

Cost of Algorithms

Inputs: parameterized by an integer n , called the size

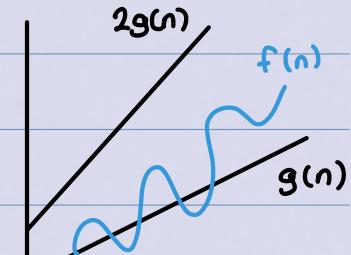
$T(I)$ = runtimes on input $I \Rightarrow$ runtime of a particular instance

$T_{\text{Worst}}(n) = \max_{I \text{ of size } n} (T(I)) \Rightarrow$ worst-case runtime (default)

$T_{\text{best}}(n) = \min_{I \text{ of size } n} (T(I)) \Rightarrow$ best-case runtime, not used much

Asymptotic Notation - consider 2 functions $f(n)$ and $g(n)$ with values in $\mathbb{R}_{>0}$

big-O: we say that $f(n) \in O(g(n))$ if there exists a $C > 0$ and n_0 such that for $n \geq n_0$, $f(n) \leq C g(n)$



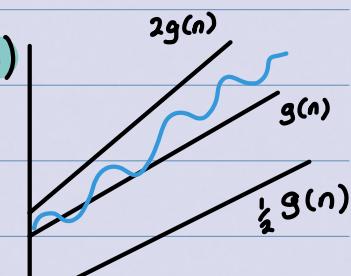
big- Ω : we say that $f(n) \in \Omega(g(n))$ if there exists a $C > 0$ and n_0 such that for $n \geq n_0$, $f(n) \geq C g(n)$

\Rightarrow equivalent to $g(n) \in O(f(n))$



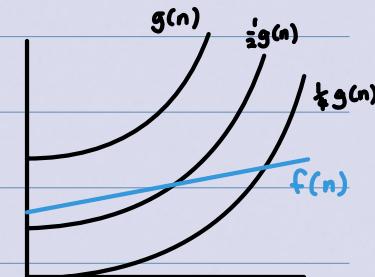
Θ : we say that $f(n) \in \Theta(g(n))$ if $f(n) \in O(g(n))$ and $f(n) \in \Omega(g(n))$.

\Rightarrow in particular true if $\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = C$ for some $0 < C < \infty$



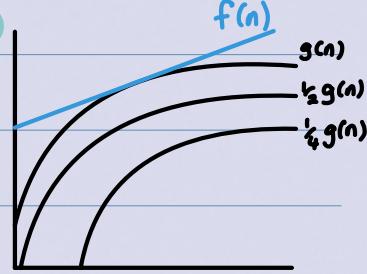
little-O: we say that $f(n) \in o(g(n))$ if for all $C > 0$, there exists an n_0 such that for $n \geq n_0$, $f(n) \leq C g(n)$

\Rightarrow equivalent to $\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 0$



little- ω : we say that $f(n) \in \omega(g(n))$ if for all $c > 0$, there exists an n_0 such that for $n \geq n_0$, $f(n) \geq c g(n)$

\Rightarrow equivalent to $\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \infty$



Examples

a) $n^k + C_{k-1} n^{k-1} + \dots + C_0 \in \Theta(n^k)$

b) $2^{n-1} \notin \Theta(2^n)$

c) $(n-1)! \in \Theta(n!)$

Definitions for Several Parameters

consider two functions $f(n, m)$, $g(n, m)$ with values in $\mathbb{R}_{>0}$

$f(n, m)$ is in $O(g(n, m))$ if there exist C, n_0, m_0 such that

$f(n, m) \leq C g(n, m)$ for $n \geq n_0$ or $m \geq m_0$

Case study: maximum subarray

Given an array $A[0, \dots, n]$, find a contiguous subarray $A[i, \dots, j]$ that maximises the sum $A[i] + \dots + A[j]$.

Example: given $A = [10, -5, 4, 3, -5, 6, -1, -1]$, the subarray $A[0, \dots, 5] = [10, -5, 4, 3, -5, 6]$ has sum $10 - 5 + 4 + 3 - 5 + 6 = 13$ is the max.

Brute Force algorithm:

runtime is $\Theta(n^3)$

but, we can improve on this!

idea: we recompute the same

sum many times in the j loop

BruteForce (A)

1. $opt = 0$
2. for ($i = 0 \rightarrow n$) {
3. for ($j = i \rightarrow n$) {
4. $Sum = 0$
5. for ($k = i \rightarrow j$) {
6. $Sum += A[k]$

BetterBruteForce (A)

```
1. opt = 0  
2. for (i=0→n) {  
3.     sum = 0  
4.     for (j=1→n) {  
5.         sum += A[j]  
6.         if (sum > opt) {  
7.             opt = sum  
8.         }  
9.     }  
10.    }  
11. return opt
```

```
7.     }  
8.     if (sum > opt) {  
9.         opt = sum  
10.    }  
11.    }  
12.    }  
13. return opt
```

→ runtime $\Theta(n^2)$

but, we can still do better using a **divide-and-conquer approach**:

idea: solve the problem twice in size $n/2$ (assuming n is a power of 2). Then, the optimal subarray (if not empty):

1. is completely in the left half $A[0, \dots, n/2]$
2. or is completely in the right half $A[n/2+1, \dots, n]$
3. or contains both $A[n/2]$ and $A[n/2+1]$

⇒ the three cases are mutually exclusive

to find the optimal subarray in case 3, we have:

$$A[i] + \dots + A[n/2] + A[n/2+1] + \dots + A[j]$$

more abstractly, we have $F(i, j) = f(i) + g(j)$, for $i \in [0, \dots, n/2]$ and $j \in [n/2+1, \dots, n]$.

To maximise $F(i, j)$, we maximise $f(i)$ and $g(j)$ independently!

Maximise Lower Half (A)

```
1. opt = A[n/2]
```

Maximise Upper Half (A)

```
1. opt = A[n/2+1]
```

```

2. sum = A[n/2]
3. for (i=n/2-1 → 0) {
4.   sum += A[i]
5.   if (sum > opt) {
6.     opt = sum
7.   }
8. }
9. return opt

```

```

2. sum = A[n/2 + 1]
3. for (i=n/2 + 1 → n) {
4.   sum += A[i]
5.   if (sum > opt) {
6.     opt = sum
7.   }
8. }
9. return opt

```

↳ runtimes are $\Theta(n)$! ↵

So, final divide and conquer algorithm:

Divide And Conquer Maximum Subarray ($A[0, \dots, n]$)

1. if ($n == 1$) return $\max(A[0], 0)$
2. opt_low = DivideAndConquerMaximumSubarray ($A[0, \dots, n/2]$)
3. opt_high = DivideAndConquerMaximumSubarray ($A[n/2+1, \dots, n]$)
4. opt_mid = MaximiseLowerHalf(A) + MaximiseUpperHalf(A)
5. return $\max(\text{opt_low}, \text{opt_mid}, \text{opt_high})$

⇒ runtime: $T(n) = 2T(n/2) + \Theta(n) \in \Theta(n\log n)$

Solving Recurrences

Consider a recursive algorithm called Algo.

Assumption: for any input of size $n \geq n_0$, Algo does:

- α recursive calls, in size either $\lfloor n/b \rfloor$ or $\lceil n/b \rceil$ ($\frac{\alpha}{b} > 1$, constant)
- between $c'n^y$ and Cn^y extra operations ($c, C \neq 0, y$ constant)

Claim: Solving the sloppy recurrence $T(n) = \alpha T(n/b) + cn^y$ for powers of b gives a valid Θ -bound for best and worst-

case runtimes.

- Remark: if we only know that we do at most cn^3 extra operations, we only get a big-O bound.

Best and Worst Case Recurrence Relations

let $T_{\text{worst}}(n)$, $T_{\text{best}}(n)$ be the worst/best cases in size n .

worst-case recurrence: $T_{\text{worst}}(1) = d$, and

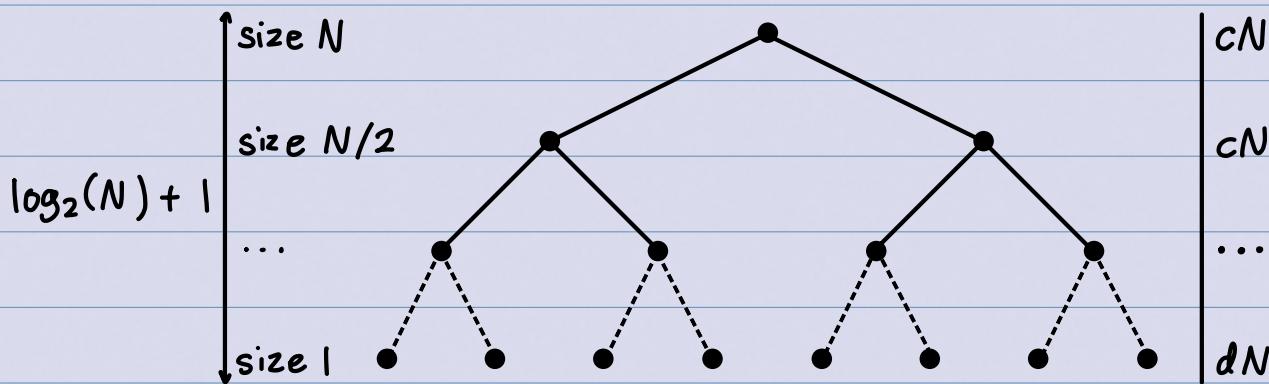
$$T_{\text{worst}}(n) \leq T_{\text{worst}}(\lceil n/2 \rceil) + T_{\text{worst}}(\lfloor n/2 \rfloor) + cn \quad \text{if } n > 1$$

best-case recurrence: $T_{\text{best}}(1) = d'$, and

$$T_{\text{best}}(n) \geq T_{\text{best}}(\lceil n/2 \rceil) + T_{\text{best}}(\lfloor n/2 \rfloor) + cn \quad \text{if } n > 1$$

we define N as the next power of 2 of n , so $N < 2n$.

the mergesort recursion tree



total: $t(N) = cN \log_2(N) + dN \leq KN \log_2(N)$ for N a power of 2

consequence: $T_{\text{worst}}(n) \leq KN \log_2(N) \leq K(2n) \log_2(2n) \leq K'n \log_2 n$,
so, $T_{\text{worst}}(n) \in O(n \log n)$

remark: same approach proves $T_{\text{best}}(n) \in \Omega(n \log n)$, and so,
 $T_{\text{best}}(n), T_{\text{worst}}(n) \in \Theta(n \log n)$

The Master Theorem

Suppose that $a \geq 1$ and $b > 1$. Consider the recurrence

$$T(n) = \alpha T(n/b) + cn^3 \quad (n \geq b), \quad T(1) = d.$$

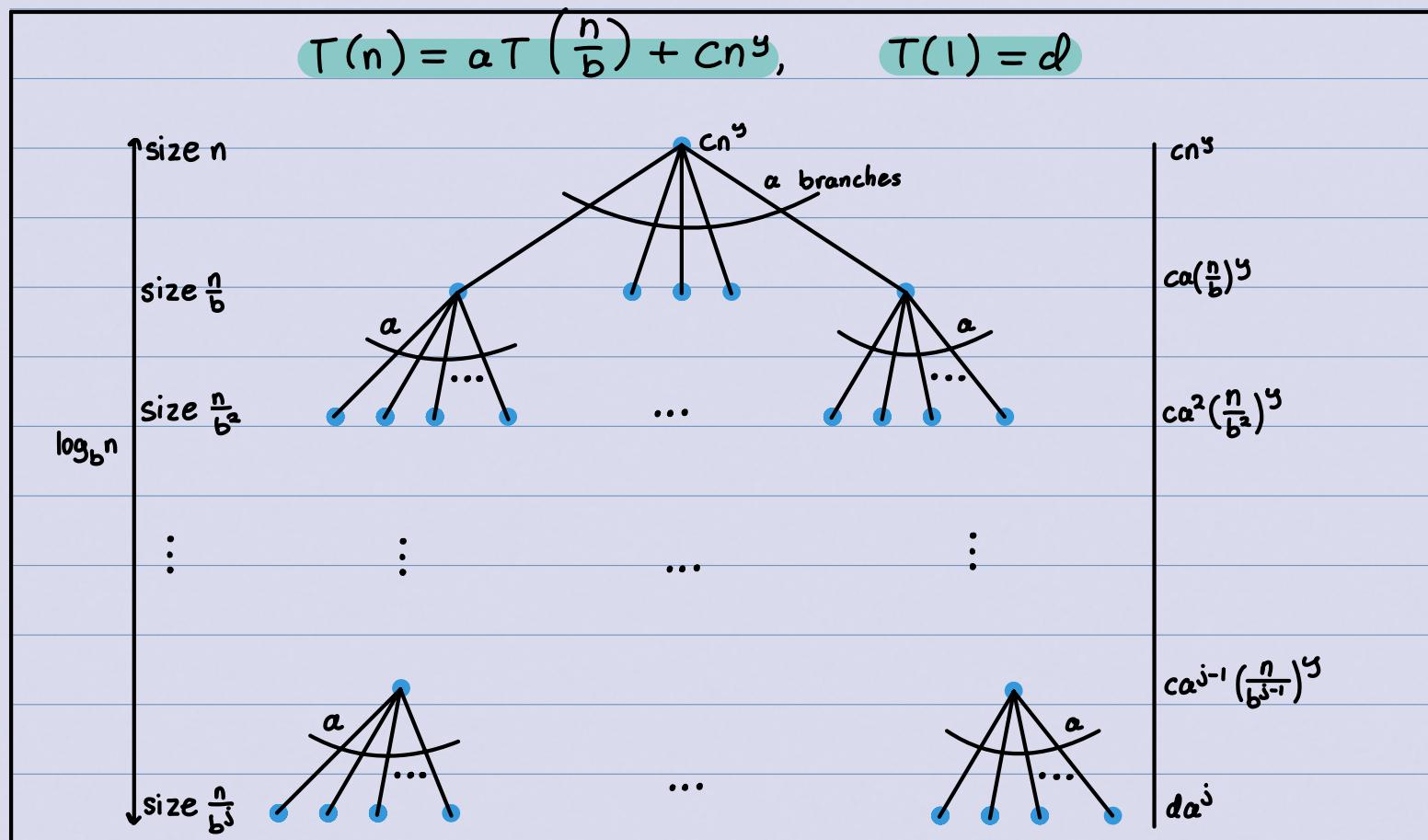
Let $x = \log_b a$ (so $a = b^x$).

Then, for n
a power of b , $T(n) \in \begin{cases} O(n^y) & \text{if } y > x \\ O(n^y \log n) & \text{if } y = x \\ O(n^x) & \text{if } y < x \end{cases}$

Recursion Tree

Suppose that $n = b^a$, $a \geq 1$, $b \geq 2$ are integers and

$$T(n) = a T(n/b) + cn^s, \quad T(1) = d$$



Breakdown of the Cost

Suppose that $a \geq 1$ and $b \geq 2$ are integers and

$$T(n) = aT(\frac{n}{b}) + cn^y, \quad T(1) = d.$$

Let $n = b^j$.

size of subproblem	# nodes	cost/node	total cost
$n = b^j$	1	cn^y	cn^y
$n/b = b^{j-1}$	a	$c(\frac{n}{b})^y$	$ca(\frac{n}{b})^y$
$n/b^2 = b^{j-2}$	a^2	$c(\frac{n}{b^2})^y$	$ca^2(\frac{n}{b^2})^y$
\vdots	\vdots	\vdots	\vdots
$n/b^{j-1} = b$	a^{j-1}	$c(\frac{n}{b^{j-1}})^y$	$ca^{j-1}(\frac{n}{b^{j-1}})^y$
$n/b^j = 1$	a^j	d	da^j
generally: $n/b^i = b^{j-i}$	a^i	$c(\frac{n}{b^i})^y$	$ca^i(\frac{n}{b^i})^y$

Computing $T(n)$:

$$\textcircled{1}: x = \log_b a, \text{ so } a = b^x. \text{ we know } n = b^j. \therefore a^j = (b^x)^j = (b^j)^x = n^x.$$

$$\text{total: } T(n) = da^j + cn^y \sum_{i=0}^{j-1} \left(\frac{a}{b^y}\right)^i = dn^x + cn^y \sum_{i=0}^{j-1} \left(\frac{a}{b^y}\right)^i$$

observation: geometric sum with ratio $r = \frac{a}{b^y} = \frac{b^x}{b^y} = b^{x-y}$!

• if $r < 1$, then $b^{x-y} < 1$, so $x < y$.

we know that $\sum_{i=0}^{j-1} r^i \in \Theta(1)$ if $r < 1$.

$$\therefore T(n) = dn^x + cn^y \cdot \Theta(1) \in \Theta(n^y). \quad \therefore x < y \Rightarrow T(n) \in \Theta(n^y)$$

if $r=0$, then $b^{\sum_{j=1}^{x-y}} = 1$, so $x=y$.

we know that $\sum_{i=0}^{r^j} r^i \in \Theta(r^j) = \Theta(\log n)$ if $r=1$

$\therefore T(n) = dn^x + cn^y \times \Theta(\log n) \in \Theta(n^y \log n)$ $\therefore x=y \Rightarrow T(n) \in \Theta(n^y \log n)$

if $r > 1$, then $b^{\sum_{j=1}^{x-y}} > 1$, so $x > y$

we know that $\sum_{i=0}^{r^j} r^i \in \Theta(r^j)$ if $r > 1$

$\therefore T(n) = dn^x + cn^y \times \Theta(r^j)$. $r^j = \frac{a^j}{b^j} = \frac{n^x}{n^y}$.

$T(n) = dn^x + cn^y \times \Theta(\frac{n^x}{n^y}) \in \Theta(n^x)$. $\therefore x > y \Rightarrow T(n) \in \Theta(n^x)$.

Examples: find Θ -bounds for the following:

1) $T(n) = 4T(\frac{n}{2}) + n$ (multiplying polynomials)

$$a=4, b=2, y=1, \text{ so } x=\log_b a = \log_2 4 = 2.$$

$\therefore x=2 > y=1, \text{ so } T(n) \in \Theta(n^2)$

2) $T(n) = 2T(\frac{n}{2}) + n^2$ (kd-trees)

$$a=2, b=2, y=2, \text{ so } x=\log_b a = \log_2 2 = 1$$

$\therefore x=1 < y=2, \text{ so } T(n) \in \Theta(n^2)$

3) $T(n) = 2T(\frac{n}{4}) + 1$ (kd-trees)

$$a=2, b=4, y=0, \text{ so } x=\log_b a = \log_4 2 = \frac{1}{2}$$

$\therefore x=\frac{1}{2} < y=0, \text{ so } T(n) \in \Theta(\sqrt{n})$

4) $T(n) = T(\frac{n}{2}) + 1$ (binary search)

$$a=1, b=2, y=0, \text{ so } x=\log_b a = \log_2 1 = 0$$

$\therefore x = O = y$, so $T(n) \in \Theta(n \log n) = \Theta(\log n)$

5) $T(n) = T(n/2) + n$ (amortized analysis of dynamic arrays)

$a=1, b=2, y=1$, so $x = \log_b a = \log_2 1 = 0$

$\therefore x = 0 < y = 1$, so $T(n) \in \Theta(n)$

Alternative: guess and prove: $T(n) = 2T(n/2) + n$, $T(1) = 0$.

guess $T(n) \leq n$. Then $T(n/2) \leq n/2$.

$$T(n) = 2T(n/2) + n \leq 2(n/2) + n = 2n \not\leq n.$$

guess $T(n) \leq kn$ for some k . Then $T(n/2) \leq kn/2$.

$$T(n) = 2T(n/2) + n \leq 2(kn/2) + n = kn + n \not\leq kn$$

guess $T(n) \leq kn \log_2 n$ for some k . Then $T(n/2) \leq kn \log_2(n/2)$

$$T(n) = 2T(n/2) + n \leq 2\left(\frac{kn \log_2(n/2)}{2}\right) + n = kn \log_2 n - kn + n \leq n \text{ for } k \geq 1.$$

$\therefore T(n) \leq kn \log n$ for $k \geq 1$, so $T(n) \in O(n \log n)$.

(proving $T(n) = \dots$ is harder)

Divide and Conquer Framework

to solve a problem in size n :

- Divide

- break the input into smaller problems

- ideally few such problems, all of size n/b for some b

- Conquer

- solve these problems recursively

- Recombine

- deduce the solution of the main problem from the subproblems

Polynomial and Matrix Multiplication

Multiplying Polynomials

Goal: given $F = F_0 + \dots + F_{n-1}x^{n-1}$ and $G = G_0 + \dots + G_{n-1}x^{n-1}$

compute $H = FG = F_0G_0 + (F_0G_1 + F_1G_0)x + \dots + F_{n-1}G_{n-1}x^{2n-2} = \sum_{i=0}^{2n-2} H_i x^i$

Remark: unit cost model, assume all f_i and g_i fit in one word. Then, input and output size $\Theta(n)$, easy algorithm in $\Theta(n^2)$:

Naive Polynomial Multiplication (F, G)

1. for ($i = 0 \rightarrow 2n-2$) {
2. $H_i = 0$
3. }
4. for ($i = 0 \rightarrow n-1$) {
5. for ($j = 0 \rightarrow n-1$) {
6. $H_{i+j} += F_i G_j$
7. }
8. }

In degree 1: $F = F_0 + F_1x$, $G = G_0 + G_1x$,

$$H = F_0G_0 + (F_0G_1 + F_1G_0)x + F_1G_1x^2$$

In higher degree: $F = F'_0(x) + F'_1(x)x^{n/2}$, $G = G'_0(x) + G'_1(x)x^{n/2}$,

$$H = F'_0(x)G'_0(x) + (F'_0(x)G'_1(x) + F'_1(x)G'_0(x))x^{n/2} + F'_1(x)G'_1(x)x^n$$

Analysis:

- 4 recursive calls in size $n/2$
 - $\Theta(n)$ additions to compute $F_0'(x)G_1'(x) + F_1'(x)G_0'(x)$
 - multiplications by $x^{n/2}$ and x^n are free
 - $\Theta(n)$ additions to obtain H
- (Sloppy) recurrence: $T(n) = 4T(n/2) + cn,$
 $\hookrightarrow a=4, b=2, y=1, \text{ so } T(n) \in \Theta(n^2)$
 \therefore , no better than the naive algorithm!

Karatsuba's Algorithm

Key Idea: a formula for degree 1 polynomials that does only 3 (instead of 4) multiplications: with $F = F_0 + F_1 x$, $G = G_0 + G_1 x$, $H = F_0 G_0 + ((F_0 + F_1)(G_0 + G_1) - F_0 G_0 - F_1 G_1)x + F_1 G_1 x^2$

In higher degree: with $F = F_0' + F_1' x^{n/2}$, $G = G_0' + G_1' x^{n/2}$
(where F_0', F_1', G_0', G_1' are polynomials of degree $\leq n/2 - 1$):
 $H = F_0' G_0' + ((F_0' + F_1')(G_0' + G_1') - F_0' G_0' - F_1' G_1')x^{n/2} + F_1' G_1' x^n$.

Analysis:

- $\Theta(n)$ additions to compute $F_0' + F_1'$ and $G_0' + G_1'$
- 3 recursive calls in size $n/2$
- multiplications by $x^{n/2}$ and x^n are free
- $\Theta(n)$ additions and subtractions to combine the results

Recurrence: $T(n) = 3T(n/2) + cn$

$\hookrightarrow a=3, b=2, y=1, \text{ so } T(n) \in \Theta(n^{\log_2 3})$

Toom-Cook:

- A family of algorithms based on similar expressions as

Karatsuba

- for $R \geq 2$, $2R-1$ recursive calls in size n/k
- so $T(n) \in \Theta(n^{\log_k(2R-1)})$
- gets as close to exponent 1 as we want (but very slowly)

Fast Fourier Transform (FFT):

- if we use complex coefficients, FFT can be used to multiply polynomials
- FFT follows the same recurrence as merge sort, $T(n)=2T(n/2)+cn$
- so we can multiply polynomials in $\Theta(n\log n)$ operations over \mathbb{C}

Multiplying Matrices

$$\Rightarrow \text{reminder: } \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \cdot \begin{bmatrix} 5 & 7 \\ 6 & 8 \end{bmatrix} = \begin{bmatrix} 1 \cdot 5 + 2 \cdot 6 & 1 \cdot 7 + 2 \cdot 8 \\ 3 \cdot 5 + 4 \cdot 6 & 3 \cdot 7 + 4 \cdot 8 \end{bmatrix} = \begin{bmatrix} 17 & 23 \\ 39 & 53 \end{bmatrix}$$

$[i \times j] \cdot [k \times l] \rightarrow$ can only multiply if $j=k$. resulting matrix is $[i \times l]$

Goal: given $A = [a_{ij}]_{1 \leq i, j \leq n}$ and $B = [b_{jk}]_{1 \leq j, k \leq n}$, compute $C=AB$

↳ remark: input and output $\Theta(n^2)$ elements, easy algorithm in $\Theta(n^3)$:

Naive Matrix Multiplication (A, B)

```
1. for (i=0 → n) {  
2.   for (j=0 → n) {  
3.     for (k=0 → n) {  
4.       Ci,k += Aij · Bjk  
5.     }  
6.   }  
7. }
```

this is $\Theta(n^3)$, we can do better! Let's try divide-and-conquer:

divide by splitting the matrices into 4 sections:

$$A = \begin{bmatrix} A_{0,0} & A_{0,1} \\ A_{1,0} & A_{1,1} \end{bmatrix} \quad B = \begin{bmatrix} B_{0,0} & B_{0,1} \\ B_{1,0} & B_{1,1} \end{bmatrix}$$

with all $A_{i,k}$ and $B_{j,k}$ of size $n/2 \times n/2$. Then,

$$C = \begin{bmatrix} A_{0,0}B_{0,0} + A_{0,1}B_{1,0} & A_{0,0}B_{0,1} + A_{0,1}B_{1,1} \\ A_{1,0}B_{0,0} + A_{1,1}B_{1,0} & A_{1,0}B_{0,1} + A_{1,1}B_{1,1} \end{bmatrix}$$

however, this is still 8 recursive calls in size $\frac{n}{2} + \Theta(n^2)$ additions which is in $\Theta(n^3)$! no improvement :)

Strassen's Algorithm

Compute:

$$Q_1 = (A_{0,0} - A_{0,1})B_{1,1}$$

$$Q_2 = (A_{1,0} - A_{1,1})B_{0,0}$$

$$Q_3 = A_{1,1}(B_{0,0} + B_{1,0})$$

$$Q_4 = A_{0,0}(B_{0,1} + B_{1,1}) \quad \text{and}$$

$$Q_5 = (A_{0,0} + A_{1,1})(B_{1,1} - B_{0,0})$$

$$Q_6 = (A_{0,0} + A_{1,0})(B_{0,0} + B_{0,1})$$

$$Q_7 = (A_{0,1} + A_{1,1})(B_{1,0} + B_{1,1})$$

$$C_{0,0} = Q_1 - Q_3 - Q_5 + Q_7$$

$$C_{0,1} = Q_4 - Q_1$$

$$C_{1,0} = Q_2 + Q_3$$

$$C_{1,1} = Q_5 + Q_6 - Q_2 - Q_4$$

now, we have 7 instead of 8 recursive calls!

$$= \Theta(n^{2.8}) < \Theta(n^3)!$$

size is $n/2$ with $\Theta(n)$ additions, so $T(n) \geq \Theta(n^{\log_2 7})$

direct generalisation: an algorithm that does k multiplications for matrices of size ℓ gives $T(n) \in \Theta(n^{\log_2 k})$

Counting Inversions

Inversion: (i, j) is an inversion if $i < j$ and $A[i] > A[j]$

Goal: given an unsorted array $A[1, \dots, n]$, find the number of inversions in it.

Example: with $A = [1, 5, 2, 6, 3, 8, 7, 4]$.

we get: $(2, 3), (2, 5), (2, 8), (4, 5), (4, 8), (6, 7), (6, 8), (7, 8)$

Remarks:

1. we show the indices where inversions occur
2. easy algorithm (2 nested loops) in $\Theta(n^2)$
3. to do better than n^2 , we cannot list all inversions

towards a divide & conquer algorithm

idea:

- C_L = number of inversions in $A[0, \dots, \frac{n}{2}]$ (first half)
- C_R = number of inversions in $A[\frac{n}{2}+1, \dots, n]$ (second half)
- C_T = number of transverse inversions with $i \leq \frac{n}{2}$ and $j > \frac{n}{2}$ (both halves)
- return $C_L + C_R + C_T$

↳ example with $A = [1, 5, 2, 6, 3, 8, 7, 4]$

$$C_L = 1 \quad \{(1, 2)\}$$

$$C_R = 3 \quad \{(5, 6), (5, 7), (6, 7)\}$$

$$C_T = 4 \quad \{(1, 4), (1, 7), (3, 4), (3, 7)\} \rightarrow \text{calculate w/ merge sort}$$

} calculated recursively

New goal: counting transverse inversions: how many pairs (i, j) with $i \leq \frac{n}{2}$, $j > \frac{n}{2}$, and $A[i] > A[j]$?

↳ eg, with $A = [1, 5, 2, 6, 3, 8, 7, 4]$, $C_T = \#_{i < 4} > 3 + \#_{i < 4} > 8 + \#_{i < 4} > 7 + \#_{i < 4} > 6$

or $C_T = \#_{j > 4} < 1 + \#_{j > 4} < 5 + \#_{j > 4} < 2 + \#_{j > 4} < 6$.

Observation: this number does not change if both sides are sorted!

⇒ assume left and right sides are sorted, so $A = [1, 2, 5, 6, 3, 4, 7, 8]$

observation 2: Since both sides sorted, merge will sort whole array:

Merge($A[1, \dots, n]$) (both halves of A sorted)

1. copy A into new array S
2. $i=1; j=n/2+1;$
3. for ($k=1 \rightarrow n$) {
4. if ($i=n/2+1$) $A[k] = S[j++]$
5. else if ($j=n+1$) $A[k] = S[i++]$
6. else if ($S[i] \leq S[j]$) $A[k] = S[i++]$
7. else $A[k] = S[j++]$
8. }

↳ goal: find c_t during merge

how? ⇒ when we insert $S[i]$ back in A, count how many $S[j]$'s have already been inserted

easy! ∵ the difference is $j - j_{\text{init}} = j - (n/2 + 1)$!

Enhanced Merge($A[1, \dots, n]$) (both halves of A sorted)

1. copy A into new array S
2. $i=1; j=n/2+1; C=0;$
3. for ($k=1 \rightarrow n$) {
4. if ($i=n/2+1$) $A[k] = S[j++]$
5. else if ($j=n+1$) $A[k] = S[i++]; C += n/2$
6. else if ($S[i] \leq S[j]$) $A[k] = S[i++]; C += j - (n/2 + 1)$
7. else $A[k] = S[j++]$
8. }
9. return C;

Example: with $A = [1, 2, 5, 6, 3, 4, 7, 8]$

- when we insert 1 back into A, $j=5$ so $C=C+0$
 - when we insert 2 back into A, $j=5$ so $C=C+0$
 - when we insert 5 back into A, $j=7$ so $C=C+2$
 - when we insert 6 back into A, $j=7$ so $C=C+2$
- $\therefore C_t = 4!$

⇒ enhanced Merge is still $\mathcal{O}(n)$, so the total remains $\mathcal{O}(n \log n)$ to count the number of inversions!

Generalised Master Theorem

Suppose that $a \geq 1$ and $b > 1$. Consider the recurrence

$$T(n) = aT\left(\frac{n}{b}\right) + f(n), \quad T(n) = d \quad (n \leq 1), \quad \inf_n f(n) > 0.$$

Let $x = \log_b a$ (so $a = b^x$).

Then $T(n) \in \begin{cases} \mathcal{O}(f(n)) & \text{if } f(n)/n^{x+\epsilon} \text{ is increasing for some } \epsilon > 0 \\ \mathcal{O}(n^x \log n) & \text{if } f(n) \in \mathcal{O}(n^x) \\ \mathcal{O}(n^x) & \text{if } f(n) \in \mathcal{O}(n^{x-\epsilon}) \text{ for some } \epsilon > 0 \end{cases}$

Example: $T(n) = 3T\left(\frac{n}{4}\right) + n \log n$

- $x = \log_4 3 < 1$, so $n^x \in o(f(n))$: can only be in the first case, still have to check
 - Set $\epsilon = 1 - x > 0$, then $f(n)/n^{x+\epsilon} = \log(n)$, increasing
- $\therefore T(n) \in \mathcal{O}(n \log n)$

Example: $T(n) = 2T\left(\frac{n}{2}\right) + n \log n$

- $x = 1$ so $n^x \in o(f(n))$: can only be in first case, still have to check

• $\forall \epsilon > 0$, $f(n)/n^{x+\epsilon} = \log n/n^\epsilon$, never increasing
∴ we can't say it

Linear Time Median

- **Median**: given $A[0, \dots, n-1]$, find the entry that would be at index $\lfloor \frac{n}{2} \rfloor$ if A was sorted
- **Selection**: given $A[0, \dots, n-1]$ and k in $\{0, \dots, n-1\}$, find the entry that would be at index k if A was sorted

⇒ reminder on quick-select:

quick-select(A, k)

A : array of size n , k : integer s.t. $0 \leq k < n$

1. $p = \text{choose-pivot}(A)$
2. $i, j = \text{partition}(A, p)$
3. if ($i \leq k < j$) { return p }
4. else if ($k < i$) { return quick-select($A[0, \dots, i-1]$, k) }
5. else if ($j < i$) { return quick-select($A[j+1, \dots, n-1]$, $k-j-1$) }

partition(A, p): reorders A so that $[< p, A[i]=p, \dots, A[j]=p, >p]$ in linear time!

Goal: find a pivot such that both i and $n-j-1$ aren't too large

Idea: Split A into groups of 5 elements $G_1, G_2, \dots, G_{n/5}$.
find the medians $m_1, m_2, \dots, m_{n/5}$ of each group $G_1, \dots, G_{n/5}$
and make array $A' = [m_1, m_2, \dots, m_{n/5}]$.
recursively call quick-select to find the median element p of A' .

Visualisation: $A = [11, \underbrace{9, 12, 3, 8}_G, \underbrace{1, 7, 2, 13, 4}_G, \dots]$, so $A' = [9, 4, \dots]$
now, quick-select(A' , $k = \frac{n}{5} \cdot \frac{1}{2} = \frac{n}{10}$) $\Rightarrow \frac{n}{10}$ is median of A'

Quick-select - using median-of-medians (A, k)

1. divide A into $\lceil \frac{n}{5} \rceil$ groups $G_1, \dots, G_{\lceil \frac{n}{5} \rceil}$ of size 5
2. find the medians $m_1, \dots, m_{\lceil \frac{n}{5} \rceil}$ of each group. call this array A' $\Theta(n)$
3. recursively run select to find the median element p of A' $T(\lceil \frac{n}{5} \rceil)$
4. $i = j = \text{partition}(A, p)$ $\Theta(n)$
5. if ($i = k$) { return p }
6. else if ($k < i$) { return $\text{select}(A[0, 1, \dots, i-1], k)$ }
7. else if ($k > i$) { return $\text{select}(A[i+1, \dots, n-1], k-i-1)$ }

Claim: with this choice of p , the indices i and $n-i-1$ are at most $\frac{7n}{10}$

Proof:

- half of the m_i 's are $\geq p$
- for each m_i , there are 3 elements in G_i that are $\geq m_i$
- so at least $\frac{3n}{10}$ elements are $\geq p$
- so at most $\frac{7n}{10}$ elements are $< p$
- so i is at most $\frac{7n}{10}$. same for $n-i-1$.

↳ **visualisation:**

G_1	G_2	
3	1	...
8	2	..
medians \Rightarrow	9	4
	11	7
	12	13

→ each $\frac{n}{10}$ elements provides 3 elements that are also $\leq p$, so $\frac{3n}{10}$ elements $\leq p$.

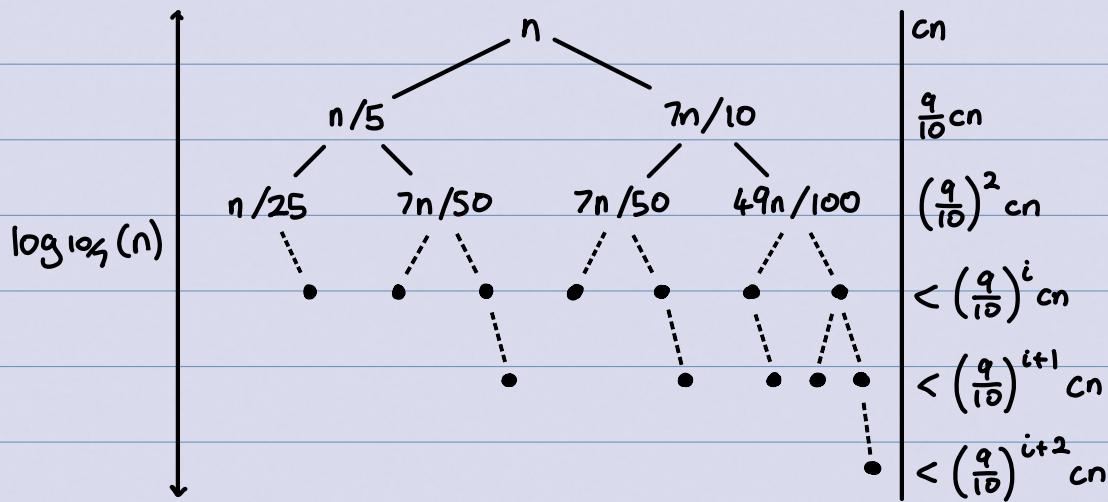
→ $\frac{n}{10}$ elements here that are $\leq p$

... → same logic applied for $\geq p$ as well

Sloppy recurrence: $T(n) = T(\lceil \frac{n}{5} \rceil) + T(\frac{7n}{10}) + cn$

Claim: this gives worst-case $T(n) \in \Theta(n)$

The recursion tree for $T(n)$ (set $T(n)=0$ for $n \leq 1$)



Key point: $T(n) < cn \times (\text{geometric sum of ratio } 9/10 < 1)$, so $T(n) \in O(n)$

Why not median of groups of 3?

- we do $n/3$ groups of 3 and find their medians $m_1, \dots, m_{n/3}$ $\Theta(n)$
- p is the median of $[m_1, \dots, m_{n/3}]$ $T(n/3)$
- half of the m_i 's are $\geq p$ $n/6$
- in each group, 2 elements are $\geq m_i$
- so overall at least $n/3$ elements are $\geq p$
- so at most $2n/3$ elements are $< p$
- so $i \leq 2n/3$ and $n-i-1 \leq 2n/3$
- recurrence is $T(n) \in T(n/3) + T(2n/3) + cn$, which gives $T(n) \in \Theta(n/\log n)$.

Closest Pairs

Goal: given n points (x_i, y_i) , find a pair (i, j) that

$$\text{minimizes the distance } d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

$$(\text{equivalent to minimizing } d_{i,j}^2 = (x_i - x_j)^2 + (y_i - y_j)^2)$$

Assumption: all x_i 's are distinct

Idea: separate the points into two halves L, R at the median x -value.

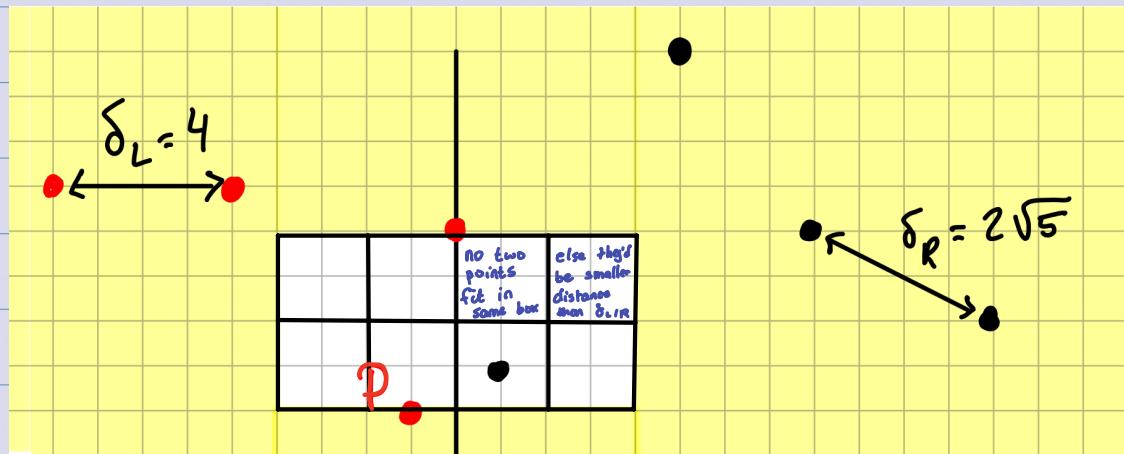
↳ $L = \text{all } n/2 \text{ points with } x \leq x_{\text{median}}$ (no other point on the median line)

$R = \text{all } n/2 \text{ points with } x > x_{\text{median}}$

find the closest pair in both L and R recursively

the closest pair is either between points in L (done), between points in R (done), or transverse (one in L , one in R).

Set $\delta = \min(\delta_L, \delta_R)$, since we only need to consider transverse pairs (P, Q) with $\text{dist}(P, R) \leq \delta$ and $\text{dist}(Q, L) \leq \delta$ for any $P = (x_P, y_P)$, enough to look at points with $y_P \leq y \leq y_P + \delta$



so it's enough to check distances $d(P, Q)$ for Q in the rectangle.

Claim: there are 8 points from our initial set (including P) in the rectangle

Proof: cover the rectangle with 8 squares of side length $\delta/2$

- they overlap along lines, but that's fine

- a square on the left contains at most one point from L

- a square on the right contains at most one point from R

Consequence: at most 8 points in the range $y_P \leq y \leq y_P + \delta$

initialisation: sort the points twice, with respect to x & y

↳ one-time cost $\Theta(n \log n)$, before recursive calls

Main algorithm: given two arrays representing the same points

(A_x sorted in x , A_y sorted y)

- find the x -median using A_x $\Theta(1)$
- for the next recursive calls, split both A_x and A_y $\Theta(n)$
- remove the points at distance $\geq \delta$ from the x -median line from A_y $\Theta(n)$
- inspect all remaining points P in A_y (= in increasing y -order)
for each P , compute the distance to the points Q in A_y
with $y_p \leq y_Q \leq y_p + \delta$ and keep the min
↳ at most 8 points need to be checked per P $\Theta(n)$

→ runtime: $T(n) = 2T(n/2) + cn$ so $T(n) \in \Theta(n \log n)$