

# Introduction to the Discrete-Time Fourier Transform and the DFT

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# The Discrete-Time Fourier Transform

- The DTFT tells us what frequency components are present

$$X(\omega) = \sum_{n=-\infty}^{\infty} x[n]e^{-j\omega n}$$

- $|X(\omega)|$  : magnitude spectrum  
 $\angle X(\omega)$  : phase spectrum
- E.g.:  $\exp(j\omega_0 n)$  has only one frequency component at  $\omega = \omega_0$ 
  - $\exp(j\omega_0 n)$  is an **infinite duration** complex sinusoid
  - $X(\omega) = 2\pi \delta(\omega - \omega_0) \quad \omega \in [-\pi, \pi)$
  - the spectrum is zero for  $\omega \neq \omega_0$
- $\cos(\omega_0 n)$  and  $\sin(\omega_0 n)$  have frequency components at  $\pm\omega_0$ 
  - phase spectra for sin and cos are different

# The Discrete-Time Fourier Transform

- The DTFT is periodic with period  $2\pi$

$$\begin{aligned}X(\omega + 2\pi) &= \sum_{n=-\infty}^{\infty} x[n]e^{-j(\omega+2\pi)n} \\ &= X(\omega)\end{aligned}$$

- $X(\omega)$  is also commonly denoted by  $X(e^{j\omega})$ 
  - the notation  $X(e^{j\omega})$  conveys the periodicity explicitly
- $X(\omega)$  over one period contains all the information
  - typically we consider either  $[0, 2\pi)$  or  $[-\pi, \pi)$
- DTFT of  $\exp(j\omega_0 n)$  over *all*  $\omega$ :

$$X(\omega) = \sum_{k=-\infty}^{\infty} 2\pi \delta(\omega - \omega_0 + 2\pi k)$$

- $x[n] = \frac{1}{2\pi} \int_{-\pi}^{\pi} X(e^{j\omega}) e^{j\omega n} d\omega$

- Example:

$$\frac{1}{2\pi} \int_{-\pi}^{\pi} 2\pi \delta(\omega - \omega_0) e^{j\omega n} d\omega = e^{j\omega_0 n}$$

- If  $\omega_0 = 0$ , then  $x[n] = 1$  for all  $n$ , i.e., **DC sequence**  
Its transform is an **impulse** located **at  $\omega = 0$**  with strength  $2\pi$

# Convolution-Multiplication Property

- Multiplication in one domain is equivalent to convolution in the other domain

- $x[n] \cdot y[n] \xleftrightarrow{\text{DTFT}} \frac{1}{2\pi} X(\omega) \circledast Y(\omega)$

- $x[n] \ast y[n] \xleftrightarrow{\text{DTFT}} X(\omega) \cdot Y(\omega)$

- $x[n] \ast y[n] = \sum_{k=-\infty}^{\infty} x[k] y[n - k]$

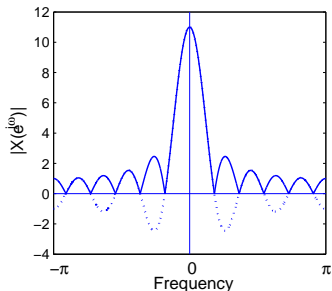
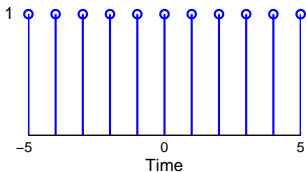
$$X(\omega) \circledast Y(\omega) = \int_{-\pi}^{\pi} X(\theta) Y(\omega - \theta) d\theta$$

# Rectangular Window and its Transform

- Rectangular window:

$$w[n] = 1 \quad n = -N, \dots, 0, \dots, N$$

- $W(\omega) = \frac{\sin(2N + 1)\omega/2}{\sin \omega/2}$



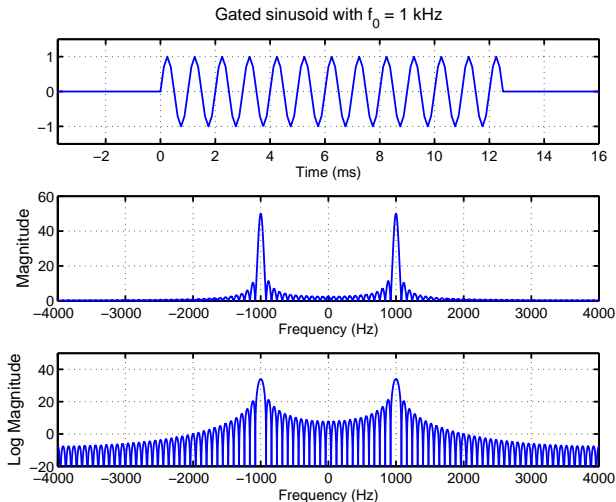
# Some Observations

- $W(e^{j\omega})|_{\omega=0} = 2N + 1$
- First zero crossing occurs when  $\omega = \frac{2\pi}{2N + 1}$
- Number of zero crossings =  $2N$
- As  $N$  increases, main lobe **height increases** and **width decreases**
- Transform of  $\exp(j\omega_0 n) w[n]$  has its mainlobe centred at  $\omega_0$

$$\begin{aligned}\text{DTFT}(x[n] \cdot w[n]) &= \frac{1}{2\pi} X(\omega) \circledast W(\omega) \\ &= \delta(\omega - \omega_0) \circledast W(\omega) \\ &= W(\omega - \omega_0)\end{aligned}$$

- $\text{DTFT}(\cos(\omega_0 n) w[n]) = \frac{1}{2} W(\omega - \omega_0) + \frac{1}{2} W(\omega + \omega_0)$

# Windowed Sinusoid Example

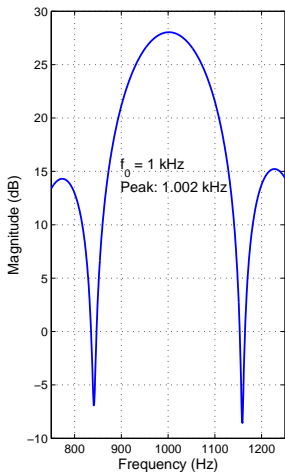
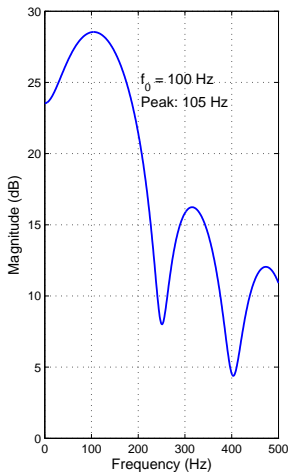




# Single Real Sinusoid Frequency Estimation

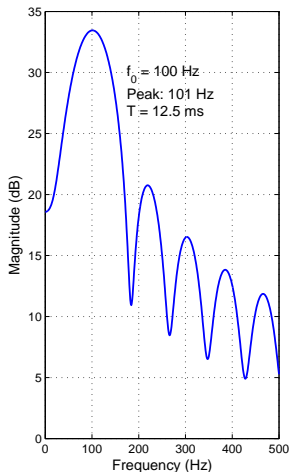
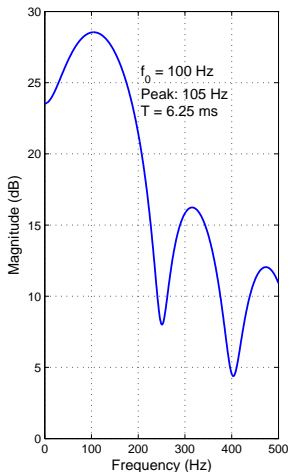
- $f_0$  is **estimated** from **peak location**
- In general, the peaks are **not exactly at  $\pm f_0$**
- This is because of **sidelobe interference**
- If  $f_0$  is closer to DC
  - sidelobe interference increases
  - shifts peak further away from true location
- Interference is least when sinusoidal frequency is at  $f_s/4$

# Examples of Peak Shifting



# Effect of Increased Data Length

- Longer duration sinusoid's spectrum is narrower
  - less sidelobe interference  $\Rightarrow$  peak closer to true value



# Use of Data Windows

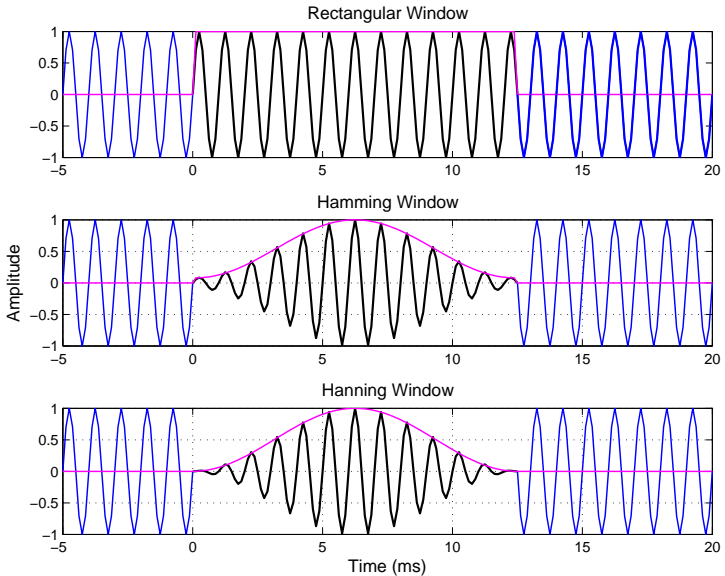
- Useful for data containing sinusoids
- Sidelobes of a stronger sinusoid will mask the main lobe of a nearby weak sinusoid
- We multiply  $x[n]$  by **data window**  $w[n]$  before computing the DTFT
  - if we merely **truncate** a signal, it is equivalent to applying a **rectangular** window
- Why consider non-rectangular windows?
  - sidelobes fall off faster
  - nearby weaker sinusoid becomes more visible
  - price paid: main lobe of each sinusoid broadens
    - **two close peaks may merge into one**

# Commonly Used Windows

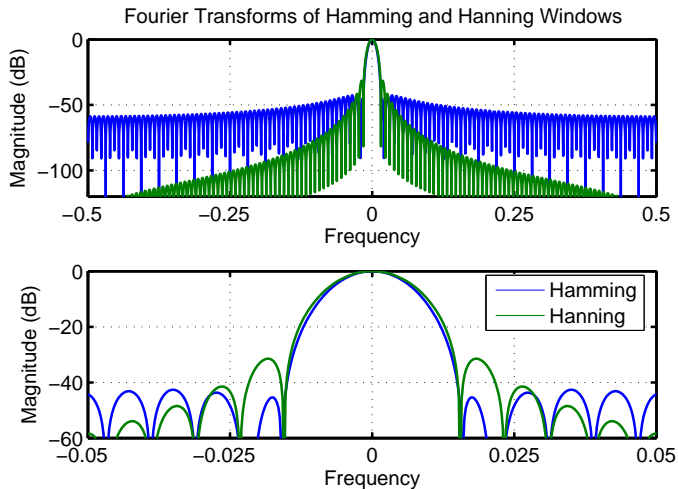
Name	$w[k]$	Fourier transform
Rectangular	1	$W_R(f) = \frac{\sin \pi f(2N+1)}{\sin \pi f}$
Bartlett	$1 - \frac{ k }{N}$	$\frac{1}{N} \left( \frac{\sin \pi fN}{\sin \pi f} \right)^2$
Hanning	$0.5 + 0.5 \cos \frac{\pi k}{N}$	$0.25 W_R \left( f - \frac{1}{2N} \right) + 0.5 W_R(f) + 0.25 W_R \left( f + \frac{1}{2N} \right)$
Hamming	$0.54 + 0.46 \cos \frac{\pi k}{N}$	$0.23 W_R \left( f - \frac{1}{2N} \right) + 0.54 W_R(f) + 0.23 W_R \left( f + \frac{1}{2N} \right)$

$$w[k] = 0 \text{ for } |k| > N$$

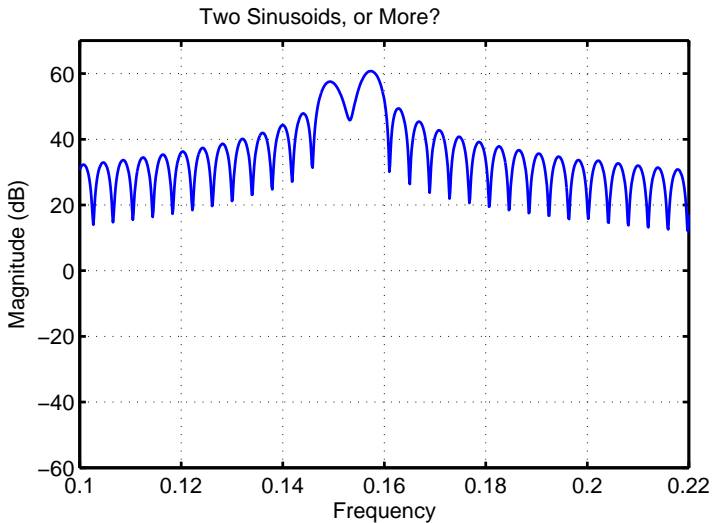
# Windowed Sinusoid



# Hamming Vs. Hanning

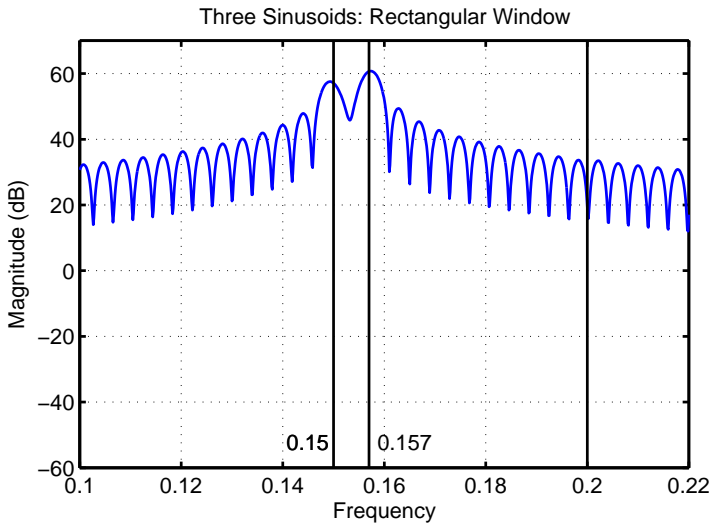


# Example: How Many Sine Waves Are there?

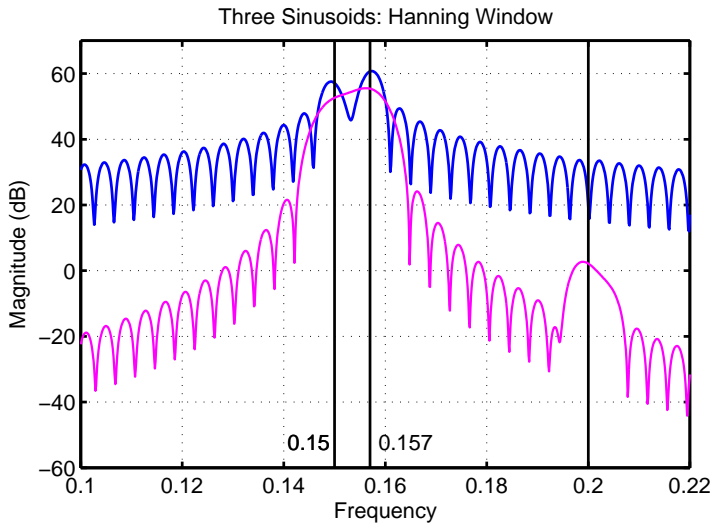




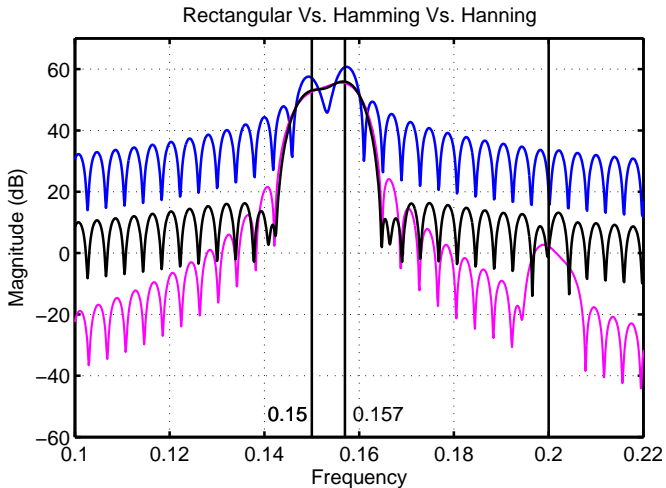
# Example: Three Sine Waves



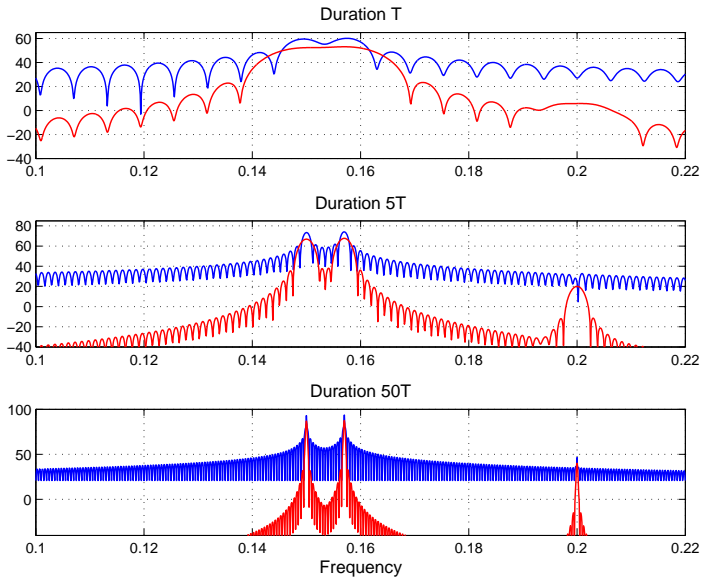
# Example: Three Sine Waves



# Three Sine Waves



# Three Sine Waves: Three Different Data Lengths



# The Discrete Fourier Transform

- Since  $\omega$  is a continuous variable,  $X(\omega)$  cannot be evaluated on a computer
- The **Discrete Fourier Transform (DFT)** is amenable to machine computation
- Let  $x[n]$  be defined over the interval  $0, 1, \dots, N - 1$  and **zero otherwise**

$$X[k] \stackrel{\text{def}}{=} \sum_{n=0}^{N-1} x[n] e^{-j\frac{2\pi k}{N}n} \quad k = 0, 1, \dots, N - 1$$

- $X[k + N] = X[k]$  i.e., only  $N$  distinct values are present
- The  $X[k]$ 's are called the **DFT coefficients**

- The inversion formula is

$$\tilde{x}[n] = \frac{1}{N} \sum_{k=0}^{N-1} X[k] e^{j\frac{2\pi k}{N}n}$$

Why is the inverse  $\tilde{x}[n]$  and not  $x[n]$ ?

- $\tilde{x}[n + N] = \tilde{x}[n]$ , i.e., inverse is **periodic** with period  $N$   
 $x[n] = \tilde{x}[n]$  for  $n = 0, 1, \dots, N - 1$
- Even though we start off with an *aperiodic* signal, the inverse transform gives a *periodic* signal
- **But over the fundamental period, the inverse transform equals the original aperiodic signal**

# DFT = Sampled Version of DTFT

- Recall

$$X(\omega) = \sum_{n=0}^{N-1} x[n] e^{-j\omega n}$$

- Evaluate  $X(\omega)$  at  $N$  uniformly spaced points in the interval  $[0, 2\pi)$ , i.e.,

$$\begin{aligned} X(\omega)|_{\omega=\frac{2\pi k}{N}} &= \sum_{n=0}^{N-1} x[n] e^{-j\frac{2\pi k}{N}n} \\ &= X[k] \end{aligned}$$

- DFT coefficients can be viewed as samples of  $X(\omega)$
- Since  $X(\omega + 2\pi) = X(\omega)$ , the samples of  $X(\omega)$  are also periodic
  - provides another explanation for why  $X[k + N] = X[k]$

# Frequency domain sampling introduces time-domain periodicity!

- Sampling in the frequency domain leads to periodic repetition in the time domain
- Repetition period is  $N$
- If we sample the DTFT at  $L (> N)$  points, the repetition period will be  $L (> N)$
- If  $x[n]$  is of duration  $N$ , then  $X(\omega)$  has to be sampled at least at  $N$  points to avoid aliasing in the time domain



# Effect of Zero-Padding

- $$X(\omega) = \sum_{n=0}^{N-1} x[n] e^{-j\omega n}$$

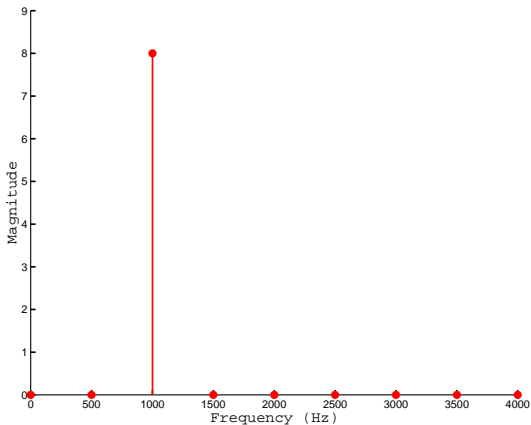
- Append  $L - N$  zeros  $x[n]$  and compute the  $L$ -point DFT of the padded sequence

- This is equivalent to sampling  $X(\omega)$  at  $L (> N)$  points:

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-j2\pi nk/L} \quad k = 0, 1, \dots, L-1$$

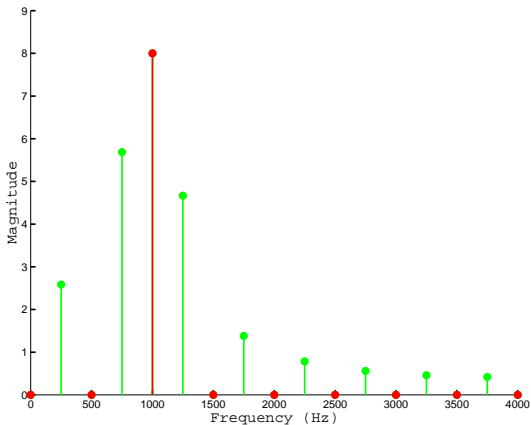
- The underlying  $X(\omega)$  remains the same, since it depends only on  $x[n]$ ,  $n = 0, 1, \dots, N-1$

# Example



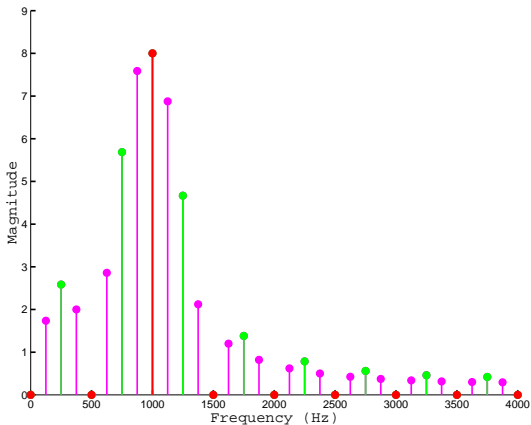
16-pt DFT of  $x[n] = \sin(2\pi n/8)$       $n = 0, 1, \dots, 15$

# Example



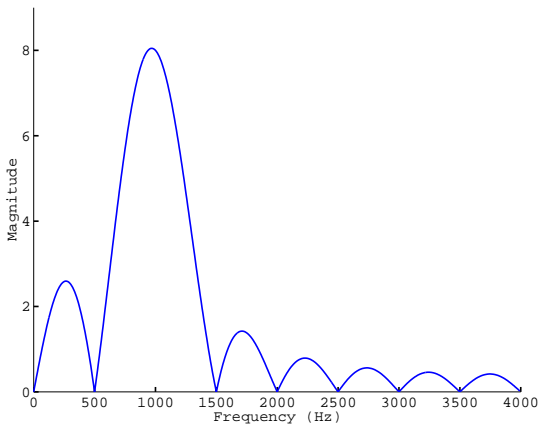
32-pt DFT of  $x[n]$ : 16 signal samples padded with 16 zeros

# Example



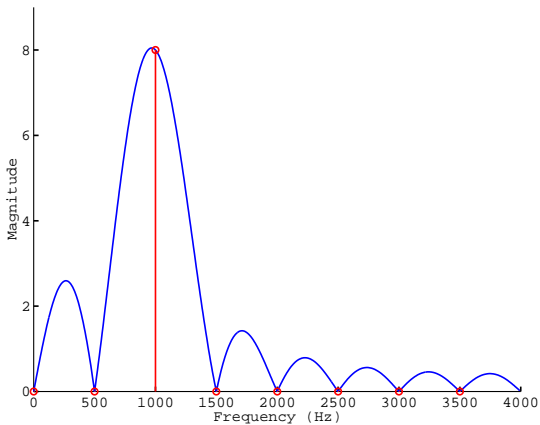
64-pt DFT of  $x[n]$  (zero-padded)

# Example



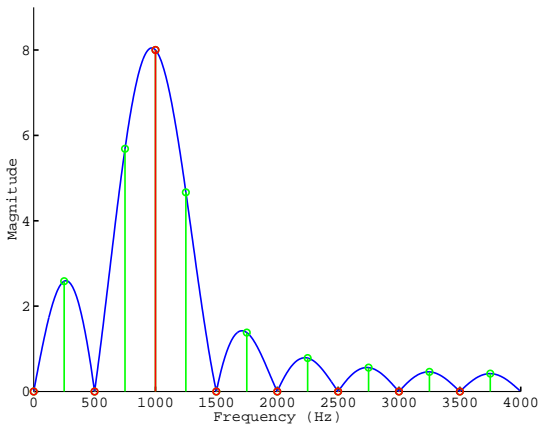
DTFT of  $x[n] = \sin(2\pi n/8)$

# Example



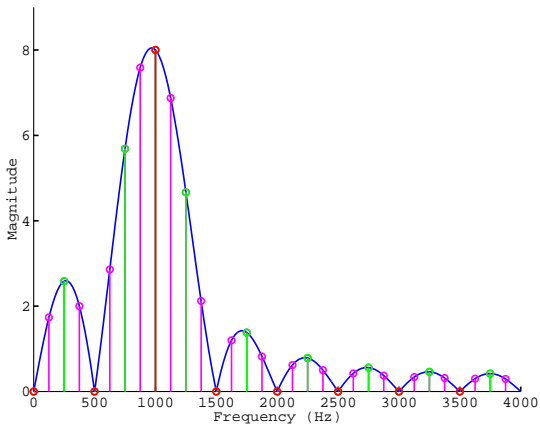
DTFT and 16-pt DFT

# Example



DTFT and 32-pt DFT

# Example



DTFT and 64-pt DFT



# Relationship Between Analog and Digital Spectra

- Recall  $x[n] = x(nT_s)$
- $x(t) \xleftrightarrow{\text{CTFT}} X(\Omega)$
- $x[n]$ 's DTFT  $X(\omega)$  is related to  $x(t)$ 's CTFT  $X(\Omega)$  as follows:
  - Amplitude scaling by  $\frac{1}{T_s}$
  - Periodic repetition due to sampling
  - Frequency axis scaling by  $F_s = \frac{1}{T_s}$

# Relationship Between Analog and Digital Frequencies

- A frequency  $\omega_0$  ( $f_0$ ) in the DTFT corresponds to  $\omega_0 \cdot F_s$  rad/s ( $f_0 \cdot F_s$  Hz)
- Converting DFT bin to digital and analog frequencies:  
Let  $X[k]$  be an  $N$ -point DFT. The digital and analog frequencies corresponding to bin  $k$  are:
  - 0-based index:  $\frac{k}{N}$        $\frac{k}{N} \cdot F_s$  Hz
  - 1-based index:  $\frac{k-1}{N}$        $\frac{k-1}{N} \cdot F_s$  Hz
- If  $F_s$  is not known, it is **not possible** to know the true analog frequency given knowledge about DTFT/DFT