



<http://elec3004.org>

Sampling & More

ELEC 3004: Digital Linear Systems: Signals & Controls

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Lecture 3

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Lecture Schedule:

Week	Date	Lecture Title
1	2-Mar	Introduction
	3-Mar	Systems Overview
2	9-Mar	Signals as Vectors & Systems as Maps
	10-Mar	Signals
3	16-Mar	Sampling & Data Acquisition & Antialiasing Filters
	17-Mar	Sampling
4	23-Mar	System Analysis & Convolution
	24-Mar	Convolution & FT
5	30-Mar	Frequency Response & Filter Analysis
	31-Mar	Filters
6	13-Apr	Discrete Systems & Z-Transforms
	14-Apr	Z-Transforms
7	20-Apr	Introduction to Digital Control
	21-Apr	Feedback
8	27-Apr	Digital Filters
	28-Apr	Digital Filters
9	4-May	Digital Control Design
	5-May	Digital Control
10	11-May	Stability of Digital Systems
	12-May	Stability
11	18-May	State-Space
	19-May	Controllability & Observability
12	25-May	PID Control & System Identification
	26-May	Digital Control System Hardware
13	31-May	Applications in Industry & Information Theory & Communications
	2-Jun	Summary and Course Review

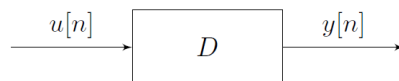


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16 March 2015 - 2

Interpretations of Systems as Maps

Then a System is a **MATRIX**



$$y = Du.$$

$$\begin{bmatrix} y[1] \\ y[2] \\ \vdots \\ y[M] \end{bmatrix} = \begin{bmatrix} D_{11} & D_{12} & \cdots & D_{1N} \\ D_{21} & D_{22} & \cdots & D_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ D_{M1} & D_{M2} & \cdots & D_{MN} \end{bmatrix} \begin{bmatrix} u[1] \\ u[2] \\ \vdots \\ u[N] \end{bmatrix}.$$

$$y[i] = \sum_j D_{ij} u[j].$$



System Analysis

[Chapter 2, Lathi]

Linear Differential Systems

$$\frac{d^n y}{dt^n} + a_{n-1} \frac{d^{n-1} y}{dt^{n-1}} + \cdots + a_1 \frac{dy}{dt} + a_0 y(t) = b_m \frac{d^m f}{dt^m} + b_{m-1} \frac{d^{m-1} f}{dt^{m-1}} + \cdots + b_1 \frac{df}{dt} + b_0 f(t) \quad (2.1a)$$

where all the coefficients a_i and b_i are constants. Using operational notation D to represent d/dt , we can express this equation as

$$\begin{aligned} (D^n + a_{n-1}D^{n-1} + \cdots + a_1D + a_0)y(t) \\ = (b_mD^m + b_{m-1}D^{m-1} + \cdots + b_1D + b_0)f(t) \end{aligned} \quad (2.1b)$$

or

$$Q(D)y(t) = P(D)f(t) \quad (2.1c)$$

where the polynomials $Q(D)$ and $P(D)$ are

$$Q(D) = D^n + a_{n-1}D^{n-1} + \cdots + a_1D + a_0 \quad (2.2a)$$

$$P(D) = b_mD^m + b_{m-1}D^{m-1} + \cdots + b_1D + b_0 \quad (2.2b)$$



Linear Differential System Order

$$Q(D)y(t) = P(D)f(t)$$

$$Q(D) = D^n + a_{n-1}D^{n-1} + \dots + a_1D + a_0$$

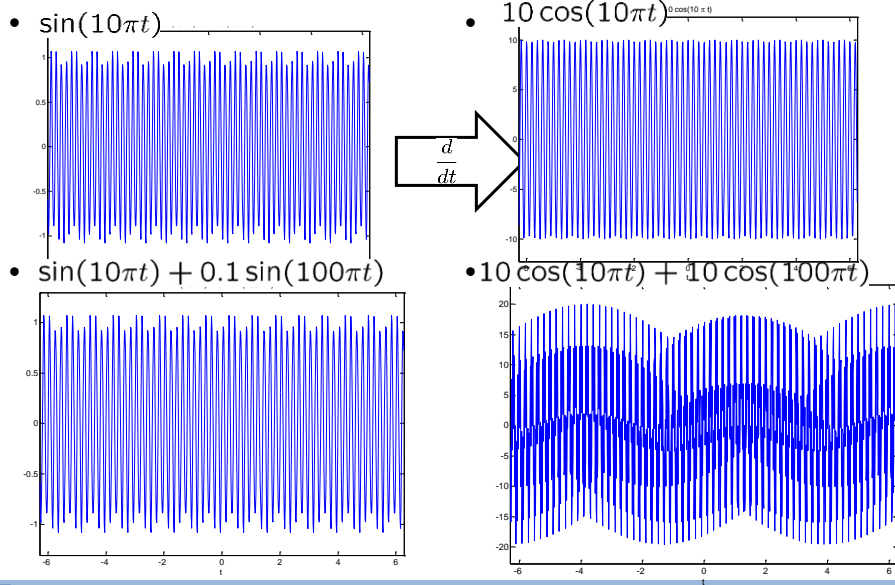
$$P(D) = b_mD^m + b_{m-1}D^{m-1} + \dots + b_1D + b_0$$

$\rightarrow y(t) = P(D)/Q(D) f(t)$
 P(D): M
 Q(D): N
 (yes, N is deNominator)

- In practice: $m \leq n$
- \therefore if $m > n$:
then the system is an
 $(m - n)^{\text{th}}$ -order differentiator of high-frequency signals!
- Derivatives magnify noise!



Derivatives magnify noise!



Zero-Input | Zero-State

Total response = zero-input response + zero-state response

Zero Input

- = The system response when the input $f(t) = 0$ so that it is the result of internal system conditions (such as energy storages, initial conditions) alone.
- It is **independent of the external input**.

Zero-State

- = the system response to the external input $f(t)$ when the system is in zero state, meaning the absence of all internal energy storages; that is, all initial conditions are zero.



System Stability

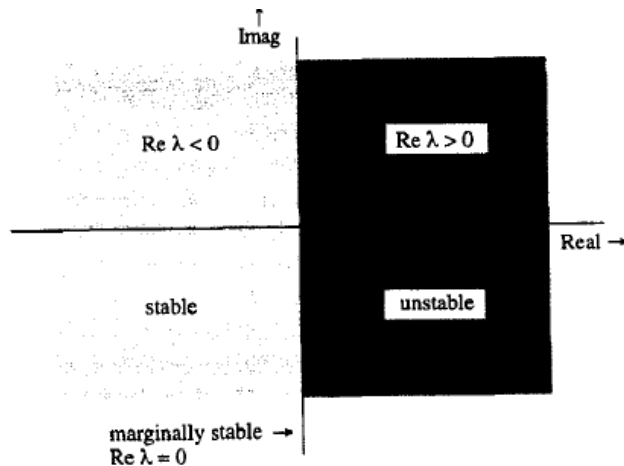
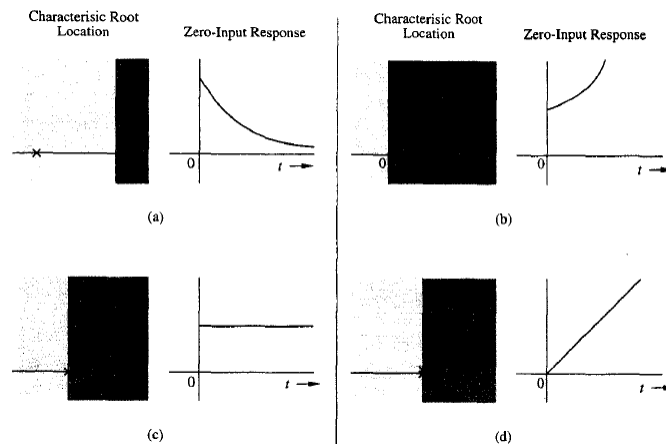


Fig. 2.15 Characteristic roots location and system stability.



System Stability [II]



Lathi, p. 150



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16 March 2015 - 11

System Stability [III]

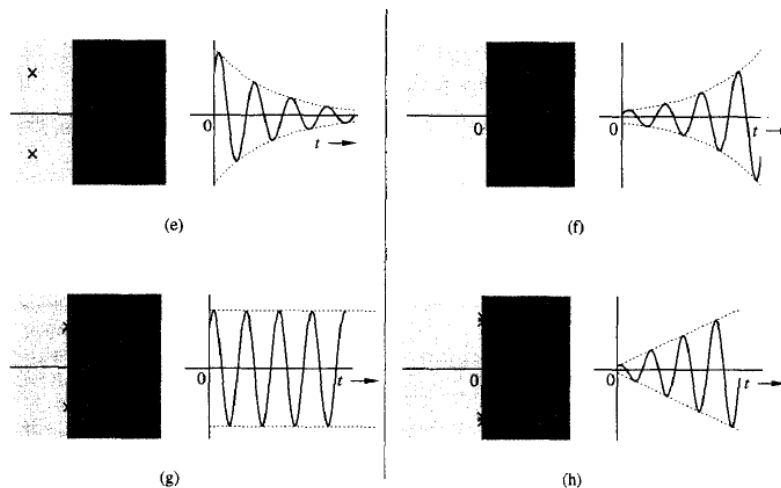


Fig. 2.16 Location of characteristic roots and the corresponding characteristic modes.



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16 March 2015 - 12

Signals Review

Signal: A carrier of (desired) information [1]

- Need **NOT** be electrical:
 - Thermometer
 - Clock hands
 - Automobile speedometer
- Need **NOT** always be given
 - “Abnormal” sounds/operations
 - Ex: “pitch” or “engine hum” during machining as an indicator for feeds and speeds



Signal: A carrier of (desired) information [2]

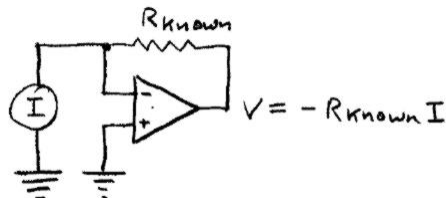
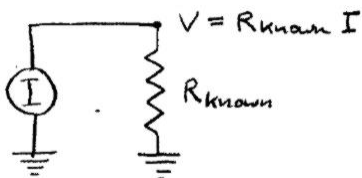
- Electrical signals
 - Voltage
 - Current
- **Digital signals**
 - **Convert analog electrical signals to an appropriate digital electrical message**
 - **Processing by a microcontroller or microprocessor**



Ex: Current-to-voltage conversion

- simple:
Precision Resistor
- better:
Use an “op amp”

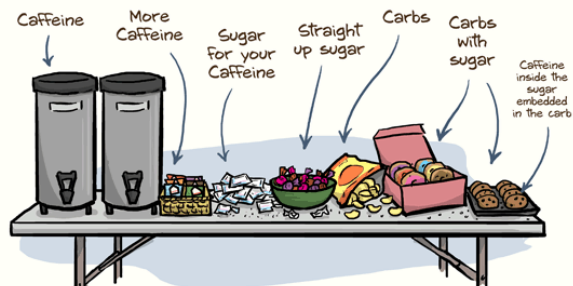
$$i = \frac{V_{\text{measured}}}{R_{\text{known}}}$$



Sampling!

Not this type of sampling ...

SEMINAR REFRESHMENTS!

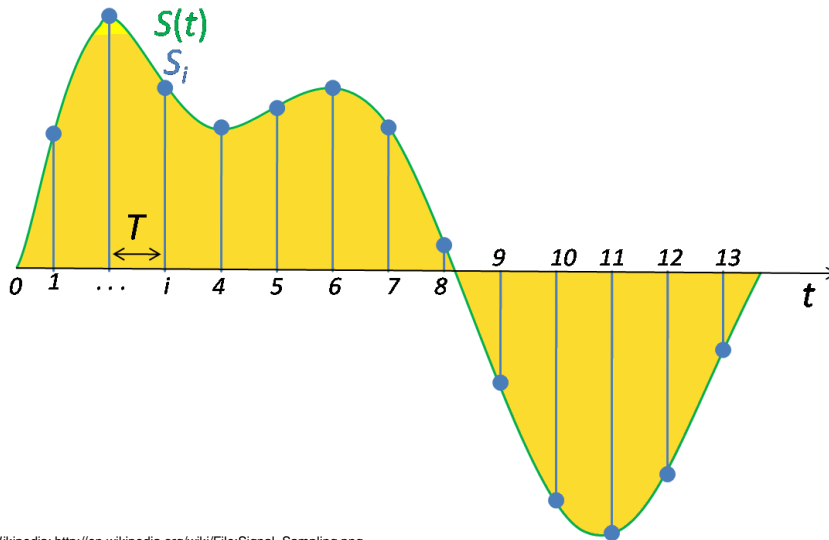


Nothing says "We are confident this seminar will be intellectually stimulating for you" like a table full of things to help you stay awake.

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This type of sampling...



Source: Wikipedia: http://en.wikipedia.org/wiki/File:Signal_Sampling.png

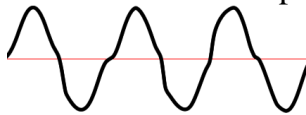


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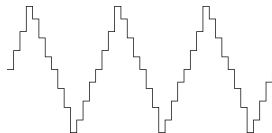
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Analog vs Digital

- Analog Signal: An analog or analogue signal is any variable signal continuous in both time and amplitude



- Digital Signal: A digital signal is a signal that is both discrete and quantized



E.g. Music stored in a CD: 44,100 Samples per second and 16 bits to represent amplitude



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16 March 2015 - 33

Digital Signal

- Representation of a signal against a discrete set
- The set is fixed in by computing hardware

$$s \in \mathbb{Z}$$

- Can be scaled or normalized ... but is limited

$$s \in \mathbb{Z}(0, \dots, 2^{16})$$

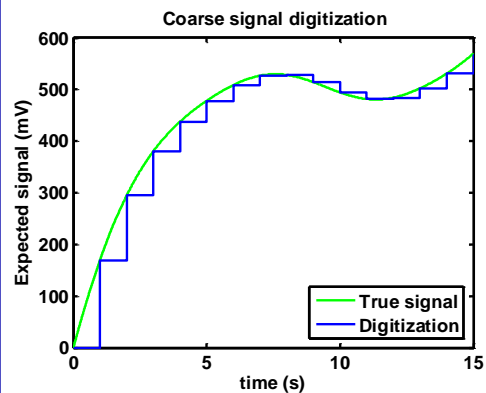
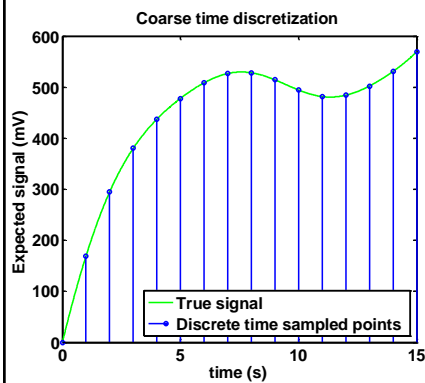
- Time is also discretized

$$s' \in \frac{\mathbb{Z}(0, \dots, 2^{16})}{2^{16}}$$

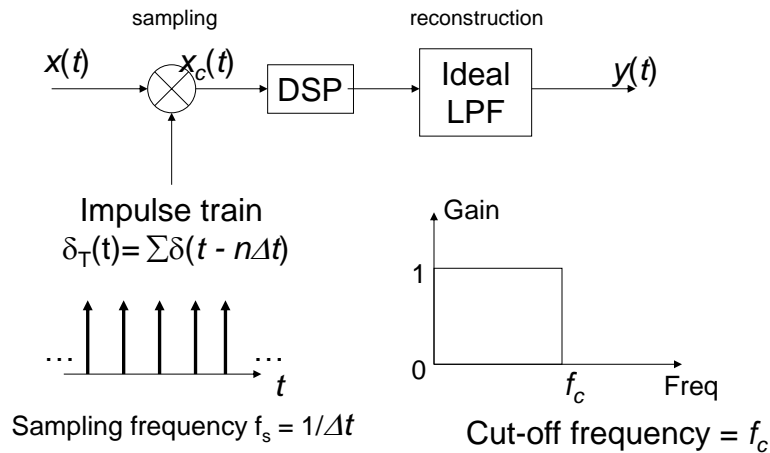


Representation of Signal

- Time Discretization
- Digitization



Mathematics of Sampling and Reconstruction



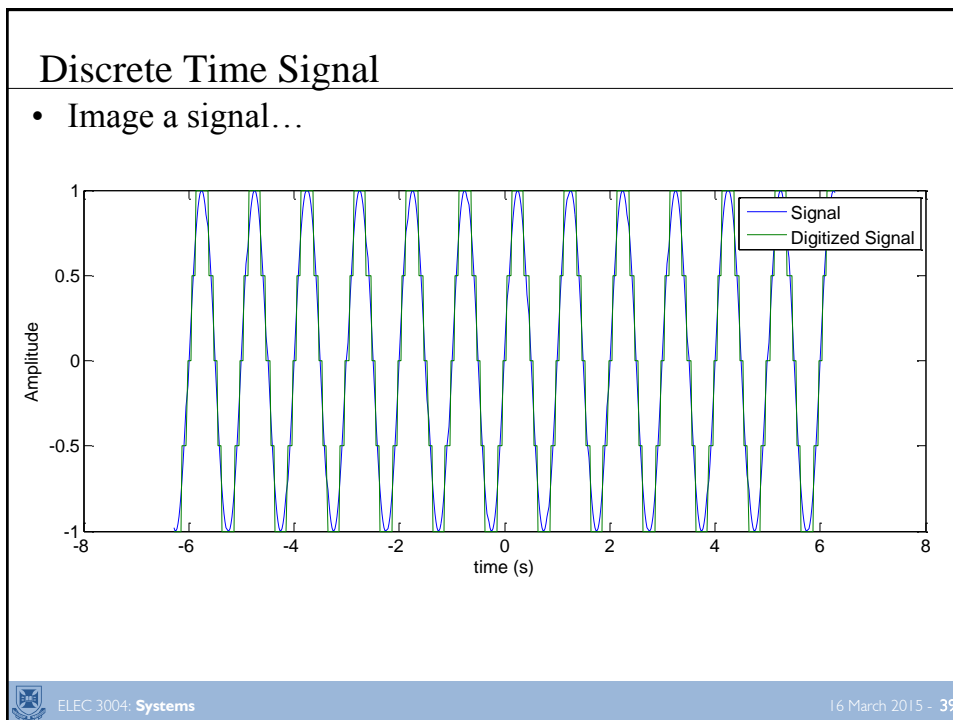
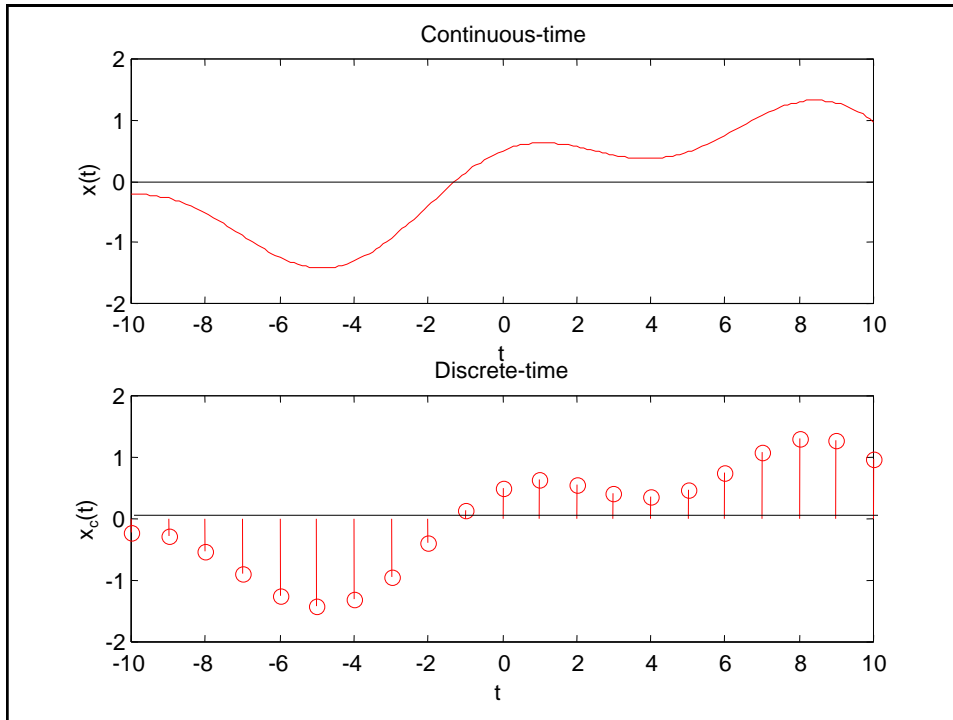
Mathematical Model of Sampling

- $x(t)$ multiplied by impulse train $\delta_T(t)$

$$\begin{aligned}
 x_c(t) &= x(t)\delta_T(t) \\
 &= x(t)[\delta(t) + \delta(t - \Delta t) + \delta(t - 2\Delta t) + \dots] \\
 &= \sum_n x(n\Delta t)\delta(t - n\Delta t)
 \end{aligned}$$

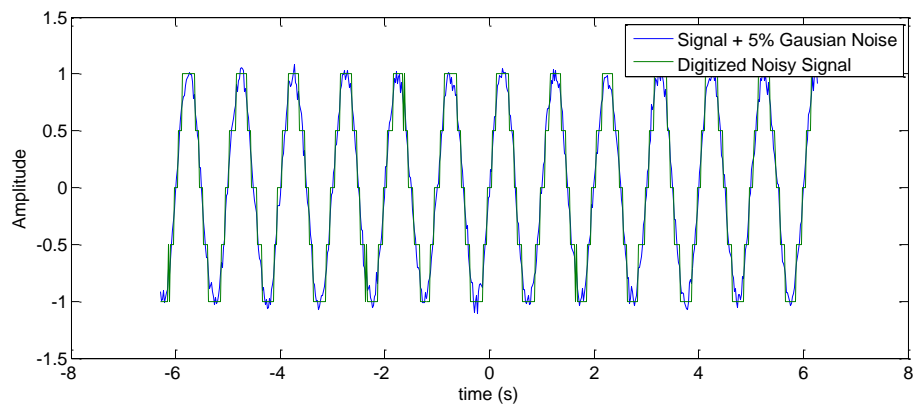
- $x_c(t)$ is a train of impulses of height $x(t)|_{t=n\Delta t}$





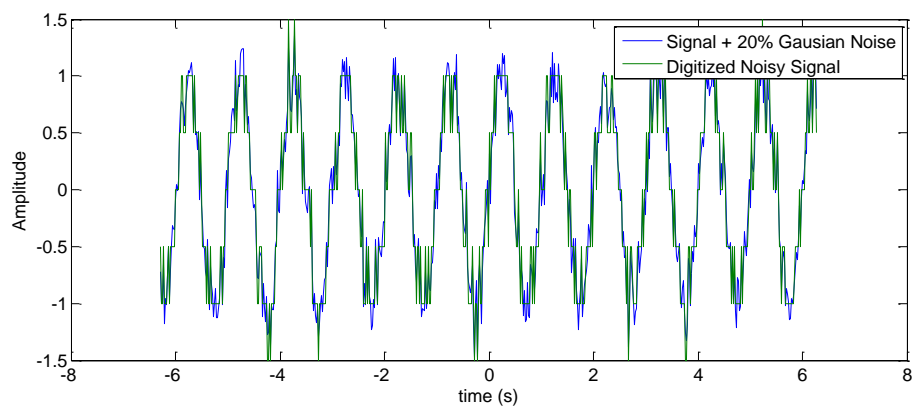
Discrete Time Signals

- Digitization helps beat the Noise!



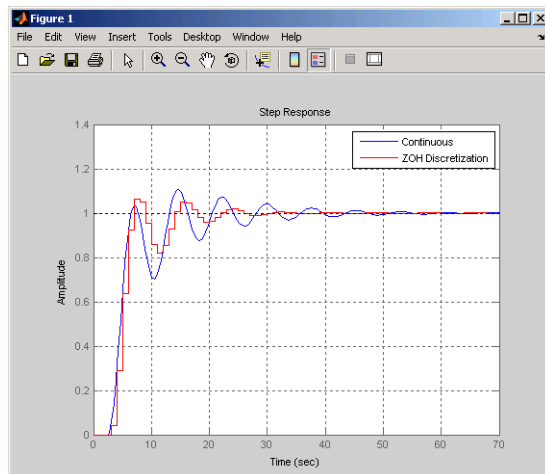
Discrete Time Signals

- But only so much...



Discrete Time Signals

- Can make control tricky!



Signal Manipulations

- Shifting

$$y(n) = x(n - n_0)$$

- Reversal

$$y(n) = x(-n)$$

- Time Scaling
(Down Sampling)

$$y(M) = x(Mn)$$

(Up Sampling)

$$y(n) = x\left(\frac{n}{N}\right)$$



Frequency Domain Analysis of Sampling

- Consider the case where the DSP performs no filtering operations
 - i.e., only passes $x_c(t)$ to the reconstruction filter
- To understand we need to look at the frequency domain
- Sampling: we know
 - multiplication in time \equiv convolution in frequency
 - $F\{x(t)\} = X(w)$
 - $F\{\delta T(t)\} = \sum \delta(w - 2\pi n/\Delta t)$,
 - i.e., an impulse train in the frequency domain



Frequency Domain Analysis of Sampling

- In the frequency domain we have

$$\begin{aligned} X_c(w) &= \frac{1}{2\pi} \left(X(w) * \frac{2\pi}{\Delta t} \sum_n \delta\left(w - \frac{2\pi n}{\Delta t}\right) \right) \\ &= \frac{1}{\Delta t} \sum_n X\left(w - \frac{2\pi n}{\Delta t}\right) \end{aligned}$$

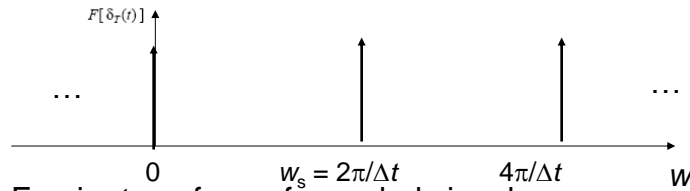
Remember
convolution with
an impulse?
Same idea for an
impulse train

- Let's look at an example
 - where $X(w)$ is triangular function
 - with maximum frequency w_m rad/s
 - being sampled by an impulse train, of frequency w_s rad/s

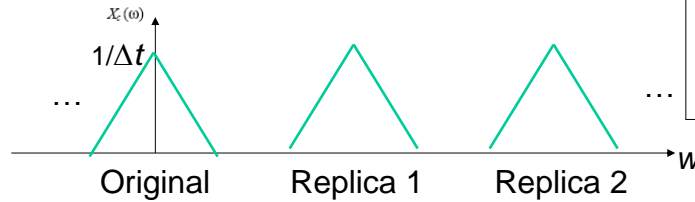


Fourier transform of original signal $X(\omega)$ (signal spectrum)

Fourier transform of impulse train $\delta_T(\omega/2\pi)$ (sampling signal)



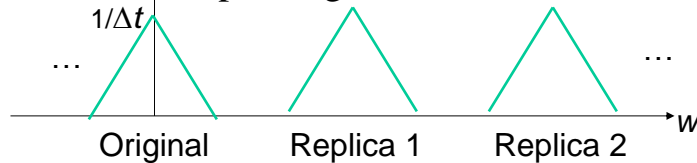
Fourier transform of sampled signal



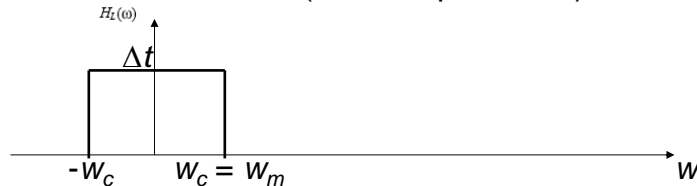
Original spectrum
convolved with
spectrum of
impulse train



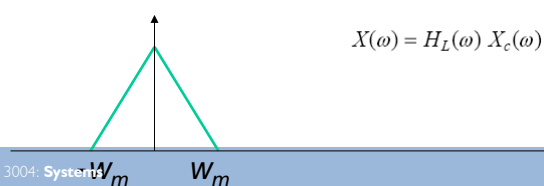
Spectrum $X_c(\omega)$ sampled signal



Reconstruction filter (ideal lowpass filter)



Spectrum of reconstructed signal



Reconstruction filter
removes the replica
spectrums & leaves
only the original

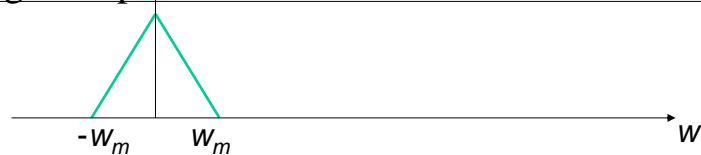


Sampling Frequency

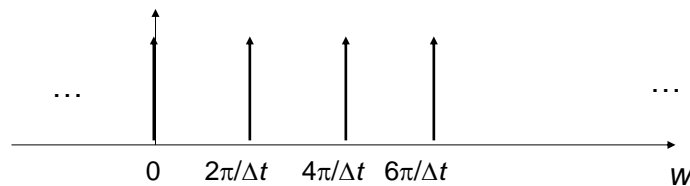
- In this example it was possible to recover the original signal from the discrete-time samples
- But is this always the case?
- Consider an example where the sampling frequency w_s is reduced
 - i.e., Δt is increased



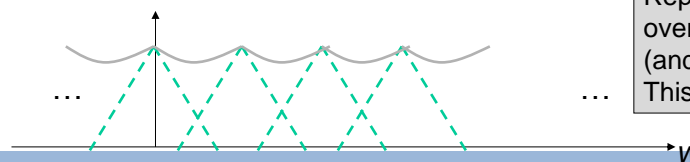
Original Spectrum



Fourier transform of impulse train (sampling signal)

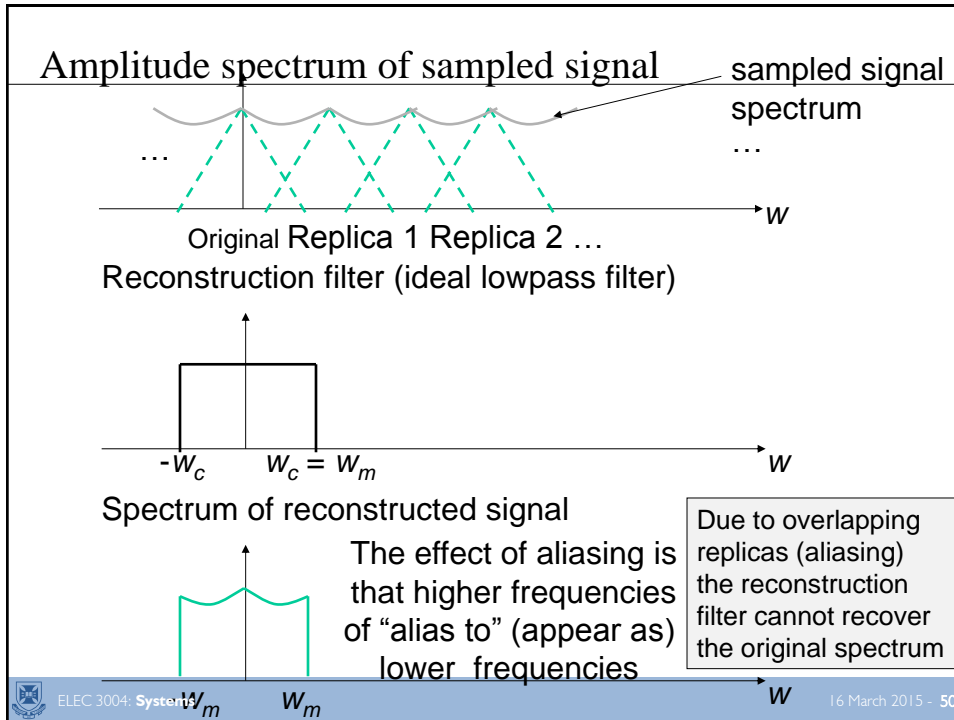


Amplitude spectrum of sampled signal



Replica spectrums overlap with original (and each other)
This is **Aliasing**





Sampling Theorem

- The Nyquist criterion states:

To prevent aliasing, a **bandlimited** signal of bandwidth ω_B rad/s must be sampled at a rate greater than $2\omega_B$ rad/s

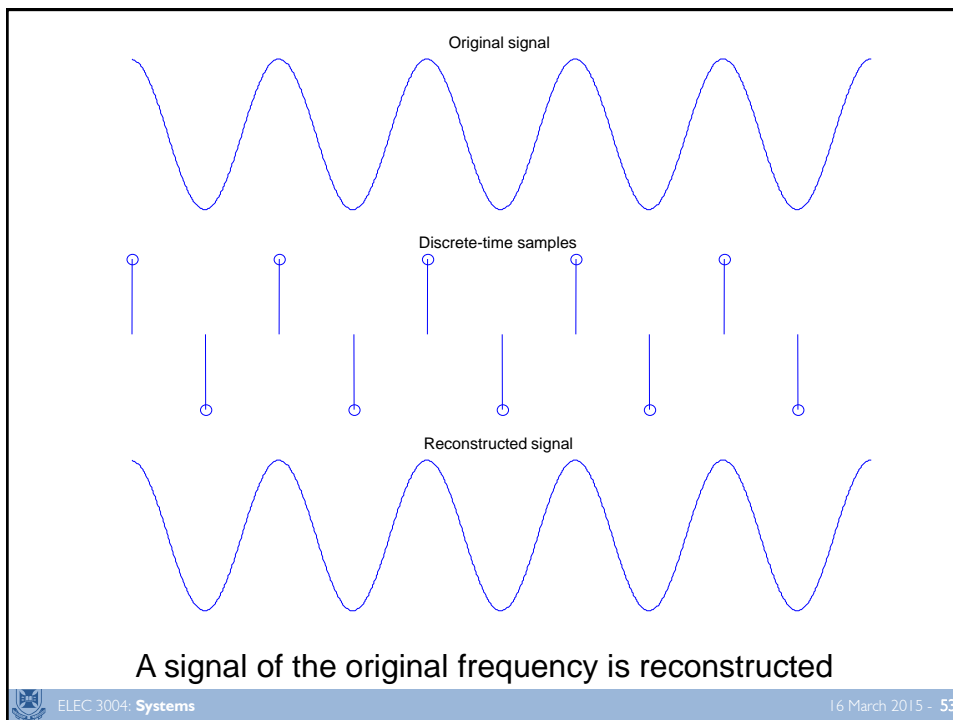
$$\omega_s > 2\omega_B$$

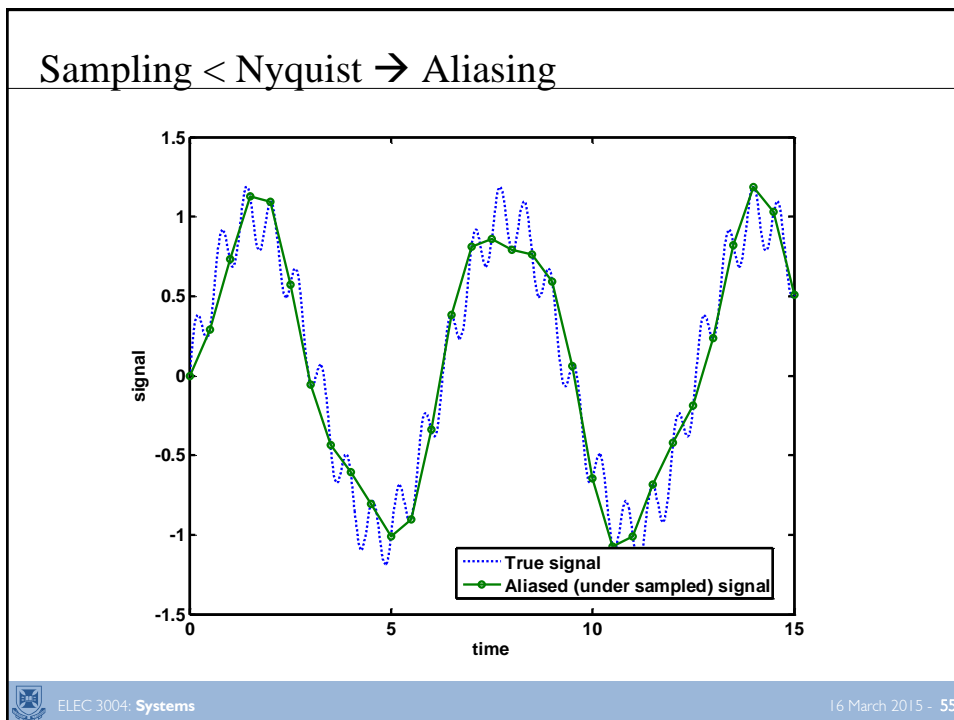
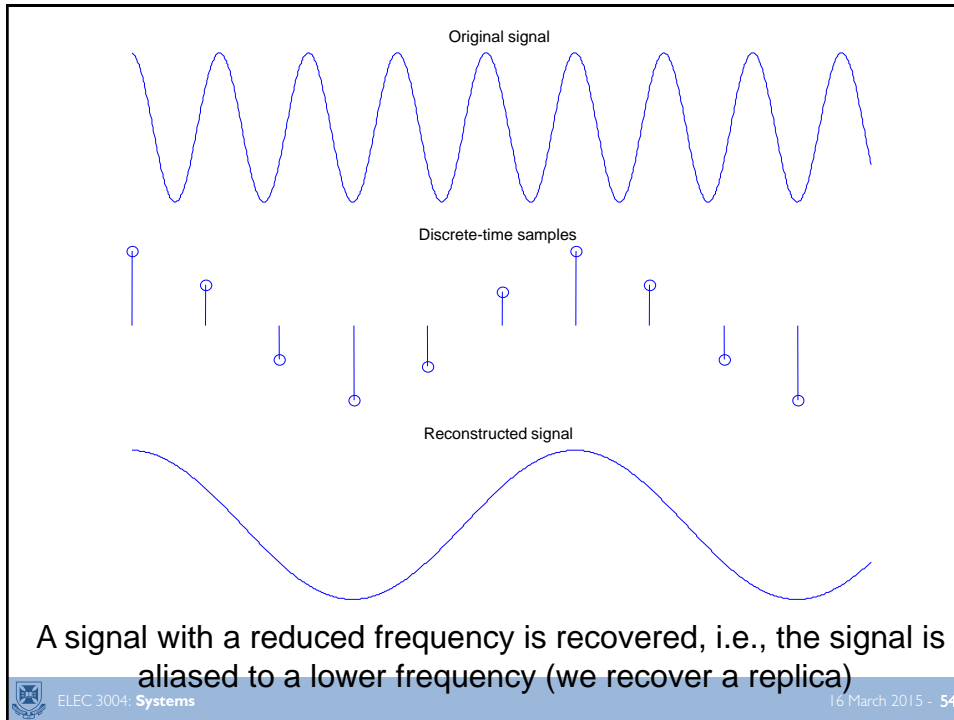
Note: this is a $>$ sign not a \geq

Also note: Most real world signals require band-limiting with a lowpass (anti-aliasing) filter

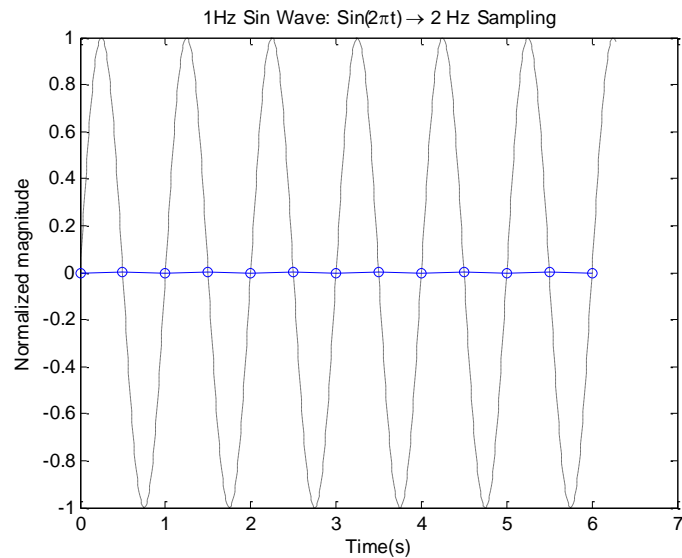
Time Domain Analysis of Sampling

- Frequency domain analysis of sampling is very useful to understand
 - sampling ($X(w) * \sum \delta(w - 2\pi n/\Delta t)$)
 - reconstruction (lowpass filter removes replicas)
 - aliasing (if $w_s \leq 2w_B$)
- Time domain analysis can also illustrate the concepts
 - sampling a sinewave of increasing frequency
 - sampling images of a rotating wheel

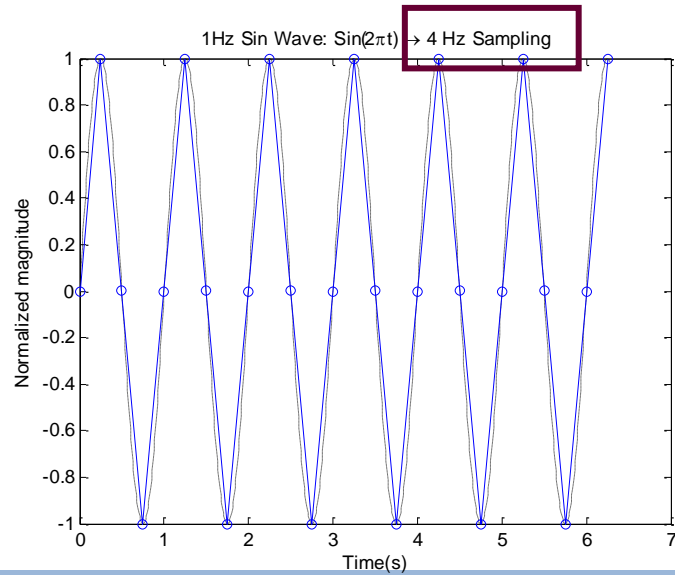


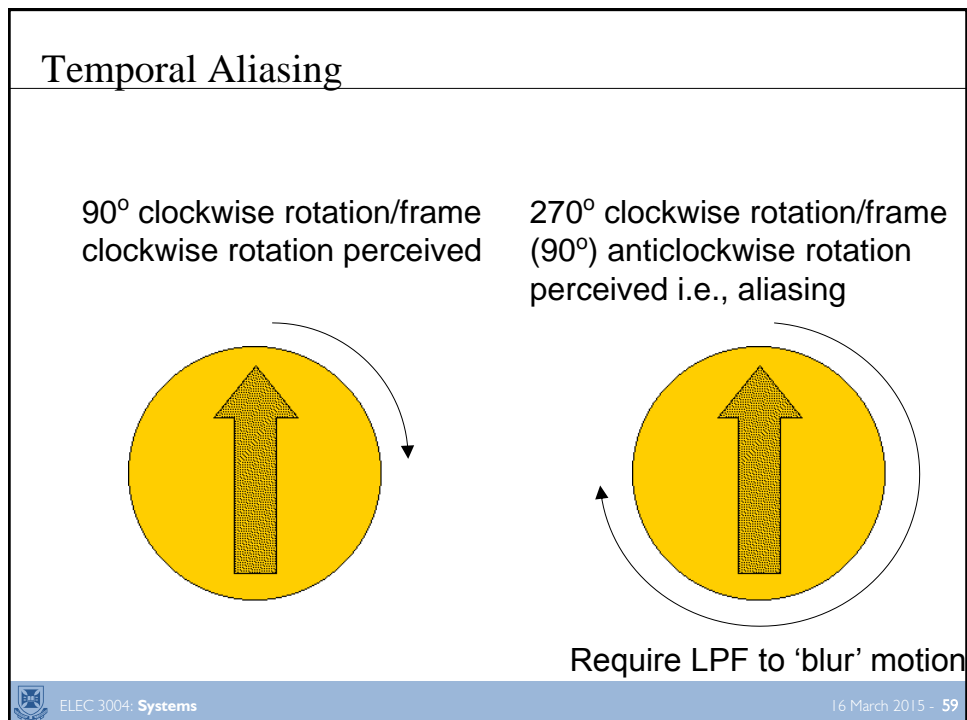
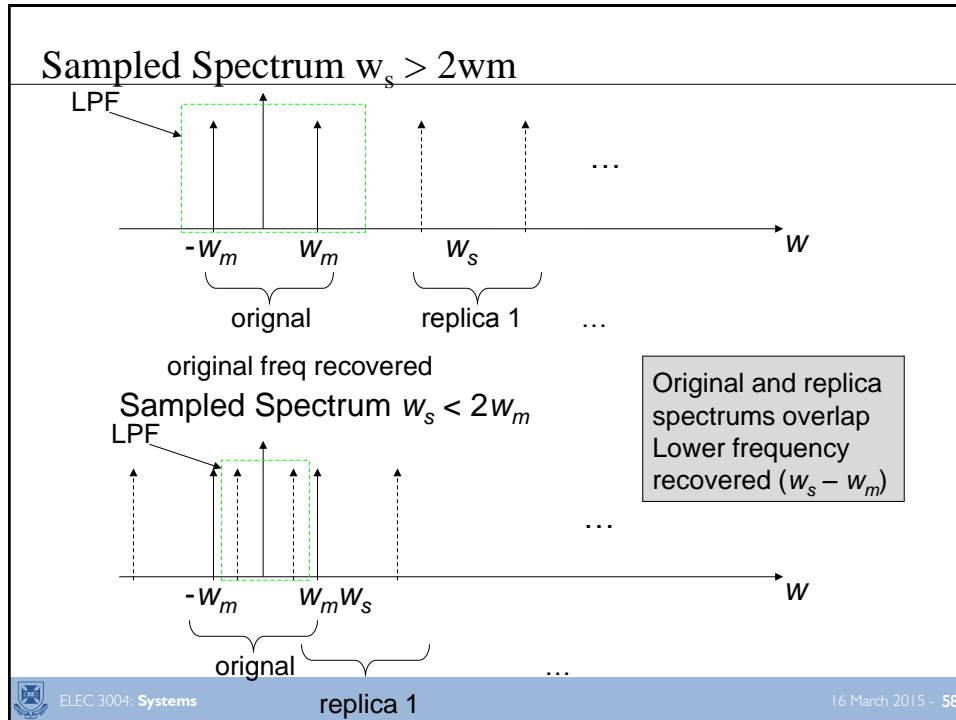


Nyquist is not enough ...



A little more than Nyquist is not enough ...





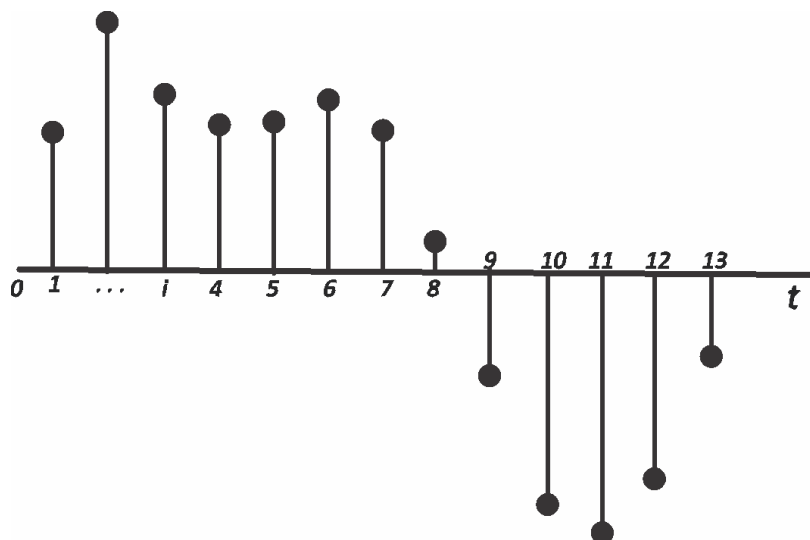
Time Domain Analysis of Reconstruction

- Frequency domain: multiply by ideal LPF
 - ideal LPF: ‘rect’ function (gain Δt , cut off w_c)
 - removes replica spectrums, leaves original
- Time domain: this is equivalent to
 - convolution with ‘sinc’ function
 - as $F^{-1}\{\Delta t \text{ rect}(w/w_c)\} = \Delta t w_c \text{ sinc}(w_c t/\pi)$
 - i.e., weighted sinc on every sample
- Normally, $w_c = w_s/2$

$$x_r(t) = \sum_{n=-\infty}^{\infty} x(n\Delta t) \Delta t w_c \text{ sinc}\left(\frac{w_c(t - n\Delta t)}{\pi}\right)$$

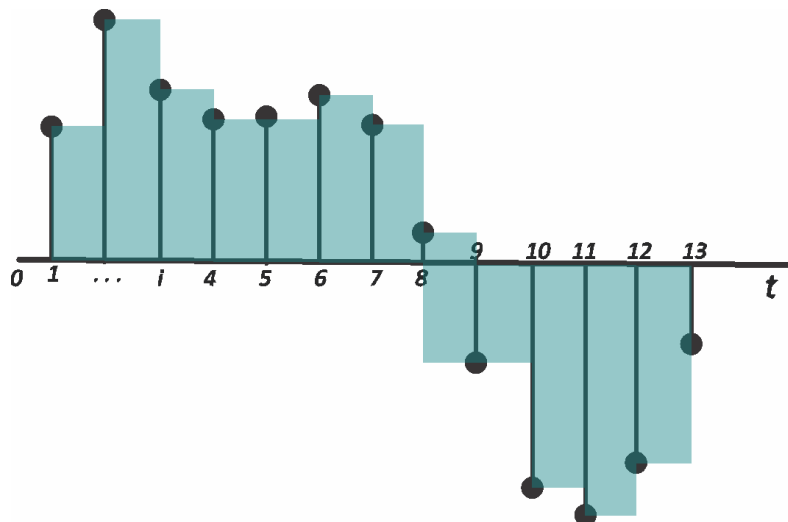


Reconstruction



Reconstruction

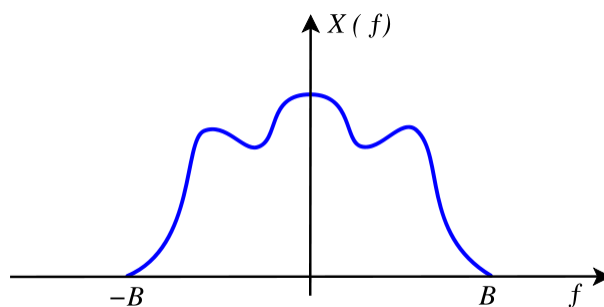
- Zero-Order Hold [ZOH]



Reconstruction

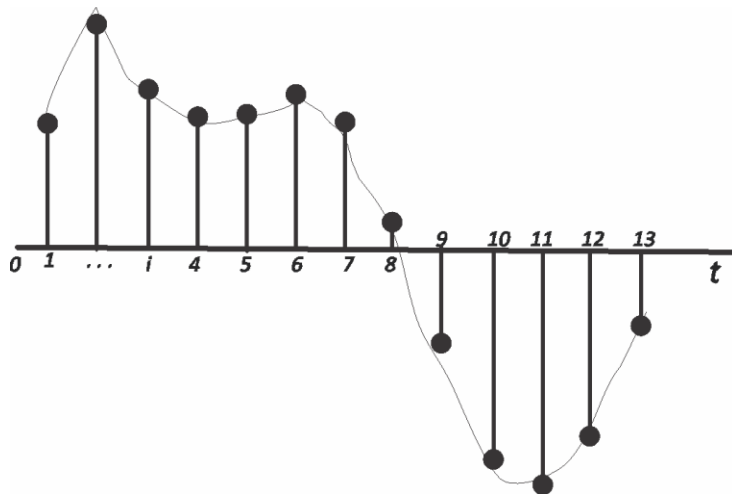
- Whittaker–Shannon interpolation formula

$$x(t) = \sum_{n=-\infty}^{\infty} x[n] \cdot \text{sinc}\left(\frac{t-nT}{T}\right)$$

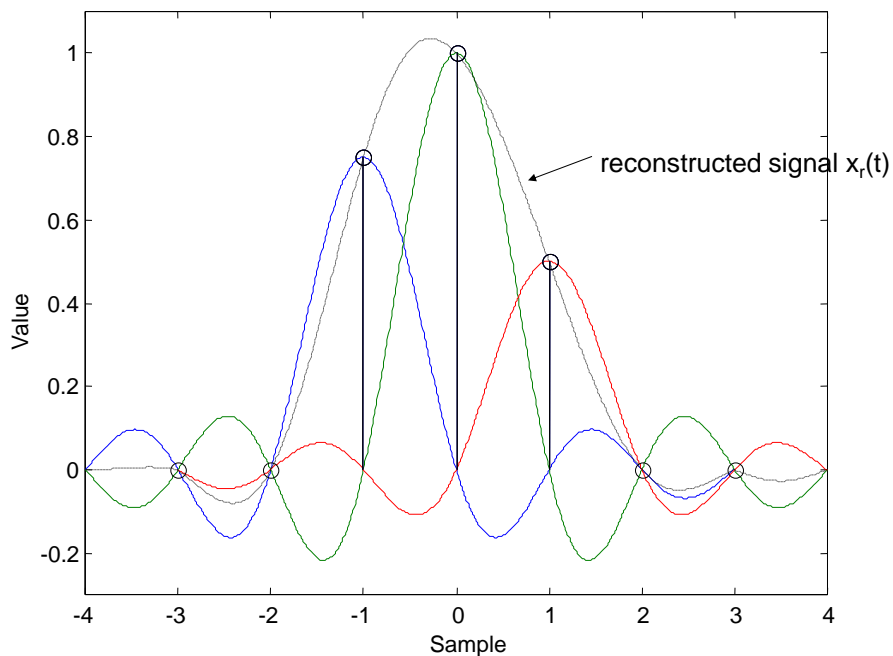


Reconstruction

- Whittaker–Shannon interpolation formula

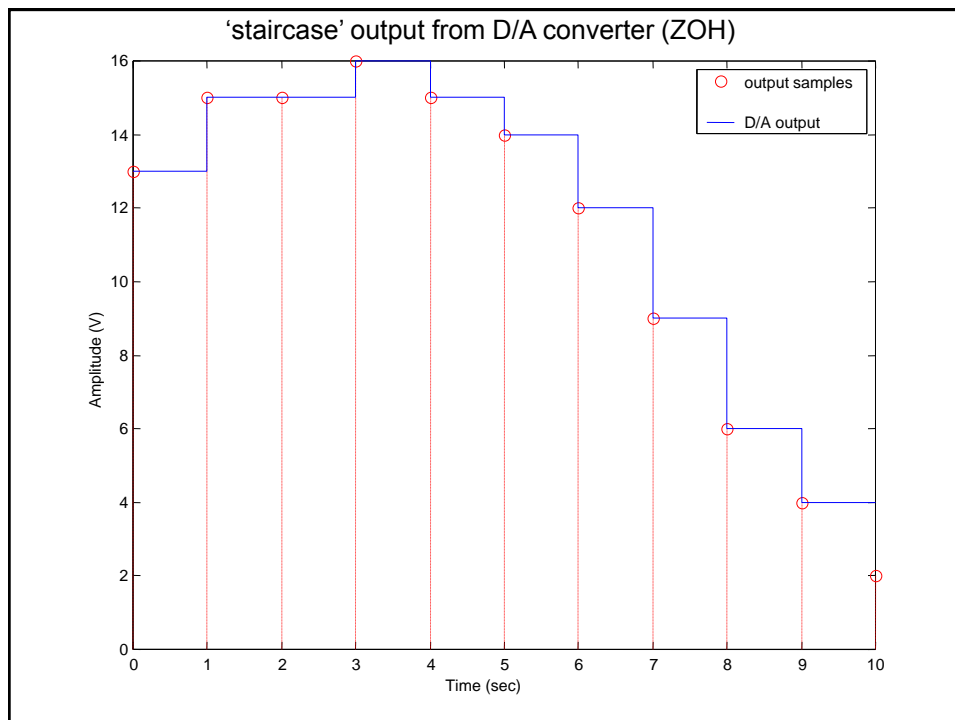


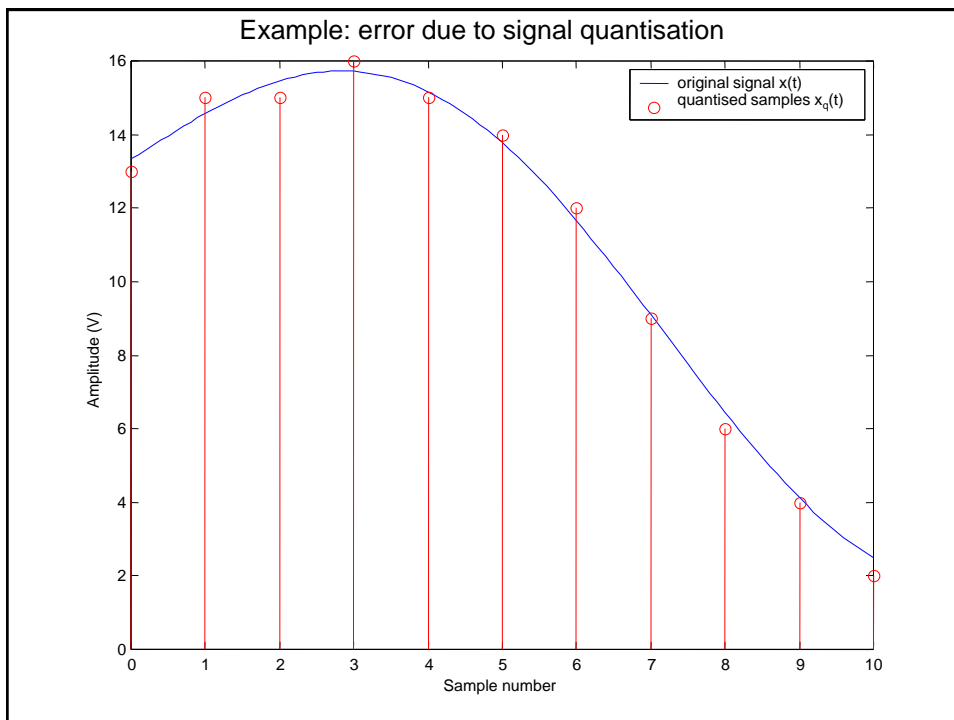
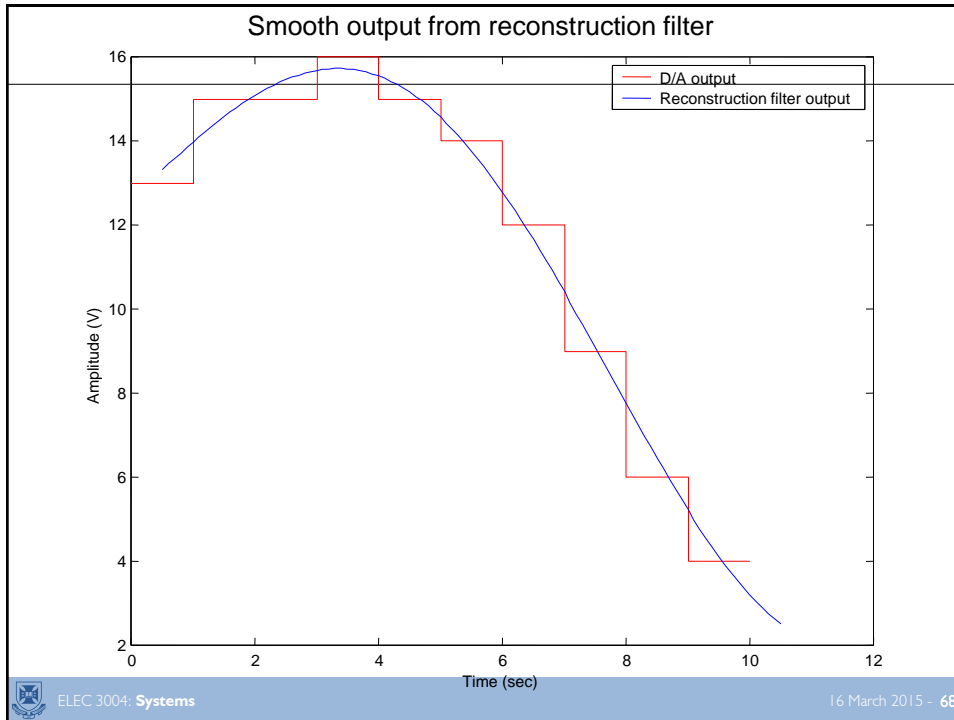
Ideal "sinc" Interpolation of sample values [0 0 0.75 1 0.5 0 0]

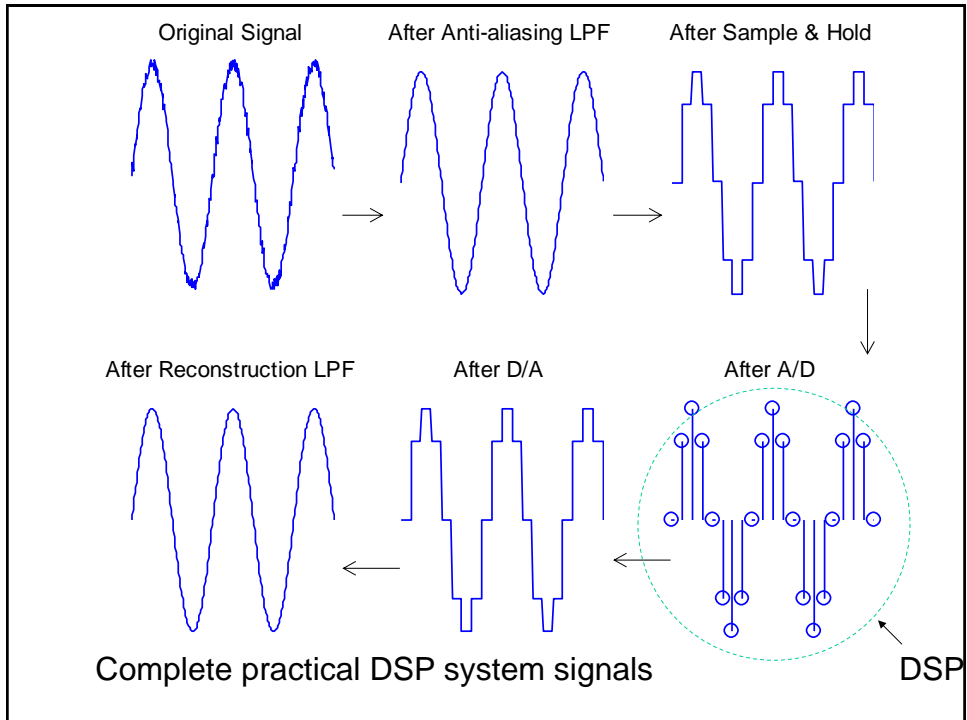


Sampling and Reconstruction Theory and Practice

- Signal is bandlimited to bandwidth WB
 - Problem: real signals are not bandlimited
 - Therefore, require (non-ideal) anti-aliasing filter
- Signal multiplied by ideal impulse train
 - problems: sample pulses have finite width
 - and not \otimes in practice, but sample & hold circuit
- Samples discrete-time, continuous valued
 - Problem: require discrete values for DSP
 - Therefore, require A/D converter (quantisation)
- Ideal lowpass reconstruction ('sinc' interpolation)
 - problems: ideal lowpass filter not available
 - Therefore, use D/A converter and practical lowpass filter

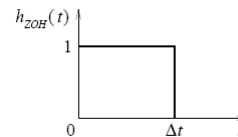




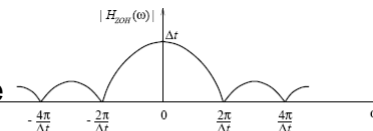


Zero Order Hold (ZOH)

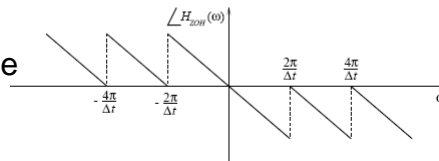
ZOH impulse response



ZOH amplitude response



ZOH phase response

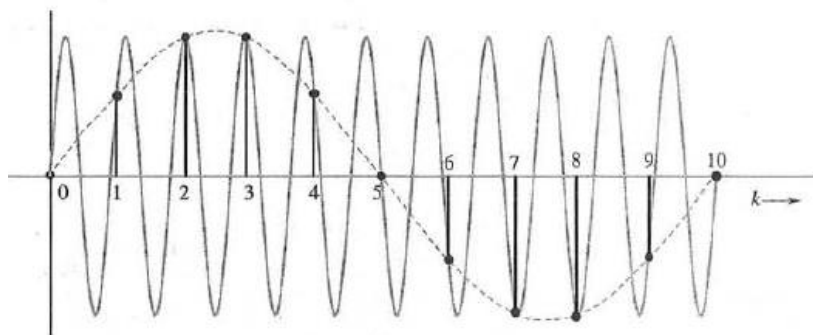


Finite Width Sampling

- Impulse train sampling not realisable
 - sample pulses have finite width (say nanosecs)
- This produces two effects,
- Impulse train has sinc envelope in frequency domain
 - impulse train is square wave with small duty cycle
 - Reduces amplitude of replica spectrums
 - smaller replicas to remove with reconstruction filter ☺
- Averaging of signal during sample time
 - effective low pass filter of original signal
 - can reduce aliasing, but can reduce fidelity ☹
 - negligible with most S/H ☺



Aliasing: Another view of this



Aliasing

- Aliasing - through sampling, two entirely different analog sinusoids take on the same “discrete time” identity

For $f[k] = \cos \Omega k$, $\Omega = \omega T$:

The period has to be less than F_h (highest frequency): $T \leq \frac{1}{2F_h}$

Thus: $0 \leq \mathcal{F} \leq \frac{\mathcal{F}_s}{2}$

ω_f : aliased frequency: $\omega T = \omega_f T + 2\pi m$



Practical Anti-aliasing Filter

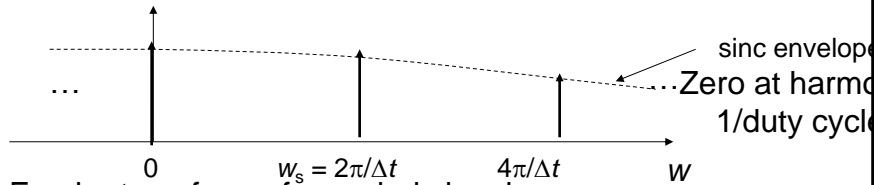
- Non-ideal filter
 - $\omega_c = \omega_s / 2$
- Filter usually 4th – 6th order (e.g., Butterworth)
 - so frequencies $> \omega_c$ may still be present
 - not higher order as phase response gets worse
- Luckily, most real signals
 - are lowpass in nature
 - signal power reduces with increasing frequency
 - e.g., speech naturally bandlimited (say $< 8\text{KHz}$)
 - Natural signals have a (approx) $1/f$ spectrum
 - so, in practice aliasing is not (usually) a problem



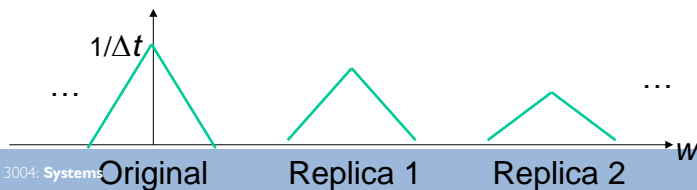
Amplitude spectrum of original signal



Fourier transform of sampling signal (pulses have finite width)

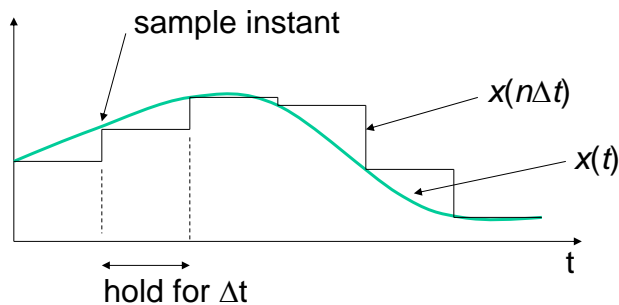


Fourier transform of sampled signal



Practical Sampling

- Sample and Hold (S/H)
 1. takes a sample every Δt seconds
 2. holds that value constant until next sample
- Produces 'staircase' waveform, $x(n\Delta t)$



Quantisation

- Analogue to digital converter (A/D)
 - Calculates nearest binary number to $x(n\Delta t)$
 - $x_q[n] = q(x(n\Delta t))$, where $q()$ is non-linear rounding fctn
 - output modeled as $x_q[n] = x(n\Delta t) + e[n]$
- Approximation process
 - therefore, loss of information (unrecoverable)
 - known as ‘quantisation noise’ ($e[n]$)
 - error reduced as number of bits in A/D increased
 - i.e., Δx , quantisation step size reduces

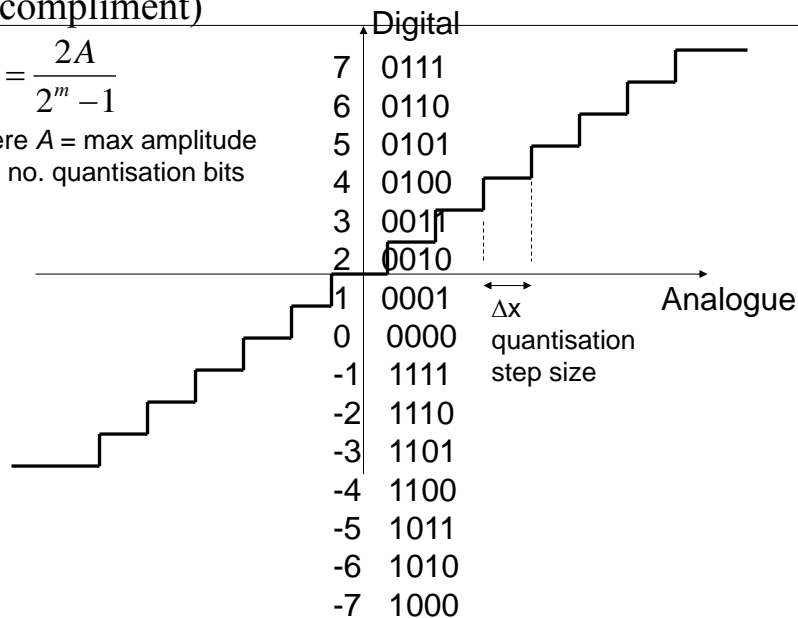
$$|e[n]| \leq \frac{\Delta x}{2}$$



Input-output for 4-bit quantiser (two's complement)

$$\Delta x = \frac{2A}{2^m - 1}$$

where A = max amplitude
 m = no. quantisation bits



Signal to Quantisation Noise

- To estimate SQNR we assume
 - $e[n]$ is uncorrelated to signal and is a
 - uniform random process
- assumptions not always correct!
 - not the only assumptions we could make...
- Also known a ‘Dynamic range’ (R_D)
 - expressed in decibels (dB)
 - ratio of power of largest signal to smallest (noise)

$$R_D = 10 \log_{10} \left(\frac{P_{\text{signal}}}{P_{\text{noise}}} \right)$$



Dynamic Range

Need to estimate:

1. Noise power
 - uniform random process: $P_{\text{noise}} = \Delta x^2/12$
2. Signal power
 - (at least) two possible assumptions
 - 1. sinusoidal: $P_{\text{signal}} = A^2/2$
 - 2. zero mean Gaussian process: $P_{\text{signal}} = \sigma^2$
 - Note: as $\sigma \approx A/3$: $P_{\text{signal}} \approx A^2/9$
 - where σ^2 = variance, A = signal amplitude

1 extra bit halves Δx
i.e., $20 \log_{10}(1/2) = 6\text{dB}$

Regardless of assumptions: R_D increases by 6dB
for every bit that is added to the quantiser



Practical Reconstruction

Two stage process:

1. Digital to analogue converter (D/A)
 - zero order hold filter
 - produces ‘staircase’ analogue output
2. Reconstruction filter
 - non-ideal filter: $w_c = w_s/2$
 - further reduces replica spectrums
 - usually 4th – 6th order e.g., Butterworth
 - for acceptable phase response



D/A Converter

- Analogue output $y(t)$ is
 - convolution of output samples $y(n\Delta t)$ with $h_{ZOH}(t)$

$$y(t) = \sum_n y(n\Delta t) h_{ZOH}(t - n\Delta t)$$

$$h_{ZOH}(t) = \begin{cases} 1, & 0 \leq t < \Delta t \\ 0, & \text{otherwise} \end{cases}$$

$$H_{ZOH}(w) = \Delta t \exp\left(\frac{-jw\Delta t}{2}\right) \frac{\sin(w\Delta t/2)}{w\Delta t/2}$$

D/A is lowpass filter with sinc type frequency response
It does not completely remove the replica spectrums
Therefore, additional reconstruction filter required



Summary

- Theoretical model of Sampling
 - bandlimited signal (ω_B)
 - multiplication by ideal impulse train ($\omega_s > 2\omega_B$)
 - convolution of frequency spectrums (creates replicas)
 - Ideal lowpass filter to remove replica spectrums
 - $\omega_c = \omega_s / 2$
 - Sinc interpolation
- Practical systems
 - Anti-aliasing filter ($\omega_c < \omega_s / 2$)
 - A/D (S/H and quantisation)
 - D/A (ZOH)
 - Reconstruction filter ($\omega_c = \omega_s / 2$)

Don't confuse
theory and
practice!

