

Lecture 3

Let us recall our algorithm for multiplying two polynomials $A(x)$ and $B(x)$:

Step 1: Convert $A(x)$ and $B(x)$ from coefficient form to point-value representation.

Step 2: Obtain their product $P(x)$ in point-value representation.

Step 3: Convert $P(x)$ into coefficient representation.

We have seen how to implement Step 1 in $O(n \log n)$ time, where $A(x)$ and $B(x)$ are degree $n-1$ polynomials.

Easy to see that Step 2 takes $O(n)$ time.

What about Step 3?

$$P(x) = \beta_0 + \beta_1 x + \beta_2 x^2 + \dots + \beta_{N-1} x^{N-1}$$

where $\beta_0, \beta_1, \dots, \beta_{N-1}$ are unknown to us.

Recall that N is the smallest power of 2 that is $\geq 2n-1$.

What we know are $P(1), P(\omega), P(\omega^2), \dots, P(\omega^{N-1})$.

That is,

$$\begin{bmatrix} P(1) \\ P(\omega) \\ \vdots \\ P(\omega^{N-1}) \end{bmatrix} = \begin{bmatrix} 1 & 1 & \dots & 1 \\ 1 & \omega & \dots & \omega^{N-1} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \omega^{N-1} & \dots & \omega^{(N-1)^2} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_{N-1} \end{bmatrix}$$

So

$$\begin{bmatrix} P_0 \\ P_1 \\ \vdots \\ P_{N-1} \end{bmatrix} = \begin{bmatrix} 1 & 1 & \dots & 1 \\ 1 & \omega & \dots & \omega^{N-1} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \omega^{N-1} & \dots & \omega^{(N-1)^2} \end{bmatrix}^{-1} \begin{bmatrix} P(1) \\ \text{Date} \\ \vdots \\ P(\omega^{N-1}) \end{bmatrix}$$

Let X denote the above $N \times N$ matrix, i.e.

$$X = \begin{bmatrix} 1 & 1 & \dots & 1 \\ 1 & \omega & \dots & \omega^{N-1} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \omega^{N-1} & \dots & \omega^{(N-1)^2} \end{bmatrix}$$

What is the inverse of X ? Any guesses?

A reasonable guess is

$$\begin{bmatrix} 1 & 1 & \dots & 1 \\ 1 & 1/\omega & \dots & 1/\omega^{N-1} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1/\omega^{N-1} & \dots & 1/\omega^{(N-1)^2} \end{bmatrix}$$

Call this matrix Y .

What is XY ?

Claim. $XY = \begin{bmatrix} N & 0 & \dots & 0 \\ 0 & N & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & N \end{bmatrix}$

Proof. Consider the (j, k) -th element of XY . This is the dot product of

$$\begin{pmatrix} 1 & \omega^j & \omega^{2j} & \dots & \omega^{(N-1)j} \end{pmatrix} \begin{pmatrix} 1 & 1 & \dots & 1 \\ \omega^k & \omega^{2k} & \dots & \omega^{(N-1)k} \\ \vdots & \vdots & \ddots & \vdots \\ \omega^{(N-1)k} & \omega^{2(N-1)k} & \dots & \omega^{(N-1)^2 k} \end{pmatrix}$$

$$= 1 + \omega^{j-k} + \omega^{2(j-k)} + \dots + \omega^{(N-1)(j-k)}$$

When $j = k$, the above sum is N .

When $j \neq k$, this is $1 + \omega^t + \dots + \omega^{t(N-1)}$ where $t = j - k$.

The sum $1 + \omega^t + \dots + \omega^{t(N-1)}$

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$$= \frac{\omega^{tN} - 1}{\omega^t - 1} = 0 \quad \text{since } \omega^N = 1. \quad \square$$

So the inverse of X is $\frac{1}{N}$ $\begin{bmatrix} 1 & 1 & \dots & 1 \\ 1 & \omega^{N-1} & \dots & \omega^{(N-1)^2} \\ 1 & \omega^{N-2} & \dots & \omega^{(N-1)(N-2)} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \omega & \dots & \omega^{N-1} \end{bmatrix}$
 (note that $\frac{1}{\omega} = \omega^{N-1}$)

Our problem now is to compute the following:

$$\frac{1}{N} \begin{bmatrix} 1 & 1 & \dots & 1 \\ 1 & \omega^{N-1} & \dots & \omega^{(N-1)^2} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \omega & \dots & \omega^{N-1} \end{bmatrix} \begin{bmatrix} q_0 \\ q_1 \\ \vdots \\ q_{N-1} \end{bmatrix}$$

where $q_0 = P(1)$, $q_1 = P(\omega)$, \dots , $q_{N-1} = P(\omega^{N-1})$.

The above matrix multiplication is called Inverse Fourier Transform.

Let us create the polynomial

$$Q(x) = q_0 + q_1 x + \dots + q_{N-1} x^{N-1}$$

We need to evaluate $Q(x)$ at $x = 1, \omega^{N-1}, \omega^{N-2}, \dots, \omega$ which are the N -th roots of 1.

Or in other words, evaluate $Q(x)$ by FFT at $x = 1, \omega, \dots, \omega^{N-1}$ to obtain the vector

$$\begin{bmatrix} Q(1) \\ Q(\omega) \\ \vdots \\ Q(\omega^{N-1}) \end{bmatrix} \text{ and permute this vector and scale it down by } N \rightsquigarrow \frac{1}{N} \begin{bmatrix} Q(1) \\ Q(\omega^{N-1}) \\ \vdots \\ Q(\omega) \end{bmatrix} \text{ These are the coefficients of } P.$$

We will now look at a problem in graphs. Date _____

- we will see a randomized algorithm for this problem.

The algorithm will make random choices and it may sometimes return the wrong answer.

However its error probability will be $\leq 1/4$.

- such an algorithm is called a Monte Carlo algorithm.

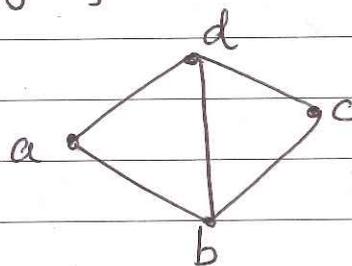
The problem we will consider is the global min-cut problem.
 the set of vertices ← the set of edges ↑

Input: a connected undirected graph $G = (V, E)$

A cut C is a subset of E such that the graph $(V, E - C)$ is disconnected.

That is, a cut C is a set of edges whose removal leaves the resulting graph disconnected.

For example, consider the graph:



Here $V = \{a, b, c, d\}$ and $E = \{(a, b), (b, c), (c, d), (a, d), (b, d)\}$.

$C = \{(a, b), (a, d)\}$ is a cut. Similarly, $C' = \{(a, b), (c, d), (b, d)\}$ is a cut and so on.

A cut corresponds to a partition of V into A and $V-A$, where neither $V-A$ nor A is empty.

We are interested in a min-cut, i.e., a minimum-size set of edges whose removal leaves the graph disconnected.

- such a cut is also called a global min-cut.

(we will later look at $s-t$ min-cut problem where we are given a pair of vertices s and t and we want a min-cut that leaves s and t in different connected components)

Let us fix a (global) min-cut C .

Suppose C has k edges, i.e., $|C| = k$.

Exercise. Show that G has at least $\frac{nk}{2}$ edges, where $|V| = n$.

What is the probability that an edge picked uniformly at random from G belongs to C ?

- the answer is $\frac{|C|}{|E|} = \frac{k}{|E|} \leq \frac{k}{nk/2}$

So the answer is $\leq 2/n$.

since $|E| \geq nk/2$.

Let e be the edge picked uniformly at random. We showed that $\Pr[e \in C] \leq 2/n$.

This means with high probability, an edge picked uniformly at random is not in C .

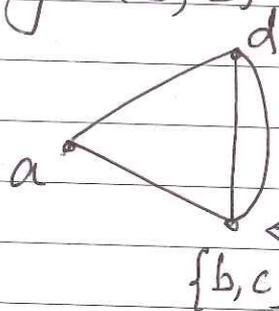
Now we want to get rid of e so that we have a smaller graph where C is still a min-cut. Date _____

Going back to our earlier example, suppose $e = (b, c)$ is the edge picked uniformly at random. What should we do with e so as to get a new graph (in fact, a smaller graph) without e such that our min-cut $C = \{(a, b), (a, d)\}$ is still a min-cut in this new graph?

Idea: Contract this edge.

What does this mean? Merge the endpoints of e into a "super-vertex". Self-loops are removed but all parallel edges are preserved.

Example: Contracting (b, c) in that graph results in the graph



this is the vertex formed by unifying b and c .

Let G_0 be the given graph G .

$G_0 \xrightarrow[\text{random edge}]{\text{contract a}}$ G_1

What do we do next? We have G_1 on $n-1$ vertices.

Let us repeat the same step.

$G_1 \xrightarrow[\text{random edge}]{\text{contract a}}$ G_2

Again repeat this step on G_2 .

So we get $G_0 \rightarrow G_1 \rightarrow G_2 \rightarrow G_3 \rightarrow \dots \rightarrow G_{n-2}$