = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \quad Y = \begin{bmatrix} E & F \\ G & H \end{bmatrix}$$

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$$P_2 = (A + B)H \quad P_6 = (B - D)(G + H)$$

$$P_3 = (C + D)E \quad P_7 = (A - C)(E + F)$$

$$P_4 = D(G - E)$$

$$T(n) = 7T(n/2) + O(n^2)$$

# Strassen Algorithm

$$X = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \quad Y = \begin{bmatrix} E & F \\ G & H \end{bmatrix}$$

$$XY = \begin{bmatrix} P_5 + P_4 - P_2 + P_6 & P_1 + P_2 \\ P_3 + P_4 & P_1 + P_5 - P_3 - P_7 \end{bmatrix}$$

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$$P_4 = D(G - E)$$

$$T(n) = 7T(n/2) + O(n^2)$$

$$T(n) = O(n^{\log_2 7}) \approx O(n^{2.81})$$