ESE 531: Digital Signal Processing

Lec 21: April 9, 2019

Fast Fourier Transform



Last Time

- Discrete Fourier Transform
 - Linear convolution through circular convolution
 - Overlap and add
 - Overlap and save
 - Circular convolution through DFT
- Today
 - The Fast Fourier Transform

Circular Convolution

Circular Convolution:

$$x_1[n] \otimes x_2[n] \stackrel{\Delta}{=} \sum_{m=0}^{N-1} x_1[m] x_2[((n-m))_N]$$

For two signals of length N

Note: Circular convolution is commutative

$$x_2[n] \otimes x_1[n] = x_1[n] \otimes x_2[n]$$

Circular Convolution

$$h[n] \otimes x[n] = \sum_{m=0}^{N-1} h[((n-m))_N]x[m]$$

Circulant matrix

Circular Convolution

$$h[n] \otimes x[n] = \begin{bmatrix} h[0] & h[N-1] & \cdots & h[1] \\ h[1] & h[0] & & h[2] \\ & & \vdots & \\ h[N-1] & h[N-2] & & h[0] \end{bmatrix} \begin{bmatrix} x[0] \\ x[1] \\ \vdots \\ x[N-1] \end{bmatrix}$$

$$= H_{c}x$$

$$W_{N} = \begin{pmatrix} w_{N}^{00} & \cdots & w_{N}^{0n} & \cdots & w_{N}^{0(N-1)} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ w_{N}^{k0} & \cdots & w_{N}^{kn} & \cdots & w_{N}^{k(N-1)} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ w_{N}^{(N-1)0} & \cdots & w_{N}^{(N-1)n} & \cdots & w_{N}^{(N-1)(N-1)} \end{pmatrix}$$

Diagonalize

$$W_{N}H_{c}W_{N}^{-1} = \begin{bmatrix} H[0] & 0 \cdots & 0 \\ 0 & H[1] \cdots & 0 \\ \vdots & 0 & H[N-1] \end{bmatrix}$$

Diagonalize

$$W_N H_c W_N^{-1} = \begin{bmatrix} H[0] & 0 \cdots & 0 \\ 0 & H[1] \cdots & 0 \\ \vdots & 0 & H[N-1] \end{bmatrix}$$

 $lue{}$ Right-Multiply by W_N

$$W_N H_c = \left[\begin{array}{ccc} H[0] & 0 \cdots & 0 \\ 0 & H[1] \cdots & 0 \\ \vdots & 0 & H[N-1] \end{array} \right] W_N$$

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$$W_N H_c = \left[egin{array}{ccc} H[0] & 0 \cdots & 0 \ 0 & H[1] \cdots & 0 \ dots & 0 & H[N-1] \end{array}
ight] W_N$$

 \square Multiply both sides by x

$$W_N H_{cX} = \left[egin{array}{ccc} H[0] & 0 & \cdots & 0 \\ 0 & H[1] & \cdots & 0 \\ \vdots & 0 & H[N-1] \end{array}
ight] W_{NX}$$

Fast Fourier Transform (FFT)



Fast Fourier Transform Algorithms

■ We are interested in efficient computing methods for the DFT and inverse DFT:

$$X[k] = \sum_{n=0}^{N-1} x[n] W_N^{kn}, \quad k = 0, \dots, N-1$$
$$x[n] = \sum_{k=0}^{N-1} X[k] W_N^{-kn}, \quad n = 0, \dots, N-1$$

$$W_N = e^{-j\left(\frac{2\pi}{N}\right)}$$
.

Reminder: Inverse DFT via DFT

■ Recall that we can use the DFT to compute the inverse DFT:

$$\mathcal{DFT}^{-1}\{X[k]\} = \frac{1}{N} \left(\mathcal{DFT}\{X^*[k]\}\right)^*$$

 Hence, we can just focus on efficient computation of the DFT.

■ Straightforward computation of an N-point DFT (or inverse DFT) requires N² complex multiplications.

Computation Order

- □ Fast Fourier transform algorithms enable computation of an N-point DFT (or inverse DFT) with the order of just N·log₂ N complex multiplications.
 - This can represent a huge reduction in computational load, especially for large N.

N	N ²	$N \cdot \log_2 N$	$\frac{N^2}{N \cdot \log_2 N}$
16	256	64	4.0
128	16,384	896	18.3
1,024	1,048,576	10,240	102.4
8,192	67,108,864	106,496	630.2

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16	256	64	4.0
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1,024	1,048,576	10,240	102.4
8,192	67,108,864	106,496	630.2
6×10^6	36×10^{12}	135×10^6	2.67×10^{5}

^{* 6}Mp image size



Eigenfunction Properties

- Most FFT algorithms exploit the following properties of W_N^{kn} :
 - Conjugate Symmetry

$$W_N^{k(N-n)} = W_N^{-kn} = (W_N^{kn})^*$$

Periodicity in n and k

$$W_N^{kn} = W_N^{k(n+N)} = W_N^{(k+N)n}$$

Power

$$W_N^2 = W_{N/2}$$

FFT Algorithms via Decimation

- Most FFT algorithms decompose the computation of a DFT into successively smaller DFT computations.
 - Decimation-in-time algorithms decompose x[n] into successively smaller subsequences.
 - Decimation-in-frequency algorithms decompose X[k] into successively smaller subsequences.
- Note: Assume length of x[n] is power of 2 ($N = 2^{\nu}$). If not, zero-pad to closest power of 2.

■ We start with the DFT

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$$X[k] = \sum_{n \text{ even}} x[n]W_N^{kn} + \sum_{n \text{ odd}} x[n]W_N^{kn}$$

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$$X[k] = \sum_{n \text{ even}} x[n]W_N^{kn} + \sum_{n \text{ odd}} x[n]W_N^{kn}$$

• These are two DFTs, each with half the number of samples (N/2)

$$X[k] = \sum_{n \text{ even}} x[n]W_N^{kn} + \sum_{n \text{ odd}} x[n]W_N^{kn}$$

Let
$$n = 2r$$
 (n even) and $n = 2r + 1$ (n odd):

$$X[k] = \sum_{n \text{ even}} x[n]W_N^{kn} + \sum_{n \text{ odd}} x[n]W_N^{kn}$$

Let n = 2r (n even) and n = 2r + 1 (n odd):

$$X[k] = \sum_{r=0}^{(N/2)-1} x[2r]W_N^{2rk} + \sum_{r=0}^{(N/2)-1} x[2r+1]W_N^{(2r+1)k}$$



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$$= \sum_{r=0}^{(N/2)-1} x[2r] W_N^{2rk} + W_N^k \sum_{r=0}^{(N/2)-1} x[2r+1] W_N^{2rk}$$

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$$= \sum_{r=0}^{(N/2)-1} x[2r] W_N^{2rk} + W_N^k \sum_{r=0}^{(N/2)-1} x[2r+1] W_N^{2rk}$$

Note that:

$$W_N^{2rk} = e^{-j\left(\frac{2\pi}{N}\right)(2rk)} = e^{-j\left(\frac{2\pi}{N/2}\right)rk} = W_{N/2}^{rk}$$

Remember this trick, it will turn up often.

Let n = 2r (n even) and n = 2r + 1 (n odd):

$$X[k] = \sum_{r=0}^{(N/2)-1} x[2r] W_N^{2rk} + \sum_{r=0}^{(N/2)-1} x[2r+1] W_N^{(2r+1)k}$$

$$= \sum_{r=0}^{(N/2)-1} x[2r] W_N^{2rk} + W_N^k \sum_{r=0}^{(N/2)-1} x[2r+1] W_N^{2rk}$$

$$X[k] = \sum_{r=0}^{(N/2)-1} x[2r] W_{N/2}^{rk} + W_N^k \sum_{r=0}^{(N/2)-1} x[2r+1] W_{N/2}^{rk}$$

Hence:

$$X[k] = \sum_{r=0}^{(N/2)-1} x[2r] W_{N/2}^{rk} + W_N^k \sum_{r=0}^{(N/2)-1} x[2r+1] W_{N/2}^{rk}$$

$$\triangleq G[k] + W_N^k H[k], \quad k = 0, \dots, N-1$$

Hence:

$$X[k] = \sum_{r=0}^{(N/2)-1} x[2r] W_{N/2}^{rk} + W_N^k \sum_{r=0}^{(N/2)-1} x[2r+1] W_{N/2}^{rk}$$

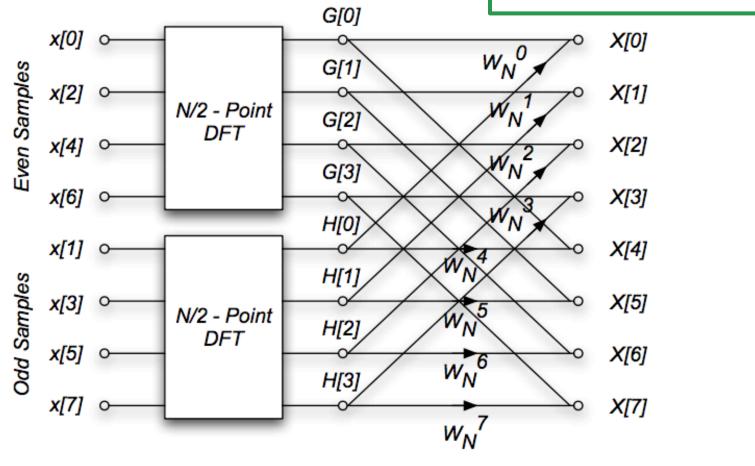
$$\triangleq G[k] + W_N^k H[k], \quad k = 0, \dots, N-1$$

where we have defined:

$$G[k] \stackrel{\triangle}{=} \sum_{r=0}^{(N/2)-1} x[2r]W_{N/2}^{rk} \Rightarrow \text{DFT of even samples}$$
 $H[k] \stackrel{\triangle}{=} \sum_{r=0}^{(N/2)-1} x[2r+1]W_{N/2}^{rk} \Rightarrow \text{DFT of odd samples}$

An 8 sample DFT can then be diagrammed as

$$X[k] = G[k] + W_N^k H[k]$$





Both G[k] and H[k] are periodic, with period N/2. For example

$$G[k] \triangleq \sum_{r=0}^{(N/2)-1} x[2r]W_{N/2}^{rk}$$

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$$G[k] \triangleq \sum_{r=0}^{(N/2)-1} x[2r] W_{N/2}^{rk}$$

$$G[k+N/2] = \sum_{r=0}^{(N/2)-1} x[2r] W_{N/2}^{r(k+N/2)}$$

$$= \sum_{r=0}^{(N/2)-1} x[2r] W_{N/2}^{rk} W_{N/2}^{r(N/2)} = 1$$

$$= \sum_{r=0}^{(N/2)-1} x[2r] W_{N/2}^{rk}$$

$$= G[k]$$

Penn ESE 531 Spring 2019 – Khanna Adapted from M. Lustig, EECS Berkeley

□ So,

$$G[k + (N/2)] = G[k]$$

$$H[k + (N/2)] = H[k]$$

□ The periodicity of G[k] and H[k] allows us to further simplify. For the first N/2 points we calculate G[k] and $W_N^kH[k]$, and then compute the sum

$$X[k] = G[k] + W_N^k H[k] \qquad \forall \{k : 0 \le k < \frac{N}{2}\}.$$

How does periodicity help for $\frac{N}{2} \le k < N$?



$$X[k] = G[k] + W_N^k H[k]$$

$$\forall \{k: 0 \leq k < \frac{N}{2}\}.$$

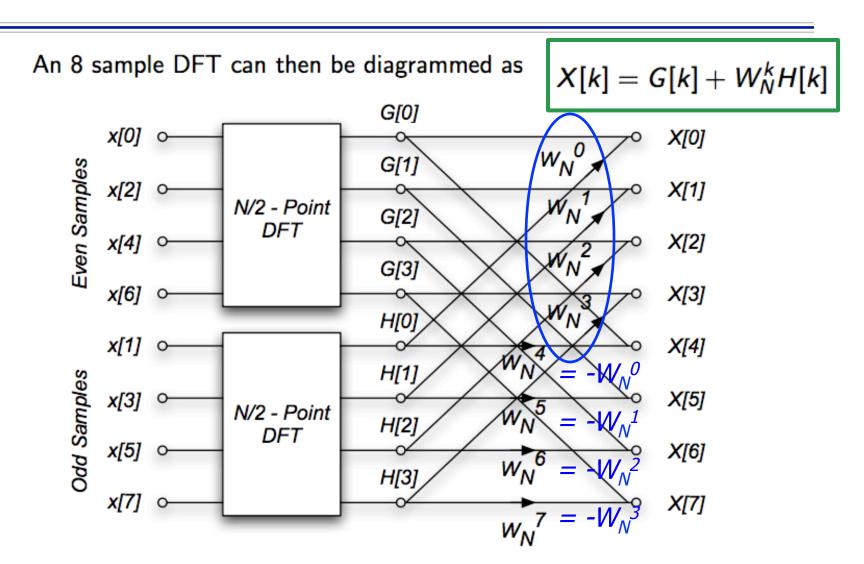
for
$$\frac{N}{2} \le k < N$$
:

$$W_N^{k+(N/2)} = ?$$

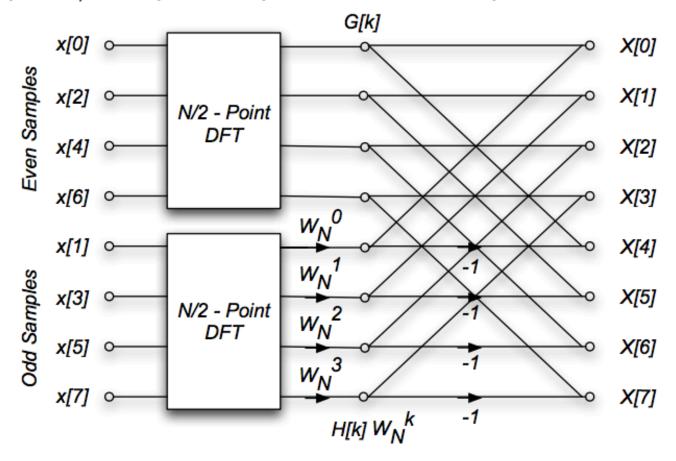
$$X[k + (N/2)] = ?$$

$$X[k + (N/2)] = G[k] - W_N^k H[k]$$

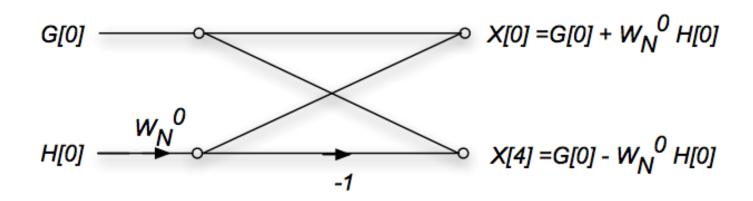
- We previously calculated G[k] and $W_N^kH[k]$.
- Now we only have to compute their difference to obtain the second half of the spectrum. No additional multiplies are required.



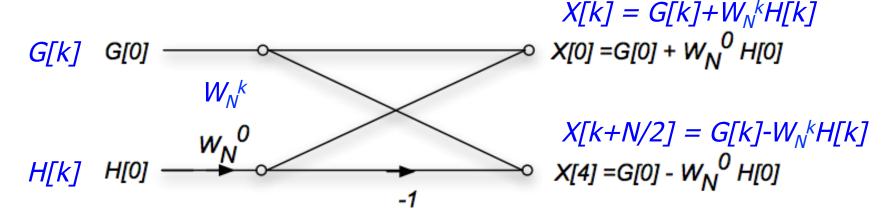
The N-point DFT has been reduced two N/2-point DFTs, plus N/2 complex multiplications. The 8 sample DFT is then:



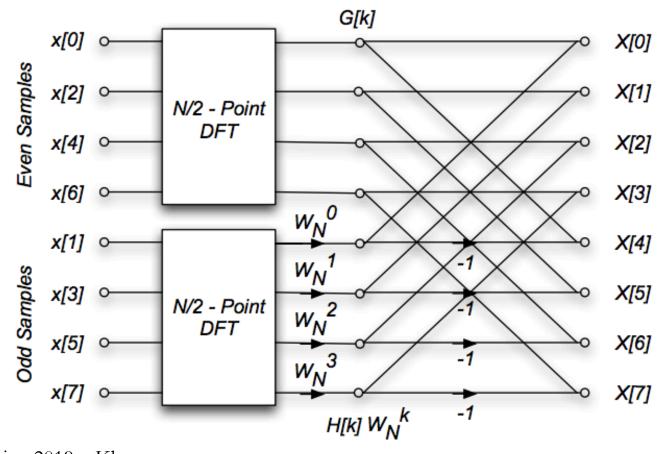
- Note that the inputs have been reordered so that the outputs come out in their proper sequence.
- We can define a *butterfly operation*, e.g., the computation of X[0] and X[4] from G[0] and H[0]:



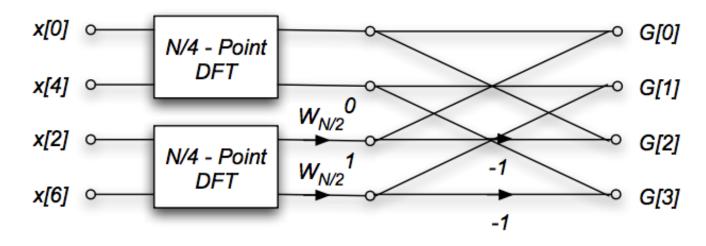
- Note that the inputs have been reordered so that the outputs come out in their proper sequence.
- We can define a *butterfly operation*, e.g., the computation of X[k] and X[k+N/2] from G[k] and H[k]:



□ Still $O(N^2)$ operations.... What should we do?



We can use the same approach for each of the N/2 point DFT's. For the N = 8 case, the N/2 DFTs look like



^{*}Note that the inputs have been reordered again.

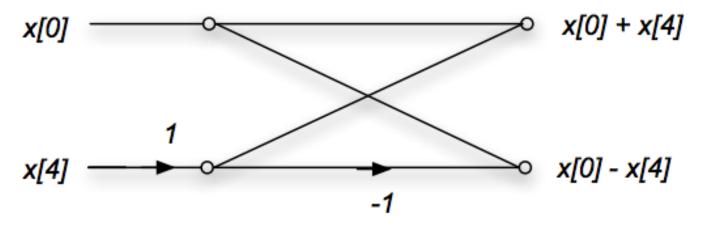


At this point for the 8 sample DFT, we can replace the N/4 = 2 sample DFT's with a single butterfly. The coefficient is

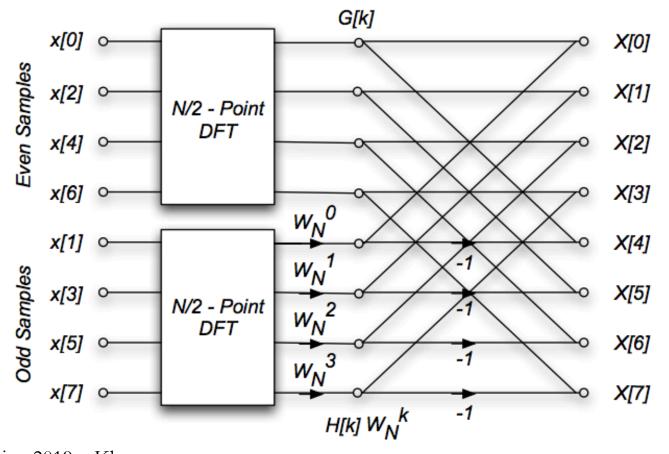
At this point for the 8 sample DFT, we can replace the N/4 = 2 sample DFT's with a single butterfly. The coefficient is

$$W_{N/4} = W_{8/4} = W_2 = e^{-j\pi} = -1$$

The diagram of this stage is then

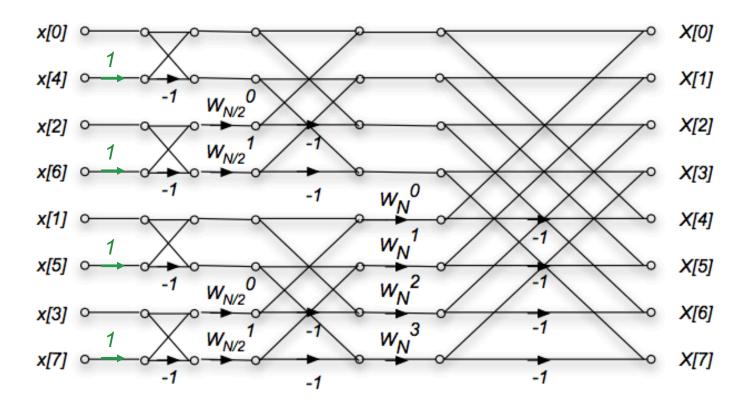


Replace N/2-point DFT with 2-point DFT and butterfly operations

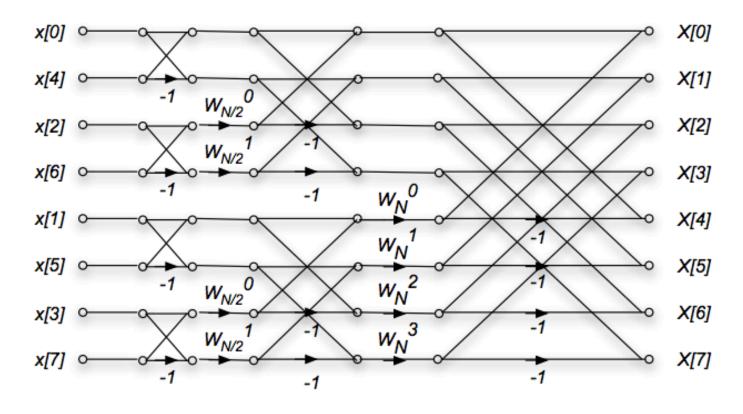




Combining all these stages, the diagram for the 8 sample DFT is:



Combining all these stages, the diagram for the 8 sample DFT is:



- $3 = \log_2(N) = \log_2(8)$ stages
- 4=N/2=8/2 multiplications in each stage
 - 1st stage has trivial multiplication

- □ In general, there are log₂N stages of decimation-in-time.
- Each stage requires N/2 complex multiplications, some of which are trivial.
- □ The total number of complex multiplications is $(N/2) \log_2 N$, or is $O(N \log_2 N)$

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- Each stage requires N/2 complex multiplications, some of which are trivial.
- □ The total number of complex multiplications is $(N/2) \log_2 N$, or is $O(N \log_2 N)$
- □ The order of the input to the decimation-in-time FFT algorithm must be permuted.
 - First stage: split into odd and even.
 - Zero low-order address bit (LSB) first
 - Next stage repeats with next zero-lower bit
 - Net effect is reversing the bit order of indexes

This is illustrated in the following table for N = 8.

Decimal	Binary	
0	000	
1	001	
2	010	
3	011	
4	100	
5	101	
6	110	
7	111	

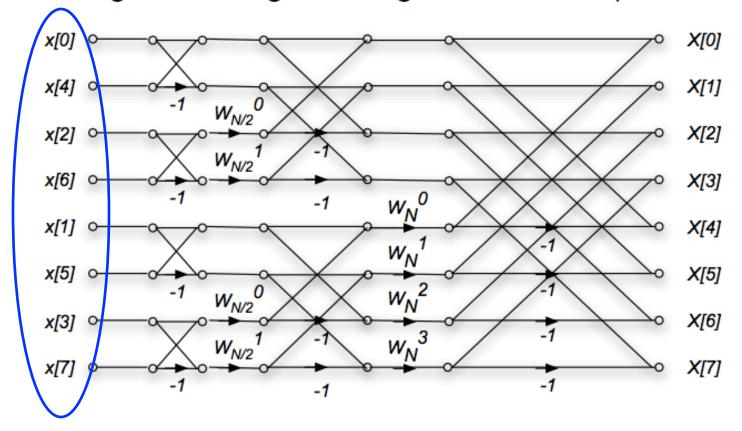
This is illustrated in the following table for N = 8.

Decimal	Binary	Bit-Reversed Binary
0	000	000
1	001	100
2	010	010
3	011	110
4	100	001
5	101	101
6	110	011
7	111	111

This is illustrated in the following table for N = 8.

Decimal	Binary	Bit-Reversed Binary	Bit-Reversed Decimal
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

Combining all these stages, the diagram for the 8 sample DFT is:



The DFT is

$$X[k] = \sum_{n=0}^{N-1} x[n] W_N^{nk}$$

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If we only look at the even samples of X[k], we can write k = 2r,

$$X[2r] = \sum_{n=0}^{N-1} x[n] W_N^{n(2r)}$$



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$$X[2r] = \sum_{n=0}^{N-1} x[n] W_N^{n(2r)}$$

We split this into two sums, one over the first N/2 samples, and the second of the last N/2 samples.

$$X[2r] = \sum_{n=0}^{(N/2)-1} x[n]W_N^{2rn} + \sum_{n=0}^{(N/2)-1} x[n+N/2]W_N^{2r(n+N/2)}$$

But
$$W_N^{2r(n+N/2)} = W_N^{2rn} W_N^{rN} = W_N^{2rn} = W_{N/2}^{rn}$$
. We can then write

$$X[2r] = \sum_{n=0}^{(N/2)-1} x[n] W_N^{2rn} + \sum_{n=0}^{(N/2)-1} x[n+N/2] W_N^{2r(n+N/2)}$$
$$= \sum_{n=0}^{(N/2)-1} x[n] W_N^{2rn} + \sum_{n=0}^{(N/2)-1} x[n+N/2] W_N^{2rn}$$

But
$$W_N^{2r(n+N/2)} = W_N^{2rn}W_N^{rN} = W_N^{2rn} = W_{N/2}^{rn}$$
. We can then write

$$X[2r] = \sum_{n=0}^{(N/2)-1} x[n] W_N^{2rn} + \sum_{n=0}^{(N/2)-1} x[n+N/2] W_N^{2r(n+N/2)}$$

$$= \sum_{n=0}^{(N/2)-1} x[n] W_N^{2rn} + \sum_{n=0}^{(N/2)-1} x[n+N/2] W_N^{2rn}$$

$$= \sum_{n=0}^{(N/2)-1} (x[n] + x[n+N/2]) W_{N/2}^{rn}$$

This is the N/2-length DFT of first and second half of x[n] summed.



$$X[2r] = DFT_{\frac{N}{2}} \{(x[n] + x[n + N/2])\}$$

 $X[2r + 1] = DFT_{\frac{N}{2}} \{(x[n] - x[n + N/2]) W_N^n\}$

(By a similar argument that gives the odd samples)

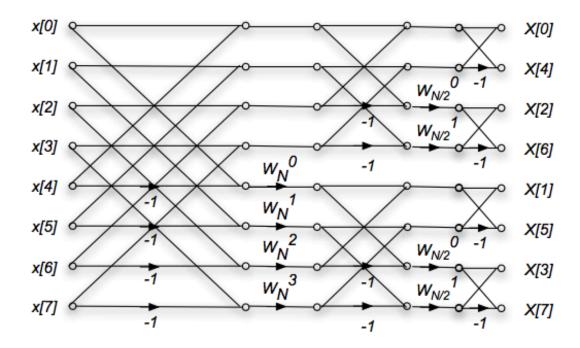
$$X[2r] = DFT_{\frac{N}{2}} \{(x[n] + x[n + N/2])\}$$

 $X[2r+1] = DFT_{\frac{N}{2}} \{(x[n] - x[n + N/2]) W_N^n\}$

(By a similar argument that gives the odd samples)

■ Continue the same approach on the N/2 DFTs, and N/4 DFTs until we reach the 2-point DFT, which is a simple butterfly operation

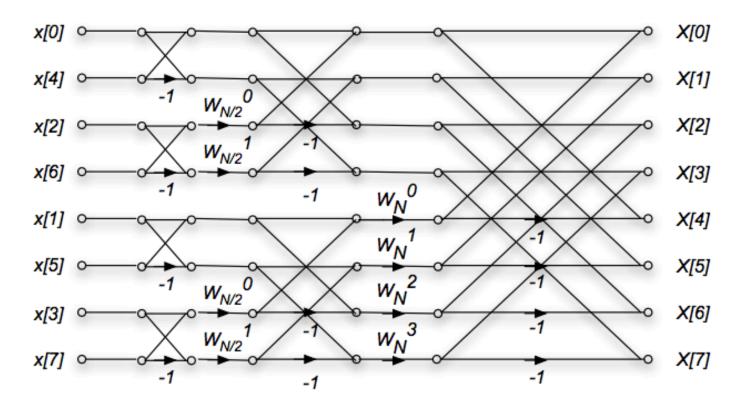
The diagram for and 8-point decimation-in-frequency DFT is as follows



This is just the decimation-in-time algorithm reversed!

The inputs are in normal order, and the outputs are bit reversed.

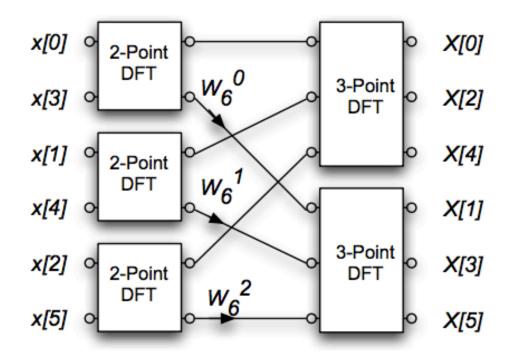
Combining all these stages, the diagram for the 8 sample DFT is:



- $3 = \log_2(N) = \log_2(8)$ stages
- 4=N/2=8/2 multiplications in each stage
 - 1st stage has trivial multiplication



- $lue{}$ A similar argument applies for any length DFT, where the length N is a composite number
- □ For example, if N=6, a decimation-in-time FFT could compute three 2-point DFTs followed by two 3-point DFTs



- □ Good component DFTs are available for lengths up to 20(ish). Many of these exploit the structure for that specific length
 - For example, a factor of

$$W_N^{N/4} = e^{-j\frac{2\pi}{N}(N/4)} = e^{-j\frac{\pi}{2}} = -j$$

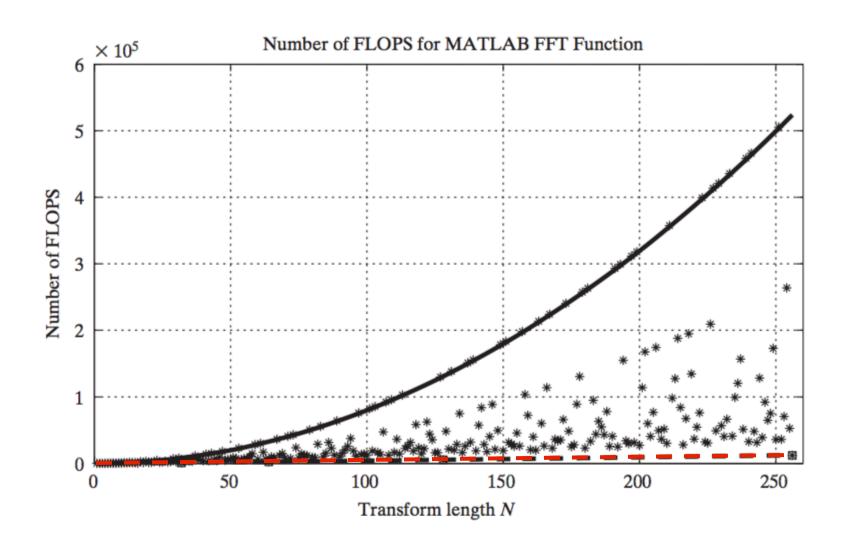
Just swaps the real and imaginary components of a complex number. Hence a DFT of length 4 doesn't require any complex multiples.

- Half of the multiples of an 8-point DFT also don't require multiplication
- Composite length FFTs can be very efficient for any length that factors into terms of this order

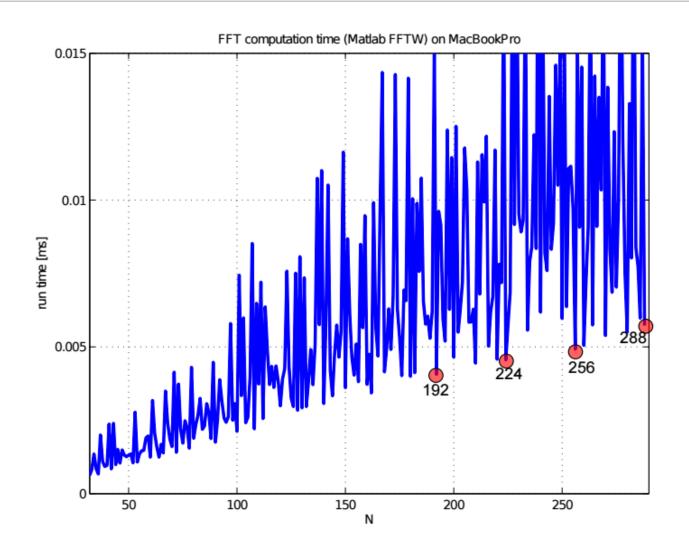
- \blacksquare For example N = 693 factors into
 - N = (7)(9)(11)
- each of which can be implemented efficiently. We would perform
 - 9 x 11 DFTs of length 7
 - 7 x 11 DFTs of length 9, and
 - 7 x 9 DFTs of length 11

- □ Historically, the power-of-two FFTs were much faster (better written and implemented).
- □ For non-power-of-two length, it was faster to zero pad to power of two.
- Recently this has changed. The free FFTW package implements very efficient algorithms for almost any filter length. Matlab has used FFTW since version 6

FFT Computation FLOPS



FFT Computation Time



FFT as Matrix Operation

$$\begin{pmatrix} X[0] \\ \vdots \\ X[k] \\ \vdots \\ X[N-1] \end{pmatrix} = \begin{pmatrix} W_N^{00} & \cdots & W_N^{0n} & \cdots & W_N^{0(N-1)} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ W_N^{k0} & \cdots & W_N^{kn} & \cdots & W_N^{k(N-1)} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ W_N^{(N-1)0} & \cdots & W_N^{(N-1)n} & \cdots & W_N^{(N-1)(N-1)} \end{pmatrix} \begin{pmatrix} x[0] \\ \vdots \\ x[n] \\ \vdots \\ x[N-1] \end{pmatrix}$$

 \square W_N is fully populated \rightarrow N² entries

FFT as Matrix Operation

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- \square W_N is fully populated \rightarrow N² entries
- \square FFT is a decomposition of W_N into a more sparse form:

$$F_{N} = \begin{bmatrix} I_{N/2} & D_{N/2} \\ I_{N/2} & -D_{N/2} \end{bmatrix} \begin{bmatrix} W_{N/2} & 0 \\ 0 & W_{N/2} \end{bmatrix} \begin{bmatrix} \text{Even-Odd Perm.} \\ \text{Matrix} \end{bmatrix}$$

□ $I_{N/2}$ is an identity matrix. $D_{N/2}$ is a diagonal matrix with entries 1, W_N , ..., $W_N^{N/2-1}$



FFT as Matrix Operation

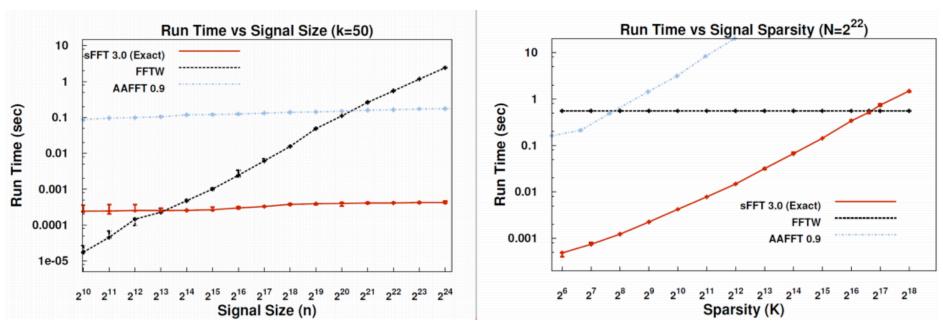
$$F_{N} = \begin{bmatrix} I_{N/2} & D_{N/2} \\ I_{N/2} & -D_{N/2} \end{bmatrix} \begin{bmatrix} W_{N/2} & 0 \\ 0 & W_{N/2} \end{bmatrix} \begin{bmatrix} \text{Even-Odd Perm.} \\ \text{Matrix} \end{bmatrix}$$

Example: N = 4

$$F_4 = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & W_4 \\ 1 & 0 & -1 & 0 \\ 0 & 1 & 0 & -W_4 \end{bmatrix} \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & -1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Beyond NlogN

- □ What if the signal x[n] has a k sparse frequency
 - A. Gilbert et. al, "Near-optimal sparse Fourier representations via sampling
 - H. Hassanieh et. al, "Nearly Optimal Sparse Fourier Transform"
 - Others...
 - O(K Log N) instead of O(N Log N)



Big Ideas

- □ Fast Fourier Transform
 - Enable computation of an N-point DFT (or DFT⁻¹) with the order of just $N \cdot \log_2 N$ complex multiplications.
 - Most FFT algorithms decompose the computation of a DFT into successively smaller DFT computations.
 - Decimation-in-time algorithms
 - Decimation-in-frequency
 - Historically, power-of-2 DFTs had highest efficiency
 - Modern computing has led to non-power-of-2 FFTs with high efficiency
 - Sparsity leads to reduced computation on order K·logN

Admin

HW 9 due Sunday