## Introduction to Algorithms 6.046J/18.401J/SMA5503



## Lecture 3

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## ALGORITHM <br> The divide-and-conquer design paradigm

1. Divide the problem (instance) into subproblems.
2. Conquer the subproblems by solving them recursively.
3. Combine subproblem solutions.

## Example: merge sort

1. Divide: Trivial.
2. Conquer: Recursively sort 2 subarrays.
3. Combine: Linear-time merge.


## Binary search

Find an element in a sorted array:

1. Divide: Check middle element.
2. Conquer: Recursively search 1 subarray.
3. Combine: Trivial.

Example: Find 9

$$
\begin{array}{lllllll}
3 & 5 & 7 & 8 & 9 & 12 & 15
\end{array}
$$

## Binary search

Find an element in a sorted array:

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## Binary search

Find an element in a sorted array:

1. Divide: Check middle element.
2. Conquer: Recursively search 1 subarray.
3. Combine: Trivial.

Example: Find 9
$\begin{array}{ll}3 & 5\end{array}$
812
15

## Binary search

Find an element in a sorted array:

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3. Combine: Trivial.

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Example: Find 9

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\begin{array}{lllllll}
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\end{array}
$$

## Recurrence for binary search



$$
\begin{aligned}
& n^{\log _{b} a}=n^{\log _{2} 1}=n^{0}=1 \Rightarrow \text { CASE } 2(k=0) \\
& \quad \Rightarrow T(n)=\Theta(\lg n) .
\end{aligned}
$$

## Powering a number

## Problem: Compute $a^{n}$, where $n \in \mathbf{N}$.

Naive algorithm: $\Theta(n)$.

## Divide-and-conquer algorithm:

$$
\begin{gathered}
a^{n}= \begin{cases}a^{n / 2} \cdot a^{n / 2} & \text { if } n \text { is even; } \\
a^{(n-1) / 2} \cdot a^{(n-1) / 2} \cdot a & \text { if } n \text { is odd }\end{cases} \\
T(n)=T(n / 2)+\Theta(1) \Rightarrow T(n)=\Theta(\lg n) .
\end{gathered}
$$

## Polynomial multiplication

Input:

$$
\begin{aligned}
& a(x)=a_{0}+a_{1} x+\ldots+a_{n} x^{n}, \\
& b(x)=b_{0}+b_{1} x+\ldots+b_{n} x^{n},
\end{aligned}
$$

Output: $\quad c(x)=a(x) * b(x)=c_{0}+c_{1} x+\ldots+c_{2 n} x^{2 n}$

$$
c_{i}=a_{0} b_{i}+a_{1} b_{i-1}+\ldots+a_{i-1} b_{1}+a_{i} b_{0}
$$

Example: $\left(a_{0}+a_{1} x\right) *\left(b_{0}+b_{1} x\right)=$

$$
\begin{array}{ll}
a_{0} b_{0}+\left(a_{0} b_{1}+a_{1} b_{0}\right) x & +a_{1} b_{1} x^{2}= \\
c_{0} & +c_{1} x
\end{array}+c_{2} x^{2}=
$$

## Motivation (more in recitations)

- Essentially equivalent to multiplying large integers:

$$
\begin{aligned}
& 6046 * 6001= \\
& \left(6 * 10^{0}+4 * 10^{1}+0 * 10^{2}+6 * 10^{3}\right) * \\
& \left(1 * 10^{0}+0^{*} 10^{1}+0 * 10^{2}+6 * 10^{3}\right)= \\
& a(10) * b(10)=c(10), \text { where } c(x)=a(x) * b(x) \\
& c(10)=c_{0} 10^{0}+c_{1} 10^{1}+\ldots+c_{6} 10^{6}
\end{aligned}
$$

- The coefficients of $c$ form the "digits" of the product $c(10)$


## How to multiply two polynomials

- From the definition: $\Theta\left(n^{2}\right)$ time
- Faster ? Use divide and conquer
- Divide:

$$
\begin{aligned}
& a(x)=a_{0}+a_{1} x+\ldots+a_{n} x^{n}= \\
& \left(a_{0}+\ldots+a_{n / 2} x^{n / 2}\right)+x^{n / 2}\left(a_{n / 2} x^{0}+\ldots+a_{n} x^{n / 2}\right)= \\
& p(x)+x^{n / 2} q(x)= \\
& p+x^{n / 2} q
\end{aligned}
$$

- In the same way: $b(x)=s+x^{n / 2} t$


## Conquer

- Observe that:

$$
\begin{aligned}
& a^{*} b= \\
& \left(p+x^{n / 2} q\right) *\left(s+x^{n / 2} t\right)= \\
& p * s+x^{n / 2}(p * t+q * s)+x^{n} q * t
\end{aligned}
$$

- But $p, q, s, t$ have degree $n / 2$
$\Rightarrow$ can compute the products recursively!
(and then perform $\Theta(\mathrm{n})$ additions)


## The great moment...


$n^{\log _{b} a}=n^{\log _{2} 4}=n^{2} \Rightarrow$ CASE $1 \Rightarrow T(n)=\Theta\left(n^{2}\right)$.

## No better than the ordinary algorithm ???

## Need to be more clever

- Compute:

$$
\begin{aligned}
& p *_{S} \\
& q^{*} t \\
& (p+q) *(s+t)=p *_{S}+\left(p *^{*}+q *_{S}\right)+q *^{*} t
\end{aligned}
$$

(all polynomials have degree $n / 2$ )

- Can extract $\left(p^{*} t+q^{*} s\right)$ without any additional multiplications!


$$
n^{\log _{b} a}=n^{\log _{2} 3}=n^{1.58496 \ldots}
$$

Much better than $\Theta\left(n^{2}\right)$ !

## Matrix multiplication

$\left.\begin{array}{l}\text { Input: } \quad A=\left[a_{i j}\right], B=\left[b_{i j}\right] . \\ \text { Output: } C=\left[c_{i j}\right]=A \cdot B .\end{array}\right\} \quad i, j=1,2, \ldots, n$.

$$
\left[\begin{array}{cccc}
c_{11} & c_{12} & \cdots & c_{1 n} \\
c_{21} & c_{22} & \cdots & c_{2 n} \\
\vdots & \vdots & \ddots & \vdots \\
c_{n 1} & c_{n 2} & \cdots & c_{n n}
\end{array}\right]=\left[\begin{array}{cccc}
a_{11} & a_{12} & \cdots & a_{1 n} \\
a_{21} & a_{22} & \cdots & a_{2 n} \\
\vdots & \vdots & \ddots & \vdots \\
a_{n 1} & a_{n 2} & \cdots & a_{n n}
\end{array}\right] \cdot\left[\begin{array}{cccc}
b_{11} & b_{12} & \cdots & b_{1 n} \\
b_{21} & b_{22} & \cdots & b_{2 n} \\
\vdots & \vdots & \ddots & \vdots \\
b_{n 1} & b_{n 2} & \cdots & b_{n n}
\end{array}\right]
$$

$$
c_{i j}=\sum_{k=1}^{n} a_{i k} \cdot b_{k j}
$$

for $i \leftarrow 1$ to $n$ do for $j \leftarrow 1$ to $n$

$$
\text { do } c_{i j} \leftarrow 0
$$

for $k \leftarrow 1$ to $n$ do $c_{i j} \leftarrow c_{i j}+a_{i k} \cdot b_{k j}$

Running time $=\Theta\left(n^{3}\right)$

## Divide-and-conquer algorithm

## IDEA:

$n \times n$ matrix $=2 \times 2$ matrix of $(n / 2) \times(n / 2)$ submatrices:

$$
\begin{aligned}
& {\left[\begin{array}{c:c}
r & s \\
\hdashline t & u
\end{array}\right]=\left[\begin{array}{c:c}
a & b \\
\hdashline c & d
\end{array}\right] \cdot\left[\begin{array}{c:c}
e & f \\
\hdashline g & h
\end{array}\right]} \\
& C=A \cdot B
\end{aligned}
$$

$r=a e+b g$
$s=a f+b h\} 8$ mults of $(n / 2) \times(n / 2)$ submatrices
$t=c e+d g \quad 4$ adds of $(n / 2) \times(n / 2)$ submatrices
$u=c f+d h$

## Analysis of D\&C algorithm



$$
n^{\log _{b} a}=n^{\log _{2} 8}=n^{3} \Rightarrow \text { CASE } 1 \Rightarrow T(n)=\Theta\left(n^{3}\right) .
$$

No better than the ordinary algorithm.

## Strassen's idea (1969)

- Multiply $2 \times 2$ matrices with only 7 recursive mults.

$$
\begin{aligned}
& P_{1}=a \cdot(f-h) \\
& P_{2}=(a+b) \cdot h \\
& P_{3}=(c+d) \cdot e \\
& P_{4}=d \cdot(g-e) \\
& P_{5}=(a+d) \cdot(e+h) \\
& P_{6}=(b-d) \cdot(g+h) \\
& P_{7}=(a-c) \cdot(e+f)
\end{aligned}
$$

$$
\begin{aligned}
& r=P_{5}+P_{4}-P_{2}+P_{6} \\
& s=P_{1}+P_{2} \\
& t=P_{3}+P_{4} \\
& u=P_{5}+P_{1}-P_{3}-P_{7}
\end{aligned}
$$

7 mults, 18 adds/subs. Note: No reliance on commutativity of mult!

## Strassen's idea

- Multiply $2 \times 2$ matrices with only 7 recursive mults.

$$
\begin{aligned}
& P_{1}=a \cdot(f-h) \\
& P_{2}=(a+b) \cdot h \\
& P_{3}=(c+d) \cdot e \\
& P_{4}=d \cdot(g-e) \\
& P_{5}=(a+d) \cdot(e+h) \\
& P_{6}=(b-d) \cdot(g+h) \\
& P_{7}=(a-c) \cdot(e+f)
\end{aligned}
$$

$$
\begin{aligned}
r= & P_{5}+P_{4}-P_{2}+P_{6} \\
= & (a+d)(e+h) \\
& +d(g-e)-(a+b) h \\
& +(b-d)(g+h) \\
= & a e+a h+d e+d h \\
& +d g-d e-a h-b h \\
& +b g+b h-d g-d h \\
= & a e+b g
\end{aligned}
$$

## Strassen's algorithm

1. Divide: Partition $A$ and $B$ into $(n / 2) \times(n / 2)$ submatrices. Form terms to be multiplied using + and - .
2. Conquer: Perform 7 multiplications of $(n / 2) \times(n / 2)$ submatrices recursively.
3. Combine: Form $C$ using + and - on $(n / 2) \times(n / 2)$ submatrices.

$$
T(n)=7 T(n / 2)+\Theta\left(n^{2}\right)
$$

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$$

$$
n^{\log _{b} a}=n^{\log _{2} 7} \approx n^{2.81} \Rightarrow \text { CASE } 1 \Rightarrow T(n)=\Theta\left(n^{\lg 7}\right)
$$

The number 2.81 may not seem much smaller than 3 , but because the difference is in the exponent, the impact on running time is significant. In fact, Strassen's algorithm beats the ordinary algorithm on today's machines for $n \geq 30$ or so.

Best to date (of theoretical interest only): $\Theta\left(n^{2.376}\right)$.

## Conclusion

- Divide and conquer is just one of several powerful techniques for algorithm design.
- Divide-and-conquer algorithms can be analyzed using recurrences and the master method (so practice this math).
- Can lead to more efficient algorithms


## VLSI layout

Problem: Embed a complete binary tree with $n$ leaves in a grid using minimal area.


## $\therefore$ H-tree embedding



$$
\begin{aligned}
L(n) & =2 L(n / 4)+\Theta(1) \\
& =\Theta(\sqrt{n})
\end{aligned}
$$

Area $=\Theta(n)$

## 

$$
T(n)=a T(n / b)+f(n)
$$

CASE 1: $f(n)=O\left(n^{\log _{b} a-\varepsilon}\right)$

$$
\Rightarrow T(n)=\Theta\left(n^{\log _{b} a}\right)
$$

CASE 2: $f(n)=\Theta\left(n^{\log b a} \lg ^{k} n\right)$

$$
\Rightarrow T(n)=\Theta\left(n^{\log _{b} a} \lg ^{k+1} n\right) .
$$

CASE 3: $f(n)=\Omega\left(n^{\log _{b} a+\varepsilon}\right)$ and $a f(n / b) \leq c f(n)$

$$
\Rightarrow T(n)=\Theta(f(n)) .
$$

$$
\begin{aligned}
& \text { Merge sort: } a=2, b=2 \Rightarrow n^{\log _{b} a}=n \\
& \quad \Rightarrow \text { CASE } 2(k=0) \Rightarrow T(n)=\Theta(n \lg n) .
\end{aligned}
$$

## Fibonacci numbers

## Recursive definition:

$$
F_{n}= \begin{cases}0 & \text { if } n=0 \\ 1 & \text { if } n=1 \\ F_{n-1}+F_{n-2} & \text { if } n \geq 2\end{cases}
$$

$\begin{array}{lllllllllll}0 & 1 & 1 & 2 & 3 & 5 & 8 & 13 & 21 & 34 & \cdots\end{array}$
Naive recursive algorithm: $\Omega\left(\phi^{n}\right)$ (exponential time), where $\phi=(1+\sqrt{5}) / 2$ is the golden ratio.

## ALGORITHM $\square$ Computing Fibonacci numbers

## Naive recursive squaring:

$F_{n}=\phi^{n} / \sqrt{5}$ rounded to the nearest integer.

- Recursive squaring: $\Theta(\lg n)$ time.
- This method is unreliable, since floating-point arithmetic is prone to round-off errors.


## Bottom-up:

- Compute $F_{0}, F_{1}, F_{2}, \ldots, F_{\mathrm{n}}$ in order, forming each number by summing the two previous.
- Running time: $\Theta(n)$.


## Recursive squaring

Theorem: $\left[\begin{array}{cc}F_{n+1} & F_{n} \\ F_{n} & F_{n-1}\end{array}\right]=\left[\begin{array}{ll}1 & 1 \\ 1 & 0\end{array}\right]^{n}$.
Algorithm: Recursive squaring. Time $=\Theta(\lg n)$.
Proof of theorem. (Induction on n.)
Base $(n=1):\left[\begin{array}{ll}F_{2} & F_{1} \\ F_{1} & F_{0}\end{array}\right]=\left[\begin{array}{ll}1 & 1 \\ 1 & 0\end{array}\right]^{1}$.

## Recursive squaring

Inductive step $(n \geq 2)$ :

$$
\begin{aligned}
{\left[\begin{array}{cc}
F_{n+1} & F_{n} \\
F_{n} & F_{n-1}
\end{array}\right] } & =\left[\begin{array}{cc}
F_{n} & F_{n-1} \\
F_{n-1} & F_{n-2}
\end{array}\right] \cdot\left[\begin{array}{ll}
1 & 1 \\
1 & 0
\end{array}\right] \\
& =\left[\begin{array}{ll}
1 & 1 \\
1 & 0
\end{array}\right]^{n-1} \cdot\left[\begin{array}{ll}
1 & 1 \\
1 & 0
\end{array}\right] \\
& =\left[\begin{array}{ll}
1 & 1 \\
1 & 0
\end{array}\right]^{n}
\end{aligned}
$$

