

CS 331, Fall 2024

Lecture 3 (9/14)

Today: - Inversions

- Matrices

- FFT

## Inversions (Part II, Section 6.1)

Input:  $L$  is list of  $n$  elements in  $\mathbb{R}$

Output: # of  $(i, j)$ :  $1 \leq i < j \leq n$   
 $L[i] > L[j]$  (inversion)

Example

$L = [3, 5, 6, 2, 4, 1]$

#. inversions:  $(i, j) = (1, 4) (2, 4) (3, 4)$   
 $(1, 6) (2, 5) (3, 5)$   
 $(4, 6) (2, 6) (3, 6)$   
 $(5, 6)$

Application: Metric between rankings "Kendall  $\tau$ "  
(e.g. company preferences)

Observation:  $n^2$  time algo: compare all pairs.

Idea: recursion?

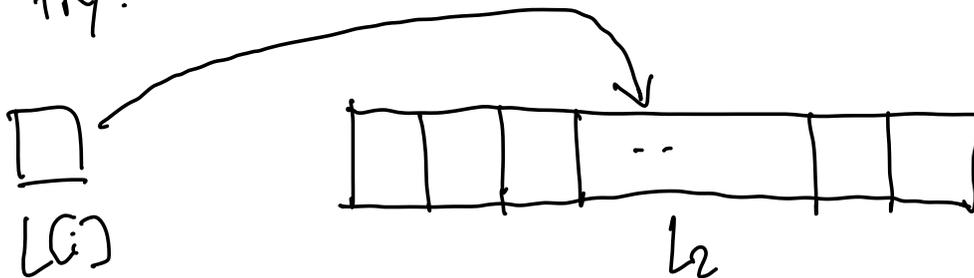


$$\text{Inversions}(L) = \text{Inversions}(L_1) \quad T\left(\frac{n}{2}\right) \\ + \text{Inversions}(L_2) \quad T\left(\frac{n}{2}\right)$$

"stitching" step  $\rightarrow + \left| \left\{ i \in \left[\frac{n}{2}\right), j \in (n) \setminus \left[\frac{n}{2}\right) : L[i] > L[j] \right\} \right|$   
???

How to do stitching faster than  $n^2$ ?

First try:



Time to compute  $\left| \left\{ j \in (n) \setminus \left[\frac{n}{2}\right) \mid L[i] < L[j] \right\} \right|$

- $O(n)$  per  $i$  (naive)
- $O(\log n)$  per  $i$  (binary search, if  $L_2$  sorted)

Inversions recurrence:

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

recurse on halves

1) sort  $L_2$

2) binary search for each  $L_1(i)$

Balanced case:  $T(n) = O(n \log^2 n)$

Improvement: piggy back off MergeSort stitching

... //  $L_1, L_2$  sorted

$i_1 \leftarrow 1, i_2 \leftarrow 1, \text{count} \leftarrow 0$  // pointers to smallest elems, # of inversions

For  $i \in L_1$ :

If  $L_1(i) \leq L_2(i_2)$ :  $L(i) \leftarrow L_1(i), i_1 \leftarrow i_1 + 1$ ,

$\text{count} \leftarrow \text{count} + (i_2 - 1)$   $O(1)$  time!

(else:  $L(i) \leftarrow L_2(i_2), i_2 \leftarrow i_2 + 1$ )

Example

$L_1$  ( 1 6  $\boxed{7}$  18 ) ( 0 3 9 45 )  $L_2$

$L$  ( 0 1 3 6 ... )  
how many  $\&$  inserted?

Improved runtime:

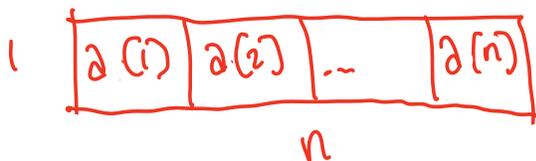
$$T(n) = 2T\left(\frac{n}{2}\right) + O(n) = O(n \log n)$$

Takeaway 1: Can enforce stronger recursive guarantees  
e.g. Sorted sublists + inversion counts.

Takeaway 2: For arrays, pointer / queue tricks save time  
e.g.  $O(\log n) \rightarrow O(1)$  per index.  
e.g. "sliding window" techniques: will revisit in Part III, Section 2

## Matrix multiplication (Part II, Section 5.1)

Warmup: Vector - vector



"inner product"  
aka  
"dot product"

$$n = \sum_{i \in [n]} a(i) b(i)$$

$O(n)$  time.

In this class, vectors are lower-case and columns ( $n \times 1$ )

Dot product of  $a, b \in \mathbb{R}^{n \times 1}$ :

$$\langle a, b \rangle = a^T b = \sum_{i \in [n]} a(i) b(i)$$

**Matrix-matrix**: dot every row/col pair

The diagram shows the multiplication of two matrices,  $A$  and  $B$ , to produce a resulting matrix  $AB$ .

- Matrix  $A$  is of size  $n \times d$ . A red arrow points to the  $i$ -th row of  $A$ , labeled "ith row". The element  $A_{i:}$  is highlighted in red.
- Matrix  $B$  is of size  $d \times k$ . A blue arrow points to the  $j$ -th column of  $B$ , labeled "jth column". The element  $B_{:j}$  is highlighted in blue.
- The resulting matrix  $AB$  is of size  $n \times k$ . The element  $A_{i:} B_{:j}$  is highlighted in red and blue.

Applications: entirety of modern ML/data science.

regression, feature learning, deep learning, ...

Intuition:  $n$ 

cat
dog
bird
$\vdots$
$d$

 $n = \# \text{ examples}$   
 $d = \# \text{ features}$

Naive matrix-matrix:  $O(d) \times nk = O(ndk)$ .  
per dot product      # entries

If  $n=d=k$ , this is  $O(n^3)$ . Linear time =  $O(n^2)$

**Aside** Block matrix multiplication works like you think!

$$\begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} \begin{pmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{pmatrix} = \begin{pmatrix} A_{11}B_{11} + A_{12}B_{21} & A_{11}B_{12} + A_{12}B_{22} \\ A_{21}B_{11} + A_{22}B_{21} & A_{21}B_{12} + A_{22}B_{22} \end{pmatrix}$$

$A_{11}, A_{12}, A_{21}, A_{22}, B_{11}, B_{12}, B_{21}, B_{22}$  are matrices

Intuition: Splitting dot product

$$A_{1:}^T B_{:1} = [A_{11}]_{1:}^T [B_{11}]_{:1} + [A_{12}]_{1:}^T [B_{12}]_{:1}$$

Naive recursion:  $T(n) = 8T(\frac{n}{2}) + O(n^2) = O(n^3)$

Strassen recursion:  $T(n) = 7T(\frac{n}{2}) + O(n^2) = O(n^{2.807...})$

World record:  $T(n) = O(n^{2.3714...})$  (galactic algorithm...)

When can we do better?

Matrix-vector

Let  $A$  is  $n \times n$   
 $b$  is  $n \times 1$

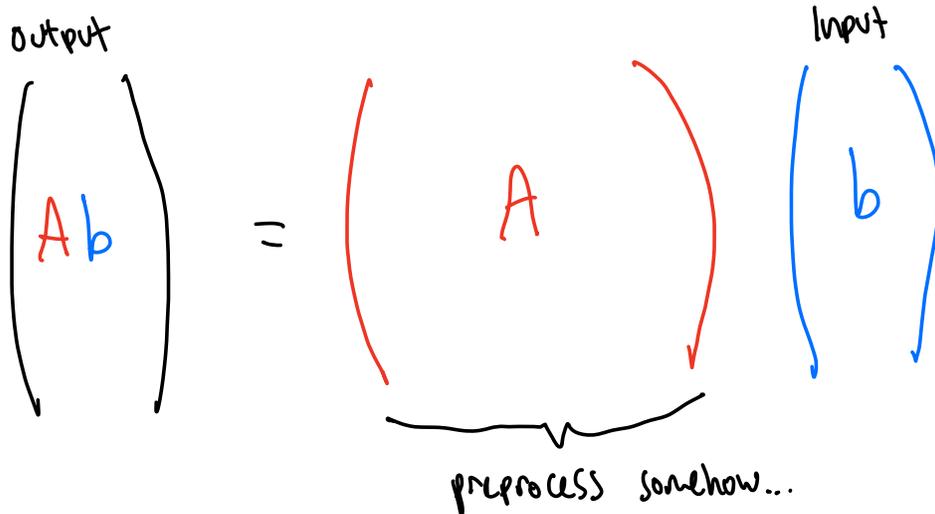
(input size:  
 $O(n^2 + n)$   
 $= O(n^2)$ )

We can compute  $Ab$  in time:

$$(O(n) \text{ per entry}) \times n = O(n^2)$$

Linear time ☺

Can we do better if  $A$  fixed,  $b$  is input?



HW I, Problem 2:  $A$  is WHT, faster than  $n^2$ !

Today:  $A$  is FFT,  $O(n \log n)$  time.

# Fast Fourier Transform (Part II, Section 5.2)

Let  $n = 2^k$ ,  $k = 1, 2, \dots$

$F_n$  is  $n \times n$  Complex matrix.

DFT $_n(b)$ : return  $F_n b$  in time  $O(n \log n)$

Applications: faster multiplication  
signal processing (learn "spectrum" of waves)

Aside

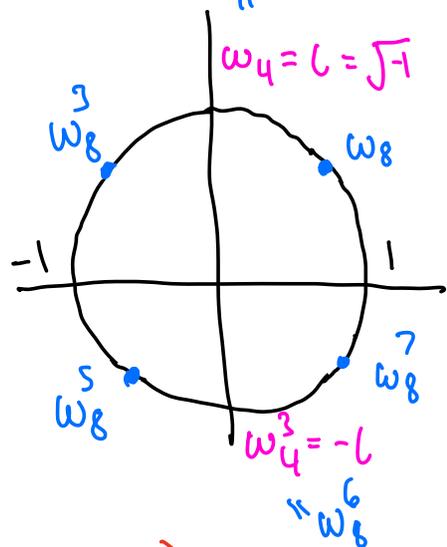
Complex numbers crash course

$$e^{i\theta} = \cos(\theta) + i \sin(\theta)$$

$$\omega_n = e^{i \cdot \frac{2\pi}{n}}$$

" $n$ th root of unity"

$\frac{2\pi}{n}$  = rotate  $\frac{1}{n}$ th of a circle



Remember:  $\omega_n^n = 1$ . (full lap around circle)

So, what is  $F_n$ ?

$$F_n(i)(j) = \omega_n^{(i-1)(j-1)}$$

Interpretation:

$i$ th row of  $F_n$

goes around unit circle,

$\frac{(i-1)}{n} \cdot 2\pi$  at a time.

$$F_1 = (1) \quad \omega_1 = 1$$

$$F_2 = \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \quad \omega_2 = -1$$

$$F_4 = \begin{pmatrix} \omega^0 & \omega^0 & \omega^0 & \omega^0 \\ \omega^0 & \omega^1 & \omega^2 & \omega^3 \\ \omega^0 & \omega^2 & \omega^0 & \omega^2 \\ \omega^0 & \omega^3 & \omega^2 & \omega^1 \end{pmatrix}$$

$$\omega \equiv \omega_4 = 1$$

$$F_8 = \begin{pmatrix} \omega^0 & \omega^0 \\ \omega^0 & \omega^1 & \omega^2 & \omega^3 & \omega^4 & \omega^5 & \omega^6 & \omega^7 \\ \omega^0 & \omega^2 & \omega^4 & \omega^6 & \omega^0 & \omega^2 & \omega^4 & \omega^6 \\ \omega^0 & \omega^3 & \omega^6 & \omega^1 & \omega^4 & \omega^7 & \omega^2 & \omega^5 \\ \omega^0 & \omega^4 & \omega^0 & \omega^4 & \omega^0 & \omega^4 & \omega^0 & \omega^4 \\ \omega^0 & \omega^5 & \omega^2 & \omega^7 & \omega^4 & \omega^1 & \omega^6 & \omega^3 \\ \omega^0 & \omega^6 & \omega^4 & \omega^2 & \omega^0 & \omega^6 & \omega^4 & \omega^2 \\ \omega^0 & \omega^7 & \omega^6 & \omega^5 & \omega^4 & \omega^3 & \omega^2 & \omega^1 \end{pmatrix}$$

$$\omega \equiv \omega_8 = \exp\left(i \cdot \frac{2\pi}{8}\right)$$

Recall

$$\omega_8^2 = \omega_4$$

(Claim:  $T(n) = 2T(\frac{n}{2}) + O(n)$ )

time to compute  $F_n b$

Aside

Two ways of thinking about  $Ab$

Way 1:  $(Ab)(i) = A_{i,:} b$

Way 2:

$$\begin{pmatrix} | & | & \dots & | \\ A_{:1} & A_{:2} & \dots & A_{:n} \\ | & | & & | \end{pmatrix} \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{pmatrix} = b_1 A_{:1} + b_2 A_{:2} + \dots + b_n A_{:n}$$

note: order doesn't matter!

Observations

(T1)

(T2)

1)  $F_n b = \begin{pmatrix} F_n \end{pmatrix}_{\text{odd}} b_{\text{odd}} + \begin{pmatrix} F_n \end{pmatrix}_{\text{even}} b_{\text{even}}$

$n \times \frac{n}{2}$     $\frac{n}{2} \times 1$     $n \times \frac{n}{2}$     $\frac{n}{2} \times 1$

2)  $\begin{pmatrix} F_n \end{pmatrix}_{\text{odd}} = \begin{pmatrix} F_{\frac{n}{2}} \\ F_{\frac{n}{2}} \end{pmatrix}$

Can compute (T1) in:  $T(\frac{n}{2}) + O(n)$  time.



About multiplication...

$$a = a_{n-1}10^{n-1} + a_{n-2}10^{n-2} + \dots + a_110^1 + a_0$$
$$= P_a(10) \quad (\text{coeffs} = \text{digits of } a)$$

$$b = b_{n-1}10^{n-1} + b_{n-2}10^{n-2} + \dots + b_110^1 + b_0$$
$$= P_b(10) \quad (\text{coeffs} = \text{digits of } b)$$

To compute  $ab$ , just need coeffs of  $P_a P_b$ .

Amazing fact:  $F_n V =$

$$\begin{pmatrix} p_v(1) \\ p_v(\omega_n) \\ p_v(\omega_n^2) \\ \vdots \\ p_v(\omega_n^{n-1}) \end{pmatrix}$$

coeffs evaluations

FFT-based multiplication:

1) Evaluate  $F_n a, F_n b$

2) let  $c = \{p_a(x) p_b(x)\}$  for  $x = 1, \omega_n, \omega_n^2, \dots, \omega_n^{n-1}$

3) Evaluate  $F_n^{-1} c$ . Gives coeffs of  $P_a P_b$ !