

CS 341: Algorithms

Lecture 3: Divide and conquer

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based on lecture notes by many other CS341 instructors

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The 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 constant b

Conquer

- solve these subproblems recursively

Recombine

- deduce the solution of the main problem from the subproblems

When should you use this?

- original problem nicely decomposable (not much overlap in the subproblems)
- combining solutions is not too costly
- subproblems are not overly unbalanced

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

$$H = FG = f_0g_0 + (f_0g_1 + f_1g_0)x + \dots + f_{n-1}g_{n-1}x^{2n-2}$$

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

```
1.   for  $i = 0, \dots, n - 1$  do
2.       for  $j = 0, \dots, n - 1$  do
3.            $h_{i+j} = h_{i+j} + f_i g_j$ 
```

Divide and conquer

Idea: write $F = F_0 + F_1x^{n/2}$, $G = G_0 + G_1x^{n/2}$. Then

$$H = F_0G_0 + (F_0G_1 + F_1G_0)x^{n/2} + F_1G_1x^n$$

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Analysis:

- 4 recursive calls in size $n/2$
- $\Theta(n)$ additions to compute $F_0G_1 + F_1G_0$
- multiplications by $x^{n/2}$ and x^n are free
- $\Theta(n)$ additions to handle overlaps

(Sloppy) recurrence: $T(n) = 4T(n/2) + cn$

- $a = 4$, $b = 2$, $y = 1$ so $T(n) \in \Theta(n^2)$

Not better than the naive algorithm. We do the same operations.

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Exercise

Use **one** multiplication of polynomials to get $F_0G_1 + F_1G_0$, starting from $F_0, F_1, G_0, G_1, F_0G_0, F_1G_1$

Karatsuba's algorithm

Idea: use the identity

$$(F_0 + F_1 x^{n/2})(G_0 + G_1 x^{n/2}) = \mathbf{F_0 G_0} + ((\mathbf{F_0} + \mathbf{F_1})(\mathbf{G_0} + \mathbf{G_1}) - \mathbf{F_0 G_0} - \mathbf{F_1 G_1})x^{n/2} + \mathbf{F_1 G_1}x^n$$

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Analysis:

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

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

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

$$\log_2 3 = 1.58\dots$$

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Remark: key idea = a formula for degree-1 polynomials that does **3** multiplications

Toom-Cook and FFT

Toom-Cook:

- a family of algorithms based on similar expressions as Karatsuba
- for $k \geq 2$, $2k - 1$ recursive calls in size n/k
- so $T(n) \in \Theta(n^{\log_k(2k-1)})$
- gets as close to exponent 1 as we want (but very slowly)

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 $\Theta(n \log(n))$ ops over \mathbb{C}

Multiplying matrices

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

Remark: input and output size $\Theta(n^2)$, easy algorithm in $\Theta(n^3)$

```
1.   for  $i = 1, \dots, n$  do
2.       for  $j = 1, \dots, n$  do
3.           for  $k = 1, \dots, n$  do
4.                $c_{i,k} = c_{i,k} + a_{i,j}b_{j,k}$ 
```

Divide and conquer

Setup: write

$$A = \begin{pmatrix} A_{1,1} & A_{1,2} \\ A_{2,1} & A_{2,2} \end{pmatrix} \quad B = \begin{pmatrix} B_{1,1} & B_{1,2} \\ B_{2,1} & B_{2,2} \end{pmatrix}$$

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

$$C = \begin{pmatrix} A_{1,1}B_{1,1} + A_{1,2}B_{2,1} & A_{1,1}B_{1,2} + A_{1,2}B_{2,2} \\ A_{2,1}B_{1,1} + A_{2,2}B_{2,1} & A_{2,1}B_{1,2} + A_{2,2}B_{2,2} \end{pmatrix}$$

Naively: 8 recursive calls in size $n/2 + \Theta(n^2)$ additions $\implies T(n) \in \Theta(n^3)$

Goal: find a better formula for 2×2 matrices

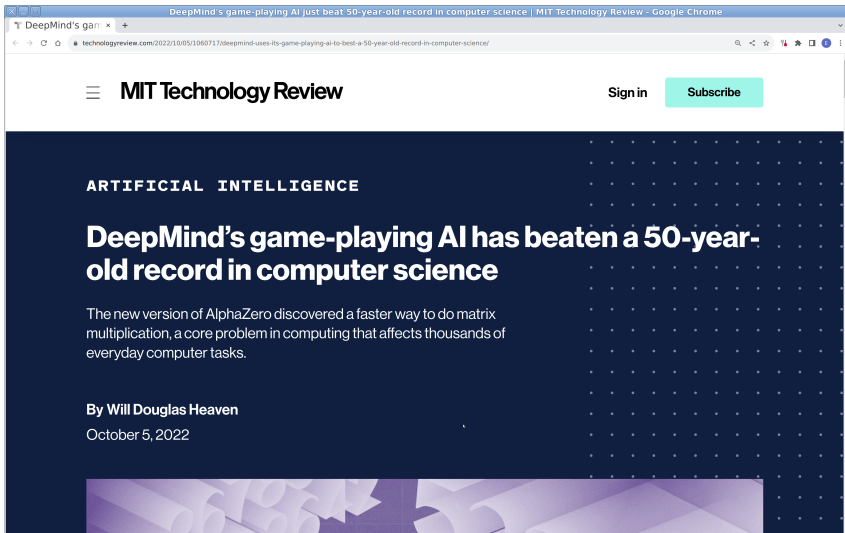
Strassen's algorithm

Compute

$$\left| \begin{array}{l} Q_1 = (A_{1,1} - A_{1,2})B_{2,2} \\ Q_2 = (A_{2,1} - A_{2,2})B_{1,1} \\ Q_3 = A_{2,2}(B_{1,1} + B_{2,1}) \\ Q_4 = A_{1,1}(B_{1,2} + B_{2,2}) \\ Q_5 = (A_{1,1} + A_{2,2})(B_{2,2} - B_{1,1}) \\ Q_6 = (A_{1,1} + A_{2,1})(B_{1,1} + B_{1,2}) \\ Q_7 = (A_{1,2} + A_{2,2})(B_{2,1} + B_{2,2}) \end{array} \right. \quad \text{and} \quad \left| \begin{array}{l} C_{1,1} = Q_1 - Q_3 - Q_5 + Q_7 \\ C_{1,2} = Q_4 - Q_1 \\ C_{2,1} = Q_2 + Q_3 \\ C_{2,2} = -Q_2 - Q_4 + Q_5 + Q_6 \end{array} \right.$$

Analysis: 7 recursive calls in size $n/2 + \Theta(n^2)$ additions $\implies T(n) \in \Theta(n^{\log_2(7)})$
 $\log_2(7) = 2.80\dots$

Faster algorithms: AI to the rescue

A screenshot of a web browser displaying an article on MIT Technology Review. The browser's address bar shows the URL: technologyreview.com/2022/10/05/1060717/deepmind-uses-its-game-playing-ai-to-beat-a-50-year-old-record-in-computer-science/. The page features the MIT Technology Review logo, a 'Sign in' link, and a green 'Subscribe' button. The article title is 'DeepMind's game-playing AI has beaten a 50-year-old record in computer science', categorized under 'ARTIFICIAL INTELLIGENCE'. The author is Will Douglas Heaven, and the date is October 5, 2022. The background of the article header is a dark blue grid pattern.

DeepMind's game-playing AI just beat 50-year-old record in computer science | MIT Technology Review - Google Chrome

technologyreview.com/2022/10/05/1060717/deepmind-uses-its-game-playing-ai-to-beat-a-50-year-old-record-in-computer-science/

MIT Technology Review

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ARTIFICIAL INTELLIGENCE

DeepMind's game-playing AI has beaten a 50-year-old record in computer science

The new version of AlphaZero discovered a faster way to do matrix multiplication, a core problem in computing that affects thousands of everyday computer tasks.

By Will Douglas Heaven
October 5, 2022

Beyond Strassen

Direct generalization

- an algorithm that does k multiplications for matrices of size ℓ gives
 $T(n) \in \Theta(n^{\log_\ell(k)})$ (we always have $k > \ell^2$, so no log)

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A challenge: find best k for small values of ℓ

- SAT solving, gradient descent, ...
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Best exponent to date (using more than just divide and conquer)

- $O(n^{2.37188})$, improves from previous record $O(n^{2.37286})$
- galactic algorithms

Counting inversions

Counting inversions

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

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

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

$(2, 3), (2, 5), (2, 8), (4, 5), (4, 8), (6, 7), (6, 8), (7, 8)$

Remark 1. we show the **indices** where inversions occur

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Remark 2. easy algorithm (two nested loops) in $\Theta(n^2)$

Remark 3. to do better than n^2 , we cannot **list** all inversions

Toward a divide and conquer algorithm

Idea

- c_ℓ = number of inversions in $A[1..n/2]$
- c_r = number of inversions in $A[n/2 + 1..n]$
- c_t = number of **transverse** inversions with $i \leq n/2$ and $j > n/2$
- return $c_\ell + c_r + c_t$

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

- $c_\ell = 1$ (2, 3)
- $c_r = 3$ (6, 7), (6, 8), (7, 8)
- $c_t = 4$ (2, 5), (2, 8), (4, 5), (4, 8)

c_ℓ and c_r done recursively. What about c_t ?

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c_ℓ and c_r done recursively. What about c_t ?

Transverse inversions

Goal: how many pairs (i, j) with $i \leq n/2$, $j > n/2$, $A[i] > A[j]$?

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

$c_t = \#i$'s greater than 3 + $\#i$'s greater than 8 + $\#i$'s greater than 7 + $\#i$'s greater than 4
or

$c_t = \#j$'s less than 1 + $\#j$'s less than 5 + $\#j$'s less than 2 + $\#j$'s less than 6

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or

$$c_t = \#j$$
's less than 1 + $\#j$'s less than 5 + $\#j$'s less than 2 + $\#j$'s less than 6

Observation: this number does not change if both sides are **sorted**, so assume that left and right are sorted after the recursive calls.

Example: With the same input, we get

$$[1, 2, 5, 6, 3, 4, 7, 8]$$

$$c_t = \#j$$
's less than 1 + $\#j$'s less than 2 + $\#j$'s less than 5 + $\#j$'s less than 6

Option 1

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- this is $O(\log(n))$ per i , so total $O(n \log(n))$
- after that, another $\Theta(n \log(n))$ for sorting
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Proof:

$$\begin{aligned}T(n) &= 2T(n/2) + n \log(n) \\&= 4T(n/4) + n \log(n/2) + n \log(n) \\&= \dots = n(\log(n) + \log(n/2) + \dots + \log(2)) \\&\leq n \log^2(n)\end{aligned}$$

Exercise

Prove $T(n) \in \Omega(n \log^2(n))$

Option 2: enhance mergesort

Observation: if left and right side are sorted, no need to sort everything, just **merge**

Goal: find c_t during merge.

Merge($A[1..n]$) (both halves of A assumed sorted)

1. copy A into a new array S
2. $i = 1; j = n/2 + 1;$
3. **for** ($k \leftarrow 1; k \leq n; k++$) **do**
4. **if** ($i > n/2$) $A[k] \leftarrow S[j++]$
5. **else if** ($j > n$) $A[k] \leftarrow S[i++]$
6. **else if** ($S[i] < S[j]$) $A[k] \leftarrow S[i++]$
7. **else** $A[k] \leftarrow S[j++]$

When we insert $S[i]$ back in A , need to count how many j 's have been processed already

EnhancedMerge($A[1..n]$) (both halves of A assumed sorted)

1. copy A into a new array S ; $c = 0$
2. $i = 1$; $j = n/2 + 1$;
3. **for** ($k \leftarrow 1$; $k \leq n$; $k++$) **do**
4. **if** ($i > n/2$) $A[k] \leftarrow S[j++]$
5. **else if** ($j > n$) $A[k] \leftarrow S[i++]$; $c = c + n/2$
6. **else if** ($S[i] < S[j]$) $A[k] \leftarrow S[i++]$; $c = c + j - (n/2 + 1)$
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Example: with $[1, 2, 5, 6, 3, 4, 7, 8]$

- 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 $c = c + 2$

Enhanced merge is still $\Theta(n)$ so total remains $\Theta(n \log(n))$.