

ALG 3.2

The Fast Fourier Transform and Applications to Multiplication

Reading Selections:
CLR: chapter 32

Auxiliary Reading:
AHU-Design Chapters 7 and 8
BB Section 7.1.3 and Chapter 9

Assume Commutative Ring

$$(\mathbf{R}, +, \cdot, 0, 1)$$

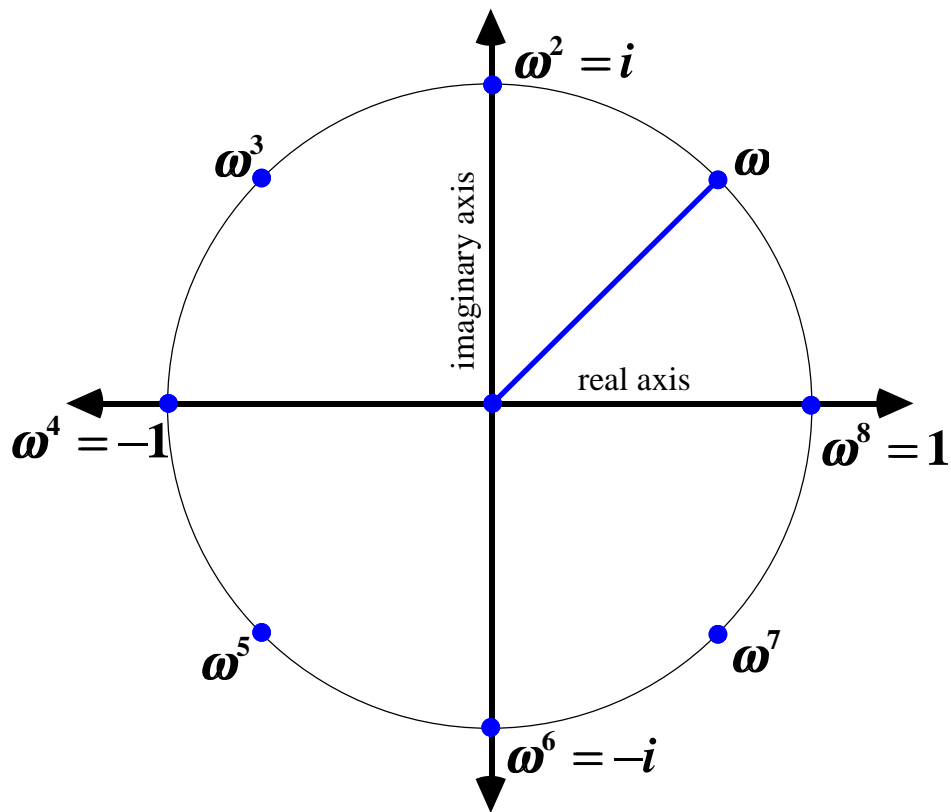
ω is *principal n th root of unity*
 $\omega^i \neq 1$ for $i=1, \dots, n-1$

if $\omega \neq 1$, $\omega^n = 1$, and

$$\sum_{j=0}^{n-1} \omega^{jp} = 0 \quad \text{for } 1 \leq p < n$$

Examples:

$$\omega = e^{2\pi i/n} \quad \text{for complex numbers}$$



Example

$\omega = e^{2\pi i/8}$ is the 8th root of unity

Fourier Matrix

$$M_n(\omega) = \begin{pmatrix} 1 & 1 & \dots & 1 \\ 1 & \omega & \dots & \omega^{n-1} \\ 1 & \omega^2 & \dots & \omega^{2(n-1)} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \omega^{n-1} & \dots & \omega^{(n-1)(n-1)} \end{pmatrix}$$

so $M(\omega)_{ij} = \omega^{ij}$ for $0 \leq i, j < n$

given $a = \begin{pmatrix} a_0 \\ \vdots \\ a_{n-1} \end{pmatrix}$

Discrete Fourier Transform is

$$\mathbf{DFT}_n(\mathbf{a}) = \mathbf{M}(\omega) \times \mathbf{a}$$

$$= \begin{pmatrix} f_0 \\ \cdot \\ \cdot \\ \cdot \\ f_{n-1} \end{pmatrix} \quad \text{where}$$
$$f_i = \sum_{k=0}^{n-1} a_k \omega^{ik}$$

Inverse Fourier Transform

$$\mathbf{DFT}_n^{-1}(\mathbf{a}) = \mathbf{M}(\omega)^{-1} \times \mathbf{a}$$

$$\textit{Theorem} \quad \mathbf{M}(\omega)_{ij}^{-1} = \frac{1}{n} \omega^{-ij}$$

proof We must show $\mathbf{M}(\omega) \cdot \mathbf{M}(\omega)^{-1} = \mathbf{I}$

$$\frac{1}{n} \sum_{k=0}^{n-1} \omega^{ik} \omega^{-kj} = \frac{1}{n} \sum_{k=0}^{n-1} \omega^{k(i-j)}$$

$$= \begin{cases} 0 & \text{if } i-j \neq 0 \\ 1 & \text{if } i-j = 0 \end{cases}$$

$$\text{using identity } \sum_{k=0}^{n-1} \omega^{kp} = 0$$

for $1 \leq p < n$

input column vector $\mathbf{a} = (a_0, \dots, a_{n-1})^T$

$$\text{DFT}_n(\mathbf{a}) = \begin{pmatrix} f_0 \\ \vdots \\ f_{n-1} \end{pmatrix} \quad \text{where}$$

$$f_i = f(\omega^i) \quad \text{and}$$

$$f(x) = \sum_{j=0}^{n-1} a_j \cdot x^j$$

Viewed as *Evaluation Problem*:

naive algorithm takes n^2 ops

Divide and Conquer gives FFT

with $O(n \log n)$ ops

for n a power of 2

Key Idea:

If ω is n^{th} root of unity

then ω^2 is $\frac{n}{2}$ -th root of unity

Algorithm FFT_n

Input $\mathbf{a} = (a_0, \dots, a_{n-1})^T$, n a power of 2

[1] If $n = 1$ then **output** \mathbf{a}

[2]

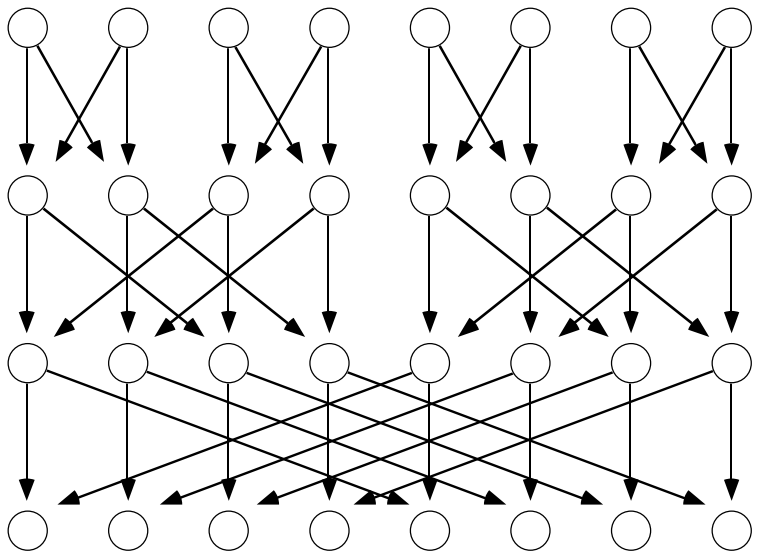
$$\begin{pmatrix} f_0^\circledast \\ \vdots \\ f_{\frac{n}{2}-1}^\circledast \end{pmatrix}^T \leftarrow \text{FFT}_{\frac{n}{2}}((a_0, a_2, \dots, a_{n-2})^T)$$

$$\begin{pmatrix} f_0'' \\ \vdots \\ f_{\frac{n}{2}-1}'' \end{pmatrix}^T \leftarrow \text{FFT}_{\frac{n}{2}}((a_1, a_3, \dots, a_{n-1})^T)$$

[3] **For** $i = 0, \dots, \frac{n}{2} - 1$ **do** $f_i \leftarrow f_i^\circledast + \omega^i f_i''$
 $f_{i+\frac{n}{2}} \leftarrow f_i^\circledast - \omega^i f_i''$

[4] **Output** $(f_0, f_1, \dots, f_{n-1})$

FFT Circuit = Butterfly



Total Recursion depth = $\log n$

Communication Distance 2^d at depth d

$$f_i = a_0 + a_1 \omega^i + a_2 \omega^{2i} + \dots + a_{n-1} \omega^{(n-1)i}$$

$$f_i = f'_i + \omega^i f''_i \quad \text{where}$$

$$f'_i = a_0 + a_2 (\omega^2)^i + a_4 (\omega^2)^{2i} + \dots + a_{n-2} (\omega^2)^{\frac{i(n-2)}{2}}$$

$$f''_i = a_1 + a_3 (\omega^2)^i + \dots + a_{n-1} (\omega^2)^{\frac{i(n-2)}{2}}$$

$$\begin{bmatrix} f_0^\circ \\ \vdots \\ f_{\frac{n}{2}-1}^\circ \end{bmatrix} = M_{\frac{n}{2}}(\omega^2) \begin{bmatrix} a_0 \\ a_2 \\ \vdots \\ a_{n-2} \end{bmatrix} = DFT_{\frac{n}{2}} \left((a_0, a_2, \dots, a_{n-2})^T \right)$$

$$\begin{bmatrix} f_0'' \\ \vdots \\ f_{\frac{n}{2}-1}'' \end{bmatrix} = M_{\frac{n}{2}}(\omega^2) \begin{bmatrix} a_1 \\ a_3 \\ \vdots \\ a_{n-1} \end{bmatrix} = DFT_{\frac{n}{2}} \left((a_1, a_3, \dots, a_{n-1})^T \right)$$

Note: $f'_{\frac{n}{2}+i} = f'_i$, $f''_{\frac{n}{2}+i} = f''_i$, $i=0, \dots, \frac{n}{2} - 1$

But $\omega^n = 1$, so $(\omega^2)^{\frac{n}{2}+i} = \omega^n \cdot (\omega^2)^i = \omega^{2i}$

for $i=0, \dots, \frac{n}{2} - 1$

Thus, $f_i = f'_i + \omega^i f''_i$ for $i=0, \dots, \frac{n}{2} - 1$

and $f_{i+\frac{n}{2}} = f'_i + \omega^{i+\frac{n}{2}} \cdot f''_i$

$= f'_i - \omega^i f''_i$ for $i=0, \dots, \frac{n}{2} - 1$

since $(\omega^2)^{\frac{n}{2}} = \omega^n = 1$, so $\omega^{\frac{n}{2}} = -1$

Operation Counts

Assume $n = 2^k$

additions

$$\begin{aligned} \text{Add}(n) &= 2 \cdot \text{Add}\left(\frac{n}{2}\right) + n \\ &= n \log n \end{aligned}$$

#multiplications

$$\begin{aligned} \text{Mult}(n) &= 2 \cdot \text{Mult}\left(\frac{n}{2}\right) + \frac{n}{2} \\ &= \frac{1}{2} n \log n \end{aligned}$$

Total Time $O(n \log n)$

note in complex FFT,

real ops is $5 n \log n$.

Applications of FFT

- (1) *Filtering on infinite input streams*
- (2) *Convolution:*
Products and Powers of Polynomials
- (3) **Division and Inversion of Polynomials**
- (4) **Multipoint Evaluation and Interpolation**

Products and Powers of Polynomials

input vectors $\mathbf{a} = (a_0, a_1, \dots, a_{n-1})^T$

$$\mathbf{b} = (b_0, b_1, \dots, b_{n-1})^T$$

convolution $\mathbf{c} = \mathbf{a} \otimes \mathbf{b}$

where $c_i = \sum_{j=0}^{n-1} a_j b_{i-j}$ for $i=0, \dots, 2n-1$

$\left(\text{and define } a_k = b_k = 0 \text{ if } k < 0 \text{ or } k \geq n \right)$

Convolution Theorem

$$\mathbf{a} \otimes \mathbf{b} = \text{FFT}_{2n}^{-1} \left(\text{FFT}_{2n}(\mathbf{a}) \cdot \text{FFT}_{2n}(\mathbf{b}) \right)$$

Application to Polynomial Products:

$$p(x) = \sum_{i=0}^{n-1} a_i x^i$$

$$q(x) = \sum_{j=0}^{n-1} b_j x^j$$

$$p(x) \cdot q(x) = \sum_{i=0}^{2n-2} c_i x^i \text{ where } c_i = \sum_{j=0}^{n-1} a_j b_{i-j}$$

Products of m polynomials

for $k=1, \dots, m$ let $P_k(x) = \sum_{i=0}^{n-1} a_{k,i} x^i$

$$\prod_{k=1}^m P_k(x) = \sum_{i=0}^{m(n-1)} c_i x^i, \text{ when } c_i = \sum_{\sum j_k = i} \prod_{k=1}^m a_{k,j_k}$$

Generalized Convolution Theorem

$$a_1 \otimes a_2 \otimes \dots \otimes a_m =$$

$$FFT_{nm}^{-1}(FFT_{nm}(a_1) \bullet FFT_{nm}(a_2) \dots FFT_{nm}(a_m))$$

$$a = (a_0, a_1, \dots, a_{n-1})^T, b = (b_0, b_1, \dots, b_{n-1})^T$$

positive wrapped convolution is $c = (c_0, c_1, \dots, c_{n-1})^T$

$$c_i = \sum_{j=0}^i a_j b_{i-j} + \sum_{j=i+1}^{n-1} a_j b_{n+i-j}$$

negative wrapped convolution is $d = (d_0, d_1, \dots, d_{n-1})^T$

$$d_i = \sum_{j=0}^i a_j b_{i-j} - \sum_{j=i+1}^{n-1} a_j b_{n+i-j}$$

"Wrapped Convolution"

Application to Modular Polynomial Products:

$$p(x) = \sum_{i=0}^{n-1} a_i x^i$$

$$q(x) = \sum_{j=0}^{n-1} b_j x^j$$

$$p(x) \cdot q(x) \text{ mod}(x^n+1)$$

$$= \sum_{i=0}^{n-1} d_i x^i \text{ since } x^n = -1 \text{ mod}(x^n+1)$$

Theorem If $\omega =$ principal n th root of unity
and $\Psi^2 = \omega$ and n has multiplicative inverse, then

$c = \text{FFT}_n^{-1}(\text{FFT}_n(a) \cdot \text{FFT}_n(b))$ is the positive

wrapped convolution of a, b . Also

$\hat{d} = \text{FFT}_n^{-1}(\text{FFT}_n(\hat{a}) \cdot \text{FFT}_n(\hat{b}))$ is the negatively

wrapped convolution of a, b

where $\hat{a} = (a_0, \Psi a_1, \dots, \Psi^{n-1} a_{n-1})^T$ and

$$\hat{b} = (b_0, \Psi b_1, \dots, \Psi^{n-1} b_{n-1})^T$$

Integer Multiplication by FFT

input n bit integers a, b

define polynomials degree $k = n/L$

$$a(x) = \sum_{i=0}^{k-1} a_i x^i, \quad 0 \leq a_i < 2^L$$

$$b(x) = \sum_{i=0}^{k-1} b_i x^i, \quad 0 \leq b_i < 2^L$$

so $a = a(2^L), \quad b = b(2^L)$

idea

(1) compute $c(x) = a(x) \cdot b(x)$
by convolution

(2) evaluate $c(2^L) = a \cdot b$

Integer Multiplication Algorithms

Time

Pollard Alg. $O(n(\log n)^2(\log \log n)^\epsilon)$ use $L = \log n$

Karp Alg. $O(n(\log n)^2)$ use $L = \sqrt{n}$

Strassen Alg. $O(n(\log n)(\log \log n))$ use $L = \sqrt{n}$
and wrapped
convolution

Pollard Algorithm

$$n = kL, \quad L = 1 + \log k$$

[1] Choose primes P_1, P_2, P_3 where

$$P_1 \cdot P_2 \cdot P_3 \geq 4 \cdot k^3$$

$$\text{and } P_i = \alpha_i \cdot 2^L + 1, \quad \alpha_i = O(1)$$

[2] Compute $C(x)$ by convolution
over finite field Z_{P_i} $i=1,2,3$

(requires k mults on $2L$ bit integers)

[3] Evaluate $C(2^L)$

Time Bounds

$$T(n) = 3k \overbrace{T(2L)}^{\substack{\text{recursive} \\ \text{mults}}} + O \overbrace{(k \log k)}^{\text{FFT}} \cdot O(L)$$

$$= 3k T(2(1 + \log k)) + O(k (\log k)^2)$$

$$\leq O(n (\log n)^2 (\log \log n)^\epsilon) \text{ for any } \epsilon > 0$$

Korp's Algorithm

$$n = 2^s = kL$$

$$k = \begin{cases} 2^{\frac{s}{2}} & \text{if } s \text{ even} \\ 2^{\frac{(s-1)}{2}} & \text{else} \end{cases}$$

- (1) Compute $C(x)$ modulo k by convolution
- (2) Compute $C(x)$ modulo $(2^{2L}+1)$ by convolution (requires $2k$ recursive mults)
- (3) Compute $C(x)$ coefficients from $c(x) \bmod k$, $c(x) \bmod (2^{2L}+1)$ by chinese remaindering
- (4) evaluate $C(2^L)$

Time

$$\begin{aligned} T(n) &= 2k \overbrace{T(2L)}^{\text{recursive mults}} + O \overbrace{(k \log k)}^{\text{FFT}} O(L) \\ &= 2\sqrt{n} T(2\sqrt{n}) + O(n \log n) \\ &= O(n (\log n)^2) \end{aligned}$$

Schönage -Strassen Algorithm

- (2') Compute $C(x) \bmod (x^k+1)$ modulo $(2^{2L}+1)$ by wrapped convolution

\Rightarrow requires only k recursive mults on $2L$ bit numbers

Time

$$\begin{aligned} T(n) &= k \overbrace{T(2L)}^{\text{recursive mults}} + O \overbrace{(k \log k)}^{\text{FFT}} O(L) \\ &= \sqrt{n} T(2\sqrt{n}) + O(n \log n) \\ &= O(n \log n)(\log \log n) \end{aligned}$$

Open Problem: Can you mult n bit integers in $O(n \log n)$ time?