CSE 431/531: Algorithm Analysis and Design (Spring 2021)

Divide-and-Conquer

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Outline

Greedy Algorithm

- mainly for combinatorial optimization problems
- trivial algorithm runs in exponential time
- greedy algorithm gives an efficient algorithm
- main focus of analysis: correctness of algorithm

Divide-and-Conquer

- not necessarily for combinatorial optimization problems
- trivial algorithm already runs in polynomial time
- divide-and-conquer gives a more efficient algorithm
- main focus of analysis: running time

Divide-and-Conquer

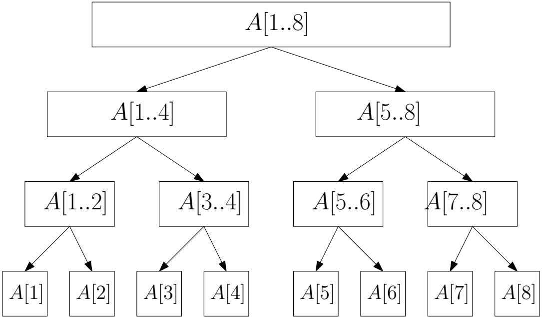
- **Divide**: Divide instance into many smaller instances
- **Conquer**: Solve each of smaller instances recursively and separately
- **Combine**: Combine solutions to small instances to obtain a solution for the original big instance

merge-sort(A, n)

1: **if** $n = 1$ **then**
2:     **return** A
3: **else**
4:     $B \leftarrow \text{merge-sort}\Big(A\big[1..\lfloor n/2 \rfloor\big], \lfloor n/2 \rfloor\Big)$
5:     $C \leftarrow \text{merge-sort}\Big(A\big[\lfloor n/2 \rfloor + 1..n\big], \lceil n/2 \rceil\Big)$
6: **return** merge$(B, C, \lfloor n/2 \rfloor, \lceil n/2 \rceil)$

- Divide: trivial
- Conquer: 4, 5
- Combine: 6

Running Time for Merge-Sort



- Each level takes running time $O(n)$
- There are $O(\lg n)$ levels
- Running time $= O(n \lg n)$
- Better than insertion sort

Running Time for Merge-Sort Using Recurrence

- $T(n) =$ running time for sorting n numbers,then

$$T(n) = \begin{cases} O(1) & \text{if } n = 1 \\ T(\lfloor n/2 \rfloor) + T(\lceil n/2 \rceil) + O(n) & \text{if } n \geq 2 \end{cases}$$

- With some tolerance of informality:

$$T(n) = \begin{cases} O(1) & \text{if } n = 1 \\ 2T(n/2) + O(n) & \text{if } n \geq 2 \end{cases}$$

- Even simpler: $T(n) = 2T(n/2) + O(n)$. (Implicit assumption: $T(n) = O(1)$ if n is at most some constant.)
- Solving this recurrence, we have $T(n) = O(n \lg n)$ (we shall show how later)

Outline

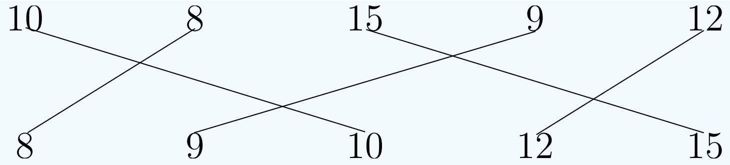
Def. Given an array A of n integers, an inversion in A is a pair (i, j) of indices such that $i < j$ and $A[i] > A[j]$.

Counting Inversions

Input: an sequence A of n numbers

Output: number of inversions in A

Example:



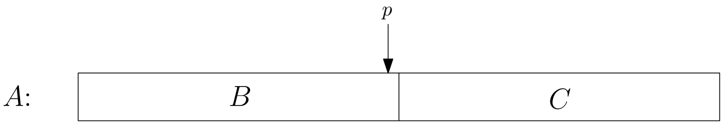
- 4 inversions (for convenience, using numbers, not indices): $(10, 8), (10, 9), (15, 9), (15, 12)$

Naive Algorithm for Counting Inversions

count-inversions(A, n)

1: $c \leftarrow 0$
2: **for** every $i \leftarrow 1$ to $n-1$ **do**
3:     **for** every $j \leftarrow i+1$ to n **do**
4:         **if** $A[i] > A[j]$ **then** $c \leftarrow c+1$
5: **return** c

Divide-and-Conquer



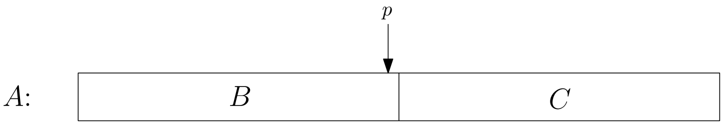
- $p = \lfloor n/2 \rfloor, B = A[1..p], C = A[p+1..n]$
- $$\#\text{invs}(A) = \#\text{invs}(B) + \#\text{invs}(C) + m$$
  $$m = \left|\left\{(i,j) : B[i] > C[j]\right\}\right|$$

Q: How fast can we compute m, via trivial algorithm?

A: $O(n^2)$

- Can not improve the $O(n^2)$ time for counting inversions.

Divide-and-Conquer

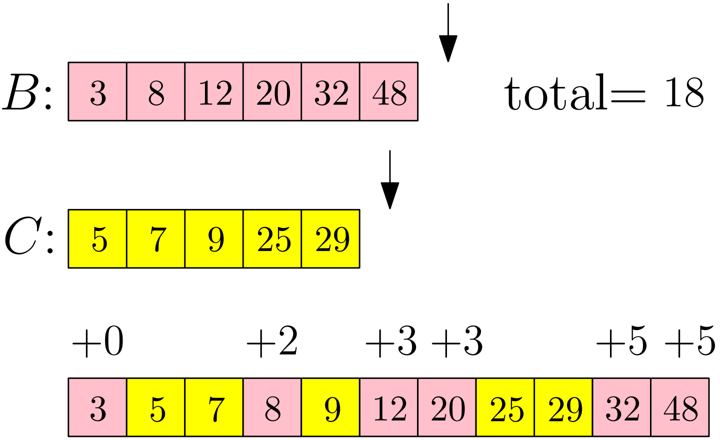


- $p = \lfloor n/2 \rfloor, B = A[1..p], C = A[p+1..n]$
- $$\#\text{invs}(A) = \#\text{invs}(B) + \#\text{invs}(C) + m$$
  $$m = \left|\left\{(i,j) : B[i] > C[j]\right\}\right|$$

Lemma If both B and C are sorted, then we can compute m in $O(n)$ time!

Counting Inversions between B and C

Count pairs i, j such that $B[i] > C[j]$:



Count Inversions between B and C

- Procedure that merges B and C and counts inversions between B and C at the same time

merge-and-count(B, C, n_1, n_2)

$count \leftarrow 0$;
$A \leftarrow []$; $i \leftarrow 1$; $j \leftarrow 1$
while $i \leq n_1$ or $j \leq n_2$ **do**
    if $j > n_2$ or $(i \leq n_1$ and $B[i] \leq C[j])$ **then**
        append $B[i]$ to A; $i \leftarrow i + 1$
        $count \leftarrow count + (j - 1)$
    else
        append $C[j]$ to A; $j \leftarrow j + 1$
return $(A, count)$

Sort and Count Inversions in A

- A procedure that returns the sorted array of A and counts the number of inversions in A:

sort-and-count(A, n)

1: **if** $n = 1$ **then**
2:     **return** $(A, 0)$
3: **else**
4:     $(B, m_1) \leftarrow$ sort-and-count$\Big(A\big[1..\lfloor n/2 \rfloor\big], \lfloor n/2 \rfloor\Big)$
5:     $(C, m_2) \leftarrow$ sort-and-count$\Big(A\big[\lfloor n/2 \rfloor + 1..n\big], \lceil n/2 \rceil\Big)$
6:     $(A, m_3) \leftarrow$ merge-and-count$(B, C, \lfloor n/2 \rfloor, \lceil n/2 \rceil)$
7:     return $(A, m_1 + m_2 + m_3)$

- Divide: trivial
- Conquer: 4, 5
- Combine: 6, 7

sort-and-count(A, n)

```
if n = 1 then
    return (A, 0)
else
    (B, m_1) ← sort-and-count(A[1..⌊n/2⌋], ⌊n/2⌋)
    (C, m_2) ← sort-and-count(A[⌊n/2⌋ + 1..n], ⌈n/2⌉)
    (A, m_3) ← merge-and-count(B, C, ⌊n/2⌋, ⌈n/2⌉)
    return (A, m_1 + m_2 + m_3)
```

- Recurrence for the running time: $T(n) = 2T(n/2) + O(n)$
- Running time $= O(n \lg n)$

Outline

Outline

Quicksort vs Merge-Sort

	Merge Sort	**Quicksort**
Divide	Trivial	Separate small and big numbers
Conquer	Recurse	Recurse
Combine	Merge 2 sorted arrays	Trivial

Quicksort Example

Assumption We can choose median of an array of size n in $O(n)$ time.

29	82	75	64	38	45	94	69	25	76	15	92	37	17	85

29	38	45	25	15	37	17	64	82	75	94	92	69	76	85

25	15	17	29	38	45	37	64	82	75	94	92	69	76	85

Quicksort

quicksort(A, n)

```
if n ≤ 1 then return A
x ← lower median of A
A_L ← elements in A that are less than x                 \\ Divide
A_R ← elements in A that are greater than x              \\ Divide
B_L ← quicksort(A_L, A_L.size)                           \\ Conquer
B_R ← quicksort(A_R, A_R.size)                           \\ Conquer
t ← number of times x appear A
return the array obtained by concatenating B_L, the array
    containing t copies of x, and B_R
```

- Recurrence $T(n) \leq 2T(n/2) + O(n)$
- Running time $= O(n \lg n)$

Assumption We can choose median of an array of size n in $O(n)$ time.

Q: How to remove this assumption?

A:

1. There is an algorithm to find median in $O(n)$ time, using divide-and-conquer (we shall not talk about it; it is complicated and not practical)
2. Choose a pivot randomly and pretend it is the median (it is practical)

Quicksort Using A Random Pivot

quicksort(A, n)

```
if n ≤ 1 then return A
x ← a random element of A (x is called a pivot)
A_L ← elements in A that are less than x                      \\ Divide
A_R ← elements in A that are greater than x                   \\ Divide
B_L ← quicksort(A_L, A_L.size)                                \\ Conquer
B_R ← quicksort(A_R, A_R.size)                                \\ Conquer
t ← number of times x appear A
return the array obtained by concatenating B_L, the array
    containing t copies of x, and B_R
```

Randomized Algorithm Model

Assumption There is a procedure to produce a random real number in $[0, 1]$.

Q: Can computers really produce random numbers?

A: No! The execution of a computer programs is deterministic!

- In practice: use pseudo-random-generator, a deterministic algorithm returning numbers that "look like" random
- In theory: assume they can.

Quicksort Using A Random Pivot

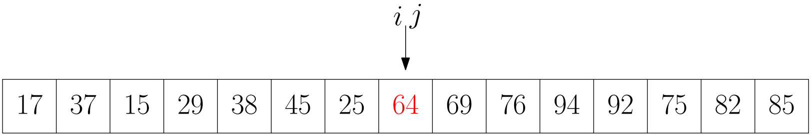
quicksort(A, n)

if $n \leq 1$ then return A
$x \leftarrow$ a random element of A (x is called a pivot)
$A_L \leftarrow$ elements in A that are less than x \\ Divide
$A_R \leftarrow$ elements in A that are greater than x \\ Divide
$B_L \leftarrow$ quicksort$(A_L, A_L.\text{size})$ \\ Conquer
$B_R \leftarrow$ quicksort$(A_R, A_R.\text{size})$ \\ Conquer
$t \leftarrow$ number of times x appear A
return the array obtained by concatenating B_L, the array containing t copies of x, and B_R

Lemma The expected running time of the algorithm is $O(n \lg n)$.

Quicksort Can Be Implemented as an "In-Place" Sorting Algorithm

- In-Place Sorting Algorithm: an algorithm that only uses "small" extra space.



- To partition the array into two parts, we only need $O(1)$ extra space.

partition(A, ℓ, r)

$p \leftarrow$ random integer between ℓ and r, swap $A[p]$ and $A[\ell]$
$i \leftarrow \ell, j \leftarrow r$
while true **do**
    while $i < j$ and $A[i] < A[j]$ do $j \leftarrow j - 1$
    if $i = j$ **then** break
    swap $A[i]$ and $A[j]$; $i \leftarrow i + 1$
    while $i < j$ and $A[i] < A[j]$ **do** $i \leftarrow i + 1$
    if $i = j$ **then** break
    swap $A[i]$ and $A[j]$; $j \leftarrow j - 1$
return i

In-Place Implementation of Quick-Sort

quicksort(A, ℓ, r)

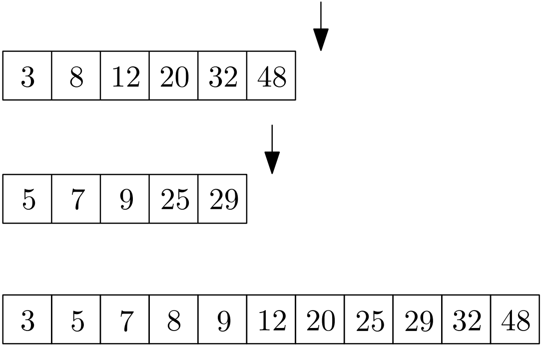
```
if ℓ ≥ r then return
m ← patition(A, ℓ, r)
quicksort(A, ℓ, m − 1)
quicksort(A, m + 1, r)
```

- To sort an array A of size n, call quicksort$(A, 1, n)$.

Note: We pass the array A by reference, instead of by copying.

Merge-Sort is Not In-Place

- To merge two arrays, we need a third array with size equaling the total size of two arrays



Outline

Comparison-Based Sorting Algorithms

Q: Can we do better than $O(n \log n)$ for sorting?

A: No, for comparison-based sorting algorithms.

Comparison-Based Sorting Algorithms

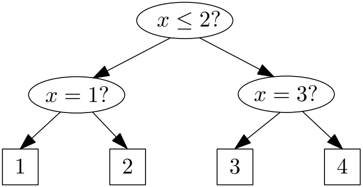
- To sort, we are only allowed to compare two elements
- We can not use "internal structures" of the elements

Lemma The (worst-case) running time of any comparison-based sorting algorithm is $\Omega(n \lg n)$.

- Bob has one number x in his hand, $x \in \{1, 2, 3, \cdots, N\}$.
- You can ask Bob "yes/no" questions about x.

Q: How many questions do you need to ask Bob in order to know x?

A: $\lceil \log_2 N \rceil$.



Comparison-Based Sorting Algorithms

Q: Can we do better than $O(n \log n)$ for sorting?

A: No, for comparison-based sorting algorithms.

- Bob has a permutation π over $\{1, 2, 3, \cdots, n\}$ in his hand.
- You can ask Bob "yes/no" questions about π.

Q: How many questions do you need to ask in order to get the permutation π?

A: $\log_2 n! = \Theta(n \lg n)$

Comparison-Based Sorting Algorithms

Q: Can we do better than $O(n \log n)$ for sorting?

A: No, for comparison-based sorting algorithms.

- Bob has a permutation π over $\{1, 2, 3, \cdots, n\}$ in his hand.
- You can ask Bob questions of the form "does i appear before j in π?"

Q: How many questions do you need to ask in order to get the permutation π?

A: At least $\log_2 n! = \Theta(n \lg n)$

Outline

Selection Problem

Input: a set A of n numbers, and $1 \leq i \leq n$

Output: the i-th smallest number in A

- Sorting solves the problem in time $O(n \lg n)$.
- Our goal: $O(n)$ running time

Recall: Quicksort with Median Finder

quicksort(A, n)

if $n \leq 1$ **then return** A
$x \leftarrow$ lower median of A
$A_L \leftarrow$ elements in A that are less than x ▷ Divide
$A_R \leftarrow$ elements in A that are greater than x ▷ Divide
$B_L \leftarrow$ quicksort(A_L, A_L.size) ▷ Conquer
$B_R \leftarrow$ quicksort(A_R, A_R.size) ▷ Conquer
$t \leftarrow$ number of times x appear A
return the array obtained by concatenating B_L, the array containing t copies of x, and B_R

Selection Algorithm with Median Finder

selection(A, n, i)

if $n = 1$ **then return** A
$x \leftarrow$ lower median of A
$A_L \leftarrow$ elements in A that are less than x $\triangleright$ Divide
$A_R \leftarrow$ elements in A that are greater than x $\triangleright$ Divide
if $i \le A_L$.size **then**
    return selection$(A_L, A_L.\text{size}, i)$ $\triangleright$ Conquer
else if $i > n - A_R$.size **then**
    return selection$(A_R, A_R.\text{size}, i - (n - A_R.\text{size}))$ $\triangleright$ Conquer
else
    return x

- Recurrence for selection: $T(n) = T(n/2) + O(n)$
- Solving recurrence: $T(n) = O(n)$

Randomized Selection Algorithm

selection(A, n, i)

if $n = 1$ **thenreturn** A
$x \leftarrow$ random element of A (called pivot)
$A_L \leftarrow$ elements in A that are less than x ▷ Divide
$A_R \leftarrow$ elements in A that are greater than x ▷ Divide
if $i \leq A_L$.size **then**
    return selection$(A_L, A_L.\text{size}, i)$ ▷ Conquer
else if $i > n - A_R$.size **then**
    return selection$(A_R, A_R.\text{size}, i - (n - A_R.\text{size}))$ ▷ Conquer
else
    return x

- expected running time $= O(n)$

Outline

Polynomial Multiplication

Input: two polynomials of degree $n-1$

Output: product of two polynomials

Example:

$$\begin{aligned}
&(3x^3+2x^2-5x+4)\times(2x^3-3x^2+6x-5)\\
=\;&6x^6-9x^5+18x^4-15x^3\\
&+4x^5-6x^4+12x^3-10x^2\\
&-10x^4+15x^3-30x^2+25x\\
&+8x^3-12x^2+24x-20\\
=\;&6x^6-5x^5+2x^4+20x^3-52x^2+49x-20
\end{aligned}$$

- **Input**: $(4,-5,2,3),(-5,6,-3,2)$
- **Output**: $(-20,49,-52,20,2,-5,6)$

Naïve Algorithm

polynomial-multiplication(A, B, n)

let $C[k] \leftarrow 0$ for every $k = 0, 1, 2, \cdots, 2n-2$
for $i \leftarrow 0$ to $n-1$ **do**
    for $j \leftarrow 0$ to $n-1$ **do**
        $C[i+j] \leftarrow C[i+j] + A[i] \times B[j]$
return C

Running time: $O(n^2)$

Divide-and-Conquer for Polynomial Multiplication

$$p(x) = 3x^3 + 2x^2 - 5x + 4 = (3x + 2)x^2 + (-5x + 4)$$
$$q(x) = 2x^3 - 3x^2 + 6x - 5 = (2x - 3)x^2 + (6x - 5)$$

- $p(x)$: degree of $n - 1$ (assume n is even)
- $p(x) = p_H(x)x^{n/2} + p_L(x)$,
- $p_H(x), p_L(x)$: polynomials of degree $n/2 - 1$.

$$\begin{aligned} pq &= \left(p_H x^{n/2} + p_L\right)\left(q_H x^{n/2} + q_L\right) \\ &= p_H q_H x^n + \left(p_H q_L + p_L q_H\right)x^{n/2} + p_L q_L \end{aligned}$$

Divide-and-Conquer for Polynomial Multiplication

$$
\begin{aligned}
pq &= \left(p_H x^{n/2} + p_L\right)\left(q_H x^{n/2} + q_L\right) \\
&= p_H q_H x^n + \left(p_H q_L + p_L q_H\right) x^{n/2} + p_L q_L
\end{aligned}
$$

$$
\begin{aligned}
\text{multiply}(p, q) = \ & \text{multiply}(p_H, q_H) \times x^n \\
& + \left(\text{multiply}(p_H, q_L) + \text{multiply}(p_L, q_H)\right) \times x^{n/2} \\
& + \text{multiply}(p_L, q_L)
\end{aligned}
$$

- Recurrence: $T(n) = 4T(n/2) + O(n)$
- $T(n) = O(n^2)$

Reduce Number from 4 to 3

$$
\begin{aligned}
pq &= \left(p_H x^{n/2} + p_L\right)\left(q_H x^{n/2} + q_L\right) \\
&= p_H q_H x^n + \left(p_H q_L + p_L q_H\right) x^{n/2} + p_L q_L
\end{aligned}
$$

- $p_H q_L + p_L q_H = (p_H + p_L)(q_H + q_L) - p_H q_H - p_L q_L$

Divide-and-Conquer for Polynomial Multiplication

$$r_H = \text{multiply}(p_H, q_H)$$
$$r_L = \text{multiply}(p_L, q_L)$$

$$\begin{aligned}\text{multiply}(p, q) = {} & r_H \times x^n \\ & + \big(\text{multiply}(p_H + p_L, q_H + q_L) - r_H - r_L\big) \times x^{n/2} \\ & + r_L\end{aligned}$$

- Solving Recurrence: $T(n) = 3T(n/2) + O(n)$
- $T(n) = O(n^{\lg_2 3}) = O(n^{1.585})$

Assumption n is a power of 2. Arrays are 0-indexed.

multiply(A, B, n)

if $n = 1$ then return $(A[0]B[0])$
$A_L \leftarrow A[0 \mathinner{..} n/2 - 1], A_H \leftarrow A[n/2 \mathinner{..} n - 1]$
$B_L \leftarrow B[0 \mathinner{..} n/2 - 1], B_H \leftarrow B[n/2 \mathinner{..} n - 1]$
$C_L \leftarrow$ multiply$(A_L, B_L, n/2)$
$C_H \leftarrow$ multiply$(A_H, B_H, n/2)$
$C_M \leftarrow$ multiply$(A_L + A_H, B_L + B_H, n/2)$
$C \leftarrow$ array of $(2n - 1)$ 0's
for $i \leftarrow 0$ to $n - 2$ **do**
    $C[i] \leftarrow C[i] + C_L[i]$
    $C[i + n] \leftarrow C[i + n] + C_H[i]$
    $C[i + n/2] \leftarrow C[i + n/2] + C_M[i] - C_L[i] - C_H[i]$
return C

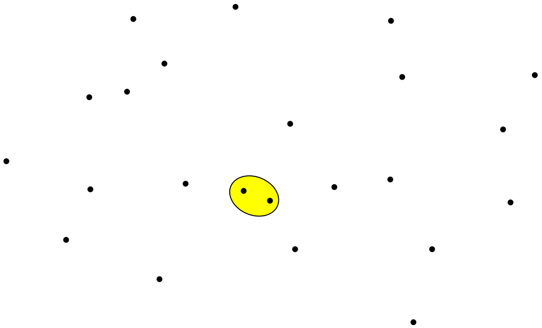
Outline

- Closest pair
- Convex hull
- Matrix multiplication
- FFT(Fast Fourier Transform): polynomial multiplication in $O(n \lg n)$ time

Closest Pair

Input: n points in plane: $(x_1, y_1), (x_2, y_2), \cdots, (x_n, y_n)$

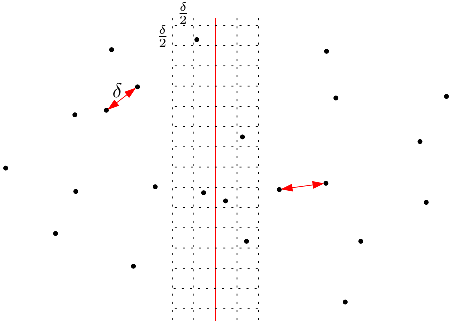
Output: the pair of points that are closest



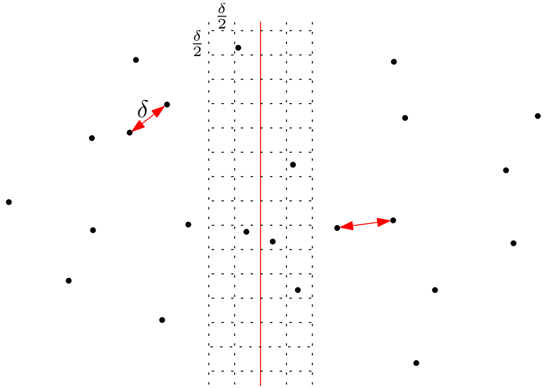
- Trivial algorithm: $O(n^2)$ running time

Divide-and-Conquer Algorithm for Closest Pair

- **Divide**: Divide the points into two halves via a vertical line
- **Conquer**: Solve two sub-instances recursively
- **Combine**: Check if there is a closer pair between left-half and right-half

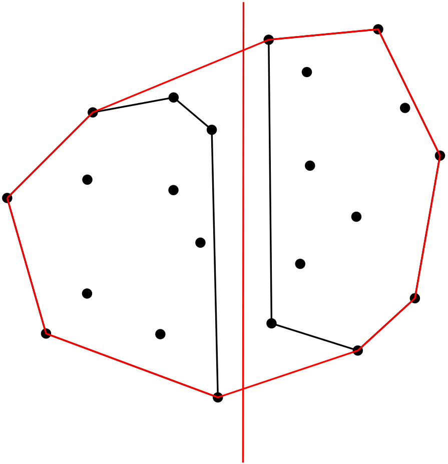


Divide-and-Conquer Algorithm for Closest Pair



- Each box contains at most one pair
- For each point, only need to consider $O(1)$ boxes nearby
- time for combine $= O(n)$ (many technicalities omitted)
- Recurrence: $T(n) = 2T(n/2) + O(n)$
- Running time: $O(n \lg n)$

$O(n \lg n)$-Time Algorithm for Convex Hull



Strassen's Algorithm for Matrix Multiplication

Matrix Multiplication

Input: two $n \times n$ matrices A and B

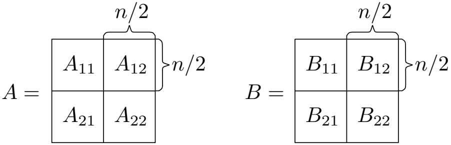
Output: $C = AB$

Naive Algorithm: matrix-multiplication(A, B, n)

```
for i ← 1 to n do
    for j ← 1 to n do
        C[i, j] ← 0
        for k ← 1 to n do
            C[i, j] ← C[i, j] + A[i, k] × B[k, j]
return C
```

- running time $= O(n^3)$

Try to Use Divide-and-Conquer



- $C = \begin{pmatrix} A_{11}B_{11} + A_{12}B_{21} & A_{11}B_{12} + A_{12}B_{22} \\ A_{21}B_{11} + A_{22}B_{21} & A_{21}B_{12} + A_{22}B_{22} \end{pmatrix}$
- matrix_multiplication(A, B) recursively calls matrix_multiplication(A_{11}, B_{11}), matrix_multiplication(A_{12}, B_{21}), $\cdots$
- Recurrence for running time: $T(n) = 8T(n/2) + O(n^2)$
- $T(n) = O(n^3)$

Strassen's Algorithm

- $T(n) = 8T(n/2) + O(n^2)$
- Strassen's Algorithm: improve the number of multiplications from 8 to 7!
- New recurrence: $T(n) = 7T(n/2) + O(n^2)$
- Solving Recurrence $T(n) = O(n^{\log_2 7}) = O(n^{2.808})$

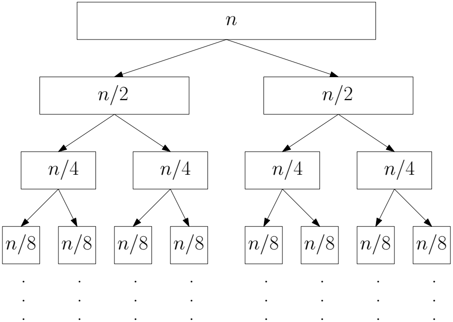
Outline

Methods for Solving Recurrences

- The recursion-tree method
- The master theorem

Recursion-Tree Method

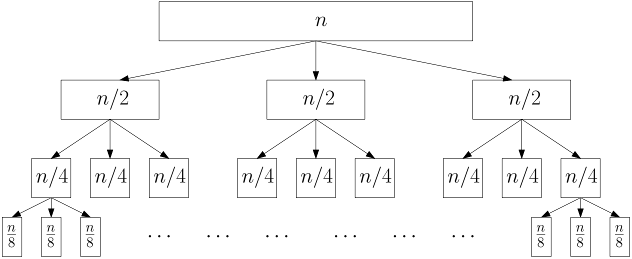
- $T(n) = 2T(n/2) + O(n)$



- Each level takes running time $O(n)$
- There are $O(\lg n)$ levels
- Running time $= O(n \lg n)$

Recursion-Tree Method

- $T(n) = 3T(n/2) + O(n)$

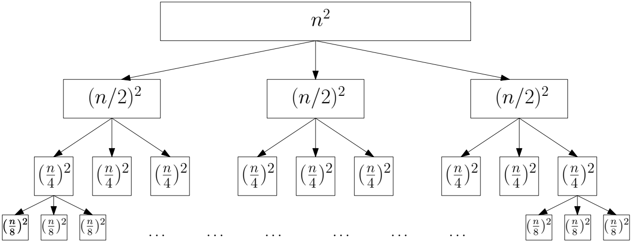


- Total running time at level i? $\frac{n}{2^i} \times 3^i = \left(\frac{3}{2}\right)^i n$
- Index of last level? $\lg_2 n$
- Total running time?

$$\sum_{i=0}^{\lg_2 n} \left(\frac{3}{2}\right)^i n = O\left(n\left(\frac{3}{2}\right)^{\lg_2 n}\right) = O(3^{\lg_2 n}) = O(n^{\lg_2 3}).$$

Recursion-Tree Method

- $T(n) = 3T(n/2) + O(n^2)$



- Total running time at level i? $\left(\frac{n}{2^i}\right)^2 \times 3^i = \left(\frac{3}{4}\right)^i n^2$
- Index of last level? $\lg_2 n$
- Total running time?

$$\sum_{i=0}^{\lg_2 n} \left(\frac{3}{4}\right)^i n^2 = O(n^2).$$

Master Theorem

Recurrences	a	b	c	time
$T(n) = 2T(n/2) + O(n)$	2	2	1	$O(n \lg n)$
$T(n) = 3T(n/2) + O(n)$	3	2	1	$O(n^{\lg_2 3})$
$T(n) = 3T(n/2) + O(n^2)$	3	2	2	$O(n^2)$

Theorem $T(n) = aT(n/b) + O(n^c)$, where $a \geq 1, b > 1, c \geq 0$ are constants. Then,

$$T(n) = \begin{cases} O(n^{\lg_b a}) & \text{if } c < \lg_b a \\ O(n^c \lg n) & \text{if } c = \lg_b a \\ O(n^c) & \text{if } c > \lg_b a \end{cases}$$

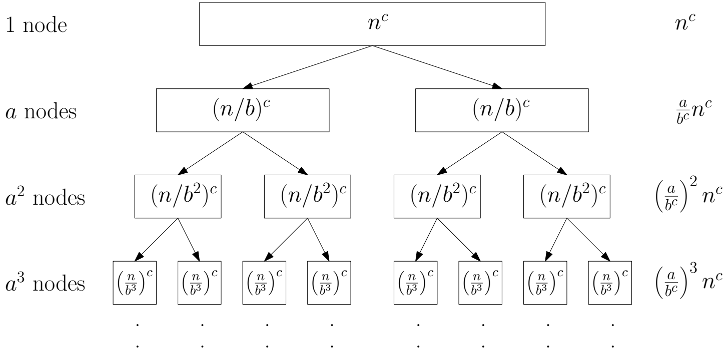
Theorem $T(n) = aT(n/b) + O(n^c)$, where $a \geq 1, b > 1, c \geq 0$ are constants. Then,

$$T(n) = \begin{cases} O(n^{\lg_b a}) & \text{if } c < \lg_b a \\ O(n^c \lg n) & \text{if } c = \lg_b a \\ O(n^c) & \text{if } c > \lg_b a \end{cases}$$

- Ex: $T(n) = 4T(n/2) + O(n^2)$. Case 2. $T(n) = O(n^2 \lg n)$
- Ex: $T(n) = 3T(n/2) + O(n)$. Case 1. $T(n) = O(n^{\lg_2 3})$
- Ex: $T(n) = T(n/2) + O(1)$. Case 2. $T(n) = O(\lg n)$
- Ex: $T(n) = 2T(n/2) + O(n^2)$. Case 3. $T(n) = O(n^2)$

Proof of Master Theorem Using Recursion Tree

$$T(n) = aT(n/b) + O(n^c)$$



- $c < \lg_b a$: bottom-level dominates: $\left(\frac{a}{b^c}\right)^{\lg_b n} n^c = n^{\lg_b a}$
- $c = \lg_b a$: all levels have same time: $n^c \lg_b n = O(n^c \lg n)$
- $c > \lg_b a$: top-level dominates: $O(n^c)$

Outline

Fibonacci Numbers

- $F_0 = 0, F_1 = 1$
- $F_n = F_{n-1} + F_{n-2}, \forall n \geq 2$
- Fibonacci sequence: $0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, \cdots$

n-th Fibonacci Number

Input: integer $n > 0$

Output: F_n

Computing F_n : Stupid Divide-and-Conquer Algorithm

Fib(n)

```
if n = 0 return 0
if n = 1 return 1
return Fib(n − 1) + Fib(n − 2)
```

Q: Is the running time of the algorithm polynomial or exponential in n?

A: Exponential

- Running time is at least $\Omega(F_n)$
- F_n is exponential in n

Computing F_n: Reasonable Algorithm

Fib(n)

```
F[0] ← 0
F[1] ← 1
for i ← 2 to n do
    F[i] ← F[i − 1] + F[i − 2]
return F[n]
```

- Dynamic Programming
- Running time $= O(n)$

Computing F_n: Even Better Algorithm

$$\begin{pmatrix} F_n \\ F_{n-1} \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} F_{n-1} \\ F_{n-2} \end{pmatrix}$$

$$\begin{pmatrix} F_n \\ F_{n-1} \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix}^2 \begin{pmatrix} F_{n-2} \\ F_{n-3} \end{pmatrix}$$

$$\cdots$$

$$\begin{pmatrix} F_n \\ F_{n-1} \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix}^{n-1} \begin{pmatrix} F_1 \\ F_0 \end{pmatrix}$$

power(n)

if $n = 0$ then return $\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$
$R \leftarrow$ power($\lfloor n/2 \rfloor$)
$R \leftarrow R \times R$
if n is odd then $R \leftarrow R \times \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix}$
return R

Fib(n)

if $n = 0$ then return 0
$M \leftarrow$ power($n - 1$)
return $M[1][1]$

- Recurrence for running time? $T(n) = T(n/2) + O(1)$
- $T(n) = O(\lg n)$

Running time $= O(\lg n)$: We Cheated!

Q: How many bits do we need to represent $F(n)$?

A: $\Theta(n)$

- We can not add (or multiply) two integers of $\Theta(n)$ bits in $O(1)$ time
- Even printing $F(n)$ requires time much larger than $O(\lg n)$

Fixing the Problem

To compute F_n, we need $O(\lg n)$ basic arithmetic operations on integers

Summary: Divide-and-Conquer

- **Divide**: Divide instance into many smaller instances
- **Conquer**: Solve each of smaller instances recursively and separately
- **Combine**: Combine solutions to small instances to obtain a solution for the original big instance

- Write down recurrence for running time
- Solve recurrence using master theorem

Summary: Divide-and-Conquer

- Merge sort, quicksort, count-inversions, closest pair, $\cdots$:
  $T(n) = 2T(n/2) + O(n) \Rightarrow T(n) = O(n \lg n)$
- Integer Multiplication:
  $T(n) = 3T(n/2) + O(n) \Rightarrow T(n) = O(n^{\lg_2 3})$
- Matrix Multiplication:
  $T(n) = 7T(n/2) + O(n^2) \Rightarrow T(n) = O(n^{\lg_2 7})$

- Usually, designing better algorithm for "combine" step is key to improve running time