

# FAST FOURIER TRANSFORM\*

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A polynomial  $\mathbf{p} = (p_0, \dots, p_n)$  is a finite sequence of real numbers. The function  $\mathbf{p}(x)$  induced by  $\mathbf{p}$  is defined by

$$\mathbf{p}(x) := \sum_{i=0}^n p_i x^i.$$

For polynomials  $\mathbf{a} = (a_0, \dots, a_n)$  and  $\mathbf{b} = (b_0, \dots, b_n)$ , we define their *sum* as  $\mathbf{a} + \mathbf{b} := (a_0 + b_0, \dots, a_n + b_n)$ , and their *product* as  $\mathbf{a} * \mathbf{b} := (c_0, \dots, c_{2n})$  where  $c_k := \sum_{j+j'=k} a_j b_{j'}$ . It is easy to verify that

$$\begin{aligned}(\mathbf{a} + \mathbf{b})(x) &= \mathbf{a}(x) + \mathbf{b}(x) \\ (\mathbf{a} * \mathbf{b})(x) &= \mathbf{a}(x) \mathbf{b}(x)\end{aligned}\tag{1}$$

for all  $x$ . So polynomial addition and multiplication are in line with the usual notions of function addition and multiplication.

Multiplying two polynomials needs  $\Theta(n^2)$  time if we follow the definition plainly. Can we do it faster? To this end we need an alternative representation.

Let us fix  $m+1$  points  $X = \{x_0, \dots, x_m\}$ . Given an arbitrary polynomial  $\mathbf{p} = (p_0, \dots, p_n)$  where  $n \leq m$ , we evaluate the function  $\mathbf{p}(x)$  on  $X$ . This can be expressed as

$$\begin{pmatrix} \mathbf{p}(x_0) \\ \mathbf{p}(x_1) \\ \vdots \\ \mathbf{p}(x_m) \end{pmatrix} = \begin{pmatrix} 1 & x_0 & \cdots & x_0^m \\ 1 & x_1 & \cdots & x_1^m \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_m & \cdots & x_m^m \end{pmatrix} \begin{pmatrix} p_0 \\ p_1 \\ \vdots \\ p_n \\ \mathbf{0} \end{pmatrix}\tag{2}$$

where  $\mathbf{0}$  pads the vector with  $m - n$  zeros. The van der Monde matrix in the middle is invertible as  $x_0, \dots, x_m$  are distinct. Hence  $(p_0, \dots, p_n)$  and  $(\mathbf{p}(x_0), \dots, \mathbf{p}(x_m))$  uniquely determine each other, and we shall call them the *standard* and *functional* representations, respectively, of the same polynomial  $\mathbf{p}$ .

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\*, The note is inspired by a lecture by Erik Demaine.

In the functional representation, polynomial product becomes point-wise product; see (1). This suggests the following method for computing  $a * b =: c$ .

- Fix  $m := 2n$  and distinct points  $x_0, \dots, x_m$ .
- Convert  $a$  and  $b$  to functional representations  $(a(x_0), \dots, a(x_m))$  and  $(b(x_0), \dots, b(x_m))$ .
- Multiply point-wise to obtain  $(c(x_0), \dots, c(x_m))$ , the functional representation of  $c$ .
- Convert  $c$  back to its standard representation.

The “multiply” step costs merely  $\Theta(n)$  time. Next we will show how to implement the conversions in  $\Theta(n \log n)$  time.

We begin with the forward conversion, i.e. evaluating a polynomial  $p = (p_0, \dots, p_n)$  at points  $X$ . A naïve implementation would incur  $\Theta(n^2)$  cost. To speed it up, let us try divide-and-conquer by breaking the evaluation at  $x \in X$  into odd and even parts:

$$\begin{aligned} p(x) &= \sum_{j=0}^n p_j x^j = \sum_{j=0}^{n/2} p_{2j} x^{2j} + \sum_{j=0}^{n/2} p_{2j+1} x^{2j+1} \\ &= \sum_{j=0}^{n/2} p_{2j} (x^2)^j + x \cdot \sum_{j=0}^{n/2} p_{2j+1} (x^2)^j \end{aligned}$$

Hence, denoting  $p_{\text{even}} := (p_0, p_2, \dots)$  and  $p_{\text{odd}} := (p_1, p_3, \dots)$ , we have the identity  $p(x) = p_{\text{even}}(x^2) + x \cdot p_{\text{odd}}(x^2)$ . This immediately leads to the following algorithm:

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fn evaluate( $p, X$ )
  if  $p = (p_0)$  then
    return  $(p_0, \dots, p_0)$ 
  else
     $X' := \{x^2 : x \in X\}$ 
     $p_{\text{even}} := (p_0, p_2, \dots)$ 
     $p_{\text{odd}} := (p_1, p_3, \dots)$ 
    return evaluate( $p_{\text{even}}, X'$ ) +  $X \cdot$  evaluate( $p_{\text{odd}}, X'$ )

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Let  $T(n)$  denote the running time. Clearly we have the recursion

$$T(n) = 2T(n/2) + \Theta(m),$$

thus  $T = \Theta(nm) = \Theta(n^2)$ . Unfortunately it is no better than the naïve solution.

But we have a last resort. So far we did not assume any specific property of the evaluation points  $X$ . Can we craft  $X$  so that it halves in size after each recursive call?

Yes! If we set  $X := \{(m+1)\text{-th roots of unity}\} \subseteq \mathbb{C}$ , then after squaring, one half of the points fold into the other half, and we obtain  $X' = \{(\frac{m+1}{2})\text{-th roots of unity}\}$ . With this choice, the running time recursion becomes

$$T(n+m) = 2T((n+m)/2).$$

Hence  $T = \Theta(n \log n)$ .

The divide-and-conquer algorithm invoked on such  $X$  is dubbed *Fast Fourier Transform*. Why is the name? Recall equation (2): the van der Monde matrix contains entries  $x_j^k = \exp\left(i \cdot \frac{2\pi jk}{m+1}\right) = \cos\left(\frac{2\pi jk}{m+1}\right) + i \cdot \sin\left(\frac{2\pi jk}{m+1}\right)$ , which form a Fourier basis. So evaluating  $p$  at  $X$  is equivalent to mixing the sine/cosine waves of different frequencies via coefficients  $p$ . In Fourier analysis jargon, the standard representation lives in *frequency domain*, and the functional representation lives in *time domain*.

How do we convert from functional representation back to standard representation? Let us derive an inverse formula based on equation (2). We claim that, with our choice of  $X$ ,

$$\begin{pmatrix} 1 & \overline{x_0} & \cdots & \overline{x_0^m} \\ 1 & \overline{x_1} & \cdots & \overline{x_1^m} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \overline{x_m} & \cdots & \overline{x_m^m} \end{pmatrix} \begin{pmatrix} 1 & x_0 & \cdots & x_0^m \\ 1 & x_1 & \cdots & x_1^m \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_m & \cdots & x_m^m \end{pmatrix} = (m+1) \cdot I.$$

where the bar over a number denotes its complex conjugate. Indeed, we can calculate the result at cell  $(j, k)$  by

$$\begin{aligned} \sum_{\ell=0}^m \overline{x_j^\ell} \cdot x_k^\ell &= \sum_{\ell=0}^m \exp\left(-i \cdot \frac{2\pi j \ell}{m+1}\right) \cdot \exp\left(i \cdot \frac{2\pi \ell k}{m+1}\right) \\ &= \sum_{\ell=0}^m \exp\left(\frac{2\pi \ell i}{m+1} \cdot (k-j)\right). \end{aligned}$$

If  $j=k$  then the result is  $m+1$ . Otherwise, the summands rotate around the unit circle in the complex plane and cancel each other, so we get a zero.

With the claim we derive

$$\begin{pmatrix} p_0 \\ p_1 \\ \vdots \\ p_n \\ \mathbf{0} \end{pmatrix} = \frac{1}{m+1} \begin{pmatrix} 1 & \bar{x}_0 & \cdots & \bar{x}_0^m \\ 1 & \bar{x}_1 & \cdots & \bar{x}_1^m \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \bar{x}_m & \cdots & \bar{x}_m^m \end{pmatrix} \begin{pmatrix} \mathbf{p}(x_0) \\ \mathbf{p}(x_1) \\ \vdots \\ \mathbf{p}(x_m) \end{pmatrix}.$$

Now comes the punchline. We pretend that  $(\mathbf{p}(x_0), \dots, \mathbf{p}(x_m))$  is a polynomial, then  $(p_0, \dots, p_n, \mathbf{0})$  is exactly its evaluation at points  $\frac{1}{m+1} \bar{X}$ . So we can recover the latter by just calling  $\text{evaluate}((\mathbf{p}(x_0), \dots, \mathbf{p}(x_m)), \frac{1}{m+1} \bar{X})!$