

# Number theoretic algorithms

Representation: We choose an integral base  $\beta > 1$ .

Any positive integer  $A$  can be represented by a vector of length  $n = \log A$ ,  $(a_0, \dots, a_{n-1})$  such that

$$A = a_{n-1} \beta^{n-1} + a_{n-2} \beta^{n-2} + \dots + a_1 \beta + a_0$$

and  $\forall 0 \leq i \leq n-1 ; 0 \leq a_i \leq \beta - 1$ .

Remark: What about sign?

Integer addition:

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## Algorithm 1.1 IntegerAddition

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**Input:**  $A = \sum_0^{n-1} a_i \beta^i$ ,  $B = \sum_0^{n-1} b_i \beta^i$ , carry-in  $0 \leq d_{\text{in}} \leq 1$

**Output:**  $C := \sum_0^{n-1} c_i \beta^i$  and  $0 \leq d \leq 1$  such that  $A + B + d_{\text{in}} = d \beta^n + C$

- 1:  $d \leftarrow d_{\text{in}}$
  - 2: **for**  $i$  **from**  $0$  **to**  $n - 1$  **do**
  - 3:    $s \leftarrow a_i + b_i + d$
  - 4:    $(d, c_i) \leftarrow (s \text{ div } \beta, s \text{ mod } \beta)$
  - 5: **return**  $C, d$ .
- 

$$\begin{array}{r} 10011 \\ 01001 \\ \hline 100 \end{array}$$

Remark: Note that if  $A$  and  $B$  are close to the maximum possible values that a computer can take then  $A+B$  will be much larger than what the computer can handle.

# Integer multiplication

A and B are again given in base  $\beta$  representation.

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## Algorithm 1.2 BasecaseMultiply

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**Input:**  $A = \sum_0^{m-1} a_i \beta^i$ ,  $B = \sum_0^{n-1} b_j \beta^j$

**Output:**  $C = AB := \sum_0^{m+n-1} c_k \beta^k$

Naive!

- 1:  $C \leftarrow A \cdot b_0$
  - 2: **for**  $j$  **from** 1 **to**  $n - 1$  **do**
  - 3:      $C \leftarrow C + \beta^j (A \cdot b_j)$
  - 4: **return**  $C$ .
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In the worst case this takes  $O(mn)$  operations.

This is roughly quadratic when  $m \approx n$ .

Question: Can we do better?

Yes! Karatsuba in 1960 gave a subquadratic time algorithm.

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## Algorithm 1.3 KaratsubaMultiply

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**Input:**  $A = \sum_0^{n-1} a_i \beta^i$ ,  $B = \sum_0^{n-1} b_j \beta^j$

**Output:**  $C = AB := \sum_0^{2n-1} c_k \beta^k$

→ **if**  $n < n_0$  **then return** **BasecaseMultiply**( $A, B$ )

$$k \leftarrow \lceil n/2 \rceil$$

$$(A_0, B_0) := (A, B) \text{ mod } \beta^k, (A_1, B_1) := (A, B) \text{ div } \beta^k$$

$$s_A \leftarrow \text{sign}(A_0 - A_1), s_B \leftarrow \text{sign}(B_0 - B_1)$$

$$C_0 \leftarrow \text{KaratsubaMultiply}(A_0, B_0)$$

$$C_1 \leftarrow \text{KaratsubaMultiply}(A_1, B_1)$$

$$C_2 \leftarrow \text{KaratsubaMultiply}(|A_0 - A_1|, |B_0 - B_1|)$$

$$\text{return } C := C_0 + (C_0 + C_1 - s_A s_B C_2) \beta^k + C_1 \beta^{2k}.$$

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Let  $k = \lceil \frac{n}{2} \rceil$ .  $A_1 = A \text{ div } \beta^k$ ;  $A_0 = A \text{ mod } \beta^k$ .

$$A = \underbrace{a_{n-1}\beta^{k-1} + a_{n-2}\beta^{k-2} + \dots + a_{k+1}\beta^{k+1}}_{A_1\beta^k} + \underbrace{a_k\beta^k + \dots + a_0}_{A_0}.$$

$$B = \underbrace{b_{n-1}\beta^{k-1} + b_{n-2}\beta^{k-2} + \dots + b_{k+1}\beta^{k+1}}_{B_1\beta^k} + \underbrace{b_k\beta^k + \dots + b_0}_{B_0}.$$

Roughly,

$$A = A_1\beta^k + A_0 \quad \text{and} \quad B = B_1\beta^k + B_0.$$

$$\begin{aligned} AB &= (A_1\beta^k + A_0)(B_1\beta^k + B_0) & T(n) : @T\left(\frac{n}{b}\right) + O(n) \\ &= \underbrace{A_1 B_1 \beta^{2k}}_{\sim} + \underbrace{(A_0 B_1 + A_1 B_0)}_{\sim} \beta^k + \underbrace{A_0 B_0}_{\sim}. & \hookrightarrow O(n^{\log_b}) \approx n^{\frac{\log n}{\log b}} \end{aligned}$$

There are 4 multiplications of size  $\frac{n}{2}$ .

Here  $T(n) = 4 T\left(\frac{n}{2}\right) + O(n)$ . //  $O(n^2)$  again.

Question: Can we reduce the no. of multiplications?

$$C_0 = A_0 B_0 \quad C_2 = |A_0 - A_1| \cdot |B_0 - B_1|.$$

$$\begin{aligned} C_1 &= A_1 B_1 \\ &= (A_0 - A_1) \cdot (B_0 - B_1). // \text{Say} \\ &= A_0 B_0 + A_1 B_1 - (A_1 B_0 + B_1 A_0). \end{aligned}$$

$$\Rightarrow A_0 B_1 + B_0 A_1 = C_0 + C_1 - C_2. \text{ Rather } C_0 + C_1 - S_A S_B C_2$$

to account for signs.

( $\sim \frac{n}{2}$  sized)

Here we are using 3 multiplications instead of 4.

$$\Rightarrow T(n) = 3T\left(\frac{n}{2}\right) + O(n).$$

// Toom-Cook

i-way algorithm

$$\Rightarrow T(n) = O(n^{\log_2 3}) \approx O(n^{1+\epsilon}).$$

Instead of  $C_2$  as above, we can also consider  $C_2$  to be  $(A_0 + A_1) \cdot (B_0 + B_1)$ .

// Using difference

$$\Rightarrow A_0 B_1 + A_1 B_0 = C'_2 - (C_1 + C_2). \quad \text{lets us store smaller numbers.}$$

Schonhage-Strassen algorithm.

$O(n \cdot \log n \cdot 2^{\log^* n})$

Runs in time  $O(n \cdot \log n \cdot \log \log n)$ .

Fürer 2007

$O(n \cdot \log n \cdot 2^{\log^* n})$

But we need more mathematical tools.

De, Kaur  
Saha Saptharishi

2008.

Discrete Fourier Transform:

Assumptions:

1. n is a power of 2

We are working over Rings  $a+b=0$

$(R, +, \times, 0, 1)$

2.  $\exists$  a multiplicative inverse for n.

→ additive inverse  
→ associativity.

That is  $\exists m$  s.t  $n \cdot m = 1$ .

$\left(\frac{1}{n}\right)$

$\mathbb{Z}/n\mathbb{Z} = \mathbb{Z} \bmod n$

3.  $\exists$  a primitive  $n^{\text{th}}$  root of  $1$ , say  $\omega$ .  
 That is  $\omega^n = 1$  and  $\forall k \in [1, n-1], \omega^k \neq 1$ .

$$\checkmark \left\{ e^{j \frac{2\pi i}{n} k} \right\}_{k=0}^{n-1}$$

$n^{\text{th}}$  roots of unity.

$$\omega = e^{j \frac{2\pi i}{n}}$$

Obs:  $\sum_{i=0}^{n-1} \omega^i = 0$ . Further,  $\sum_{i=0}^n \omega^{ij} = 0 \quad \forall j \neq 0$ .

DFT matrix  $A$ :

$$0 \leq i, j \leq n-1, \quad A_{ij} = \omega^{ij}$$

$$\left( \tilde{A}^{-1} \right)_{ij} = \frac{1}{n} \omega^{-i \cdot j}.$$

Definition:

Let  $\vec{a} = (a_0, a_1, \dots, a_{n-1})$ . Then the discrete Fourier Transform of  $\vec{a}$  is given as follows:

$$F_n(\vec{a}) = A \cdot (\vec{a})^T \quad \xrightarrow{\text{transpose.}}$$

$$\begin{aligned} b_0 &= \begin{bmatrix} \omega^0 & \omega^0 & \dots & \omega^0 \\ \omega^0 & \omega^1 & \omega^2 & \dots \\ \omega^0 & \omega^2 & \omega^4 & \dots \\ \dots & \dots & \dots & \dots \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_{n-1} \end{bmatrix} \\ b_n &= \\ b_{n-1} &= \end{aligned}$$

DFT of  
 $\vec{a}$ .

Inverse DFT of  $\vec{a} = \tilde{A}^{-1} \cdot (\vec{a})^T$ .

Note that  $\text{DFT}(\text{Inv-DFT})(\vec{a}) = (\vec{a})^T$ .

and  $\text{Inv-DFT}(\text{DFT})(\vec{a}) = (\vec{a})^T$ .

Qn: What is the complexity of computing  $\text{DFT}(\vec{a})$ ?

# Fast Fourier Transform: [Cooley-Tukey]

Let  $(\vec{b})^T = A \cdot (\vec{a})^T$ . // we want to obtain  $(\vec{b})_i \forall i$ .

$$b_i = \sum_{j=0}^{n-1} w^{ij} \cdot a_j = \left( \sum_{j=0}^{n_2-1} w^{ij} a_j \right) + w^{\frac{n}{2}i} \left( \sum_{j=0}^{\frac{n}{2}-1} w^{ij} a_{j+\frac{n}{2}} \right)$$

$\nwarrow$

$(w^{ij})$

$\sum_{j=0}^{\frac{n}{2}-1} w^{ij} a_{j+\frac{n}{2}}$

$\sum_{j=0}^{\frac{n}{2}-1} w^{ij} a_j$

Note that  $w^{\frac{n}{2}} = -1$ .

$$\Rightarrow b_i = \sum_{j=0}^{\frac{n}{2}-1} w^{ij} \left( a_j + (-1)^i \cdot a_{j+\frac{n}{2}} \right)$$

$i$  is even

$$\sum_{j=0}^{\frac{n}{2}-1} w^{ij} \left( a_j + a_{j+\frac{n}{2}} \right)$$

$i$  is odd.

$$\sum_{j=0}^{\frac{n}{2}-1} w^{ij} \left( a_j - a_{j+\frac{n}{2}} \right)$$

$$= \sum_{j=0}^{n-1} w^{ij} \cdot a_j$$

②

$$\left. \begin{array}{l} C_k = a_k + a_{k+\frac{n}{2}} \\ D'_k = a_k - a_{k+\frac{n}{2}} \end{array} \right\} \quad \begin{array}{l} \forall 0 \leq k \leq \frac{n}{2}-1. \\ i = 2p \\ i = 2p+1. \end{array}$$

Qn: Can we write ① or ② as Fourier Transforms of size  $\frac{n}{2}$ ?

For that we need  $\frac{n}{2}$ th root of unity.

Obs:  $w^2$  is a  $\frac{n}{2}$ th root of unity.

$$F_n(\vec{a}) = A(\vec{a})^T$$

Say  $i = 2p$  for some  $p$ . i = 2p

$$\textcircled{1} = \sum_{j=0}^{\frac{n}{2}-1} w^{ij} C_j = \sum_{j=0}^{\frac{n}{2}-1} (w^2)^{p,j} C_j = \left[ F_{\frac{n}{2}}(\vec{C}) \right]_p$$

$w^{2p,j} \rightarrow (w^2)^{p,j}$

Else say  $i = 2p+1$  for some  $p$ .

$$\textcircled{2} = \sum_{j=0}^{\frac{n}{2}-1} w^{ij} D'_j = \sum_{j=0}^{\frac{n}{2}-1} (w^2)^{p,j} \cdot (\underline{w^j \cdot D'_j}) = \left[ F_{\frac{n}{2}}(\vec{D}) \right]_p$$

where  $\underline{D'_{ik}} = D'_{ik} \cdot \underline{w^k}$   
 $= (a_{ik} - a_{k+\frac{n}{2}}) \cdot w^k$

Putting it all together, we get that

$$b_i = \left[ F_n(\vec{a}) \right]_i = \begin{cases} \left[ F_{\frac{n}{2}}(\vec{C}) \right]_{\frac{i}{2}} & \text{if } i \text{ is even,} \\ \left[ F_{\frac{n}{2}}(\vec{D}) \right]_{\frac{i-1}{2}} & \text{otherwise.} \end{cases}$$

$$\Rightarrow T(n) = 2 \cdot T\left(\frac{n}{2}\right) + cn$$

$$= O(n \cdot \log n).$$

## Convolution of two vectors:

Let  $\vec{a} = (a_0, \dots, a_{n-1})$  and  $\vec{b} = (b_0, \dots, b_{n-1})$  Then the convolution of  $a$  and  $b$  is as follows

$$\forall 0 \leq i \leq 2n-2, (a * b)_i = \sum_{\substack{j+k=i \\ 0 \leq j, k \leq n-1}} a_j b_k.$$

Rewriting this, we get that

$$\forall i \leq n-1, (a * b)_i = \sum_{j=0}^i a_j \cdot b_{i-j} .$$

and

$$\forall i \geq n, (a * b)_i = \sum_{j=i-(n-1)}^{n-1} a_j \cdot b_{i-j} .$$

Obs: Let  $a' = (a_0, \dots, a_{n-1}, \overbrace{0, \dots, 0}^n)$  and  $b' = (b_0, \dots, b_{n-1}, \overbrace{0, \dots, 0}^n)$ .

Then  $(a * b)_i = \sum_{j=0}^i a'_j \cdot b'_{i-j} .$

$$\xrightarrow{(F_{2n}(a') \odot F_{2n}(b'))} = F_{2n}(a * b)$$

Theorem:

$$\underline{\underline{F_{2n}^{-1}}}\left(F_{2n}(a') \odot F_{2n}(b')\right) = \underline{a * b} .$$

$$(a_1, \dots, a_n) \odot (b_1, \dots, b_n) \\ = (a_1 b_1, \dots, a_n b_n)$$

↑ pointwise multiplication.

As a result  $a * b$  can be computed in time  $O(n \log n)$ .  
 $A = a_n x^{n-1} + \dots + a_0 ;$

Application: Univariate polynomial multiplication.

Let  $\underline{P_A}(x) = a_{n-1} x^{n-1} + a_{n-2} x^{n-2} + \dots + a_0$

$$\underline{A} = \underline{P_A}(\underline{\beta})$$

and  $\underline{P_B}(x) = b_{n-1} x^{n-1} + b_{n-2} x^{n-2} + \dots + b_0 .$

$$\underline{B} = \underline{P_B}(\underline{\beta})$$

Then  $\underline{P_A}(x) \cdot \underline{P_B}(x) = \sum_{i=0}^{2n-1} (a * b)_i x^i .$

$$A \cdot B = (P_A \cdot P_B)(\beta).$$

} From above,  
we get that  
the product can  
be obtained in  
 $O(n \log n)$  time.

Next class: DFT in mod-m rings; Chinese Remaindering  
and Schönhage-Strassen algorithm.

$$\begin{array}{c} \text{Z mod } z^m + 1 \\ \downarrow \\ \text{Z mod m} \end{array}$$