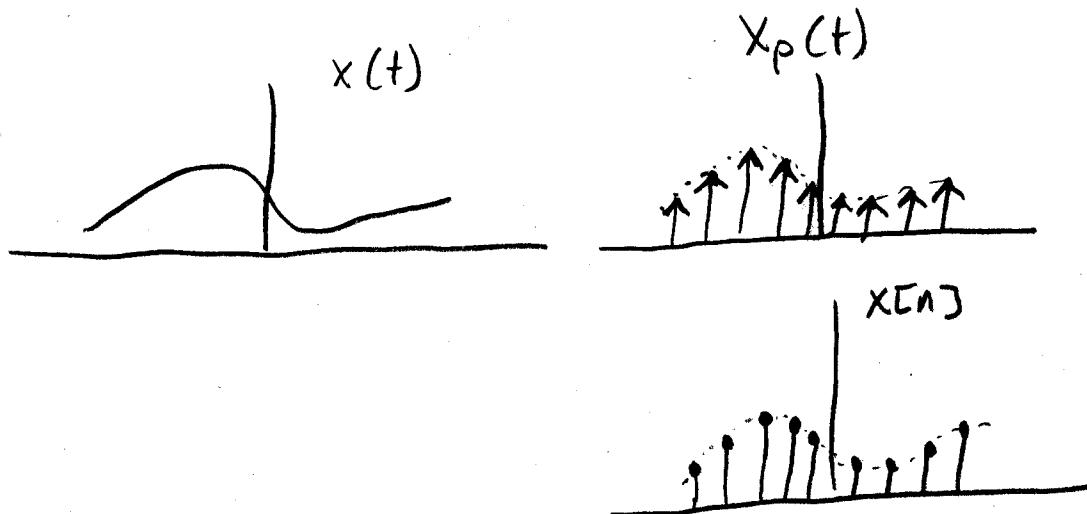


The DFT

- For a discrete-time signal $x[n]$, we have seen that the Fourier Transform $X(e^{j\omega})$ is always periodic (with period 2π).
- For periodic continuous-time signals like $e^{j\omega_0 t}$, $\cos \omega_0 t$, and $\sin \omega_0 t$, we saw that the Fourier transform $X(\omega)$ consisted exclusively of impulses.
 - ⇒ In a sense, a continuous-time signal that contains only impulses is discrete, because it is nonzero only at a countable number of places.
 - ⇒ We used this concept in sampling when we "picked off" the weights of the impulses in $x_p(t)$ to get $x[n]$:



- So we have seen that

Discrete in time \rightarrow periodic in frequency

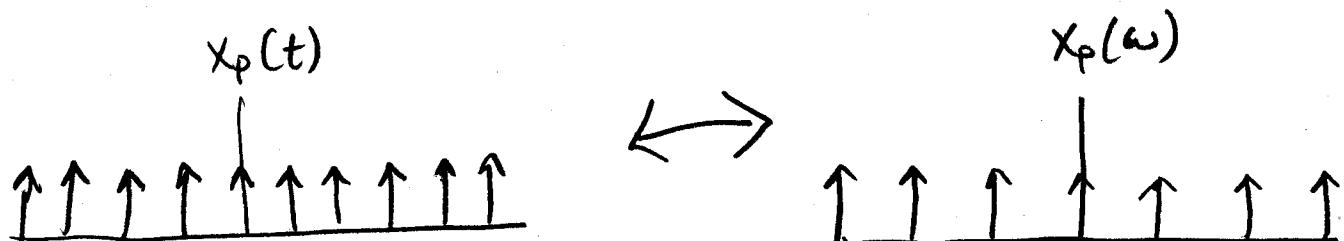
Periodic in time \rightarrow discrete in frequency

- In fact, it is one of the most fundamental duality properties of all Fourier representations that

\Rightarrow A signal that is periodic in one domain is discrete in the other.

NOTE: This implies that a signal that is both periodic and discrete in one domain must be periodic and discrete in the other domain.

EX: the periodic impulse train $x_p(t)$:



- This concept that

discrete & periodic $\xleftrightarrow{\mathcal{F}}$ discrete & periodic

is the main idea behind the Discrete Fourier Transform, or "DFT".

Preliminaries: the Discrete Time Fourier Series (DFS)

- Suppose $X[n]$ is a discrete-time periodic signal with period N .
- Then, similar to the continuous-time case, $X[n]$ can be written in a Fourier series

$$X[n] = \frac{1}{N} \sum_{k=0}^{N-1} A_k e^{j k \omega_0 n} \quad (3.1)$$

$\omega_0 = \frac{2\pi}{N}$
- Since the signal is discrete and periodic with period N , it has only N distinct values... or N "degrees of freedom".
- This implies that only N basis functions $e^{j(k\omega_0)n}$, $0 \leq k \leq N-1$ are needed to represent the signal [just like three vectors $\vec{i}, \vec{j}, \vec{k}$, are sufficient in \mathbb{R}^3].

- So, whereas the continuous-time Fourier series generally required an infinite number of terms in the sum,
 - The DFS sum (3.1) has only N terms.
 - The DFS coefficients A_k are given by
- $$A_k = \sum_{n=0}^{N-1} x[n] e^{-jkw_0 n} \quad (4.1)$$
- A dot product (as always) between the signal and (the conjugates of) the basis functions.
- NOTE : Since $w_0 = \frac{2\pi}{N}$, we have that
- $$\begin{aligned} e^{j(k+N)w_0 n} &= e^{j(k+N)\frac{2\pi}{N} n} \\ &= e^{jk\frac{2\pi}{N} n} e^{j2\pi n} \\ &= e^{jk\frac{2\pi}{N} n} \underbrace{e^{j2\pi n}}_1 \\ &= e^{jkw_0 n} \end{aligned}$$
- Thus, even though the DFS sum (3.1) has only N terms and N coefficients A_k , one may speak of a coefficient A_{k+N} that would be multiplied times $e^{j(k+N)w_0 n} = e^{jkw_0 n}$, and so must be the same as A_k . DFT-4

- So we have the following :
 - $X[n]$ periodic with period N , specified completely by any N consecutive samples.
 - A_k , periodic with period N , specified completely by any N consecutive samples.
 - To find the fundamental period of the A_k^{sr} , take dot products of the basis functions with any one period of $X[n]$, as in (4.1).
 - To find the fundamental period of $X[n]$, add up any one period of the A_k^{sr} times their respective basis functions, as in (3.1),

- It is customary to write

$$x(k) = A_k$$

$$W_N = e^{-j2\pi/N} = e^{-j\omega_0}$$

- The DFS equations (3.1) and (4.1) then become :

$$x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X(k) W_N^{-kn} \quad (5.1)$$

$$X(k) = \sum_{n=0}^{N-1} x[n] W_N^{kn} \quad (5.2)$$

DFT

- Now suppose we sample a continuous-time signal and acquire N samples only. (This will always be the case in real life, since you will probably not live long enough to sample forever.)
 - This gives us a discrete-time signal $x[n]$ defined for $n = 0, 1, 2, \dots, N-1$ only.
 - Suppose that
 1. We want a frequency representation of $x[n]$.
 2. We want both $x[n]$ and the frequency representation to be processed in a computer (DSP),
- The discrete-time Fourier transform will not do, because ω is a continuous variable in $X(e^{j\omega})$, so this cannot be handled by the DSP chip.
- The solution is to assume that $x[n], 0 \leq n \leq N-1$, is one period of a periodic discrete-time signal, which we will call $\tilde{x}[n]$.

- writing a DFS for $\tilde{x}[n]$ (the periodic signal)
 then gives us a discrete and periodic
 frequency representation for $x[n]$:

$$X(k) = \sum_{n=0}^{N-1} x[n] W_N^{kn} \quad (7.1) \quad \left. \begin{array}{l} 0 \leq n \leq N-1 \\ 0 \leq k \leq N-1 \end{array} \right\}$$

$$x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X(k) W_N^{-kn} \quad (7.2)$$

- Eq. (7.1) is the DFT of $x[n]$.

- Eq (7.2) is the IDFT of $X(k)$.

\Rightarrow We consider that $x[n]$ is one period of $\tilde{x}[n]$
 and that $X(k)$ is one period of the associated
 A_k^{SI} .

\Rightarrow The DFT $X(k)$ and IDFT $x[n]$ are both
 of finite length N .

\rightarrow We often write

$$x[n] = \text{IDFT} \{ X(k) \}$$

$$X(k) = \text{DFT} \{ x[n] \}$$

$$x[n] \xleftrightarrow{\text{DFT}} X(k).$$

DFT Properties

- Relationship to discrete-time Fourier transform:

- INSTEAD of considering the N samples

$x[n]$, $0 \leq n \leq N-1$, to be one period of a periodic signal $\hat{x}[n]$, we could consider them to be the only nonzero samples of a signal $\hat{x}[n]$ given by

$$\hat{x}[n] = \begin{cases} x[n], & 0 \leq n \leq N-1 \\ 0, & \text{otherwise} \end{cases} \quad (8.1)$$

- In this case, $\hat{x}[n]$ has a discrete-time Fourier transform $\hat{X}(e^{j\omega})$.
- The relationship between $\hat{X}(e^{j\omega})$ and the DFT $X(k)$ is

$$X(k) = \hat{X}(e^{j\omega}) \Big|_{\omega=2\pi k/N}, \quad 0 \leq k \leq N-1 \quad (8.2)$$

$\Rightarrow X(k)$ is N equally spaced samples of the Fourier transform $\hat{X}(e^{j\omega})$ placed in $-\pi \leq \omega \leq \pi$

$\Rightarrow X(k)$ is N equally spaced samples along the unit circle of $\hat{X}(z)$.

- Linearity:

$$aX_1[n] + bX_2[n] \xrightarrow{\text{DFT}} aX_1(k) + bX_2(k)$$

- Even Symmetry: (about the middle of the signal)

if $X[n] = X[N-n]$, $0 \leq n \leq N-1$,

then $X(k) = X(N-k)$, $0 \leq k \leq N-1$.

- Odd Symmetry: (about the middle of the signal)

if $X[n] = -X[N-n]$, $0 \leq n \leq N-1$,

then $X(k) = -X(N-k)$, $0 \leq k \leq N-1$,

- Conjugate Symmetry for Real signals:

if $X[n]$ is real, then

$$|X(k)| = |X(N-k)| ,$$

$$\arg X(k) = -\arg X(N-k),$$

$$\operatorname{Re}[X(k)] = \operatorname{Re}[X(N-k)], \quad 0 \leq k \leq N-1$$

$$\operatorname{Im}[X(k)] = -\operatorname{Im}[X(N-k)].$$

- Time Shifting :

- Let $\tilde{x}[n] = \tilde{x}[n-l]$, where $\tilde{x}[n]$, as before, is the periodic extension of $x[n]$.

• Then

$$\tilde{x}[n] \xleftrightarrow{\text{DFT}} W_N^{lk} X(k)$$

- Duality :

$$\text{DFT}\{X(k)\} = N x[n]$$

- Parseval's Theorem :

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

NOTE : When we wish to emphasize the fact that $X(k)$ is an N-point DFT, we can write

$$X(k) = \text{DFT}_N \{x[n]\}$$

$$x[n] = \text{IDFT}_N \{X(k)\}$$

Circular Convolution

- Suppose $x[n]$ is an N_1 -point finite length signal, defined for $0 \leq n \leq N_1 - 1$.
- Suppose H is an LTI system with impulse response $h[n]$ that is nonzero only for $0 \leq n \leq N_2 - 1$.
- Then we can consider $h[n]$ to be a finite length signal of length N_2 , defined only for $0 \leq n \leq N_2 - 1$.
- We cannot directly multiply the DFT's of $x[n]$ and $h[n]$, because they have different lengths, so the samples $X(k)$ and $H(k)$ aren't taken at the same frequencies.
- Suppose we zero-pad $x[n]$ and $h[n]$ to length $\max(N_1, N_2)$. Then we can multiply the DFT's!
- Then $Y(k) = X(k)H(k)$ is the $\max(N_1, N_2)$ -point DFT of
$$y[n] = \tilde{x}[n] * h[n]$$

\Rightarrow This is called the circular convolution of $x[n]$ and $h[n]$, written

$$y[n] = x[n] \text{ } \bigcirc_{\max(N_1, N_2)} \text{ } h[n].$$

$\Rightarrow y[n]$ is the plain old convolution ("linear convolution") of $h[n]$ with the periodic extension of $x[n]$ with period $\max(N_1, N_2)$.

\Rightarrow This is not the same as the linear convolution of $h[n]$ with $\hat{x}[n]$ in (8.1), which is usually what we want.

- So, when we multiply DFT's, we get circular convolution in time, not linear convolution.

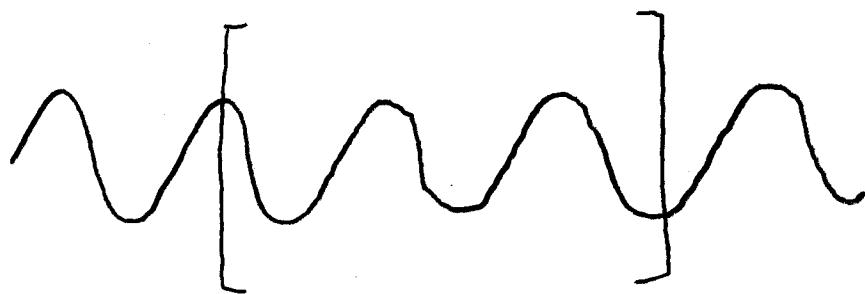
NOTE: "zero padding" means adding zeros to the right side of a signal to extend its length.

NOTE: zero padding $x[n]$ changes the length of the DFT $X(k)$, which gives us a different set of samples of $\hat{X}(e^{j\omega})$ with increased frequency resolution.

- The important question is,
 - Since multiplying DFT's gives us circular convolution
 - Can we somehow implement the linear convolution
- $$Y[n] = \hat{X}[n] * h[n]$$
- using circular convolution?
- \Rightarrow The answer is yes.
- All we have to do is zero pad both $x[n]$ and $h[n]$ to length $N_1 + N_2 - 1$.
 - Then the circular convolution and linear convolution will be the same,
 - This is how convolution by spectral multiplication is actually implemented in most modern applications.

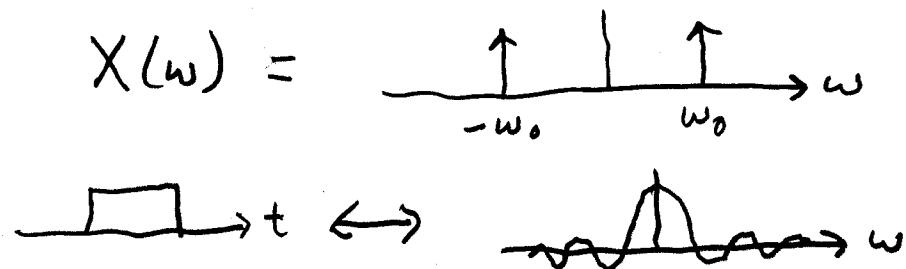
Note on the DFT

- Suppose $x(t) = \cos \omega_0 t \xrightarrow{\mathcal{F}} X(\omega) = 2\pi[\delta(\omega - \omega_0) + \delta(\omega + \omega_0)]$
- Suppose we sample N points to get $x[n]$, $0 \leq n \leq N-1$,
- Then we take the N-point DFT to get $X(k)$.
- What will $X(k)$ look like?
 - If our N samples capture exactly an integer number of periods of $x(t)$, then $X(k)$ will have only two nonzero samples.
 - This is not what usually happens.
 - Usually, we get some noninteger number of periods;

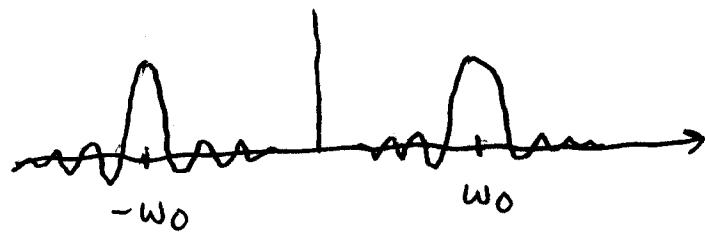


- This means $\tilde{x}[n]$, the periodic extension of $x[n]$, has big discontinuities in it
- $X(k)$ will show a lot of nonzero samples in this case.

- This "effect" is called frequency "leakage", or "edge effects".
- How should we think about this?
- The finite segment of $x(t)$ that we are sampling is $x(t)$ times a boxcar.



- So the spectrum of the finite segment of $x(t)$ that we are sampling is the convolution of $X(\omega)$ with a sync:



- In practice, it is common to "window" $x(t)$ with some window function $w(t)$ that has a "skinnier" spectrum than the boxcar

- This mitigates the frequency leakage (edge effects).
- Usually, the windowing is accomplished by sampling $x(t)$ as before to get $x[n]$, and then multiplying $x[n]$ by $w[n]$ (the samples of the window).

FFT

- Computation of the DFT (5.2)

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

requires N complex multiplies for each k , or N^2 complex multiplies total.

- The "Fast Fourier Transform", or FFT, is a tricky way to implement the DFT that re-uses intermediate calculations to reduce the number of multiplies to $N \log_2 N$.
- The basic FFT algorithms require N to be a power of 2.

- If $N = 2^{10} = 1024$, then

$$\begin{aligned} N^2 &= 1,048,576 \\ N \log_2 N &= 10,240 \end{aligned} \quad \left. \begin{array}{l} \\ \end{array} \right\} \text{wow!!}$$

Decimation-in-Time FFT

- Let $x[n]$ have length N , $0 \leq n \leq N-1$.
- Suppose N is a power of 2.
- Let $u[n] = x[2n]$, $0 \leq n \leq \frac{N}{2}-1$, contain the "even numbered" samples of $x[n]$.
- Let $v[n] = x[2n+1]$, $0 \leq n \leq \frac{N}{2}-1$, contain the "odd numbered" samples of $x[n]$.

- Then

$$\begin{aligned} X(k) &= \sum_{n=0}^{N-1} x[n] W_N^{kn} \\ &= \sum_{n=0}^{\frac{N}{2}-1} \left\{ x[2n] W_N^{2nk} + x[2n+1] W_N^{(2n+1)k} \right\} \\ &= \sum_{n=0}^{\frac{N}{2}-1} u[n] W_{\frac{N}{2}}^{nk} + W_N^k \sum_{n=0}^{\frac{N}{2}-1} v[n] W_{\frac{N}{2}}^{nk} \\ &= U(k) + W_N^k V(k), \quad 0 \leq k \leq \frac{N}{2}-1 \end{aligned}$$

- So we have written $X(k)$, an N -point DFT, as the sum of two $\frac{N}{2}$ -point DFT's.
- This can be repeated until $X(k)$ is finally written as a sum of N one-point DFT's.
- Calculating $X(k)$ in this way is the basic decimation-in-time FFT algorithm, which requires only $N \log_2 N$ multiplies.
- There is also a decimation-in-frequency algorithm that begins by splitting up the even and odd numbered samples of $X(k)$ instead of $x[n]$.

NOTE: Basic FFT algorithms "jumble up" the order of the frequency samples.

- Some routines fix this up before they return, and some do not.
- Always read the documentation to find out the order of the frequency samples when you call an FFT routine.