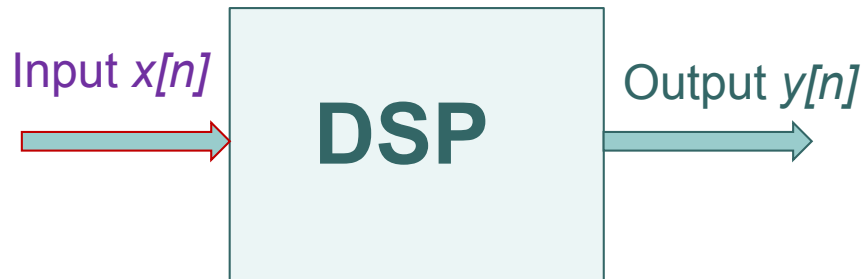


# What is Digital Signal Processing (DSP)?

- **Signals convey information**

- DSP: modify signals with computers (and/or DSP circuits)

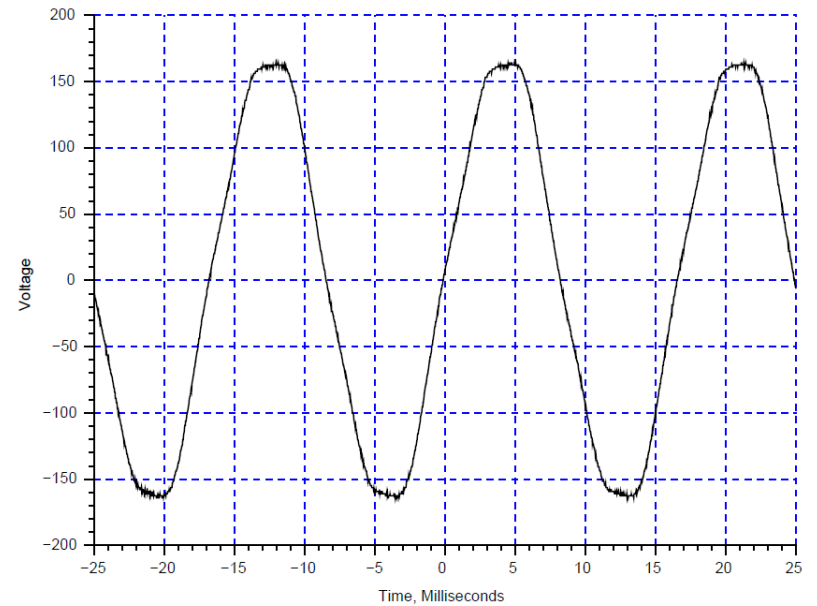
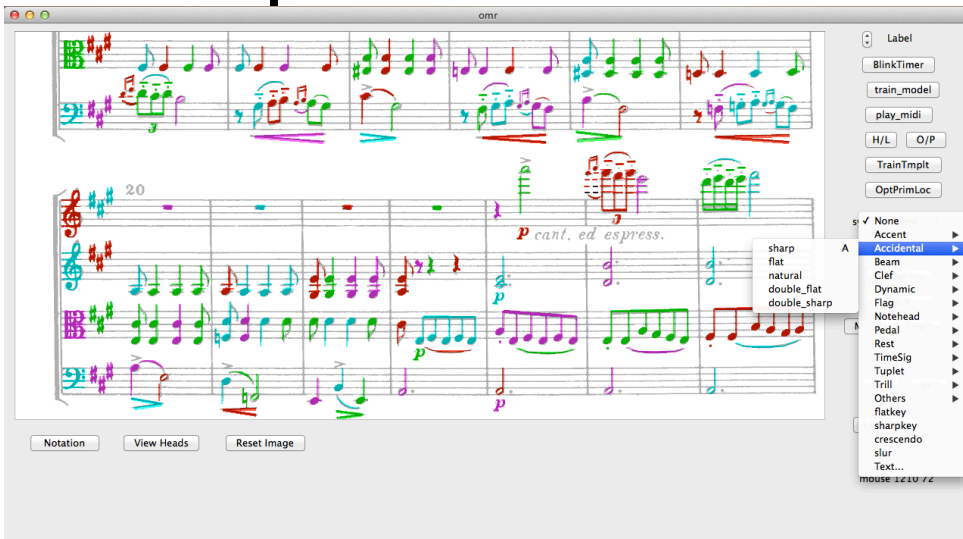


- DSP: represent,  
transform,  
manipulate, enhance, and analyze signals

- Digital ?

$x[n]$  = a sequence of numbers;  $x[n]=\{50,10,-50,\dots\}$   
 $x$  values from an interval

# What is DSP ?

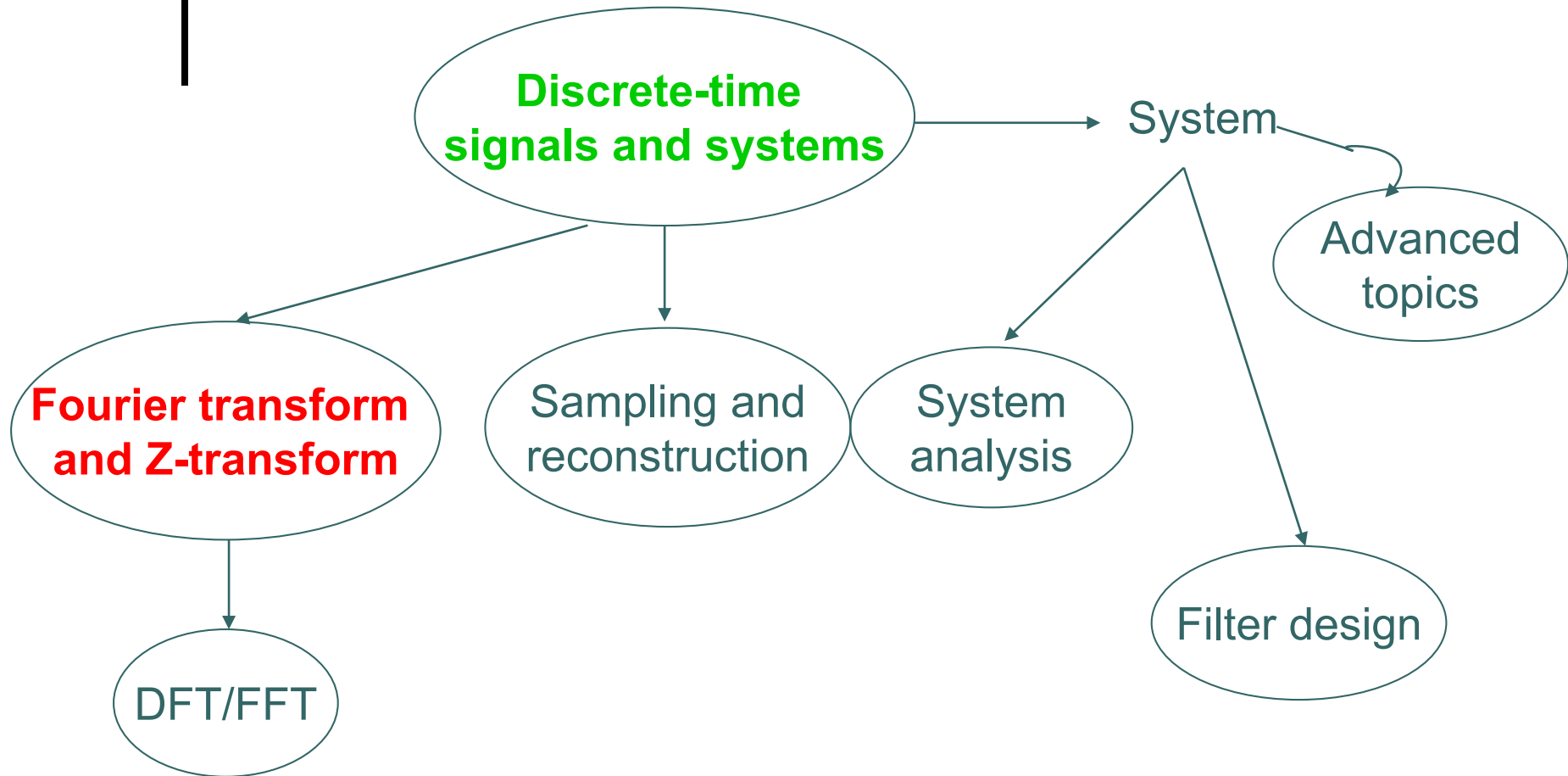




# Applications of DSP

- Speech processing
  - Enhancement – noise filtering
  - Coding, synthesis, and recognition
- Image processing
  - Enhancement, coding, pattern recognition
- Multimedia processing
  - Media transmission, digital TV, video conferencing
- Telecommunications
- Biomedical engineering
- Navigation, radar, GPS
- Control, robotics, machine vision
- ...

# Course at a glance



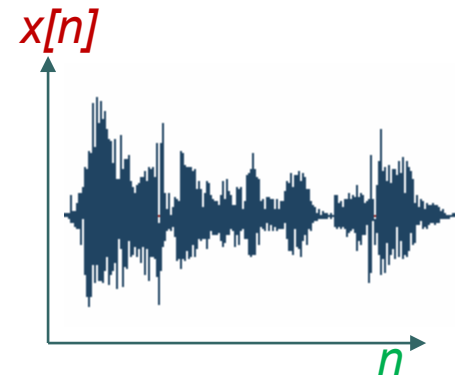


# Outline

- **Introduction**
- DT signals
- Transformation of the independent variable
- DT LTI Systems & Convolution
- Frequency content of signals
- Fourier Transform
- Frequency response & difference equations

# What is a signal?

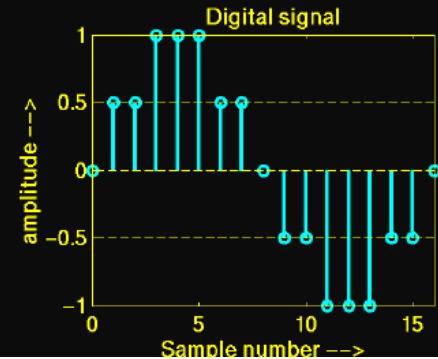
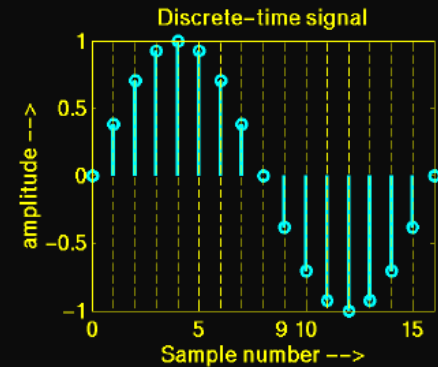
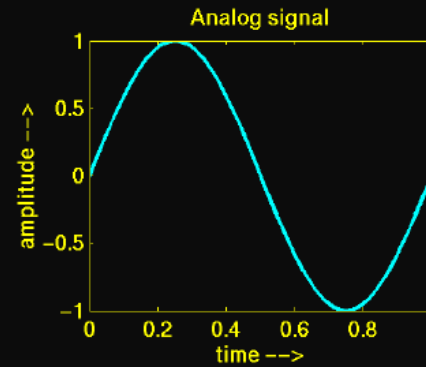
- A flow of information
  - **Speech:** 1-Dimension signal as a function of time  $x(n)$
  - **Image:** 2-dimension signal as a function of space  $x(i,j)$
  - **Video:** 3-dimension signal as a function of space and time  $x(i,j,n)$



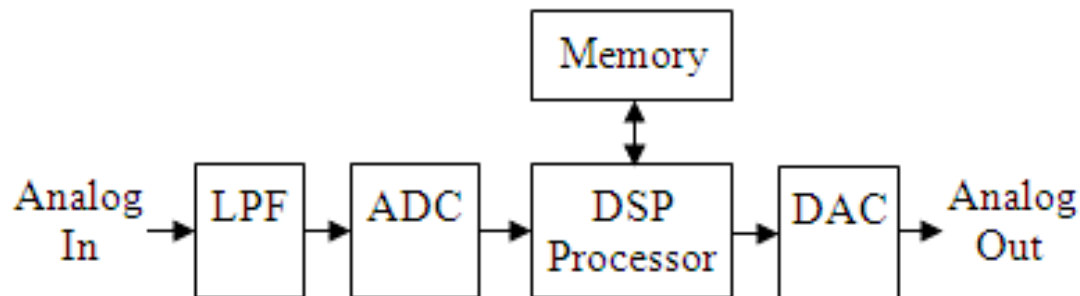
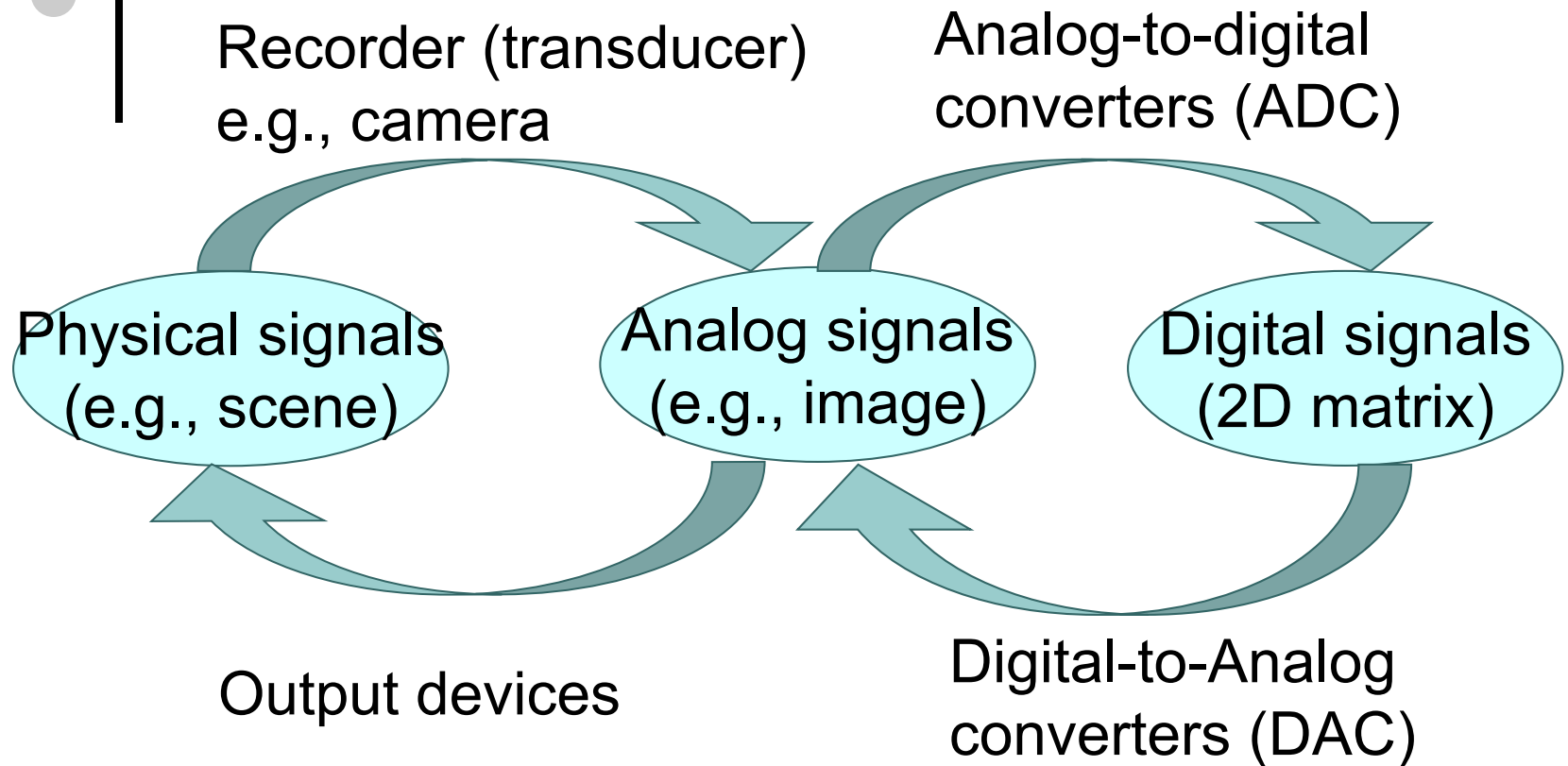
- $x[n]$  a function of the independent variable  $n$ 
  - $n$  represents the time of a speech signal
  - $x$  the strength (amplitude) of the speech signal

# Types of signals

- Discrete-time signals  $x[n]$ 
  - $n$  a discrete time
  - ➔  $x(n)$  defined at discrete  $n$
- Continuous-time signals  $x(t)$ 
  - $t$  continuous
  - ➔  $x(t)$  defined at all times  $t$
- $x(n)$  continuous-amplitude
- $x(n)$  discrete-amplitude
- Analog signals: both time and amplitude are continuous
- Digital signals: both time and amplitude are discrete



# Typical DSP system components







# Pros and cons of DSP

## ○ Pros

- Easy to duplicate
- Stable and robust: not varying with temperature, storage without deterioration
- Flexibility and upgrade: use a general computer or microprocessor

## ○ Cons

- Limitations of ADC and DAC
  - ➔ Lost of information
- High power consumption due to complexity of a DSP implementation
  - ➔ unsuitable for simple, low-power applications
- Limited to signals with relatively low bandwidths (frequency)



# Key History of DSP

- **Prior to 1950's**: analog signal processing using specialized electronic circuits or mechanical devices
- **1950's**: computer simulation before analog implementation, thus cheap to try out
- **1965**: Fast Fourier Transforms (FFTs) by Cooley and Tukey – make real time DSP possible
- **1980's**: integrated circuit (IC) technology boosting DSP



# Outline

- **DT signals**
- Transformation of the independent variable
- DT LTI Systems & Convolution
- Frequency content of signals
- Fourier Transform
- Frequency response

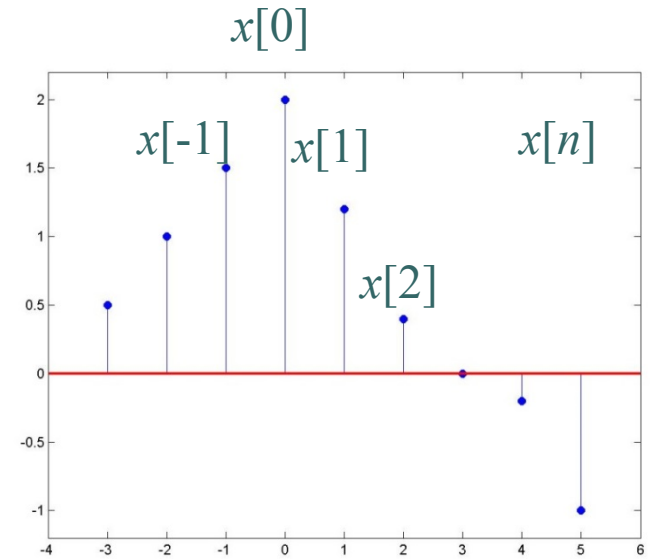
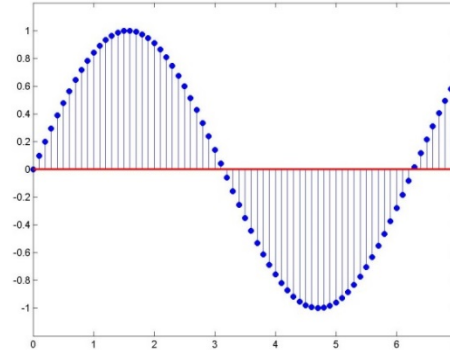
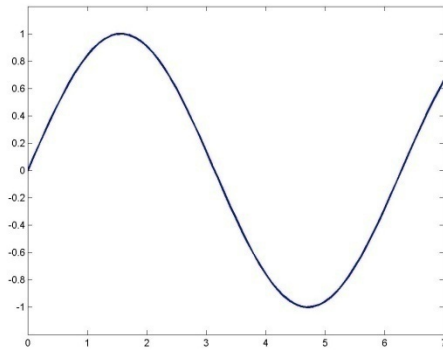
# Discrete-time signals

- Sequences of numbers

$$x = \{x[n]\}, \quad -\infty < n < \infty; n \text{ integer}$$

- Sampling of an analog signal

$$x[n] = x_a(nT), -\infty < n < \infty; T \text{ the sampling period}$$



- Total energy

$$E = \sum_{n=-\infty}^{\infty} |x[n]|^2$$

- Average power

$$P = \lim_{N \rightarrow \infty} \frac{1}{2N+1} \sum_{n=-N}^N |x[n]|^2$$



# Sequence operations

- **Product & sum** of two sequences  $x[n]$  and  $y[n]$ :  
→ sample-by-sample production and sum
- **Multiplication** of a sequence  $x[n]$  by a number  $\alpha$   
→ multiplication of each sample value by  $\alpha$
- **Delay** or shift of a sequence  $x[n]$

$$y[n] = x[n - n_0]$$

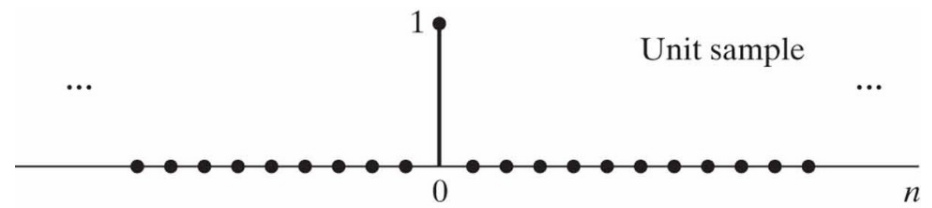
where  $n_0$  is an integer

# Some basic signals

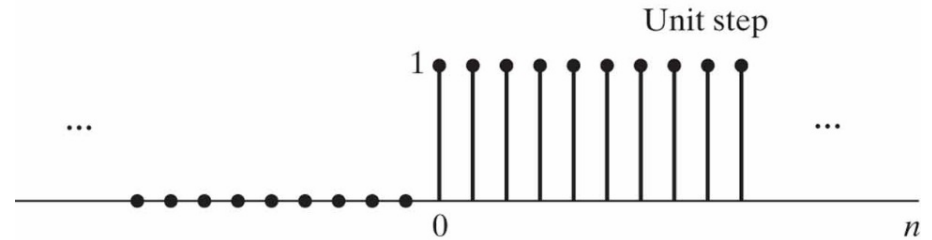
## Combining basic sequences:

- Exponential and unit step:  
an exponential that is zero for  $n < 0$

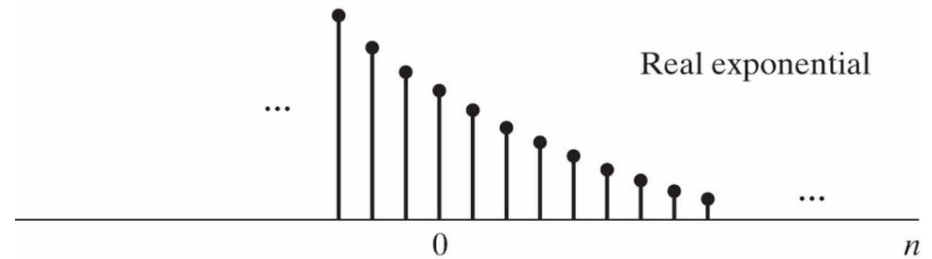
$$x[n] = A\alpha^n u[n] = \begin{cases} A\alpha^n, & n \geq 0 \\ 0, & n < 0 \end{cases}$$



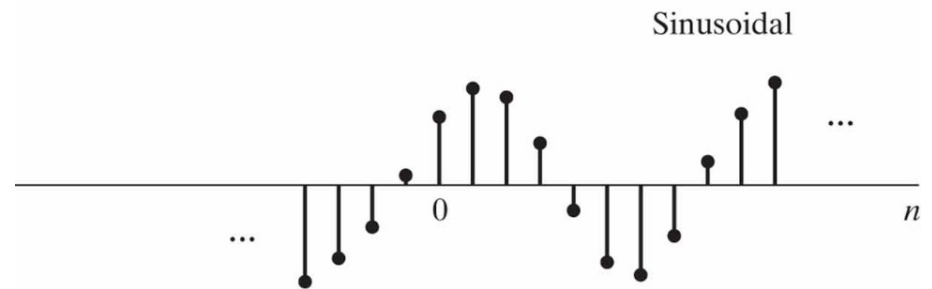
(a)



(b)



(c)

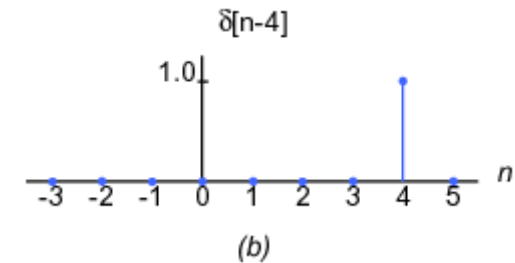
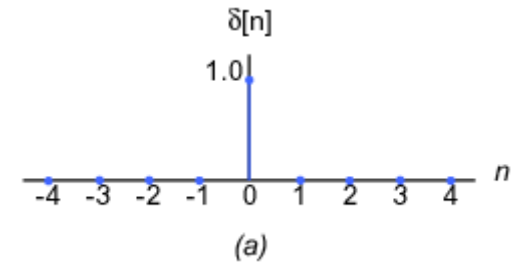


(d)

# Basic Signals: Impulse

- Unit sample sequence

$$\delta[n] = \begin{cases} 0, & n \neq 0, \\ 1, & n = 0, \end{cases}$$



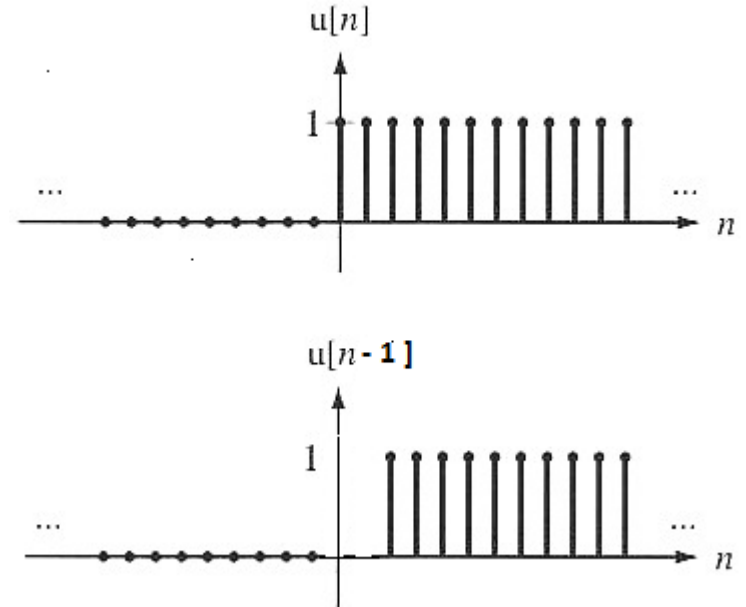
- Any sequence can be represented as a sum of scaled, delayed impulses

$$x[n] = a_{-3}\delta[n+3] + a_{-2}\delta[n+2] + \dots + a_5\delta[n-5]$$

- More generally 
$$x[n] = \sum_{k=-\infty}^{\infty} x[k]\delta[n-k]$$

# Basic Signals: Unit step

$$u[n] = \begin{cases} 1, & n \geq 0, \\ 0, & n < 0, \end{cases}$$



- Related to the impulse by

$$u[n] = \delta[n] + \delta[n-1] + \delta[n-2] + \dots$$

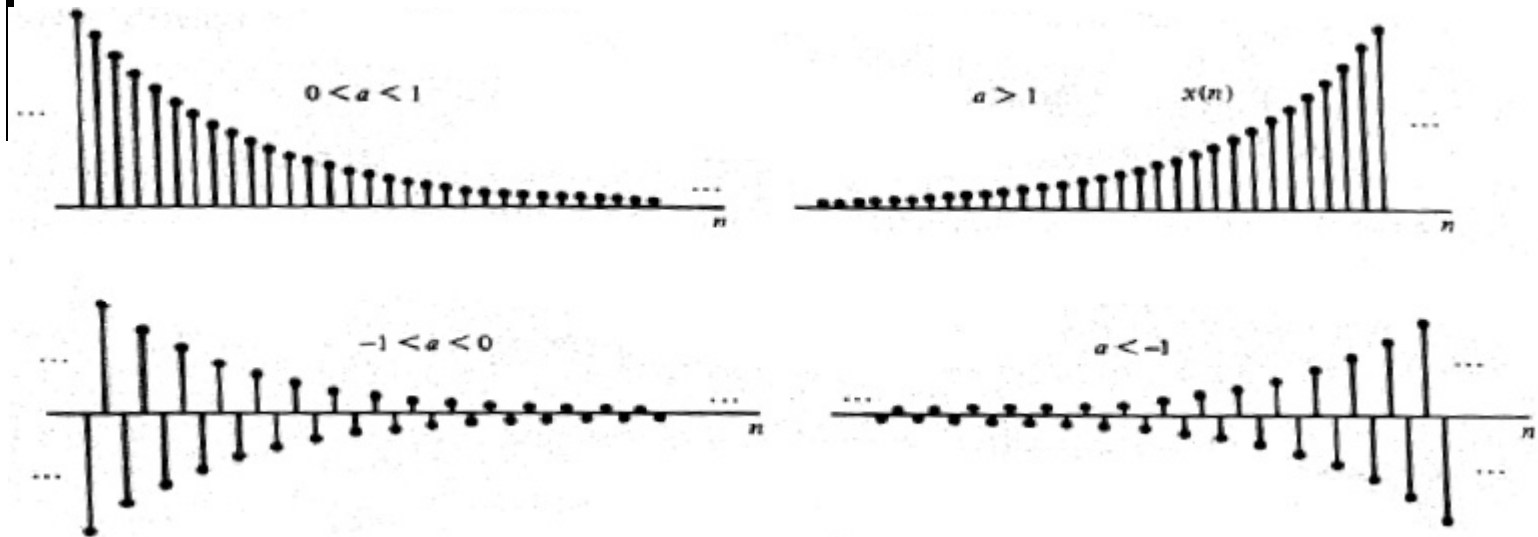
or

$$u[n] = \sum_{k=-\infty}^{\infty} u[k] \delta[n-k] = \sum_{k=0}^{\infty} \delta[n-k]$$

- Conversely,  $\delta[n] = u[n] - u[n-1]$

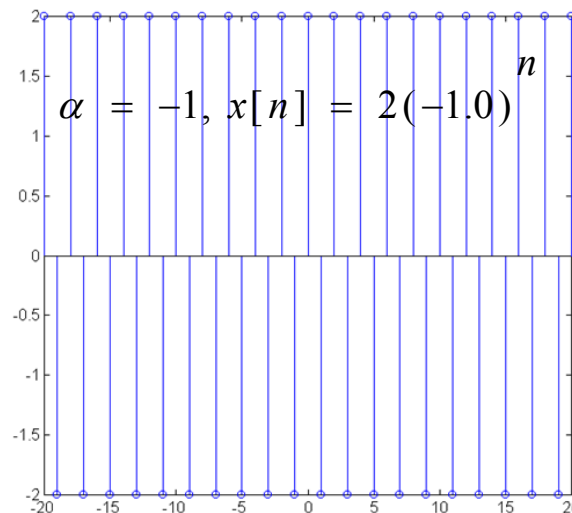
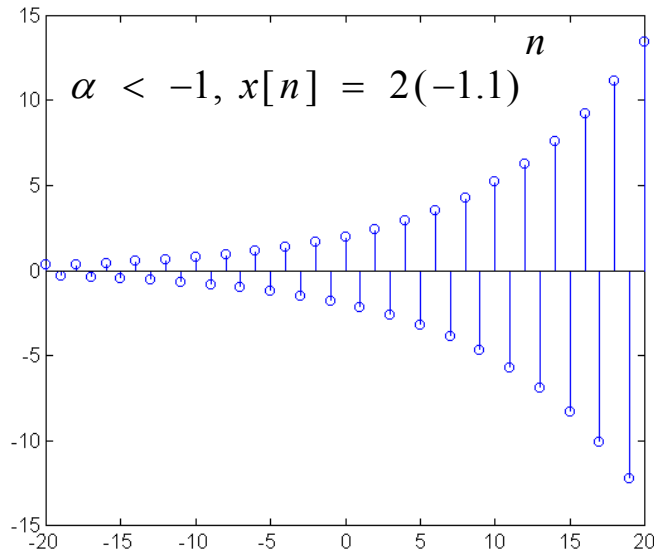
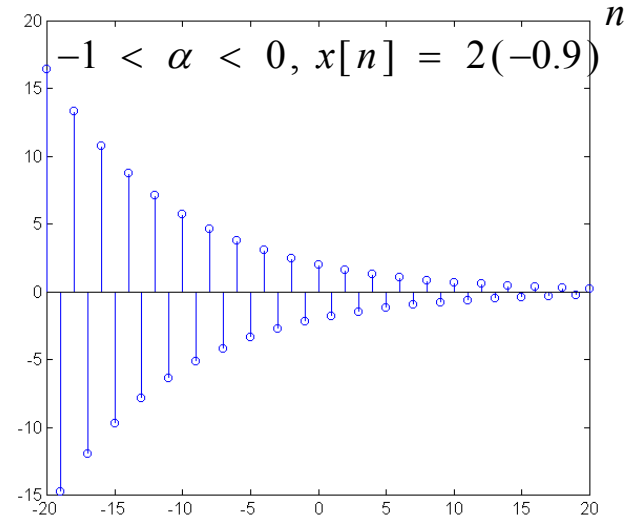
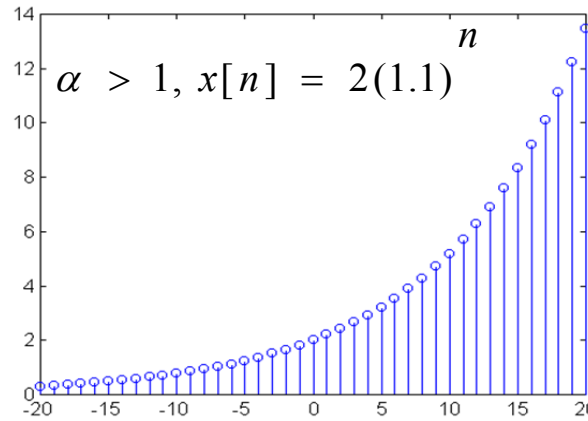
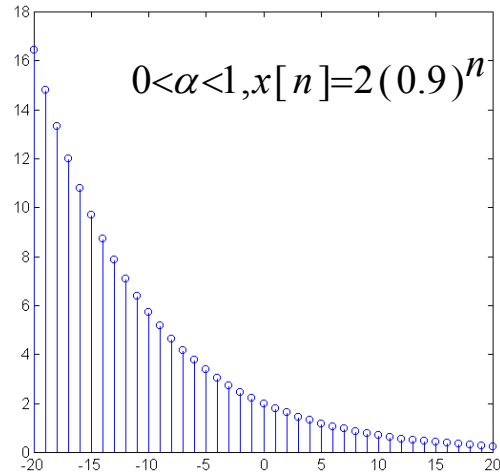


# Basic Signals: Exponential $x[n] = A\alpha^n$



- If  $A$  and  $\alpha$  are real numbers, the sequence is real
- If  $0 < \alpha < 1$  and  $A$  is positive, the sequence values are positive and decrease with increasing  $n$
- If  $-1 < \alpha < 0$ , the sequence values alternate in sign, but decrease in magnitude with increasing  $n$
- If  $|\alpha| > 1$ , the sequence values increase with increasing  $n$

# Real Exponential Signal $x[n] = A\alpha^n$



# Basic Signals: Sinusoidal Signals

$$x[n] = A \cos(\omega_o n + \theta)$$

$$\omega_o = 2\pi f_o$$

$\omega_o$  : angular frequency (radians)

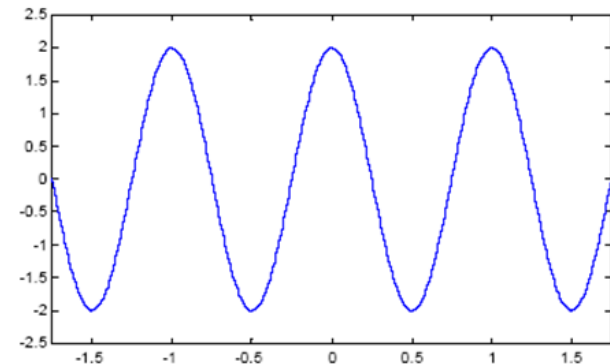
$f_o$  : frequency (cycles/second, Hz)

$N$ : Period  $N=1/f=2\pi/\omega_o$

$\theta$  : Phase (shift)

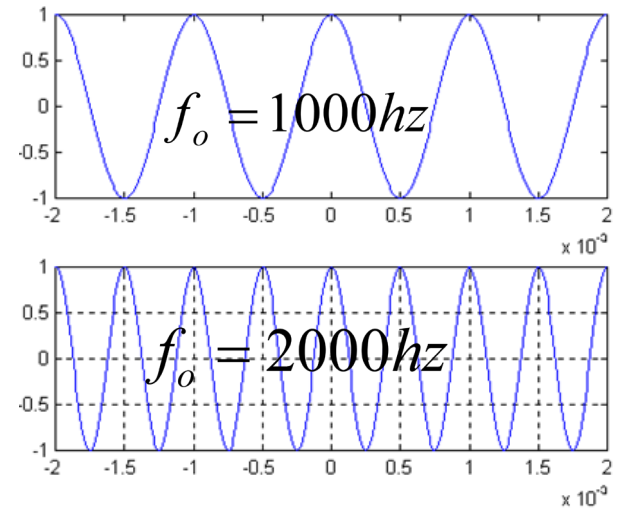
$A$ : Amplitude

- Sinusoidal signals: important because they can be used to synthesize any signal
  - An arbitrary signal can be expressed as a sum of many sinusoidal signals with different frequencies, amplitudes and phases
  - Music notes are essentially sinusoids at different frequencies
- **Phase shift**: how much the max. of the sinusoidal signal is shifted away from  $t=0$



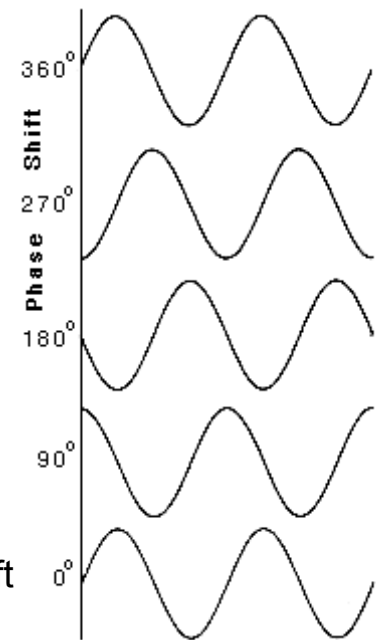
# Sinusoidal Signals $x[n] = A \cos(\omega_o n + \theta)$

- Higher frequency : higher oscillation : more cycles/second (?)



$\omega_o$

- The **phase  $\theta$**  is the offset in the displacement from a specified reference point at time  $t = 0$
- $\theta$  represents a "shift" from zero phase
- For infinitely long sinusoids, a change in  $\theta$  is the same as a shift in time



Signals with different phase shift compared to the bottom signal

# Basic signals:

## Complex Exponential Sequence $x[n] = Ae^{(j\omega_0 n + \theta)}$

- Complex number: Cartesian representation:  $z = x + jy$

$j = \sqrt{-1}$  and  $x, y$  are real numbers

Magnitude of  $z$  is  $|z| = \sqrt{x^2 + y^2}$

Phase of  $z$  is  $\theta = \angle z = \tan^{-1} \frac{y}{x}$

- Polar representation:  $z = |z|e^{j\theta} = |z|\cos\theta + j|z|\sin\theta$

- Complex conjugate:

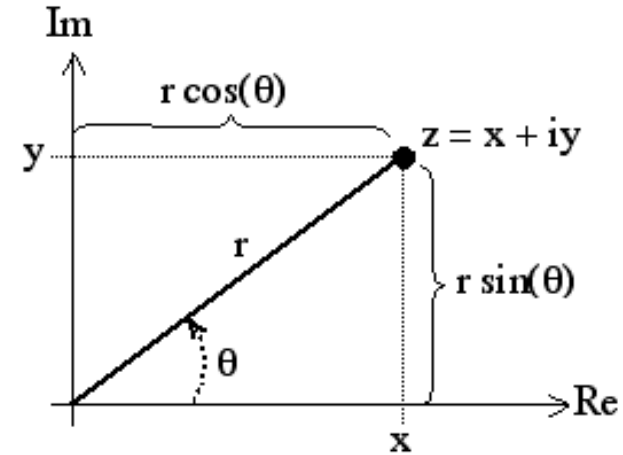
$z^* = x - jy$  Note:  $(z + z^*)$  and  $(zz^*)$  are real

- Euler formula:

$$e^{j\theta} = \cos(\theta) + j\sin(\theta)$$

$$e^{\theta} + e^{-\theta} = 2\cos(\theta)$$

$$e^{\theta} - e^{-\theta} = j2\sin(\theta)$$





# Complex Exponential Sequence

- $x[n] = Ae^{(j\omega_0 n + \theta)} = A \cos(\omega_0 n + \theta) + jA \sin(\omega_0 n + \theta)$

$\theta$  is the phase shift (initial phase)

- $Ae^{(j\omega_0 n + \theta)}$  are closely related to sinusoidal  $A \cos(\omega_0 n + \theta)$

Example : 
$$A \cos(\omega_0 n + \theta) = \frac{A}{2} e^{j\theta} e^{j\omega_0 n} + \frac{A}{2} e^{-j\theta} e^{-j\omega_0 n}$$

- $n$  dimensionless  $\Rightarrow$  both  $\omega_0$  and  $\theta$  have units of radians

- We note, for  $\omega_0 = \pi$ , odd multiple of  $\pi$ ,  $e^{j\pi n} = (e^{j\pi})^n = (-1)^n$ , the signal oscillates rapidly, changing sign at each point in time



# Complex Exponentials: Periodicity

- CT : a sinusoid and a complex exponential signal are both periodic

$$x(t) = A \cos(\Omega_0 t + \theta) \text{ and } x(t) = e^{j\Omega_0 t}$$

- A DT periodic sequence is defined as  $x[n] = x[n + N]$ ,  $\forall n$  where the period  $N$  is necessarily an integer

For  $e^{j\omega_0 n}$  to be periodic with period  $N > 0$ ,

$$e^{j\omega_0 (n+N)} = e^{j\omega_0 n}, \text{ or equivalently } e^{j\omega_0 N} = 1 \therefore \omega_0 N \text{ must be a multiple of } 2\pi$$

$$\text{i.e. } \omega_0 N = 2\pi m, \text{ or equivalently } \frac{\omega_0}{2\pi} = \frac{m}{N},$$

$\Rightarrow e^{j\omega_0 n}$  is periodic if  $\omega_0 / 2\pi$  a rational number

is not periodic otherwise



# Complex Exponentials: Frequency

- For a CT signal

$$x(t) = A \cos(\Omega_0 t + \theta)$$

as  $\Omega_0$  increases,  $x(t)$  oscillates more and more rapidly

- For the DT signal

- Consider  $e^{j(\omega_0 + 2\pi)n} = e^{j2\pi n} e^{j\omega_0 n} = e^{j\omega_0 n}$

$\Rightarrow$  the exponential at frequency  $\omega_0 + 2\pi$  is the same as that at  $\omega_0$

- Similarly at frequencies  $\omega_0 \pm 2\pi, \omega_0 \pm 4\pi$ , and so on

$\Rightarrow$  Because of this periodicity of  $2\pi$ , we need only to consider frequency interval of  $2\pi$  in the case of DT signals

- Consider  $x[n] = A \cos(\omega_0 n + \theta)$ ,

as  $\omega_0$  increases from 0 to  $\pi$ ,  $x[n]$  oscillates more and more rapidly

as  $\omega_0$  increases from  $\pi$  to  $2\pi$ , the oscillations become slower





## Complex Exponentials: Frequency

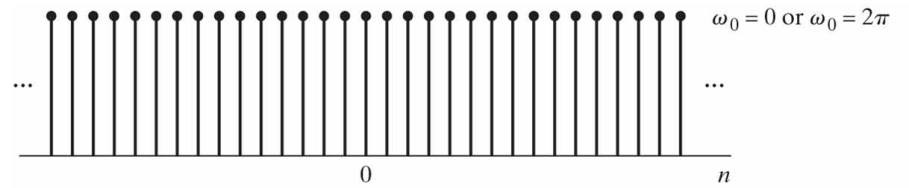
Because of implied periodicity,  $e^{j\omega_0 n}$  does not have a continually increasing rate of oscillation as  $\omega_0$  is increased in magnitude

- Increasing  $\omega_0$  from 0 (d.c., constant sequence, no oscillation) the oscillation increases until  $\omega_0 = \pi$ , thereafter the oscillation will decrease to 0, i.e. a d.c. signal at  $\omega_0 = 2\pi$
- $\Rightarrow$  low frequencies occurs at  $\omega_0 = 0, \pm 2\pi, \pm \text{even multiple of } \pi$
- $\Rightarrow$  High frequencies are at  $\omega_0 = \pm\pi, \pm 3\pi, \pm \text{odd multiple of } \pi$

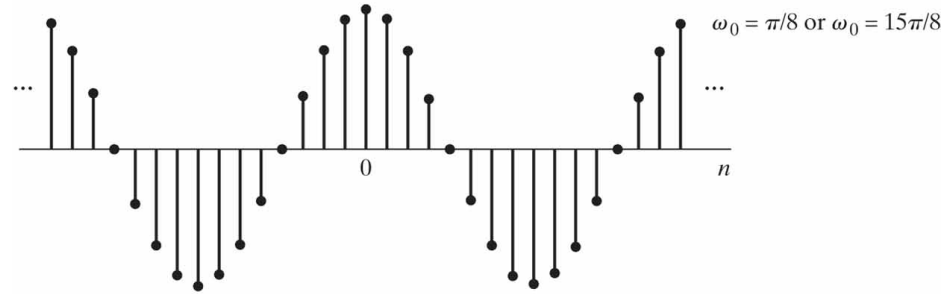
$\cos \omega_0 n$  for different  
 $\omega_0$



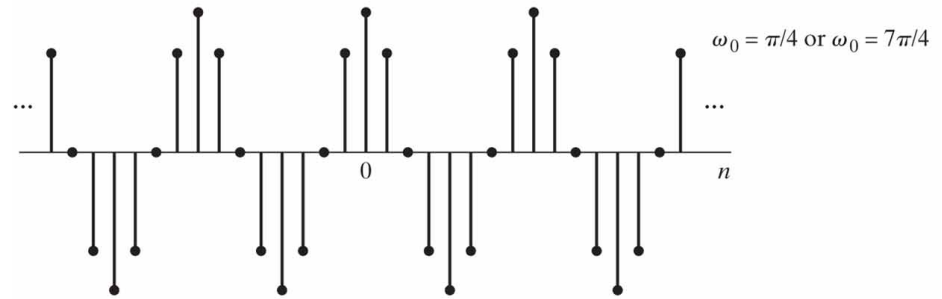
As  $\omega_0$  increases from zero toward  $\pi$   
(parts a-d), the sequence oscillates more  
rapidly



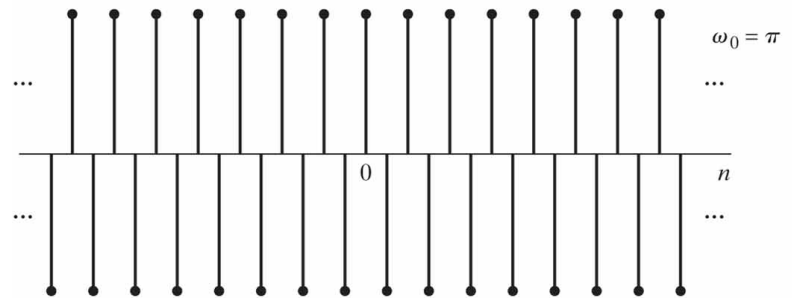
(a)



(b)



(c)



(d)



# CT versus DT complex exponentials

$$e^{j\Omega_0 t}$$

Distinct signals for distinct values of  $\Omega_0$

The larger  $\Omega_0$ , the higher the rate of oscillation

Periodic for any choice of  $\Omega_0$

Fundamental frequency  $\Omega_0$

Fundamental period  $T$

$\Omega_0 = 0$ :  $T$  undefined

$$\Omega_0 \neq 0 : T = \frac{2\pi}{\Omega_0}$$

$$e^{j\omega_0 n}$$

Identical signals for  $\omega_0 = 2\pi k$  (multiples of  $2\pi$ )

Periodic only if  $\omega_0 = \frac{2\pi m}{N}$  (integer  $N > 0$  and  $m$ )

Fundamental frequency  $\frac{\omega_0}{m}$

Fundamental period  $N$

$\omega_0 = 0$ :  $N$  undefined

$\omega_0 \neq 0 : N = m \frac{2\pi}{\omega_0}$  (or  $\frac{N}{m} = \frac{2\pi}{\omega_0}$  rational #)

# General Complex Exponential Sequence

$$x[n] = A\alpha^n,$$

where  $A$  and  $\alpha$  are complex numbers

◦ Case 1: Let  $\alpha = e^{j\omega_o}$  and  $A = e^{j\theta} \therefore x[n] = e^{j\theta} e^{j\omega_o n} = e^{j(\omega_o n + \theta)}$

$$\Rightarrow x[n] = \cos(\omega_o n + \theta) + j \sin(\omega_o n + \theta)$$

$\omega_o$  the frequency

$\theta$  the phase

And

$$\operatorname{Re}\{x[n]\} = \cos(\omega_o n + \theta)$$

$$\operatorname{Im}\{x[n]\} = \sin(\omega_o n + \theta)$$



# General Complex Exponential Signals

- Case 2: For general complex  $A$  and  $\alpha$

$$\alpha = r_{\alpha} e^{j\omega_o} \text{ and } A = r_A e^{j\theta} \therefore x[n] = A\alpha^n = r_A r_{\alpha}^n e^{j(\omega_o n + \theta)}$$

$$\Rightarrow x[n] = r_A r_{\alpha}^n \cos(\omega_o n + \theta) + j r_A r_{\alpha}^n \sin(\omega_o n + \theta)$$

$r_{\alpha} = 1 \Rightarrow$  real & imaginary parts are sinusoidal

$r_{\alpha} < 1 \Rightarrow$  sinusoidal decaying exponentially

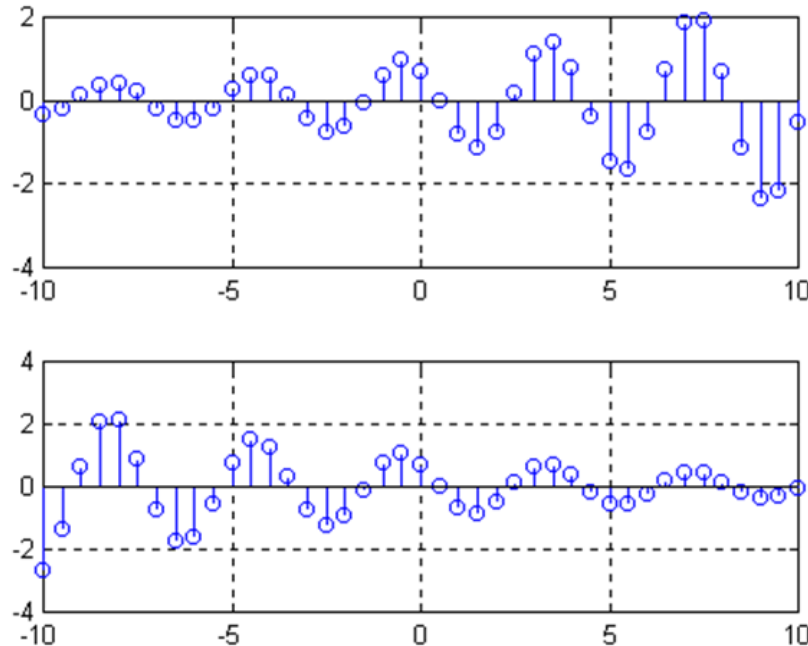
$r_{\alpha} > 1 \Rightarrow$  sinusoidal growing exponentially

# Growing & Decaying exponential

## Growing

- Population growth as function of generation
- Total return on investment as a function of day, month or quarter
- Credit card interest

```
pi=3.142;  
t=-10:1:10;  
f=2000;  
w=2*pi*f;  
r=0.1;  
x=zeros(size(t));  
x=exp((r+w*i)*t);  
theta=pi/4;  
c=1*exp(i*theta);  
y=c*x;  
subplot(2,1,1);  
plot(t,y);  
grid;
```



## Decaying:

- Response of RLC circuits
- Mechanical systems having both damping & restoring forces, e.g., automotive suspension system

```
r=-0.1;  
x=zeros(size(t));  
x=exp((r+w*i)*t);  
theta=pi/4;  
c=1*exp(i*theta);  
y=c*x;  
subplot(2,1,2);  
plot(t,y);  
grid;
```



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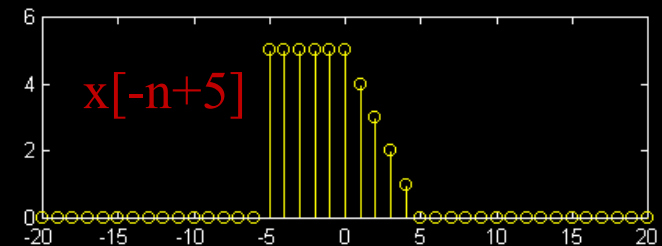
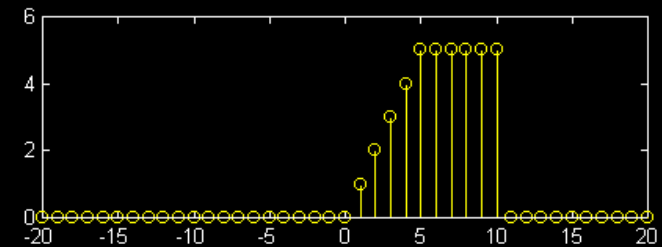
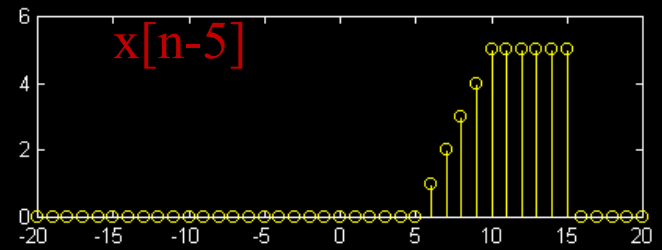
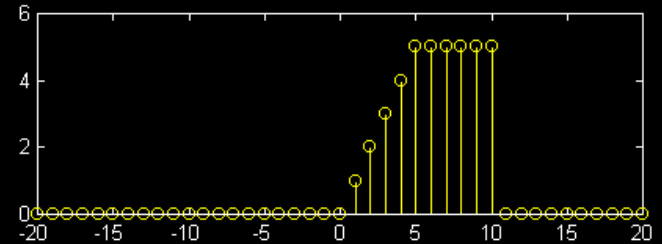
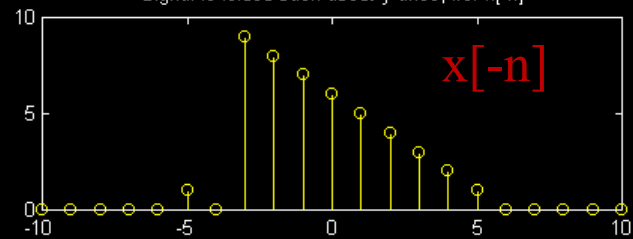
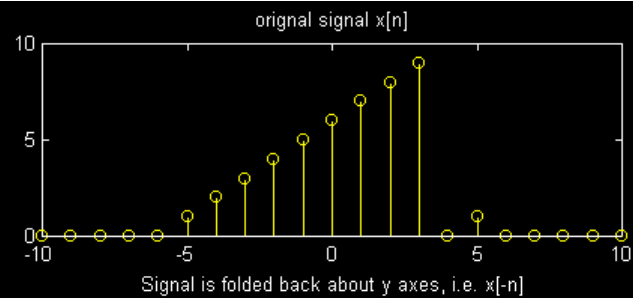
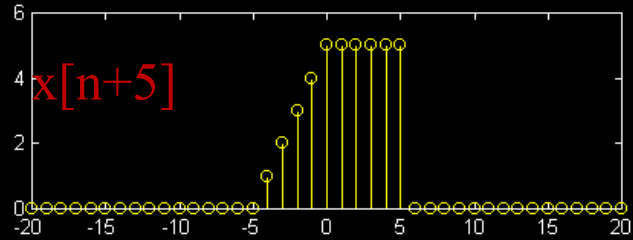
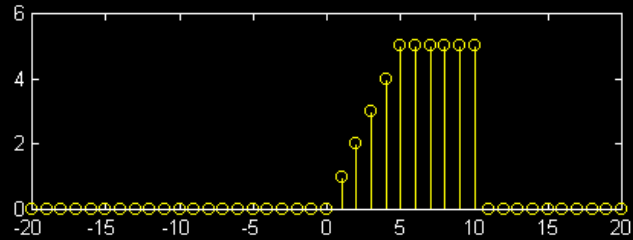


# Transformation of Independent Variable (time axes)

- Time shift  $x[n-b]$
- Time reversal  $x[-n]$
- Time scaling  $x[2n]$
- Combinations of these:  $x[an-b]$ ,  $a$  &  $b$  are constants
- An application: Aircraft control system:
  - Input = pilot actions
  - These action are transformed by electrical & mechanical system of the aircraft to changes to aircraft trust or position control surfaces such as the rudder & ailerons
  - Finally these changes affect the dynamics & kinematics such as the aircraft velocity and heading

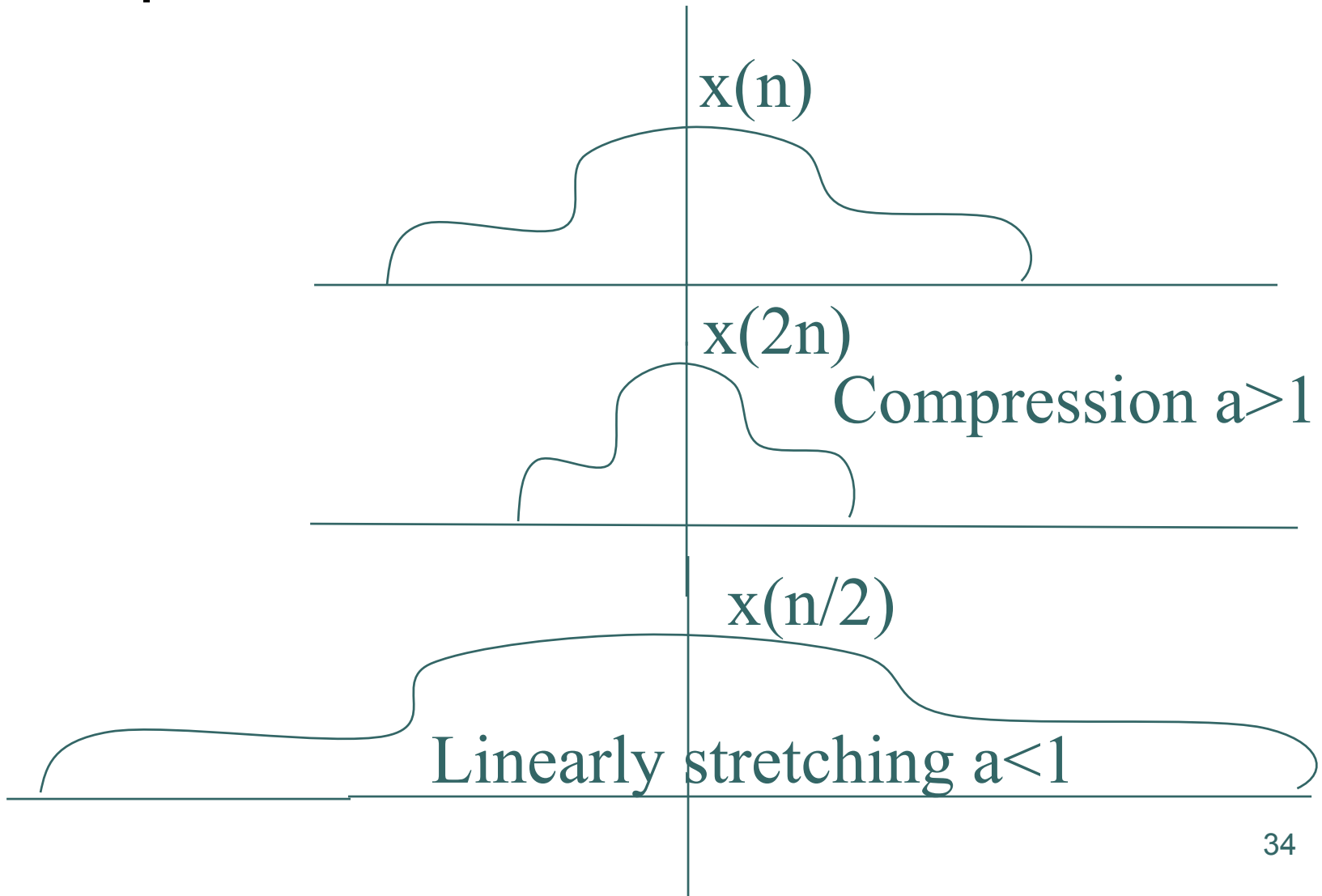


# Examples



# Examples

Time scaling  $y(n)=x(an)$





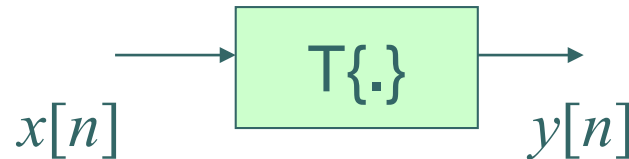
# Outline

- Introduction
- DT signals
- Transformation of the independent variable
- **DT LTI Systems & Convolution**
- Frequency content of signals
- Fourier transform & Frequency response

# Discrete-time systems

$$y[n] = T\{x[n]\}$$

- An operator (transformation) that maps input into output



- Examples:

- Delay system  $y[n] = x[n - n_d], \quad -\infty < n < \infty$

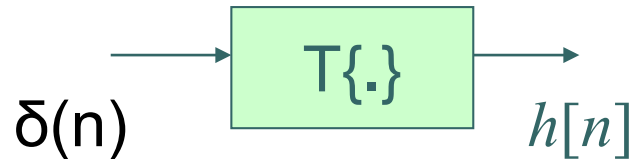
- Memoryless system  $y[n] = (x[n])^2, \quad -\infty < n < \infty$

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

# LTI systems

## Impulse response

- What if the input to the system is an impulse  $\delta(n)$  ?



- The output is called the response to an impulse (impulse response)  $h(n)$
- But what properties should such system has?*
  - Linear &*
  - Time Invariant*

**→ LTI**

# Linear systems (Linearity)

- A system is linear if and only if

additivity property

$$T\{x_1[n] + x_2[n]\} = T\{x_1[n]\} + T\{x_2[n]\} = y_1[n] + y_2[n]$$

and

$$T\{ax[n]\} = aT\{x[n]\} = ay[n]$$

scaling property

where  $a$  is an arbitrary constant

- Combined into superposition

$$T\{ax_1[n] + bx_2[n]\} = aT\{x_1[n]\} + bT\{x_2[n]\} = ay_1[n] + by_2[n]$$



# Examples

- Accumulator system – a linear system

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

$$y_1[n] = \sum_{k=-\infty}^n x_1[k], \quad y_2[n] = \sum_{k=-\infty}^n x_2[k]$$

$$y_3[n] = \sum_{k=-\infty}^n (ax_1[k] + bx_2[k]) = ay_1[n] + by_2[n]$$

- A nonlinear system

$$y[n] = \log_{10}(|x[n]|)$$

Consider  $x_1[n] = 1$  and  $x_2[n] = 10$



# Time-invariant systems

$$x_1[n] = x[n - n_0] \Rightarrow y_1[n] = y[n - n_0]$$

- For which a time shift (or delay) of the input sequence causes a corresponding shift in the output sequence
- Example: Accumulator system

$$y[n] = \sum_{k=-\infty}^n x[k] \quad ; \quad y[n - n_0] = \sum_{k=-\infty}^{n-n_0} x[k]$$

$$y_1[n] = \sum_{k=-\infty}^n x_1[k] = \sum_{k=-\infty}^n x[k - n_0] = \sum_{k_1=-\infty}^{n-n_0} x[k_1] = y[n - n_0]$$



# LTI systems and Convolution

## Proof

- A **linear** system is completely characterised by its impulse response

We know:  $x[n] = \sum_{k=-\infty}^{\infty} x[k]\delta[n-k]$

$$h[n] = T\{\delta[n]\} \quad (\text{response of } T\{\} \text{ to an impulse})$$

$$h[n-k] = T\{\delta[n-k]\} \quad (\text{time-invariant})$$

$$\Rightarrow y[n] = T\{x[n]\} = T\left\{\sum_{k=-\infty}^{\infty} x[k]\delta[n-k]\right\} = \sum_{k=-\infty}^{\infty} x[k]T\{\delta[n-k]\} \quad (\text{linear})$$

- **LTI**  $y[n] = \sum_{k=-\infty}^{\infty} x[k]h[n-k] = \sum_{k=-\infty}^{\infty} x[n-k]h[k]$   
 $\quad = x[n] * h[n] = h[n] * x[n]$  **← Convolution sum**

# Computation of the convolution sum

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

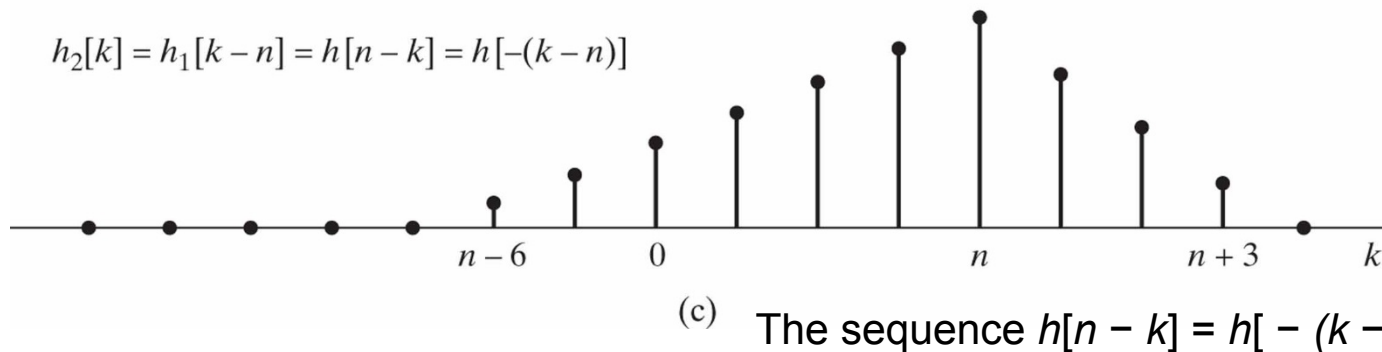
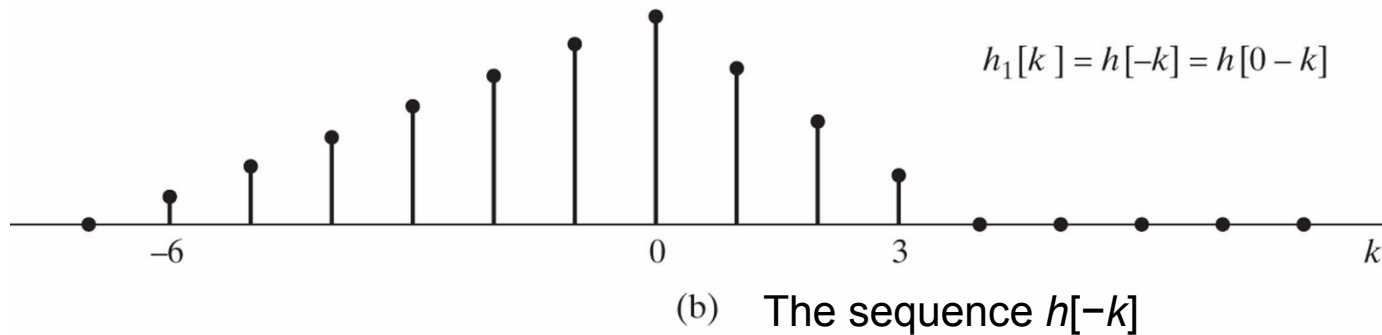
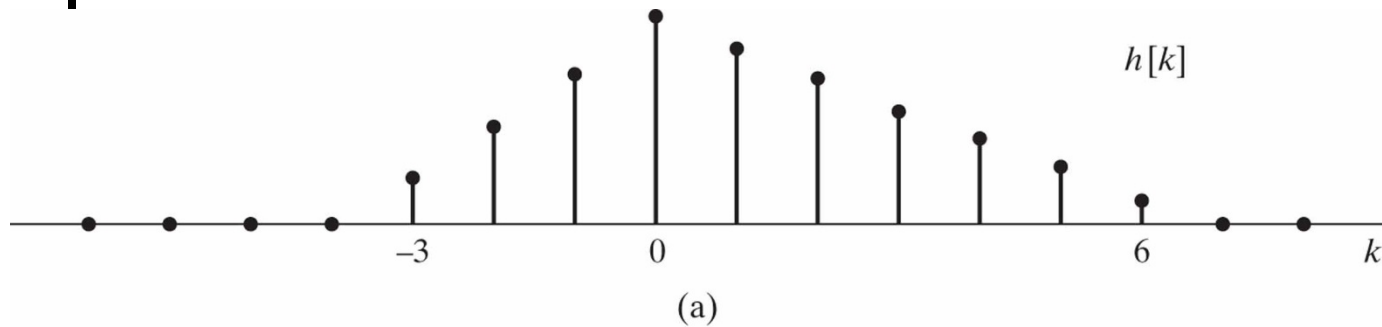
- Obtain the sequence  $h[n-k]$ 
  - Reflecting  $h[k]$  about the origin to get  $h[-k]$
  - Shifting the origin of the reflected sequence to  $k=n$
- Multiply  $x[k]$  and  $h[n-k]$  for
- Sum the products to compute the output sample  $y[n]$
- Interpretation of convolution operation
  - replacing each pixel by a weighted sum of its neighbors

---

## Example

- Low-pass: the weights sum = weighted average
- High-pass: the weighted sum = left neighbors – right neighbors

# Forming the sequence $h[n-k]$



# Discrete convolution

## Example

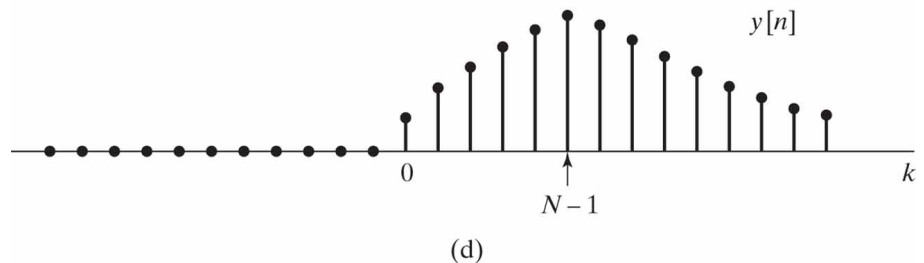
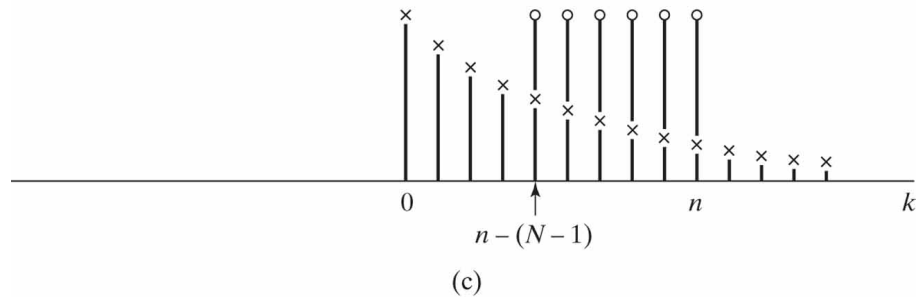
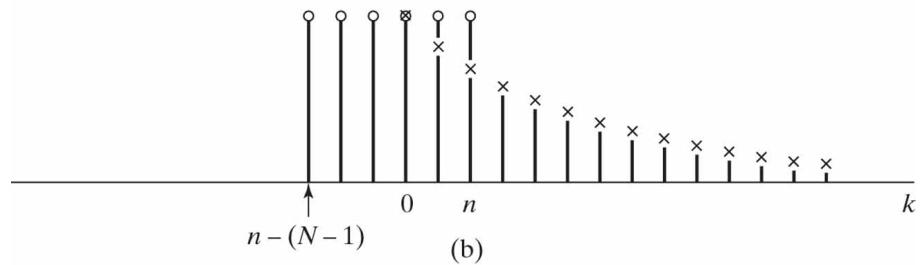
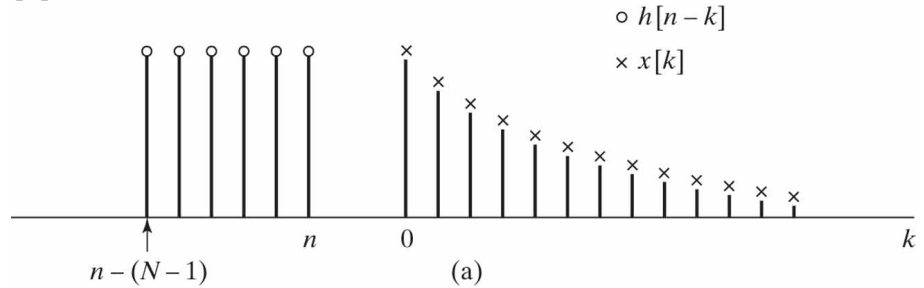
### Impulse response

$$h[n] = u[n] - u[n - N]$$

$$= \begin{cases} 1, & 0 \leq n \leq N-1, \\ 0, & \text{otherwise.} \end{cases}$$

### Input $x[n] = a^n u[n]$

$$y[n] = \begin{cases} 0, & n < 0, \\ \frac{1 - a^{n+1}}{1 - a}, & 0 \leq n \leq N-1, \\ a^{n-N+1} \left( \frac{1 - a^N}{1 - a} \right), & N-1 < n. \end{cases}$$





# Convolution Example

$$h[n] = 2\delta[n] - 2\delta[n-1]$$

$$x[n] = u[n+1] - u[n-1] + 2\delta[n-2]$$

$$\text{Find } y[n] = x[n] * h[n]$$

- The sequence  $h[n]$  consists of two samples.
  - Therefore, convolving  $x[n]$  and  $h[n]$  can be simplified by convolving  $x[n]$  with  $h[n]$  one sample at a time.
    - For example,  $h[n] = 4\delta[n] - 2\delta[n-1]$  can be convolved by convolving  $x[n]$  first with  $h_1[n] = 4\delta[n]$  and then convolving  $x[n]$  with  $h_2[n] = -2\delta[n-1]$
- Finally, the convolution sum ( $y[n]$ ) can be then obtained by adding the two sequences (adding sample by corresponding sample).
- In doing this, the output  $y[n]$  is
$$y[n] = 3\delta[n+1] + \delta[n] - \delta[n-1] + 6\delta[n-2] - 4\delta[n-3]$$
- The same can be represented graphically which is just as good.



# Properties of LTI systems

## Defined by convolution and $h[n]$

- **Causality:** the output sequence value at the index  $n=n_0$  depends only on the input sequence values for  $n \leq n_0$
- Example  $y[n] = x[n - n_d]$ ,  $-\infty < n < \infty$ 
  - Causal for  $n_d \geq 0$
  - Noncausal for  $n_d < 0$
- **Stability:** A system is stable in the (bounded input bounded output) BIBO sense if and only if every bounded input sequence produces a bounded output sequence
- Example  $y[n] = (x[n])^2$ ,  $-\infty < n < \infty$



# Properties of LTI systems

## Defined by convolution and $h[n]$

- Commutative

$$x[n] * h[n] = h[n] * x[n]$$

- Linear

$$x[n] * (h_1[n] + h_2[n]) = x[n] * h_1[n] + x[n] * h_2[n]$$

- Cascade connection

$$h[n] = h_1[n] * h_2[n]$$

- Parallel connection

$$h[n] = h_1[n] + h_2[n]$$

- Stable  $\sum_{k=-\infty}^{\infty} |h[k]| < \infty$

- Causality  $h[n] = 0, \quad n < 0$



# Outline

- Introduction
- DT signals
- Transformation of the independent variable
- LTI Systems & Convolution
- **Frequency content of signals**
- Fourier transform
- Relation between Fourier representations
- Frequency response





# Signal Representation

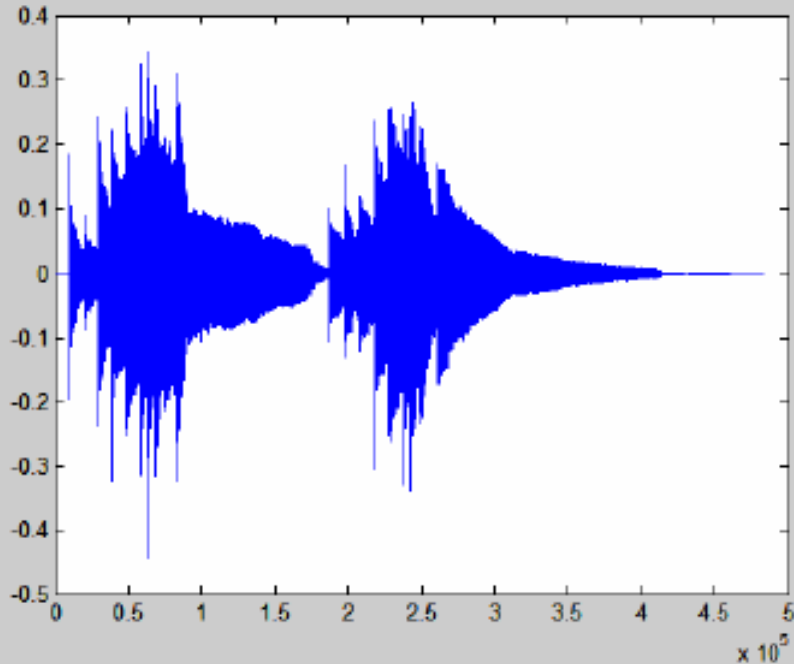
- Time-domain representation  $x(n)$ 
  - Waveform based
  - Periodic / non-periodic signals
  - Sound amplitude, temperature reading, stock price
- Frequency-domain representation  $X(e^{j\omega})$ 
  - Periodic signals
  - Sinusoidal signals
  - Frequency analysis for periodic signals
  - Concepts of frequency, bandwidth, filtering



# Frequency content in signals

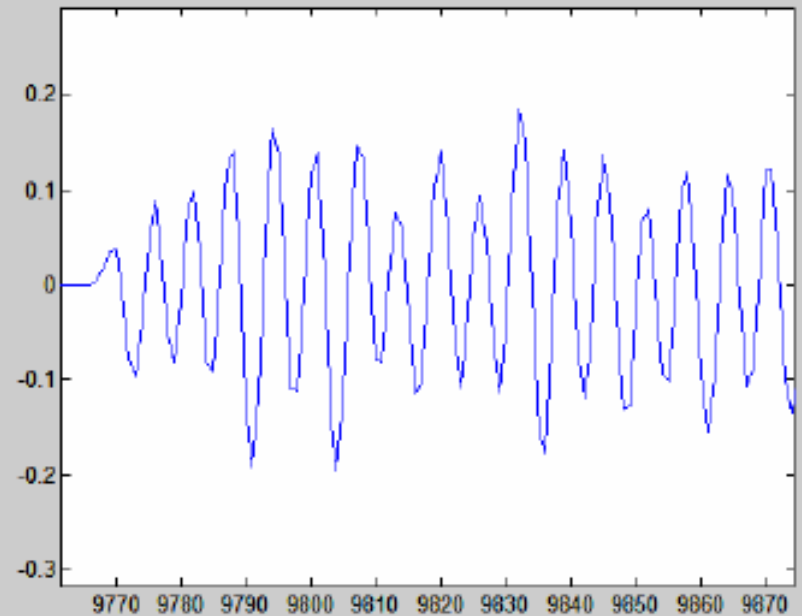
- A **constant** : only zero frequency component (DC component)
- **Slowly** varying : contain low frequency only
- **Fast** varying : contain very high frequency
- **Sharp** transition : contain from low to high frequency
  
- A **sinusoid** : Contain only a single frequency component
- **Periodic** signals : Contain the fundamental frequency and harmonics : Line spectrum
  
- **Real-world** signal: contain different frequencies =  $\Sigma$  sinusoid
- Music: :
  - contain both slowly varying and fast varying components, wide bandwidth

# Sample Music Waveform



Entire waveform

```
» [y,fs]=wavread('sc01_L.wav');  
» sound(y,fs);  
» figure; plot(y);
```

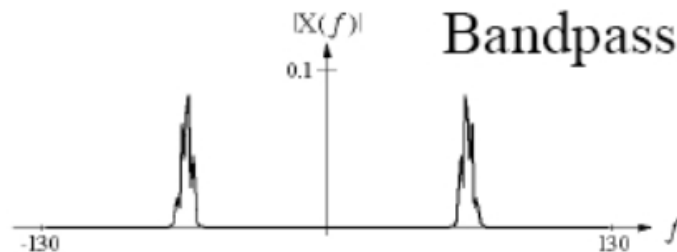
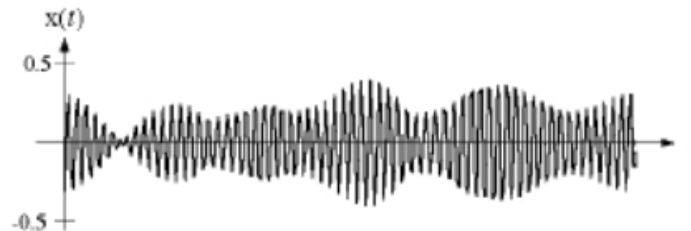
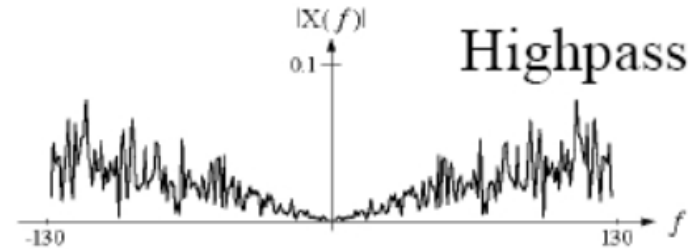
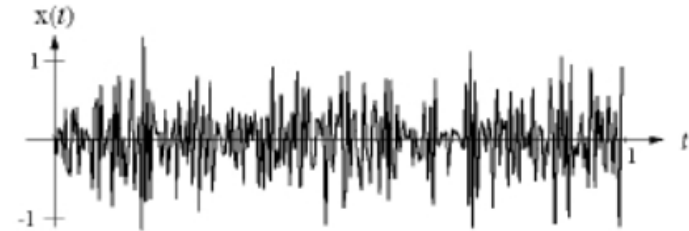
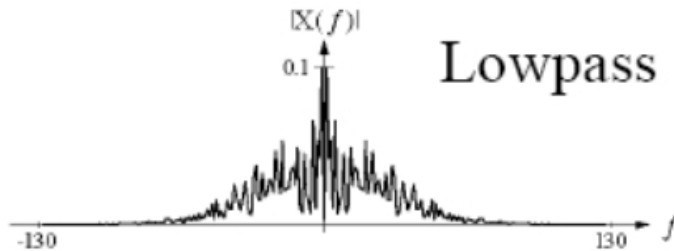
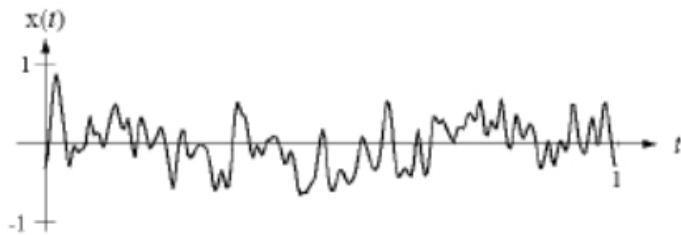


Blown-up of a section

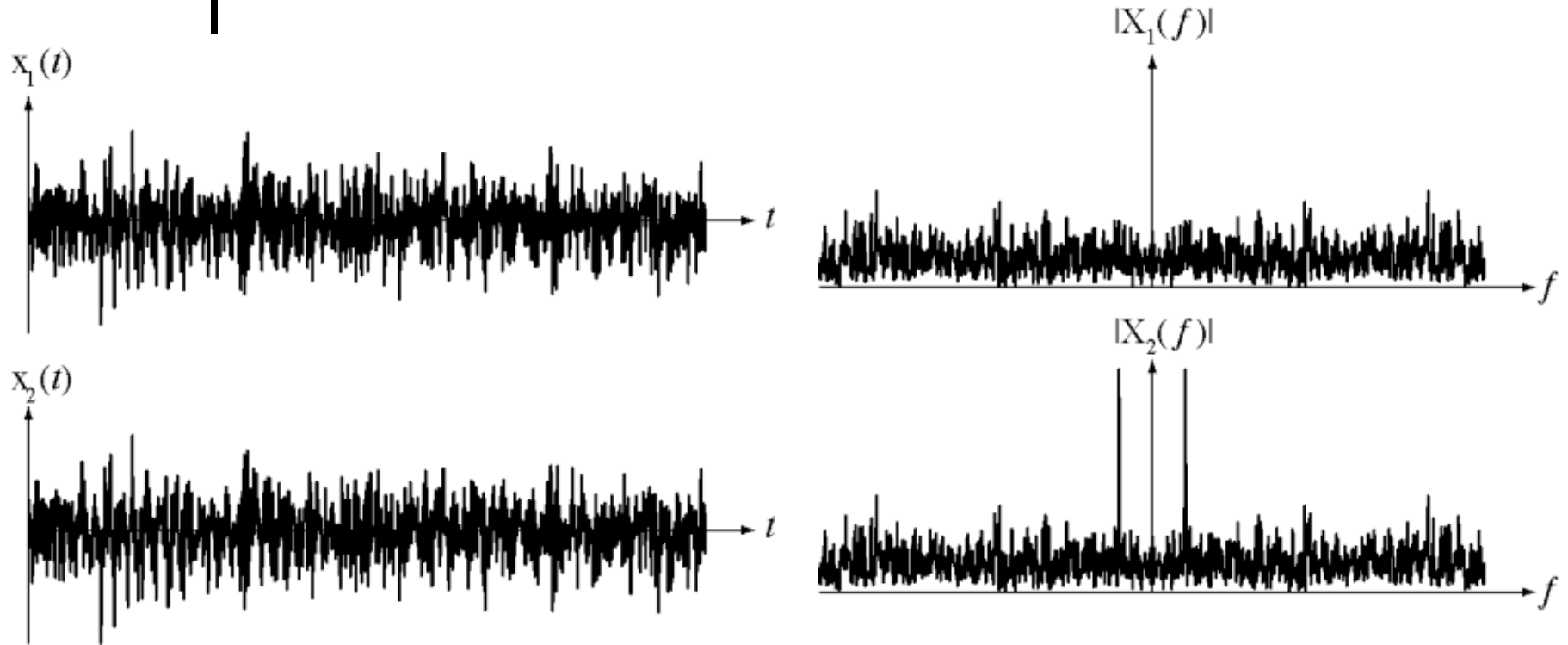
```
» v=axis;  
» axis([1.1e4,1.2e4,-.2,.2])
```

Music typically has more periodic structure than speech  
Structure depends on the note being played

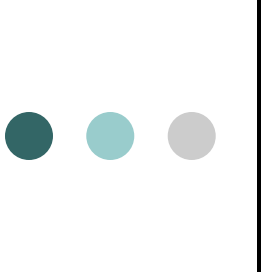
# Frequency content in signals



# Spectrum analyzer



- $x_1(t)$  &  $x_2(t)$  look similar
- A spectrum analyzer reveals the difference:
  - ➔  $x_2(t)$  contains a sinusoid that causes the two large “spikes”



# What is the frequency of an arbitrary signal?

- Sinusoidal signals have a distinct (unique) frequency
- An arbitrary signal  $x(t)$  does not have a unique frequency
  - $x(t)$  can be decomposed into many sinusoidal signals with **different** frequencies, each with **different** magnitude and phase
- ***Spectrum*** of  $x(t)$ :
  - the plot of the magnitudes and phases of different frequency components of  $x(t)$
- ***Fourier analysis***: find spectrum for signals
- ***Bandwidth*** of  $x(t)$ : the spread of the frequency components with significant energy existing in a signal
  - Difference between min and max frequency



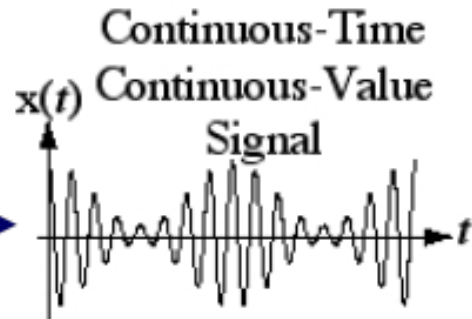
# Outline

- Introduction
- DT signals
- Transformation of the independent variable
- DT LTI Systems & Convolution
- Impulse response and diff. equations
- Frequency content of signals
- **Fourier Transform**
- Frequency response

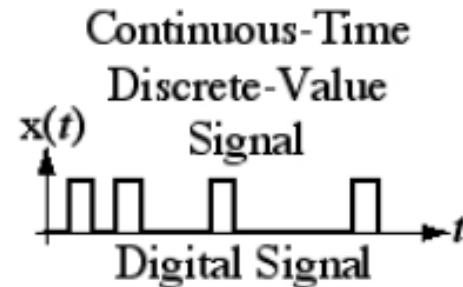
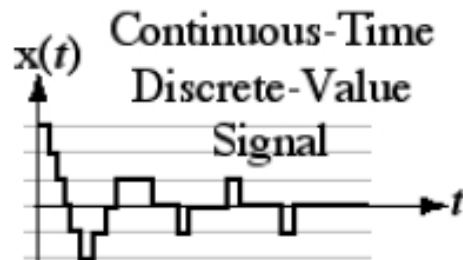
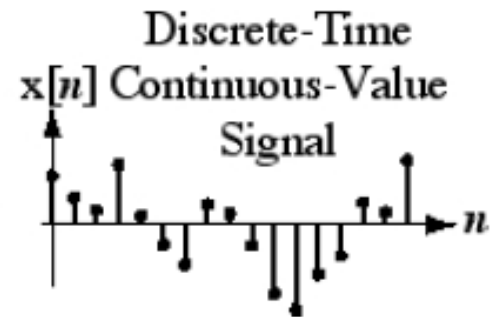
# Fourier Analysis: Types of signals

Periodic

Analog

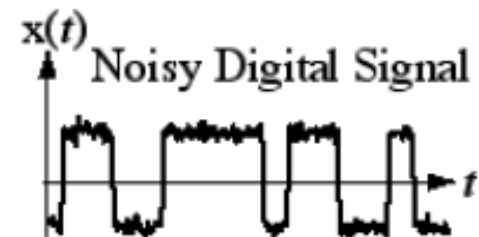
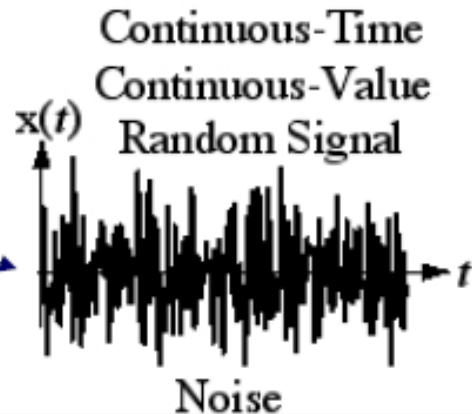


Digital



Digital Signal

Non-periodic



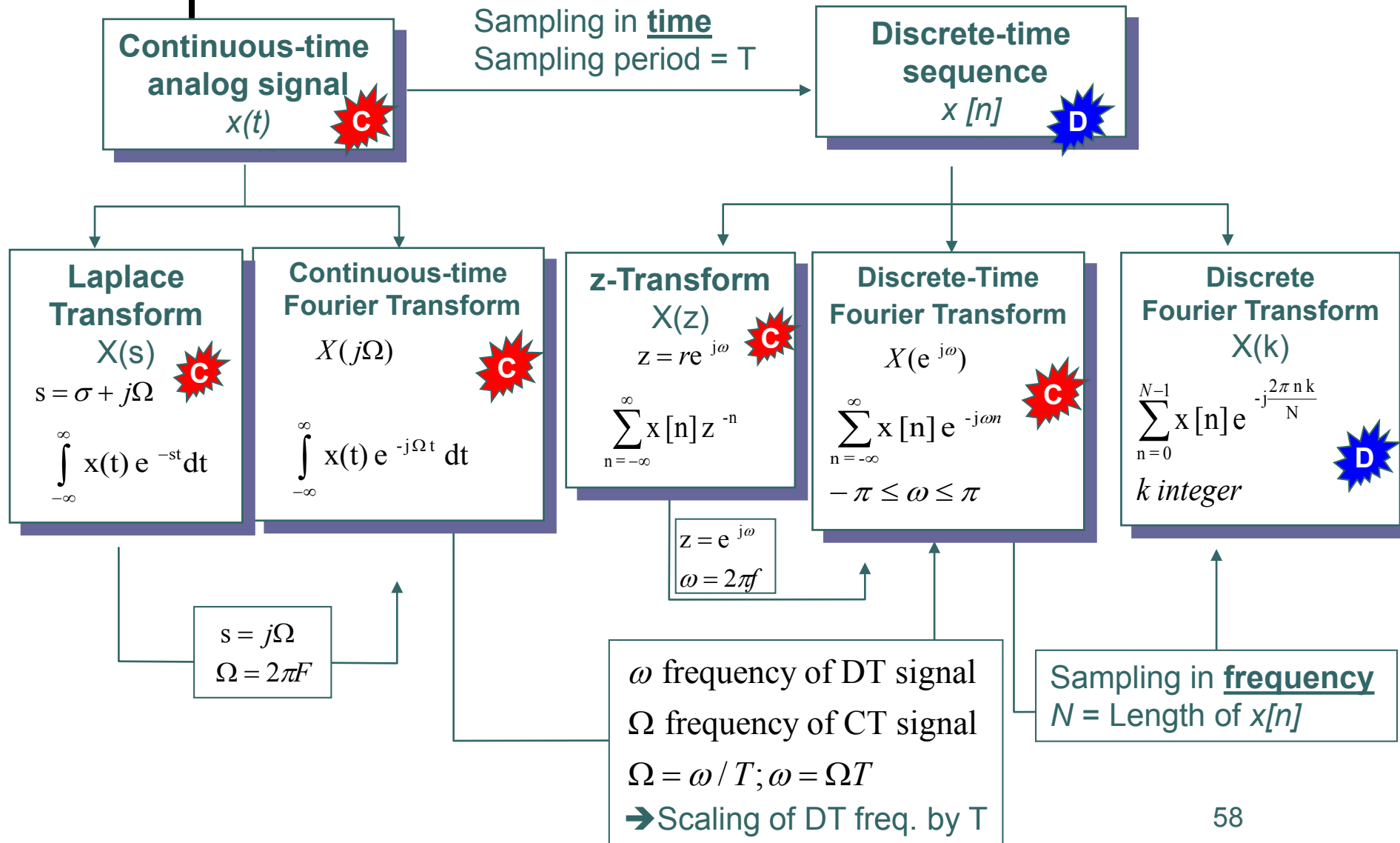
Noise



# Overview of Fourier Analysis Methods

	Periodic in Time Discrete in Frequency	Aperiodic in Time Continuous in Frequency
Continuous in Time  Aperiodic in Frequency	⊗ CT Fourier Series : CT - $P_T \Rightarrow$ DT $a_k = \frac{1}{T} \int_0^T x(t) e^{-jk\omega_0 t} dt$ ⊗ CT Inverse Fourier Series : DT $\Rightarrow$ CT - $P_T$ $x(t) = \sum_{k=-\infty}^{\infty} a_k e^{jk\omega_0 t}$	⊗ CT Fourier Transform : CT $\Rightarrow$ CT $X(j\omega) = \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt$ ⊗ Inverse CT Fourier Transform : CT $\Rightarrow$ CT $x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(j\omega) e^{j\omega t} d\omega$
Discrete in Time  Periodic in Frequency	⊗ DT Fourier Series DT - $P_N \Rightarrow$ DT - $P_N$ $X[k] = \sum_{n=0}^{N-1} x[n] e^{-j\omega_0 kn}$ ⊗ Inverse DT Fourier Series DT - $P_N \Rightarrow$ DT - $P_N$ $x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X[k] e^{j\omega_0 kn}$	⊗ DT Fourier Transform : DT $\Rightarrow$ CT + $P_{2\pi}$ $X(e^{j\omega}) = \sum_{n=-\infty}^{\infty} x[n] e^{-j\omega n}$ ⊗ Inverse DT Fourier Transform : CT + $P_{2\pi} \Rightarrow$ DT $x[n] = \frac{1}{2\pi} \int_{2\pi} X(e^{j\omega}) e^{j\omega n} d\omega$

# Fourier Analysis Methods



# Overview of Fourier symbols

	Variable	Period	Continuous Frequency	Discrete Frequency
DT $x[n]$	$n$	$N$	$\omega$	$k$ $\omega_k = 2\pi k / N$
CT $x(t)$	$t$	$T$	$\Omega$	$k$ $\omega_k = 2\pi k / T$

- **DT-FT**: Discrete in time; Aperiodic in time; Continuous in Frequency; Periodic in Frequency
- **CT-FT**: Continuous in time; Aperiodic in time; Continuous in Frequency; Aperiodic in Frequency
- **DT-FS**: Discrete in time; Periodic in time; Discrete in Frequency; Periodic in Frequency
- **CT-FS**: Continuous in time; Periodic in time; Discrete in Frequency; Aperiodic in Frequency



# DT Fourier Transform

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

→ DTFT represents a DT aperiodic signal

- as a sum of infinitely many complex exponentials
- with the frequency varying continuously in  $(-\pi, \pi)$
- DTFT is periodic → only need to determine it for  $(-\pi, \pi)$
- Often FT is a complex function (magnitude+phase)

$$X(e^{j\omega}) = X_{\text{Re}}(e^{j\omega}) + jX_{\text{Im}}(e^{j\omega}) = |X(e^{j\omega})| e^{j\angle X(e^{j\omega})}$$

- A FT is unique, i.e., different signals have different FT
- FT is the frequency domain representation of the original function
- FT describes which frequencies are present in the original function
- The original signal can be recovered from its FT, and vice versa

# Limitation of Fourier transform

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

- Condition for the convergence of the infinite sum

$$|X(e^{j\omega})| = \left| \sum_{n=-\infty}^{\infty} x[n]e^{-j\omega n} \right| \leq \sum_{n=-\infty}^{\infty} |x[n]| |e^{-j\omega n}| \leq \sum_{n=-\infty}^{\infty} |x[n]| < \infty$$

- If  $x[n]$  is **absolutely** summable, its FT (sufficient condition)

- Example: Exponential + unit step

$$x[n] = a^n u[n] \quad |a| < 1: \quad X(e^{j\omega}) = \frac{1}{1 - ae^{-j\omega}}$$

$$a = 1: \quad X(e^{j\omega}) = \frac{1}{1 - e^{-j\omega}} + \sum_{k=-\infty}^{\infty} \pi \delta(\omega + 2\pi k)$$

$$|a| > 1: \quad \text{No}$$

# Example: a constant sequence

- Constant sequence  $x[n] = 1$

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

→ Its FT is defined as the periodic impulse train

$$X(e^{j\omega}) = \sum_{r=-\infty}^{\infty} 2\pi \delta(\omega + 2\pi r)$$

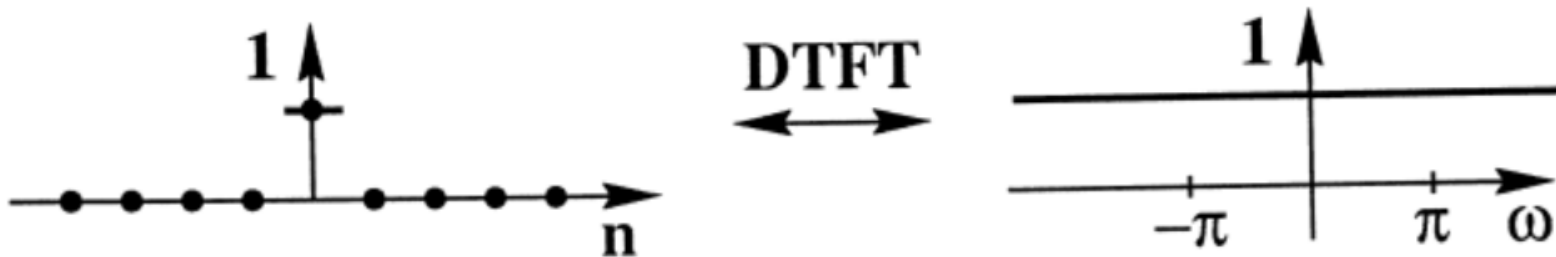


# Example: impulse

1.  $x(n] = \delta(n]$

$$X(e^{j\omega}) = \sum_n \delta(n] e^{-j\omega n}$$

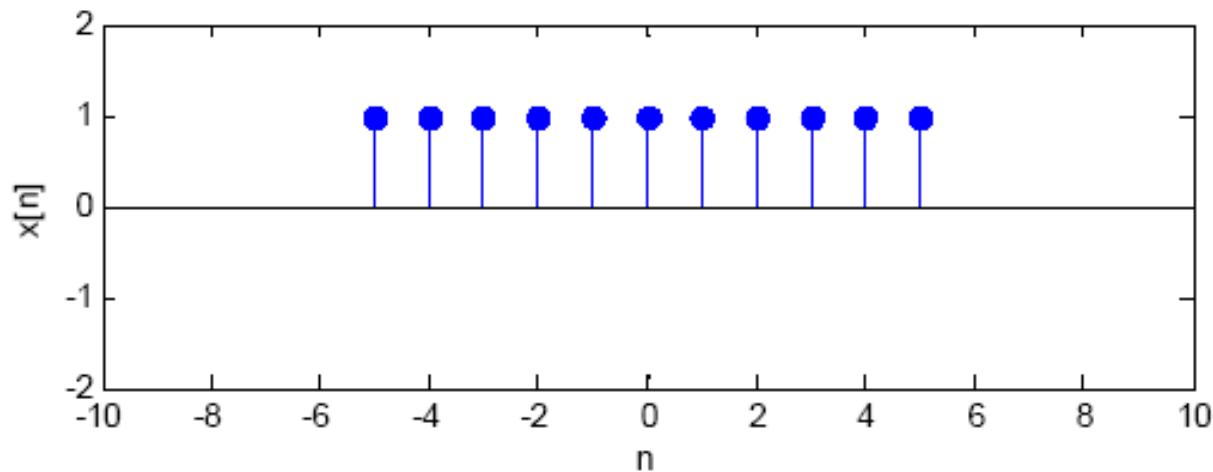
$$= 1 \quad (\text{by sifting property})$$



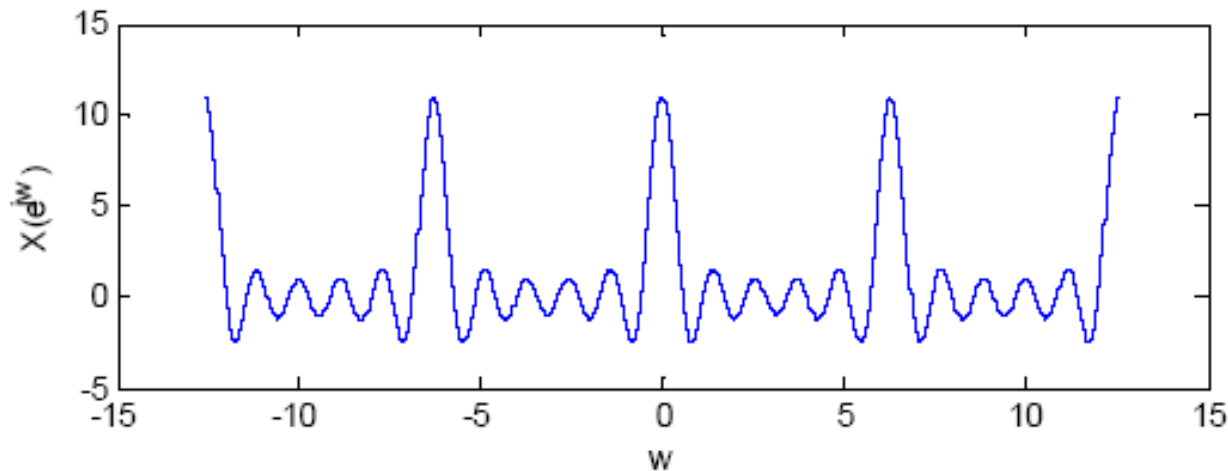
# Example: rectangle

$$x[n] = \begin{cases} 1, & |n| \leq 5 \\ 0, & \text{e.w.} \end{cases} \longrightarrow$$

$$X(e^{j\omega}) = \sum_{n=-5}^5 e^{-j\omega n} = \frac{\sin[\omega(11/2)]}{\sin[\omega/2]}$$



**Aperiodic**



**Periodic**

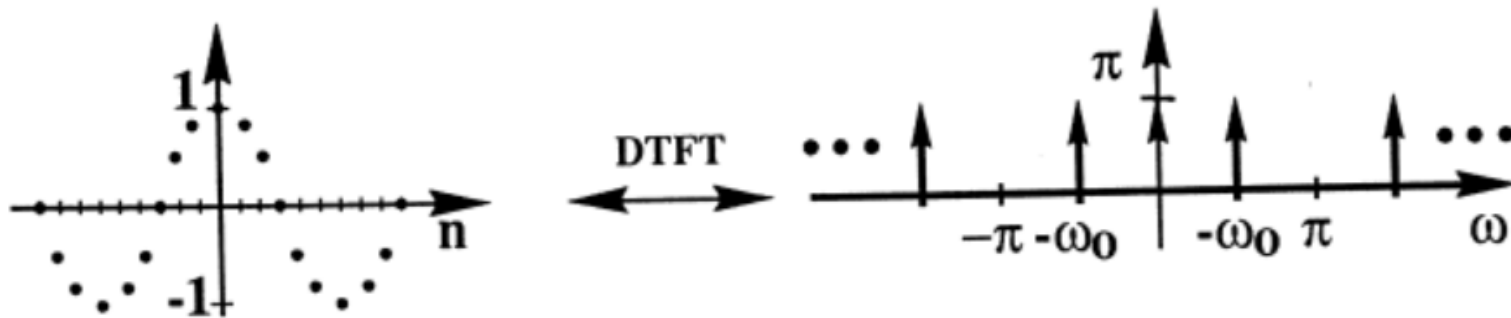


# Example: exp / sinusoid

$$3. e^{j\omega_0 n} \xleftrightarrow{\text{DTFT}} \text{rep}_{2\pi}[2\pi \delta(\omega - \omega_0)]$$

(by modulation property)

$$4. \cos(\omega_0 n) \xleftrightarrow{\text{DTFT}} \text{rep}_{2\pi}[\pi \delta(\omega - \omega_0) + \pi \delta(\omega + \omega_0)]$$



**TABLE 2.2**    **FOURIER TRANSFORM THEOREMS**

Sequence	Fourier Transform
$x[n]$	$X(e^{j\omega})$
$y[n]$	$Y(e^{j\omega})$
1. $ax[n] + by[n]$	$aX(e^{j\omega}) + bY(e^{j\omega})$
2. $x[n - n_d]$ ( $n_d$ an integer)	$e^{-j\omega n_d} X(e^{j\omega})$
3. $e^{j\omega_0 n} x[n]$	$X(e^{j(\omega - \omega_0)})$
4. $x[-n]$	$X(e^{-j\omega})$ $X^*(e^{j\omega})$ if $x[n]$ real.
5. $nx[n]$	$j \frac{dX(e^{j\omega})}{d\omega}$
6. $x[n] * y[n]$	$X(e^{j\omega})Y(e^{j\omega})$
7. $x[n]y[n]$	$\frac{1}{2\pi} \int_{-\pi}^{\pi} X(e^{j\theta})Y(e^{j(\omega - \theta)})d\theta$

Parseval's theorem:

$$8. \sum_{n=-\infty}^{\infty} |x[n]|^2 = \frac{1}{2\pi} \int_{-\pi}^{\pi} |X(e^{j\omega})|^2 d\omega$$

$$9. \sum_{n=-\infty}^{\infty} x[n]y^*[n] = \frac{1}{2\pi} \int_{-\pi}^{\pi} X(e^{j\omega})Y^*(e^{j\omega})d\omega$$

**TABLE 2.3** FOURIER TRANSFORM PAIRS

Sequence	Fourier Transform
1. $\delta[n]$	1
2. $\delta[n - n_0]$	$e^{-j\omega n_0}$
3. 1 $(-\infty < n < \infty)$	$\sum_{k=-\infty}^{\infty} 2\pi \delta(\omega + 2\pi k)$
4. $a^n u[n]$ $( a  < 1)$	$\frac{1}{1 - ae^{-j\omega}}$
5. $u[n]$	$\frac{1}{1 - e^{-j\omega}} + \sum_{k=-\infty}^{\infty} \pi \delta(\omega + 2\pi k)$
6. $(n+1)a^n u[n]$ $( a  < 1)$	$\frac{1}{(1 - ae^{-j\omega})^2}$
7. $\frac{r^n \sin \omega_p(n+1)}{\sin \omega_p} u[n]$ $( r  < 1)$	$\frac{1}{1 - 2r \cos \omega_p e^{-j\omega} + r^2 e^{-j2\omega}}$
8. $\frac{\sin \omega_c n}{\pi n}$	$X(e^{j\omega}) = \begin{cases} 1, &  \omega  < \omega_c, \\ 0, & \omega_c <  \omega  \leq \pi \end{cases}$
9. $x[n] = \begin{cases} 1, & 0 \leq n \leq M \\ 0, & \text{otherwise} \end{cases}$	$\frac{\sin[\omega(M+1)/2]}{\sin(\omega/2)} e^{-j\omega M/2}$
10. $e^{j\omega_0 n}$	$\sum_{k=-\infty}^{\infty} 2\pi \delta(\omega - \omega_0 + 2\pi k)$
11. $\cos(\omega_0 n + \phi)$	$\sum_{k=-\infty}^{\infty} [\pi e^{j\phi} \delta(\omega - \omega_0 + 2\pi k) + \pi e^{-j\phi} \delta(\omega + \omega_0 + 2\pi k)]$



# Examples: Determining a FT using FT theorems

$$x[n] = a^n u[n-5]$$

$$x_1[n] = a^n u[n] \overset{F}{\leftrightarrow} X_1(e^{j\omega}) = \frac{1}{1 - ae^{-j\omega}}$$

$$x_2[n] = x_1[n-5] \quad (\text{i.e.} = a^{n-5} u[n-5])$$

$$X_2(e^{j\omega}) = e^{-j5\omega} X_1(e^{j\omega}) = \frac{e^{-j5\omega}}{1 - ae^{-j\omega}}$$

$$x[n] = a^5 x_2[n] \quad (\text{i.e.} = a^n u[n-5])$$

$$X(e^{j\omega}) = \frac{a^5 e^{-j5\omega}}{1 - ae^{-j\omega}}$$

# Example: Convolution

- Let  $h[n] = \left(\frac{1}{2}\right)^n u[n]$  and  $x[n] = \left(\frac{1}{7}\right)^n u[n]$
- Find the output  $y[n]$
- Solution 1:** solve using convolution of  $h[n]$  and  $x[n]$  !!!
- Solution 2:** Use properties of FT:

- Convolution in time  $\rightarrow$  multiplication in frequency

$$y[n] = h[n] * x[n] \Rightarrow Y(e^{j\omega}) = H(e^{j\omega})X(e^{j\omega})$$

- We know:
$$h[n] = a^n u[n] \Rightarrow H(e^{j\omega}) = \frac{1}{1 - ae^{-j\omega}}, \quad a < 1$$
$$\Rightarrow H(e^{j\omega}) = \frac{1}{1 - \frac{1}{2}e^{-j\omega}} \quad \text{and} \quad X(e^{j\omega}) = \frac{1}{1 - \frac{1}{7}e^{-j\omega}}$$

# Example: Convolution

- Thus 
$$Y(e^{j\omega}) = H(e^{j\omega})X(e^{j\omega}) = \left(\frac{1}{1 - \frac{1}{7}e^{-j\omega}}\right)\left(\frac{1}{1 - \frac{1}{2}e^{-j\omega}}\right)$$

- What is  $y[n]$ ? It is the inverse FT

- Use partial fraction expansion method 
$$Y(e^{j\omega}) = \frac{-2/5}{1 - \frac{1}{7}e^{-j\omega}} + \frac{7/5}{1 - \frac{1}{2}e^{-j\omega}}$$

- We know

$$x[n] = a^n u[n] \Leftrightarrow X(e^{j\omega}) = \frac{1}{1 - ae^{-j\omega}} \quad ; \quad a < 1$$

- Recall: a FT is unique (different signals in time give different FT)

$$\frac{-2/5}{1 - \frac{1}{7}e^{-j\omega}} \Leftrightarrow -\frac{2}{5}\left(\frac{1}{7}\right)^n u[n] \quad \text{and} \quad \frac{7/5}{1 - \frac{1}{2}e^{-j\omega}} \Leftrightarrow \frac{7}{5}\left(\frac{1}{2}\right)^n u[n]$$

- The inverse FT 
$$y[n] = -\frac{2}{5}\left(\frac{1}{7}\right)^n u[n] + \frac{7}{5}\left(\frac{1}{2}\right)^n u[n]$$

# Symmetry properties of the FT

$x[n]$  is even (or symmetric) when  $x[n] = x[-n]$   
 $x[n]$  is odd (or antisymmetric) when  $x[n] = -x[-n]$

$$x[n] = x_e[n] + x_o[n]$$

$$\text{conjugate-symmetric sequence: } x_e[n] = \frac{1}{2}(x[n] + x^*[-n]) = x_e^*[-n]$$

$$\text{conjugate-antisymmetric sequence: } x_o[n] = \frac{1}{2}(x[n] - x^*[-n]) = -x_o^*[-n]$$

$$\text{even sequence is conjugate-symmetric: } x_e[n] = x_e[-n]$$

$$\text{odd sequence is conjugate-antisymmetric: } x_o[n] = -x_o[-n]$$

---

According to Table 2.1 (property 5&6)

$$x_e[n] \xrightarrow{\mathcal{F}} X_R(e^{j\omega}) = \mathcal{R}e\{X(e^{j\omega})\}$$

$$x_o[n] \xrightarrow{\mathcal{F}} jX_I(e^{j\omega}) = j\mathcal{I}m\{X(e^{j\omega})\}$$

$$\begin{aligned} X(e^{j\omega}) &= X_{\text{Re}}(e^{j\omega}) + jX_{\text{Im}}(e^{j\omega}) \\ &= |X(e^{j\omega})| e^{j\angle X(e^{j\omega})} \end{aligned}$$

# Duality property of Fourier transform

$$X(e^{j\omega}) = X_e(e^{j\omega}) + X_o(e^{j\omega})$$

$$\text{conjugate-symmetric FT: } X_e(e^{j\omega}) = \frac{1}{2} (X(e^{j\omega}) + X^*(e^{-j\omega}))$$

$$\text{conjugate-antisymmetric FT: } X_o(e^{j\omega}) = \frac{1}{2} (X(e^{j\omega}) - X^*(e^{-j\omega}))$$

$$\text{conjugate-symmetric Function : } X_e(e^{j\omega}) = X_e^*(e^{-j\omega})$$

$$\text{conjugate-antisymmetric Function : } X_o(e^{j\omega}) = -X_o^*(e^{-j\omega})$$

---

According to Table 2.1 (property 3&4)

$$\mathcal{R}\{x[n]\} \xrightarrow{\mathcal{F}} X_e(e^{j\omega})$$

$$j\mathcal{I}\{x[n]\} \xrightarrow{\mathcal{F}} X_o(e^{j\omega})$$



**TABLE 2.1** SYMMETRY PROPERTIES OF THE FOURIER TRANSFORM

Sequence $x[n]$	Fourier Transform $X(e^{j\omega})$
1. $x^*[n]$	$X^*(e^{-j\omega})$
2. $x^*[-n]$	$X^*(e^{j\omega})$
3. $\mathcal{Re}\{x[n]\}$	$X_e(e^{j\omega})$ (conjugate-symmetric part of $X(e^{j\omega})$ )
4. $j\mathcal{Im}\{x[n]\}$	$X_o(e^{j\omega})$ (conjugate-antisymmetric part of $X(e^{j\omega})$ )
5. $x_e[n]$ (conjugate-symmetric part of $x[n]$ )	$X_R(e^{j\omega}) = \mathcal{Re}\{X(e^{j\omega})\}$
6. $x_o[n]$ (conjugate-antisymmetric part of $x[n]$ )	$jX_I(e^{j\omega}) = j\mathcal{Im}\{X(e^{j\omega})\}$
<i>The following properties apply only when <math>x[n]</math> is real:</i>	
7. Any real $x[n]$	$X(e^{j\omega}) = X^*(e^{-j\omega})$ (Fourier transform is conjugate symmetric)
8. Any real $x[n]$	$X_R(e^{j\omega}) = X_R(e^{-j\omega})$ (real part is even)
9. Any real $x[n]$	$X_I(e^{j\omega}) = -X_I(e^{-j\omega})$ (imaginary part is odd)
10. Any real $x[n]$	$ X(e^{j\omega})  =  X(e^{-j\omega}) $ (magnitude is even)
11. Any real $x[n]$	$\angle X(e^{j\omega}) = -\angle X(e^{-j\omega})$ (phase is odd)
12. $x_e[n]$ (even part of $x[n]$ )	$X_R(e^{j\omega})$
13. $x_o[n]$ (odd part of $x[n]$ )	$jX_I(e^{j\omega})$

## Example: Problem 2.55/c



Figure P2.44-1

$x[n]$  is a real even function shifted by 2 to right.

$x_e[n]$  is equal to  $x[n]$  before shifting  $\rightarrow x_e[n] = x_e^*[-n] \xrightarrow{\mathcal{F} \text{ by property 5/ Table 2.1}} \mathcal{R}e\{X(e^{j\omega})\}$

Thus, It has a real value in FT or  $\angle \mathcal{F}(x_e[n]) = 0$

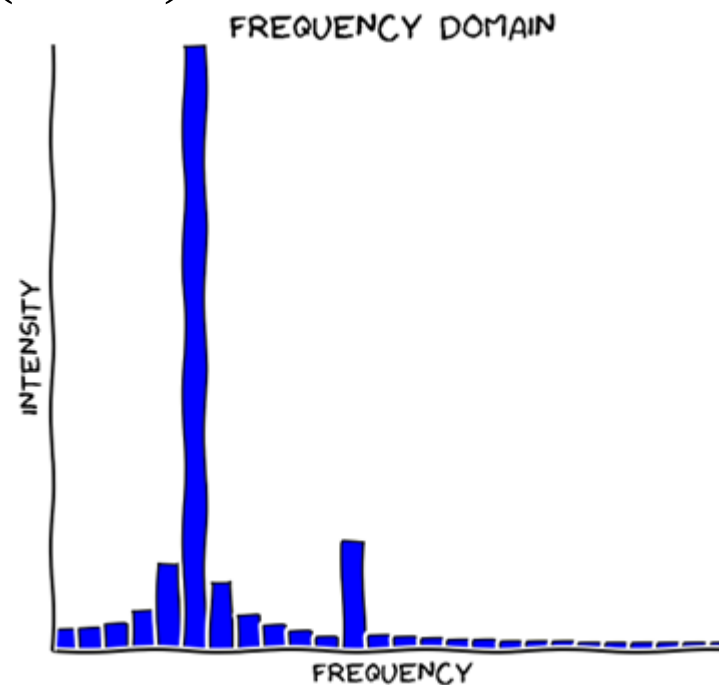
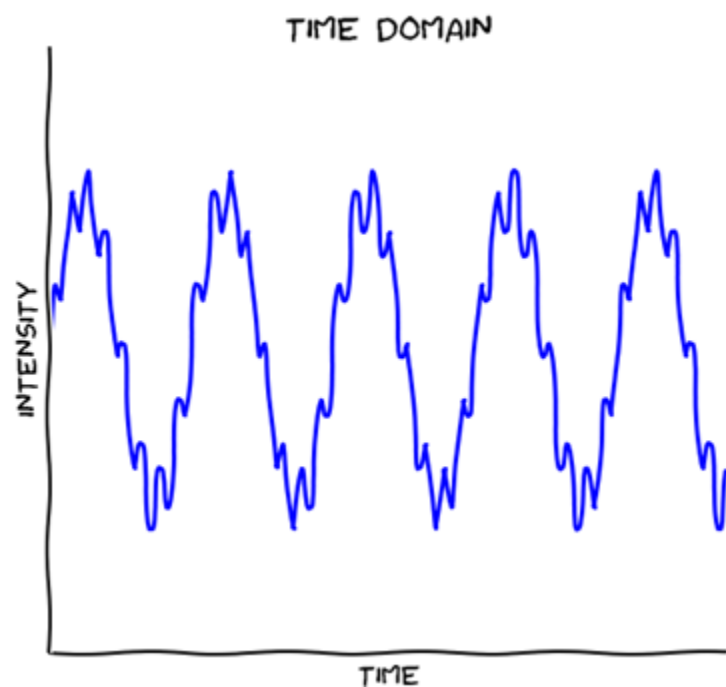
According to shifting property by 2 to right:

$$X(e^{j\omega}) = \mathcal{F}(x_e[n]) e^{-j2\omega}$$

$\mathcal{F}(x_e[n])$  is a zero phase real function of  $\omega$ .

# Application of FT: $Y(e^{j\omega}) = DSP\{ X(e^{j\omega}) \}$

$$x[n] \Leftrightarrow X(e^{j\omega}) \quad \forall \omega$$



$$Y(e^{j\omega}) = DSP\{ X(e^{j\omega}) \} \Leftrightarrow y[n] \neq x[n]$$

# Application of FT: Filtering (remove noise)



= 3

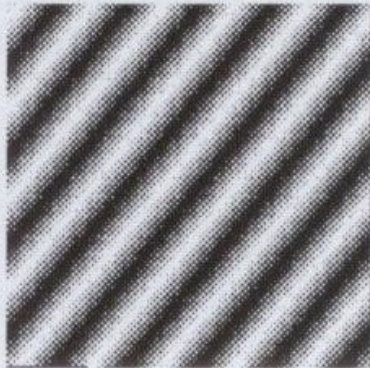


+ 5



+

+ 10



+ 23



+ ...

# Application of FT: Signal Compression

Original



With 4/64  
Coefficients  $\omega$



With 8/64  
Coefficients  $\omega$



With 16/64  
Coefficients  $\omega$







# Outline

- Introduction
- DT signals
- Transformation of the independent variable
- DT LTI Systems & Convolution
- Frequency content of signals
- Fourier Transform
- **Frequency response & filters**
- Difference equation & systems

# System response

8 A DT signal is a sum of scaled, delayed **impulses**  $x[n] = \sum_{k=-\infty}^{\infty} x[k] \delta[n-k]$

System response to **an impulse**  $\rightarrow$  **impulse response** of LTI systems

$$x[n] = \delta[n] \rightarrow y[n] = h[n]$$

System response to **any**  $x[n]$

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

System response to **exp**  $x[n] = e^{j\omega n}$

Convolution sum !

$$y[n] = T\{e^{j\omega n}\} = h[n] * e^{j\omega n} = \sum_{k=-\infty}^{\infty} h[k] e^{j\omega(n-k)} \left( \sum_{k=-\infty}^{\infty} h[k] e^{-j\omega k} \right) e^{j\omega n} = \underline{H(e^{j\omega})} e^{j\omega n}$$

$$H(e^{j\omega}) = \sum_{k=-\infty}^{\infty} h[k] e^{-j\omega k}$$

# LTI System input and output

Input

$$x[n] = \delta[n]$$

$$x[n]$$

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

$$x[n] = e^{j\omega n}$$

$$x[n] \Leftrightarrow X(e^{j\omega})$$

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

Output

$$\Rightarrow y[n] = h[n] \Leftrightarrow H(e^{j\omega}) = \sum_{k=-\infty}^{\infty} h[k] e^{-j\omega k}$$

$$\Rightarrow y[n] = h[n] * x[n]$$

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

$$\Rightarrow y[n] = H(e^{j\omega}) \cdot e^{j\omega n}$$

$$\Rightarrow Y(e^{j\omega}) = H(e^{j\omega}) X(e^{j\omega})$$

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





# Frequency response

- The frequency response is always a periodic function of the frequency variable  $\omega$  with period  $2\pi$

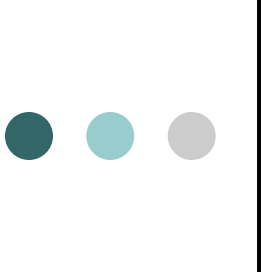
$$H(e^{j(\omega+2\pi)}) = \sum_{n=-\infty}^{\infty} h[n]e^{-j(\omega+2\pi)n} = \sum_{n=-\infty}^{\infty} h[n]e^{-j\omega n}e^{-j2\pi n} = H(e^{j\omega})$$

- Only specify over the interval  $-\pi < \omega \leq \pi$
  - The 'low frequencies' are close to 0
  - The 'high frequencies' are close to  $\pm\pi$
- The frequency response is generally complex

$$H(e^{j\omega}) = H_R(e^{j\omega}) + jH_I(e^{j\omega})$$

$$= |H(e^{j\omega})| e^{j\angle H(e^{j\omega})}$$

← describes changes in magnitude and phase



## Example: The frequency response of the ideal delay system

$$y[n] = x[n - n_d] \rightarrow h[n] = \delta[n - n_d]$$

$$h[n] \Leftrightarrow H(e^{j\omega}) = \sum_{n=-\infty}^{\infty} \delta[n - n_d] e^{-j\omega n} = e^{-j\omega n_d}$$

$$H_R(e^{j\omega}) = \cos(\omega n_d), \quad H_I(e^{j\omega}) = -\sin(\omega n_d)$$

$$|H(e^{j\omega})| = 1, \quad \angle H(e^{j\omega}) = -\omega n_d$$



# Filters & frequency response

A filter remove unwanted signal components and/or enhance wanted ones

## Four Main Filter Types:

- **Low-pass**: most common
  - Passes low frequencies, attenuates highs
- **High-pass**:
  - Passes high frequencies, attenuates lows
  - Used to brighten a signal
  - Careful: can also increase noise
- **Band-pass**:
  - Passes band of frequencies, attenuates those above and below band
  - Most common in implementations of DFF to separate out harmonics
- **Band-stop (band-reject)**:
  - Stops band of frequencies, passes those above and below band

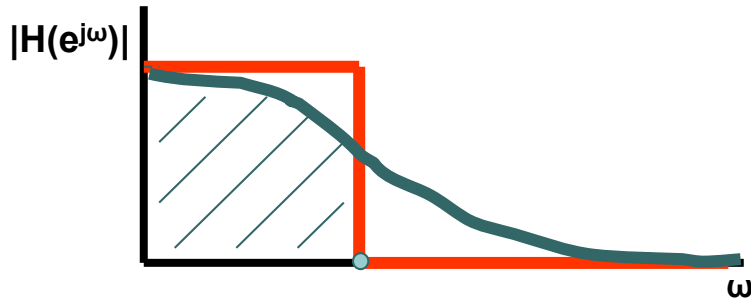
Filter specification through frequency response (magnitude and phase)

# Types of Filters

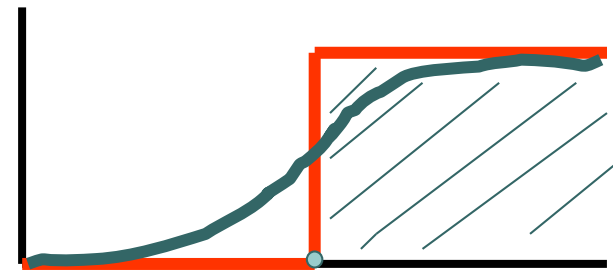
Ideal filters

Real filters

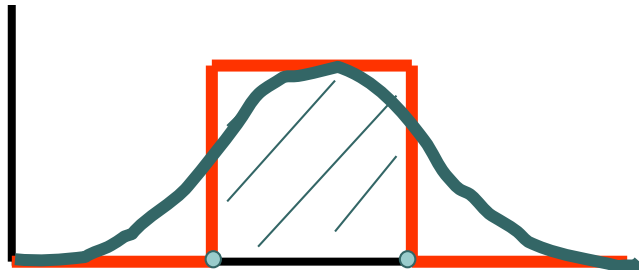
lowpass



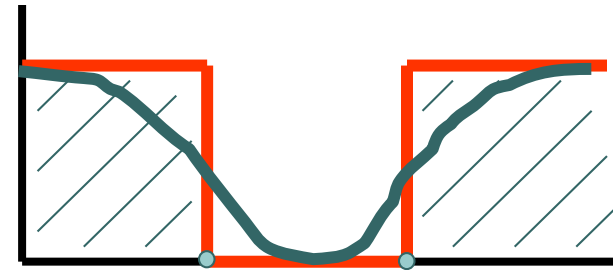
highpass



bandpass



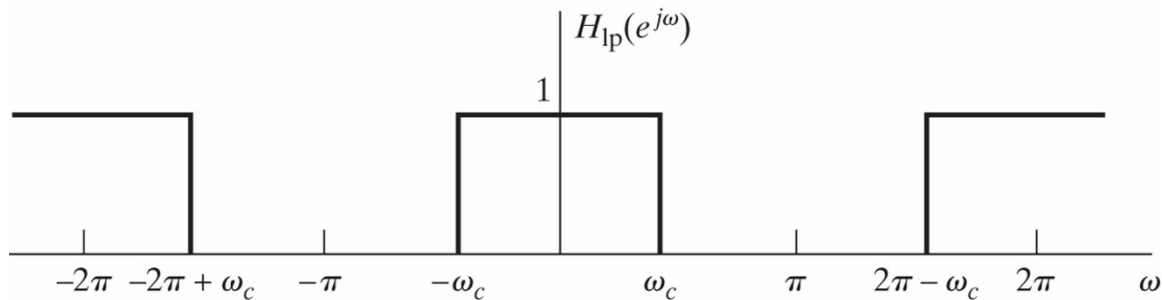
bandstop



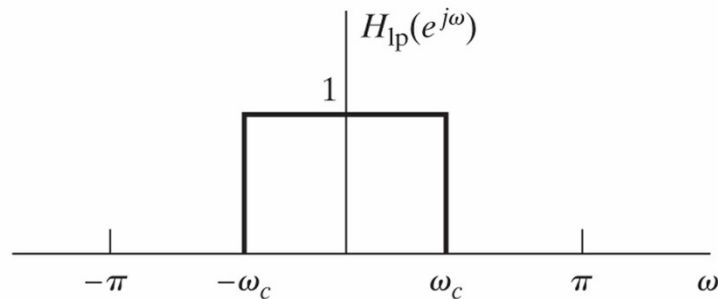
**Ideal frequency-selective** filter has **unity** frequency response over a certain range of frequencies, and is **zero** at the remaining frequencies

# Example: Lowpass filter

- Low-pass filter: passes only low frequencies and rejects high frequencies of an input signal  $x[n]$



(a) periodicity of the frequency response

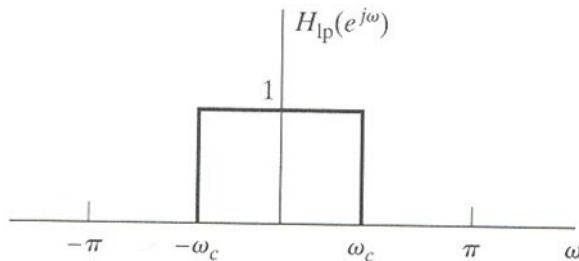


(b) One period of the periodic frequency response

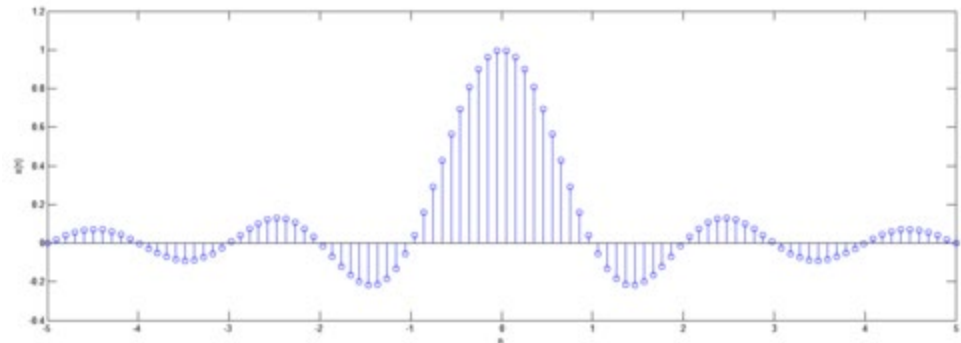
# Example : ideal lowpass filter

## Frequency response

$$H_{lp}(e^{j\omega}) = \begin{cases} 1, & |\omega| < \omega_c \\ 0, & \omega_c < |\omega| \leq \pi \end{cases}$$



$$\Leftrightarrow h_{lp}[n] = \frac{1}{2\pi} \int_{-\omega_c}^{\omega_c} e^{j\omega n} d\omega = \frac{\sin \omega_c n}{\pi n}, \quad -\infty < n < \infty$$



→ Not stable?  $h[n]$  is not absolutely summable  $\sum_{k=-\infty}^{\infty} |h[k]| < \infty$

→ Non-causal?  $h[n] = 0, \quad n < 0$



## Example : ideal lowpass filter

$$H_{lp}(e^{j\omega}) = \begin{cases} 1, & |\omega| < \omega_c \\ 0, & \omega_c < |\omega| \leq \pi \end{cases} \quad \leftrightarrow \quad h_{lp}[n] = \frac{1}{2\pi} \int_{-\omega_c}^{\omega_c} e^{j\omega n} d\omega = \frac{\sin \omega_c n}{\pi n}, \quad -\infty < n < \infty$$

➔ We cannot implement the ideal lowpass filter in practice because  $h[n]$  is *infinitely long* in time

➔ it is *noncausal* (we cannot shift it to make causal  $h[n]$  extends all the way to time)

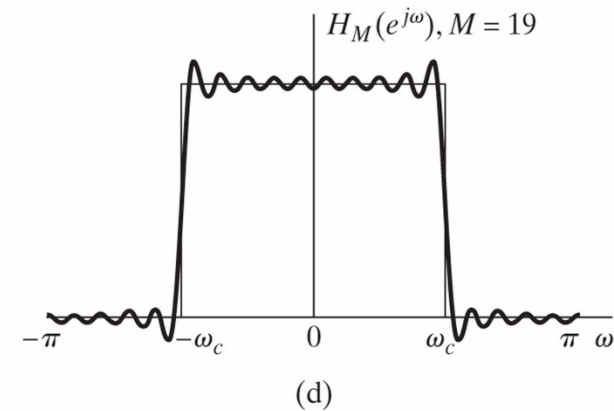
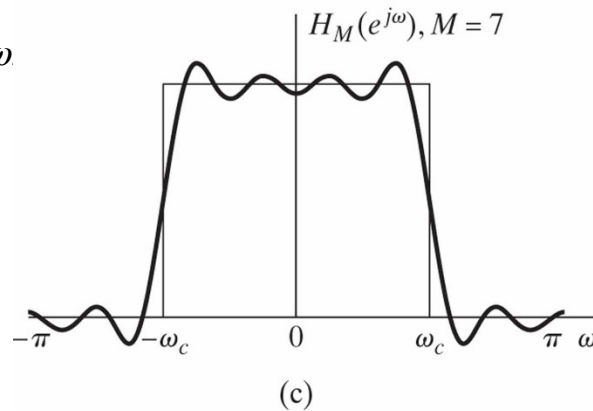
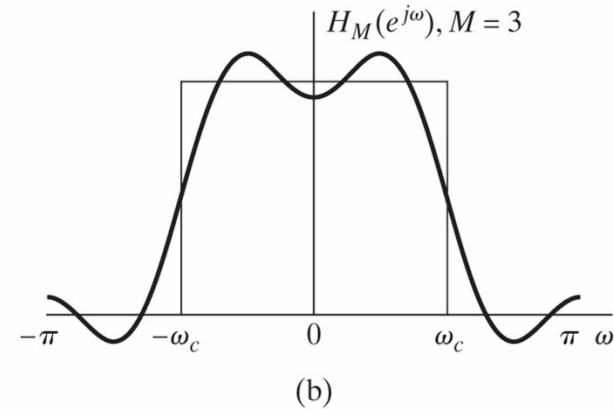
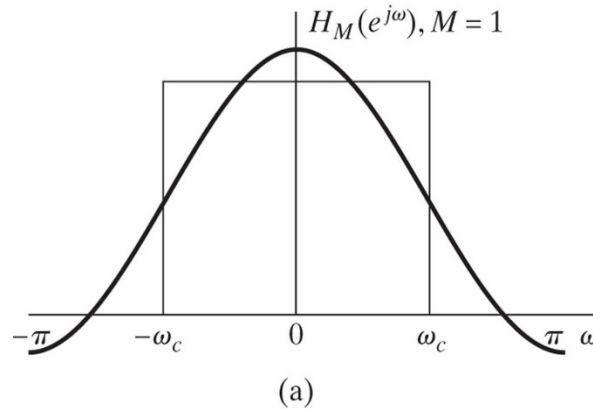
➔ We will have to accept some sort of compromise in the design of any practical lowpass filter

# Example : real lowpass filter

Filter design?

$$H_{lp}(e^{j\omega}) = \sum_{n=-\infty}^{\infty} \frac{\sin \omega_c n}{\pi n} e^{-j\omega n}$$

$$H_M(e^{j\omega}) = \sum_{n=-M}^M \frac{\sin \omega_c n}{\pi n} e^{-j\omega n}$$



Convergence of the  $H_M(e^{j\omega})$

(The oscillatory behavior at  $\omega = \omega_c$  is called the Gibbs phenomenon)



# FIR Systems via $h[n]$

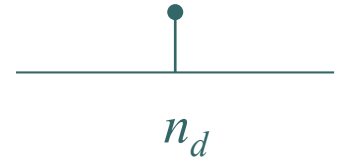
- Finite-duration impulse response (FIR) filters
  - The impulse response has only a finite number of nonzero samples

- Examples:

- Ideal delay

$$y[n] = x[n - n_d], \quad -\infty < n < \infty$$

$$h[n] = \delta[n - n_d], \quad n_d \text{ a positive integer}$$



- Forward difference

$$y[n] = x[n + 1] - x[n]$$

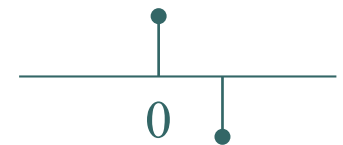
$$h[n] = \delta[n + 1] - \delta[n]$$



- Backward difference

$$y[n] = x[n] - x[n - 1]$$

$$h[n] = \delta[n] - \delta[n - 1]$$



# IIR systems via $h[n]$

- Infinite-duration impulse response (IIR) system
  - The impulse response is infinite in duration

- Example: Accumulator  $y[n] = \sum_{k=-\infty}^n x[k]$

$$h[n] = \sum_{k=-\infty}^n \delta[k] = u[n]$$



- Stability?  $\sum_{n=-\infty}^{\infty} |h[n]| \stackrel{?}{<} \infty$

- FIR systems are always stable, if each of  $h[n]$  values is finite in magnitude

$$h[n] = a^n u[n] \text{ with } |a| < 1$$

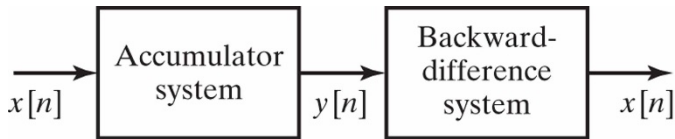
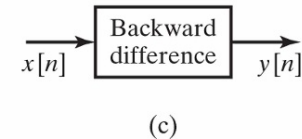
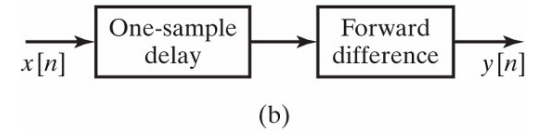
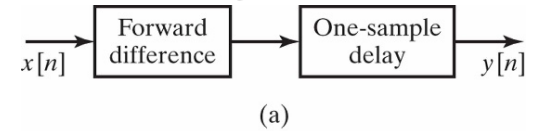
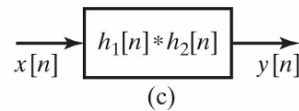
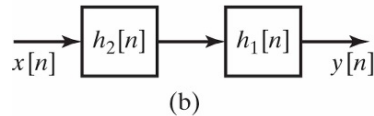
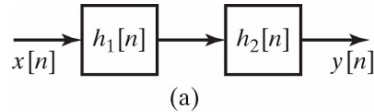
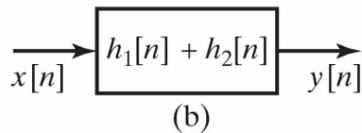
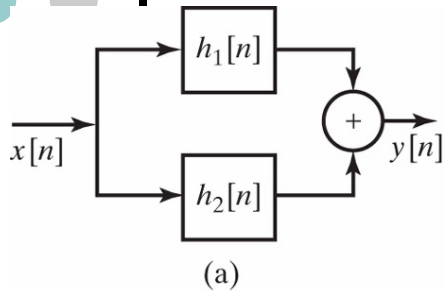
- IIR systems can be stable, e.g.  $\Rightarrow \sum_{n=0}^{\infty} |a|^n = 1/(1-|a|) < \infty$



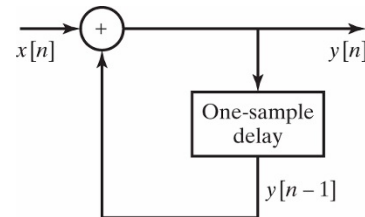
# Outline

- Introduction to DSP
- DT signals
- Transformation of the independent variable
- DT LTI Systems & Convolution
- Frequency content of signals
- Fourier transform
- Frequency response & filters
- **Difference equations & systems**

# Combining systems; block diagrams

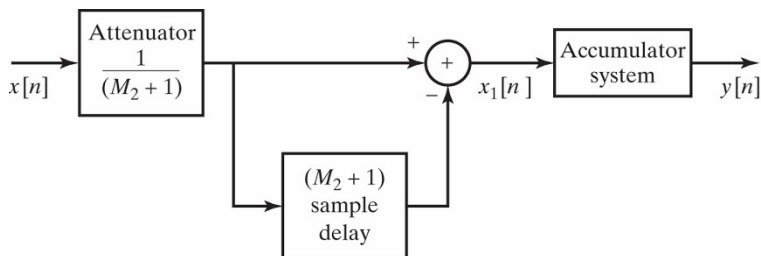


Identity system: accumulator cascaded with backward difference (backward difference is the inverse system for the accumulator)



A recursive system representing an accumulator

$$y[n] = \sum_{k=-\infty}^n x[k] = x[n] + y[n-1]$$



A recursive form of a moving-average system

$$y[n] = \frac{1}{M + 1} \sum_{k=0}^M x[n-k]$$

# LTI systems characterized by Difference Equations

- remember linear differential equations?  $\frac{d}{dt}y(t) - y(t) = x(t)$
- A **difference equation** is the discrete-time analogue of a *differential equation*. We simply use differences ( $x[n] - x[n-1]$ ) rather than derivatives ( $\frac{d}{dt}x(t)$ ).
- An important *subclass* of linear systems consists of those whose input  $x[n]$  and output  $y[n]$  obey an  $N$ -th order **Linear Constant Coefficient Difference Equation**

$$\sum_{k=0}^N (a_k y[n-k]) = \sum_{k=0}^M (b_k x[n-k])$$

**Example : Moving average system**  $y[n] = \frac{1}{M_1 + M_2 + 1} \sum_{k=M_1}^{M_2} (x[n-k])$

**Example : Recursive System**  $y[n] = \sum_{k=1}^N (\alpha_k y[n-k]) + x[n]$

- $y[n-k]$  represents delayed outputs &  $x[n-k]$  represents delayed inputs
- $N$  represents the order (delay/memory) of the difference equation
- Because this equation relies on past values of the output, to compute a numerical solution, certain past outputs (called “initial conditions”) must be known

# LTI systems characterized by Difference Equations

- A linear constant-coefficient difference equation (LCCDE) shows the relationship between consecutive values of a sequence and the difference among them

$$\sum_{k=0}^N a_k y[n-k] = \sum_{m=0}^M b_m x[n-m]$$

- LCCDE is often a recursive formula: a system output can be computed from current and past values

$$y[n] + 7y[n-1] + 2y[n-2] = x[n] - 4x[n-1]$$

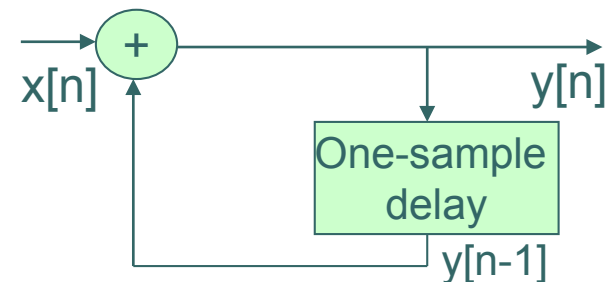
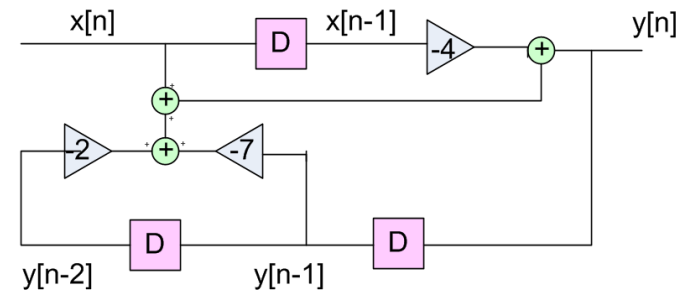
$$\Rightarrow y[n] = x[n] - 4x[n-1] - 7y[n-1] - 2y[n-2]$$

- Accumulator

$$y[n] = \sum_{k=-\infty}^n x[k]; y[n-1] = \sum_{k=-\infty}^{n-1} x[k]$$

$$y[n] = x[n] + \sum_{k=-\infty}^{n-1} x[k] = x[n] + y[n-1]$$

$$y[n] - y[n-1] = x[n]$$





# LTI systems characterized by Difference Equations or Frequency response

- Consider an LTI system with the LCCDE

$$\sum_{k=0}^N a_k y[n-k] = \sum_{k=0}^M b_k x[n-k]$$

- Re-write to easily express a recursive output:

$$y[n] = - \left( \sum_{k=1}^N (a_k y[n-k]) \right) + \sum_{k=0}^M (b_k x[n-k])$$

- In FT domain:

$$Y(e^{j\omega}) \sum_{k=0}^N a_k e^{j\omega k} = X(e^{j\omega}) \sum_{k=0}^M b_k e^{j\omega k} \Rightarrow H(e^{j\omega}) = \frac{Y(e^{j\omega})}{X(e^{j\omega})} = \frac{\sum_{k=0}^M b_k e^{j\omega k}}{\sum_{k=0}^N a_k e^{j\omega k}}$$

- Given LCCD; we can find the frequency response
- Given the frequency response; we can find LCCD