

# The Fast Fourier Transform (FFT)

Known for centuries, first published in 1965 by Cooley/Tukey

A direct computation of DFT for vector of length  $N$  takes  $N^2$  multiplications. FFT takes  $O(N \log N)$  (if  $N=2^p$ )

$$W = \sqrt[N]{1} = e^{\frac{2\pi i}{N}}, \text{ so } W^N = 1, W^{\frac{N}{2}} = -1$$

$$\text{DFT: } \hat{f}_k = \sum_{m=0}^{N-1} f_m W^{mk} \quad \begin{matrix} k=0 \dots N-1 \\ m=0 \dots N-1 \end{matrix}$$

Assume  $N$  is even

$$k = k_1 \cdot \frac{N}{2} + k_2$$

$$\begin{matrix} k_1 = 0, 1 \\ k_2 = 0 \dots \frac{N}{2}-1 \end{matrix}$$

$$m = m_1 + 2m_2$$

$$\begin{matrix} m_1 = 0, 1 \\ m_2 = 0 \dots \frac{N}{2}-1 \end{matrix}$$

example:  $N=8$

$m, k$	0	1	2	3	4	5	6	7
$k_1$	0	0	0	0	1	1	1	1
$k_2$	0	1	2	3	0	1	2	3
$m_1$	0	1	0	1	0	1	0	1
$m_2$	0	0	1	1	2	2	3	3

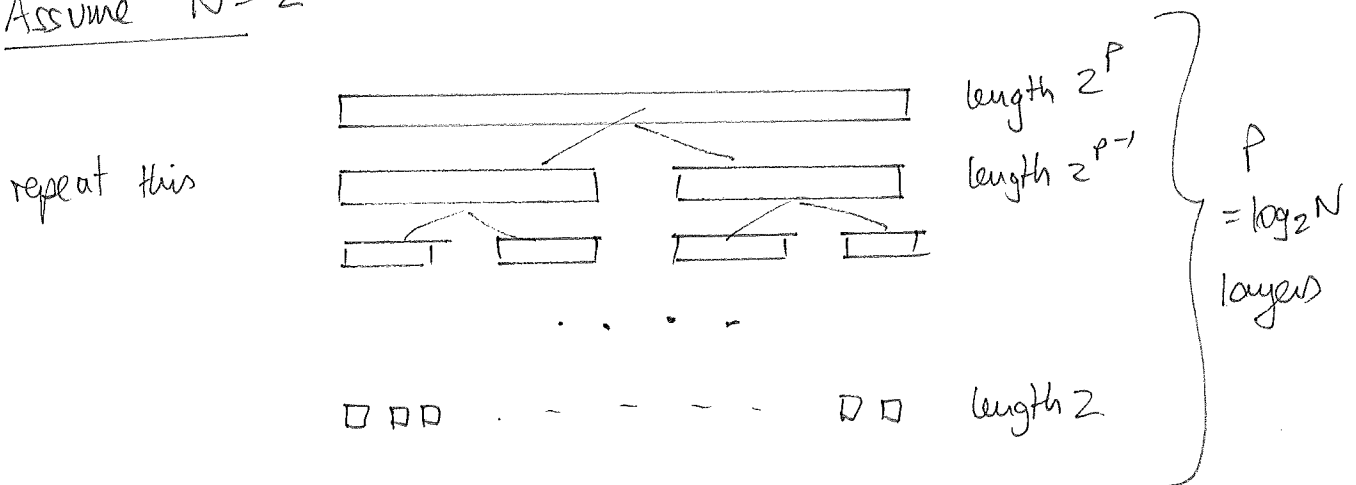
$$\begin{aligned} \hat{f}_{k_1 \cdot \frac{N}{2} + k_2} &= \sum_{m_1=0}^1 \sum_{m_2=0}^{\frac{N}{2}-1} f_{m_1+2m_2} W^{(m_1+2m_2)(k_1 \cdot \frac{N}{2} + k_2)} \\ &= \underbrace{W^{m_1 k_1 \frac{N}{2}}}_{=(-1)^{m_1 k_1}} \cdot \underbrace{W^{m_2 k_1 N}}_{=1} \cdot W^{m_1 k_2} \cdot \underbrace{W^{2m_2 k_2}}_{=(W^2)^{m_2 k_2}} \end{aligned}$$

$$\begin{aligned}
 \hat{f}_{k_1 \frac{N}{2} + k_2} &= \sum_{m_1=0}^1 (-1)^{m_1 k_1} \omega^{m_1 k_2} \sum_{m_2=0}^{\frac{N}{2}-1} f_{m_1 + 2m_2} (\omega^2)^{m_2 k_2} \\
 &= \underbrace{\sum_{m_2=0}^{\frac{N}{2}-1} f_{2m_2} (\omega^2)^{m_2 k_2}}_{m_1=0} + (-1)^{k_1} \omega^{k_2} \underbrace{\sum_{m_2=0}^{\frac{N}{2}-1} f_{2m_2+1} (\omega^2)^{m_2 k_2}}_{m_1=1} \quad (*)
 \end{aligned}$$

$\underbrace{\quad}_{m_1=0}$  = DFT of terms with even subscript  
 $\underbrace{\quad}_{m_1=1}$  = DFT of terms with odd subscript  
 "twiddle factor"

What we have done is to write the original DFT of length  $N$  as a combination of 2 DFTs of length  $\frac{N}{2}$ , plus  $O(N)$  operations to put them together.

Assume  $N = 2^P$



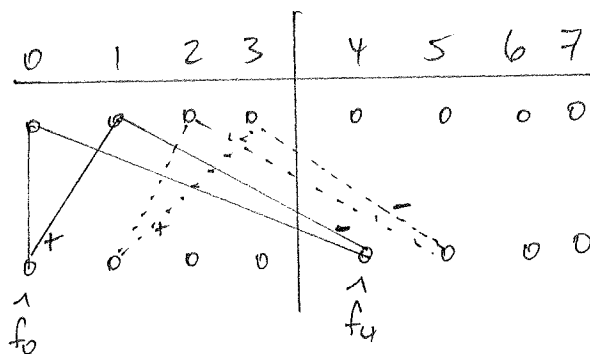
This is where the  $O(N \log N)$  operation count comes from.

Combine the two sums in  $\textcircled{*}$  into one, but split the left side into  $k_1=0$  and  $k_1=1$ :

$$\begin{aligned} \underline{k_1=0} \quad \hat{f}_{k_2} &= \sum_{m_2=0}^{\frac{N}{2}-1} f_{2m_2} (w^2)^{m_2 k_2} + w^{k_2} \sum_{m_2=0}^{\frac{N}{2}-1} f_{2m_2+1} (w^2)^{m_2 k_2} \\ &= \sum_{m_2=0}^{\frac{N}{2}-1} \underbrace{[f_{2m_2} + w^{k_2} f_{2m_2+1}]}_{\text{"butterfly operation"}} (w^2)^{m_2 k_2} \end{aligned}$$

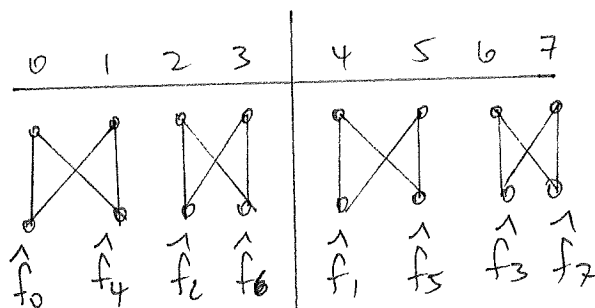
$$\underline{k_1=1} \quad \hat{f}_{k_2 + \frac{N}{2}} = \sum_{m_2=0}^{\frac{N}{2}-1} [f_{2m_2} - w^{k_2} f_{2m_2+1}] (w^2)^{m_2 k_2}$$

Example first layer for  $N=8$



problem  $f_0, f_1$  combine into  $\hat{f}_0, \hat{f}_4$  but we can't store  $\hat{f}_4$  where  $f_4$  used to be

solution store  $\hat{f}_4$  where  $f_0$  used to be instead



What is the order?

answer: bit-reversed subscripts

$$N=8=2^3$$

	3-bit binary	reverse	
0	000	000	0
1	001	100	4
2	010	010	2
3	011	110	6
4	100	001	1
5	101	101	5
6	110	011	3
7	111	111	7

compare

### Generalizations

- ① Instead of dividing by 2, you could use 3, 5, ...  
For good results,  $N$  should factor into powers of small prime numbers.

If  $N$  = prime, there is no speedup.

You may have to pad the data with a few zeros to get to a good  $N$

② the DFT originally goes complex  $\rightarrow$  complex.  
If your data is real, you can save some effort.

The FT of real signal has real part even, imaginary part odd. You could put half the signal in real part of a shorter vector, the other half in imaginary part, and sort things out by splitting  $\hat{f}$  into even/odd parts.

Even better, use real version of DFT, such as the DCT (discrete cosine transform, used in JPEG)

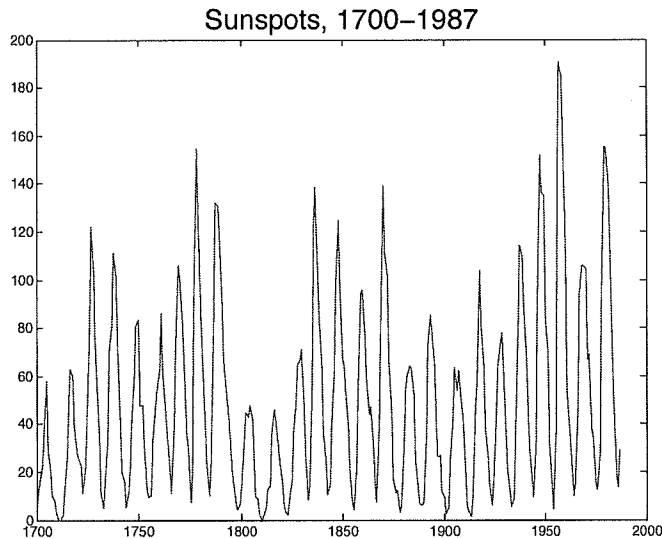
### Applications

①  $\hat{f} * \hat{g} \xrightarrow{\text{DFT}} \hat{f} \cdot \hat{g}$   
convolution  $\rightarrow$  multiplication

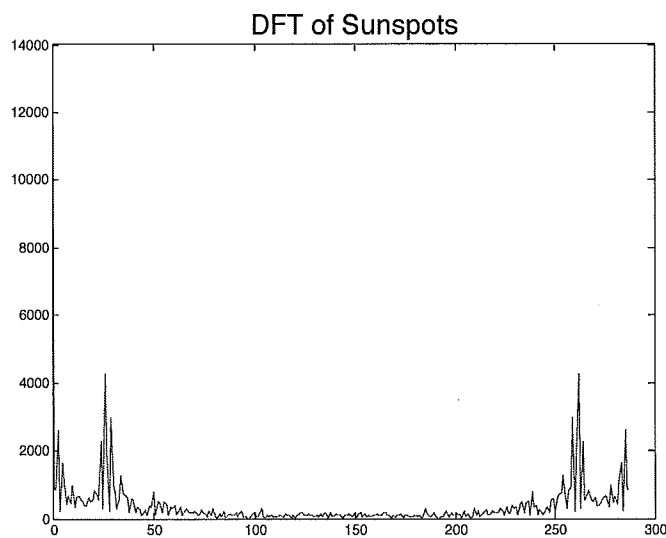
②  $\begin{pmatrix} a_1 & a_2 & \dots & a_n \\ a_n & a_1 & a_2 & \dots & a_{n-1} \\ a_{n-1} & a_n & a_1 & \dots & a_{n-2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_2 & a_3 & \dots & \dots & a_1 \end{pmatrix} \xrightarrow{\text{DFT}} \begin{pmatrix} \hat{a}_1 & & & & \\ & \hat{a}_2 & & & \\ & & \ddots & & \\ & & & \ddots & \\ & & & & \hat{a}_n \end{pmatrix}$   
circulant matrix  $\rightarrow$  diagonal matrix

## Example for applying FFT

- Assume signal is real, length  $N$
- Take FFT. The transform will be complex.  
Real part is even around middle  
Imaginary part is odd
- We usually look at absolute value.  
This is even about middle.  
Only values in first half are relevant
- peak at 0 is the average. You can ignore that
- if there is a big peak at index  $k$   
(starting with index 0, not 1), that indicates  
a component with  $k$  periods in the  $N$  data points  
 $\Rightarrow$  period  $\frac{N}{k}$
- Sometimes a strong peak "bleeds over" into  
nearby values. Maybe the actual period does  
not fit neatly into the signal length, or the  
period fluctuates a little.

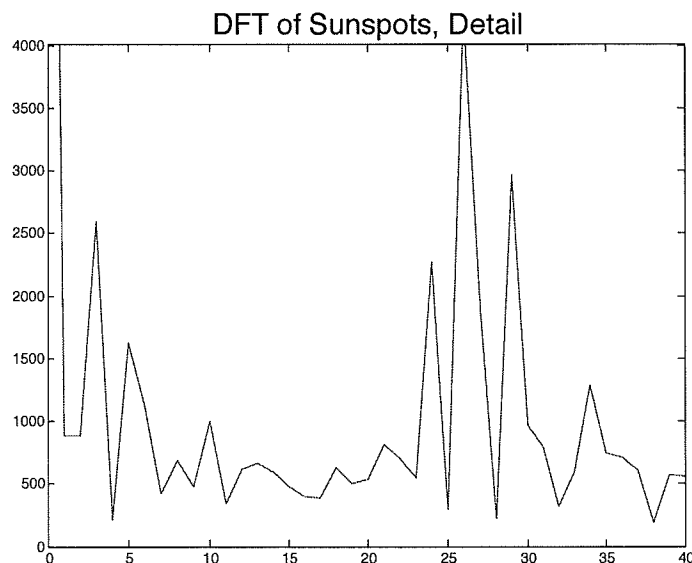


count of sunspots per year,  
1700 - 1987



Note: - big peak at 0  
(hard to see)  
does not mean anything

- big peak around 30
- plot is symmetric about middle;  
only left half is relevant



- peak is at index 26  
signal length is 288  
 $\Rightarrow$  peak corresponds to  
26 periods in 288 years  
period is  $\approx \frac{288}{26} \approx 11$  years
- other peaks at 24, 29 may be  
caused by same period
- more minor peaks at 3, 5  
indicate periodicity around  
 $\frac{288}{4} = 72$  years