

Bioengineering 280A Principles of Biomedical Imaging

Fall Quarter 2005
Linear Systems Lecture 2

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Representation of 1D Function

From the sifting property, we can write a 1D function as

$g(x) = \int_{-\infty}^{\infty} g(\xi)\delta(x - \xi)d\xi$. To gain intuition, consider the approximation

$$g(x) \approx \sum_{n=-\infty}^{\infty} g(n\Delta x) \frac{1}{\Delta x} \Pi\left(\frac{x - n\Delta x}{\Delta x}\right)\Delta x.$$



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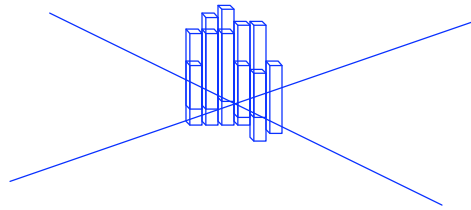
Representation of 2D Function

Similarly, we can write a 2D function as

$$g(x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(\xi, \eta) \delta(x - \xi, y - \eta) d\xi d\eta.$$

To gain intuition, consider the approximation

$$g(x, y) \approx \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} g(n\Delta x, m\Delta y) \frac{1}{\Delta x} \Pi\left(\frac{x - n\Delta x}{\Delta x}\right) \frac{1}{\Delta y} \Pi\left(\frac{y - m\Delta y}{\Delta y}\right) \Delta x \Delta y.$$

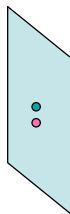


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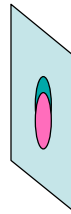
Impulse Response

Intuition: the impulse response is the response of a system to an input of infinitesimal width and unit area.

Original
Image



Blurred Image



Since any input can be thought of as the weighted sum of impulses, a linear system is characterized by its impulse response(s).

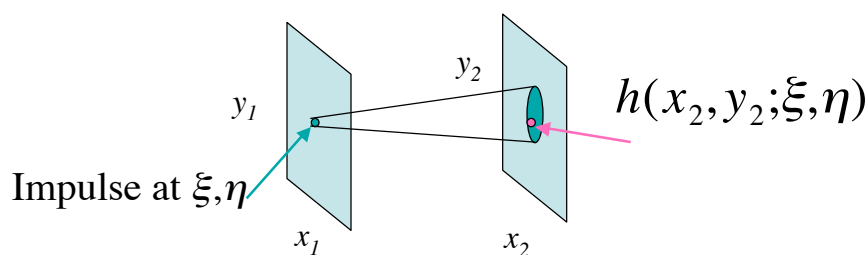
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Impulse Response

The impulse response characterizes the response of a system over all space to a Dirac delta impulse function at a certain location.

$$h(x_2; \xi) = L[\delta(x_1 - \xi)] \quad \text{1D Impulse Response}$$

$$h(x_2, y_2; \xi, \eta) = L[\delta(x_1 - \xi, y_1 - \eta)] \quad \text{2D Impulse Response}$$



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Superposition Integral

What is the response to an arbitrary function $g(x_1, y_1)$?

$$\text{Write } g(x_1, y_1) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(\xi, \eta) \delta(x_1 - \xi, y_1 - \eta) d\xi d\eta.$$

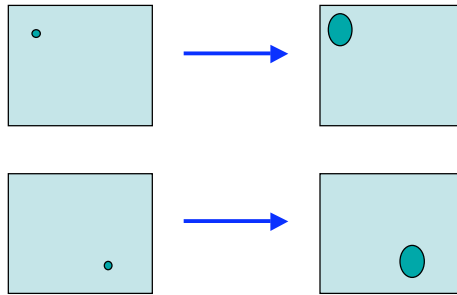
The response is given by

$$\begin{aligned} I(x_2, y_2) &= L[g_1(x_1, y_1)] \\ &= L\left[\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(\xi, \eta) \delta(x_1 - \xi, y_1 - \eta) d\xi d\eta\right] \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(\xi, \eta) L[\delta(x_1 - \xi, y_1 - \eta)] d\xi d\eta \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(\xi, \eta) h(x_2, y_2; \xi, \eta) d\xi d\eta \end{aligned}$$

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Space Invariance

If a system is space invariant, the impulse response depends only on the difference between the output coordinates and the position of the impulse and is given by $h(x_2, y_2; \xi, \eta) = h(x_2 - \xi, y_2 - \eta)$



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2D Convolution

For a space invariant linear system, the superposition integral becomes a convolution integral.

$$\begin{aligned} I(x_2, y_2) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(\xi, \eta) h(x_2, y_2; \xi, \eta) d\xi d\eta \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(\xi, \eta) h(x_2 - \xi, y_2 - \eta) d\xi d\eta \\ &= g(x_2, y_2) ** h(x_2, y_2) \end{aligned}$$

where $**$ denotes 2D convolution. This will sometimes be abbreviated as $*$, e.g. $I(x_2, y_2) = g(x_2, y_2) * h(x_2, y_2)$.

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1D Convolution

For completeness, here is the 1D version.

$$\begin{aligned}I(x) &= \int_{-\infty}^{\infty} g(\xi)h(x;\xi)d\xi \\ &= \int_{-\infty}^{\infty} g(\xi)h(x - \xi)d\xi \\ &= g(x) * h(x)\end{aligned}$$

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Convolution with Dirac delta function

$$\begin{aligned}g(x) * \delta(x) &= \int_{-\infty}^{\infty} g(\xi)\delta(x - \xi)d\xi \\ &= g(x)\end{aligned}$$

$$\begin{aligned}g(x) * \delta(x - \Delta) &= \int_{-\infty}^{\infty} g(\xi)\delta(x - \Delta - \xi)d\xi \\ &= g(x - \Delta)\end{aligned}$$

Convolution of $g(x)$ with a shifted Dirac delta function just shifts $g(x)$

$$\begin{aligned}g(x, y) * \delta(x, y) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(\xi, \eta)\delta(x - \xi, y - \eta)d\xi d\eta \\ &= g(x, y)\end{aligned}$$

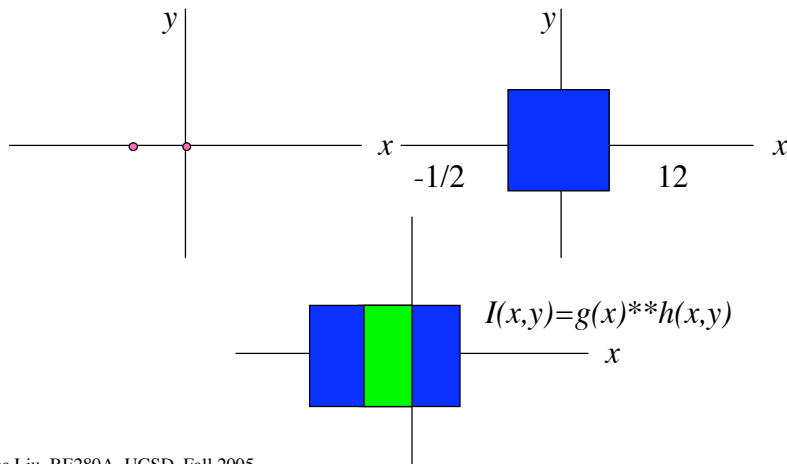
$$\begin{aligned}g(x, y) * \delta(x - x_0, y - y_0) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(\xi, \eta)\delta(x - x_0 - \xi, y - y_0 - \eta)d\xi d\eta \\ &= g(x - x_0, y - y_0)\end{aligned}$$

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2D Convolution Example

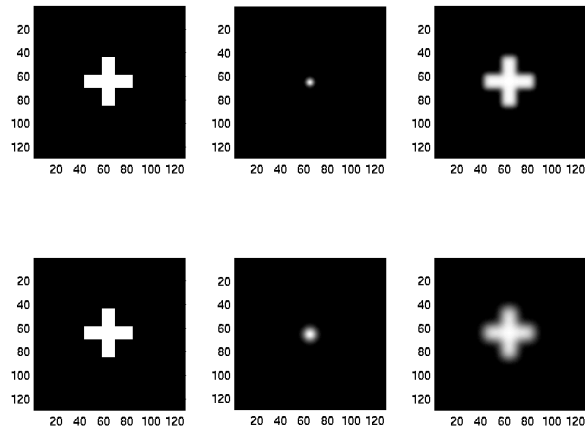
$$g(x) = \delta(x+1/2, y) + \delta(x, y)$$

$$h(x) = \text{rect}(x, y)$$



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2D Convolution Example

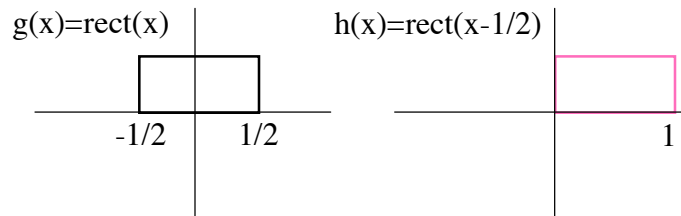


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1D Convolution Review

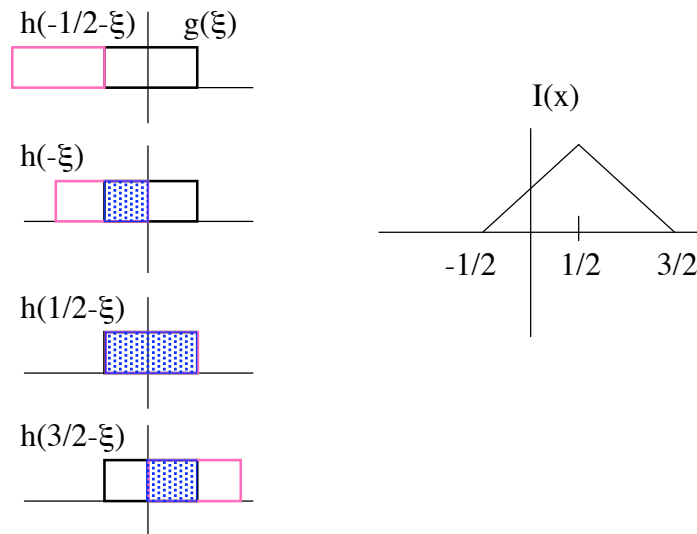
$$g(x) * h(x) = \int_{-\infty}^{\infty} g(\xi)h(x - \xi)d\xi$$

Basic Rule: Flip one function, slide it past the other function, and integrate as you go.



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1D Convolution Review



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Convolution/Modulation Theorem

$$\begin{aligned}F\{g(x) * h(x)\} &= \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} g(u) * h(x-u) du \right] e^{-j2\pi k_x x} dx \\&= \int_{-\infty}^{\infty} g(u) \int_{-\infty}^{\infty} h(x-u) e^{-j2\pi k_x x} dx du \\&= \int_{-\infty}^{\infty} g(u) H(k_x) e^{-j2\pi k_x u} du \\&= G(k_x) H(k_x)\end{aligned}$$

Convolution in the spatial domain transforms into multiplication in the frequency domain. Dual is modulation

$$F\{g(x)h(x)\} = G(k_x) * H(k_x)$$

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2D Convolution/Multiplication

Convolution

$$F[g(x,y) ** h(x,y)] = G(k_x, k_y) H(k_x, k_y)$$

Multiplication

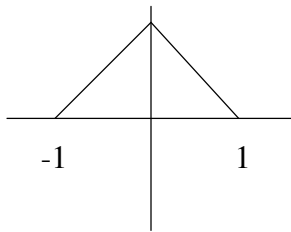
$$F[g(x,y)h(x,y)] = G(k_x, k_y) ** H(k_x, k_y)$$

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Application of Convolution Thm.

$$\Lambda(x) = \begin{cases} 1 - |x| & |x| < 1 \\ 0 & \text{otherwise} \end{cases}$$

$$F(\Lambda(x)) = \int_{-1}^1 (1 - |x|) e^{-j2\pi k_x x} dx = ??$$

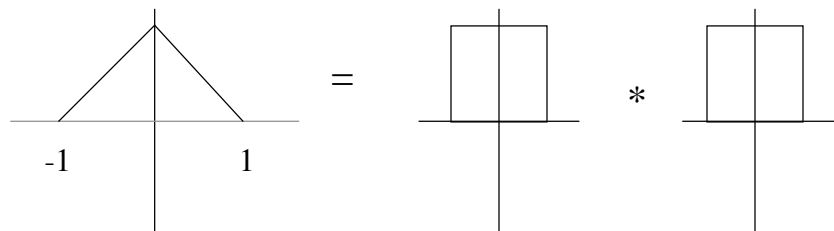


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Application of Convolution Thm.

$$\Lambda(x) = \Pi(x) * \Pi(x)$$

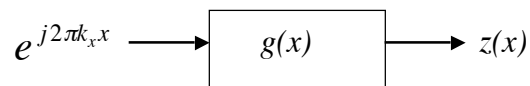
$$F(\Lambda(x)) = \text{sinc}^2(k_x)$$



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Eigenfunctions

The fundamental nature of the convolution theorem may be better understood by observing that the complex exponentials are eigenfunctions of the convolution operator.



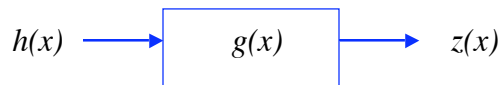
$$\begin{aligned} z(x) &= g(x) * e^{j2\pi k_x x} \\ &= \int_{-\infty}^{\infty} g(u) e^{j2\pi k_x (x-u)} du \\ &= G(k_x) e^{j2\pi k_x x} \end{aligned}$$

The response of a linear shift invariant system to a complex exponential is simply the exponential multiplied by the FT of the system's impulse response.

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Eigenfunctions

Now consider an arbitrary input $h(x)$.



Recall that we can express $h(x)$ as the integral of weighted complex exponentials.

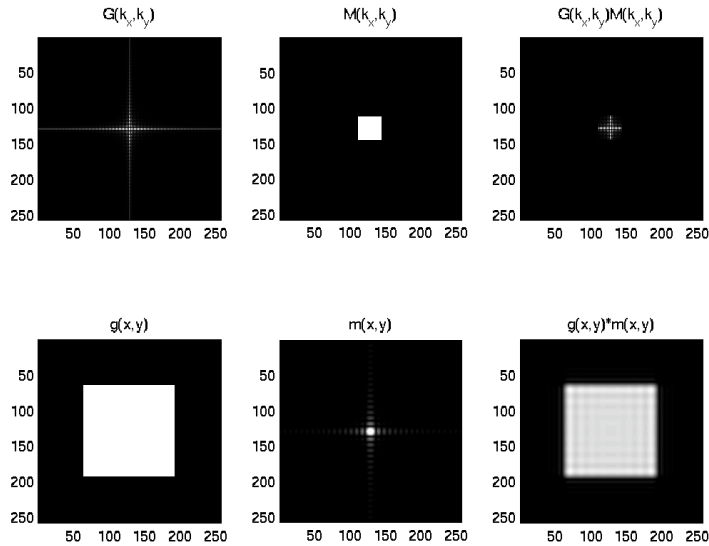
$$h(x) = \int_{-\infty}^{\infty} H(k_x) e^{j2\pi k_x x} dk_x$$

Each of these exponentials is weighted by $G(k_x)$ so that the response may be written as

$$z(x) = \int_{-\infty}^{\infty} G(k_x) H(k_x) e^{j2\pi k_x x} dk_x$$

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Convolution Example



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Analog vs. Digital

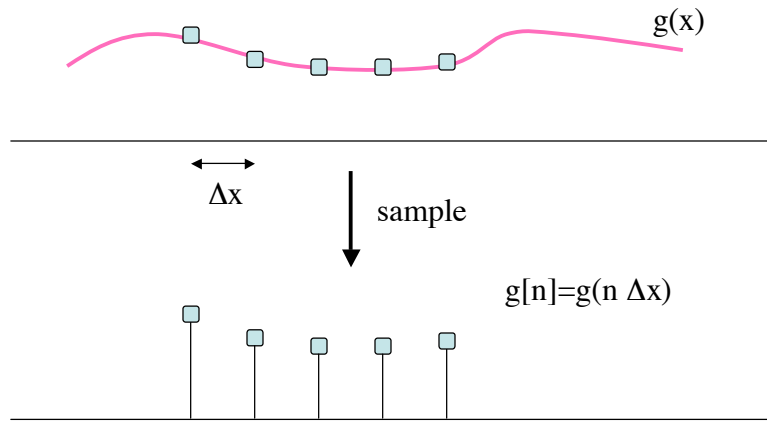
The Analog World:

Continuous time/space, continuous valued signals or images, e.g. vinyl records, photographs, x-ray films.

The Digital World:

Discrete time/space, discrete-valued signals or images, e.g. CD-Roms, DVDs, digital photos, digital x-rays, CT, MRI, ultrasound.

The Process of Sampling



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Questions

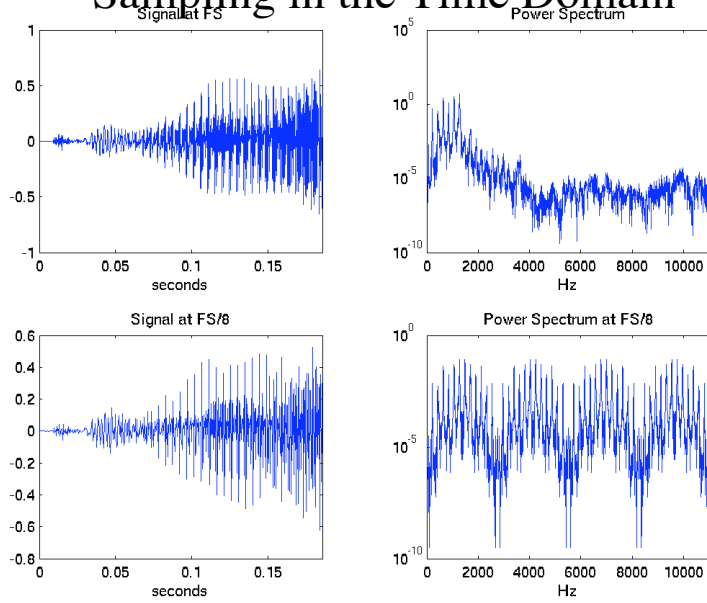
How finely do we need to sample?

What happens if we don't sample finely enough?

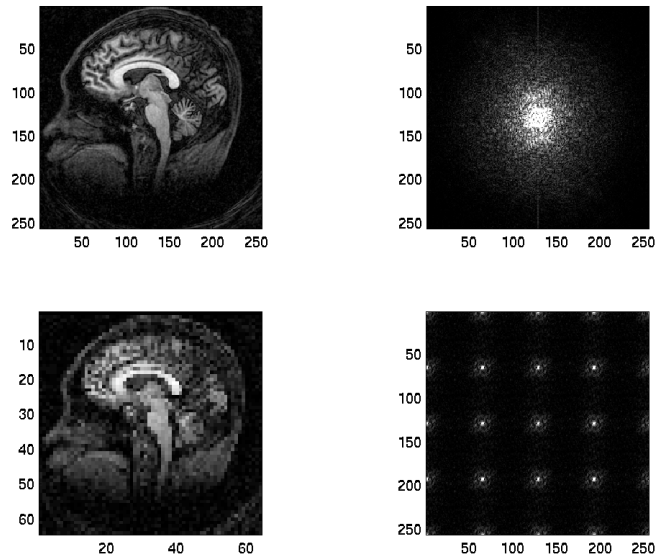
Can we reconstruct the original signal or image from its samples?

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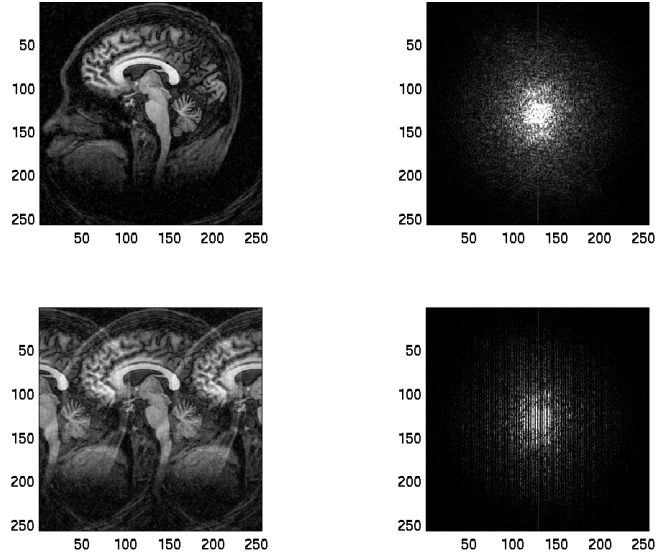
Sampling in the Time Domain



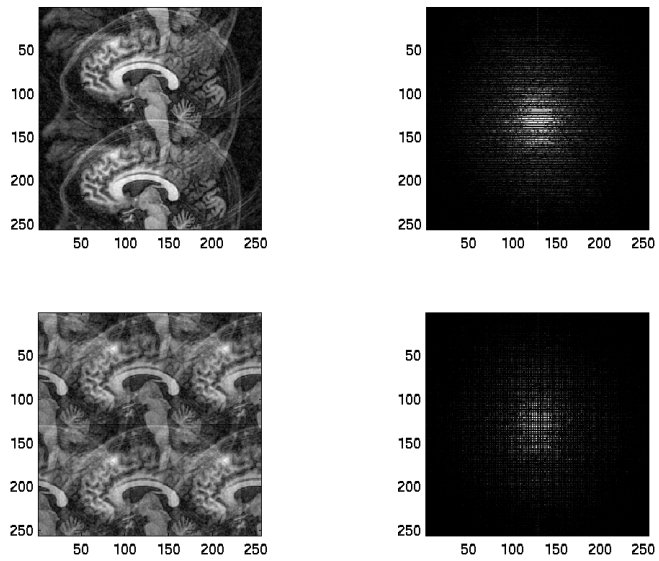
Sampling in Image Space



Sampling in k-space



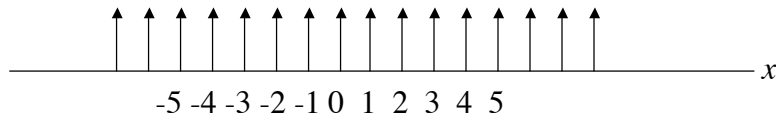
Sampling in k-space



Th

Comb Function

$$\text{comb}(x) = \sum_{n=-\infty}^{\infty} \delta(x - n)$$

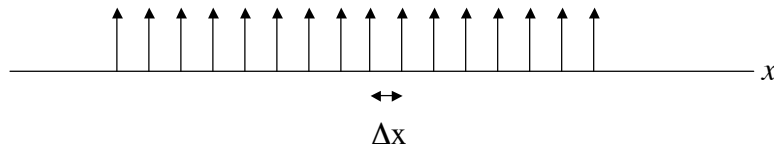


Other names: Impulse train, bed of nails, shah function.

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Scaled Comb Function

$$\begin{aligned} \text{comb}\left(\frac{x}{\Delta x}\right) &= \sum_{n=-\infty}^{\infty} \delta\left(\frac{x}{\Delta x} - n\right) \\ &= \sum_{n=-\infty}^{\infty} \delta\left(\frac{x - n\Delta x}{\Delta x}\right) \\ &= \Delta x \sum_{n=-\infty}^{\infty} \delta(x - n\Delta x) \end{aligned}$$



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1D spatial sampling

$$\begin{aligned}
 g_s(x) &= g(x) \frac{1}{\Delta x} \text{comb}\left(\frac{x}{\Delta x}\right) \\
 &= g(x) \sum_{n=-\infty}^{\infty} \delta(x - n\Delta x) \\
 &= \sum_{n=-\infty}^{\infty} g(n\Delta x) \delta(x - n\Delta x)
 \end{aligned}$$

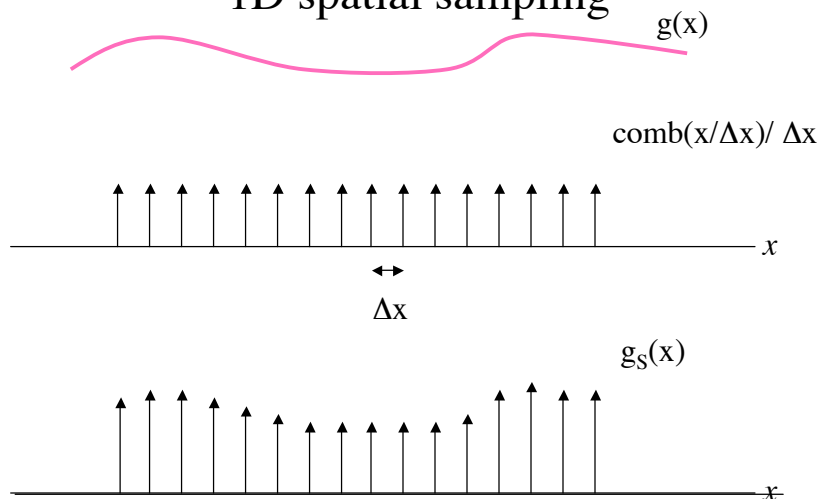
Recall the sifting property $\int_{-\infty}^{\infty} g(x) \delta(x - a) = g(a)$

But we can also write $\int_{-\infty}^{\infty} g(a) \delta(x - a) = g(a) \int_{-\infty}^{\infty} \delta(x - a) = g(a)$

So, $g(x) \delta(x - a) = g(a) \delta(x - a)$

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1D spatial sampling



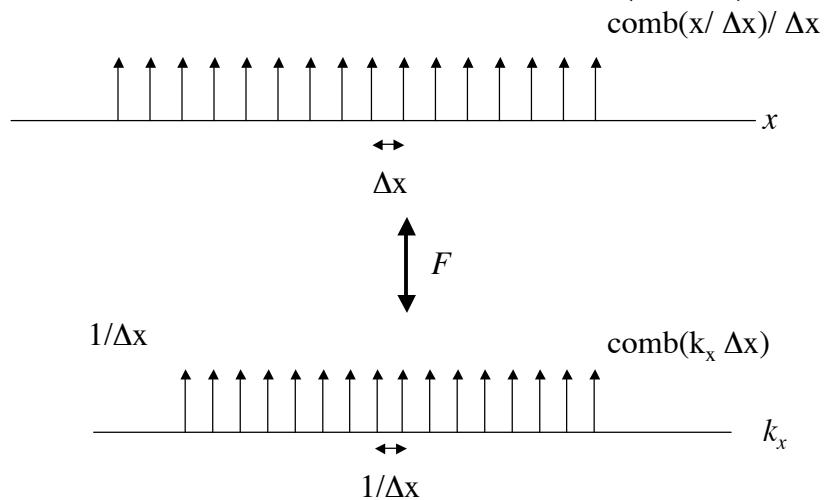
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Fourier Transform of comb(x)

$$\begin{aligned}
 F[\text{comb}(x)] &= \text{comb}(k_x) \\
 &= \sum_{n=-\infty}^{\infty} \delta(k_x - n) \\
 \\
 F\left[\frac{1}{\Delta x} \text{comb}\left(\frac{x}{\Delta x}\right)\right] &= \frac{1}{\Delta x} \Delta x \text{comb}(k_x \Delta x) \\
 &= \sum_{n=-\infty}^{\infty} \delta(k_x \Delta x - n) \\
 &= \frac{1}{\Delta x} \sum_{n=-\infty}^{\infty} \delta\left(k_x - \frac{n}{\Delta x}\right)
 \end{aligned}$$

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Fourier Transform of comb(x/ Δx)



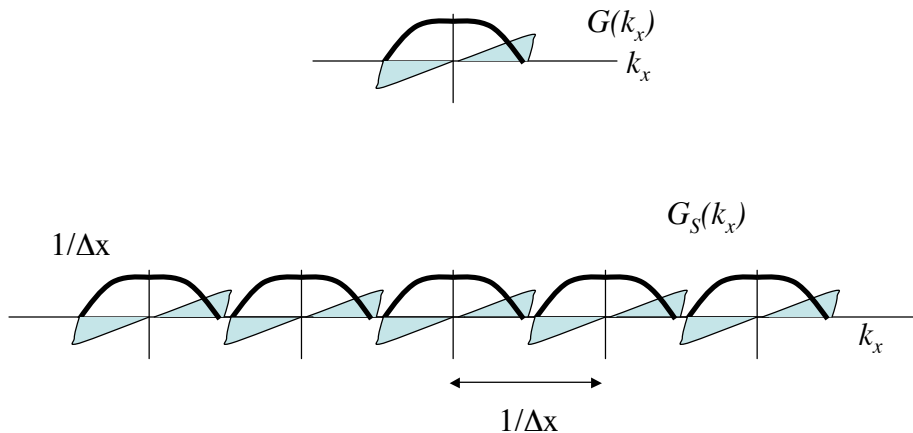
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Fourier Transform of $g_S(x)$

$$\begin{aligned}
 F[g_S(x)] &= F\left[g(x) \frac{1}{\Delta x} \text{comb}\left(\frac{x}{\Delta x}\right)\right] \\
 &= G(k_x) * F\left[\frac{1}{\Delta x} \text{comb}\left(\frac{x}{\Delta x}\right)\right] \\
 &= G(k_x) * \frac{1}{\Delta x} \sum_{n=-\infty}^{\infty} \delta\left(k_x - \frac{n}{\Delta x}\right) \\
 &= \frac{1}{\Delta x} \sum_{n=-\infty}^{\infty} G(k_x) * \delta\left(k_x - \frac{n}{\Delta x}\right) \\
 &= \frac{1}{\Delta x} \sum_{n=-\infty}^{\infty} G\left(k_x - \frac{n}{\Delta x}\right)
 \end{aligned}$$

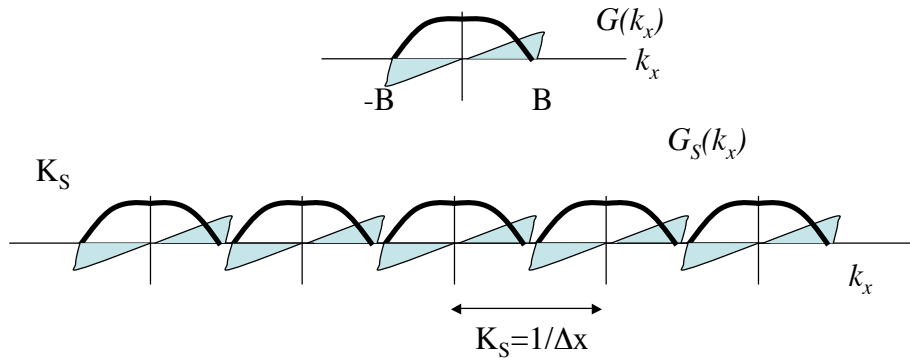
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Fourier Transform of $g_S(x)$



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Nyquist Condition



To avoid overlap, we require that $1/\Delta x > 2B$ or $K_S > 2B$ where $K_S = 1/\Delta x$ is the sampling frequency

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Example

Assume that the highest spatial frequency in an object is $B = 2 \text{ cm}^{-1}$.

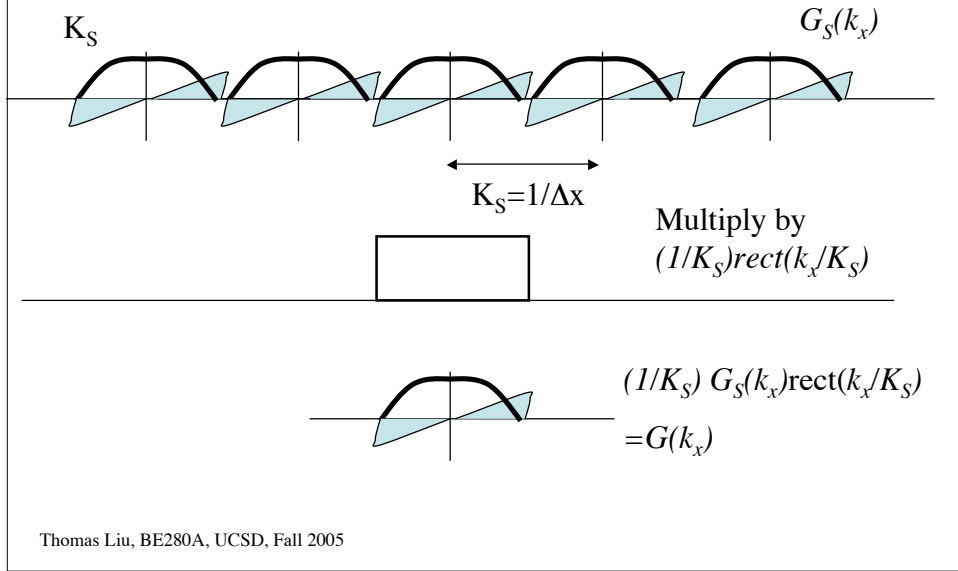
Thus, smallest spatial period is 0.5 cm.

Nyquist theorem says we need to sample with $\Delta x < 1/2B = 0.25 \text{ cm}$

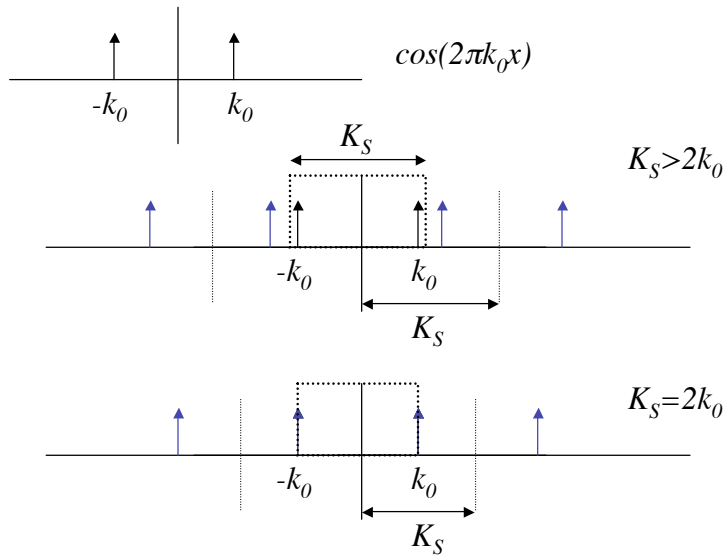
This corresponds to 2 samples per spatial period.

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Reconstruction from Samples



Example Cosine Reconstruction



Reconstruction from Samples

If the Nyquist condition is met, then

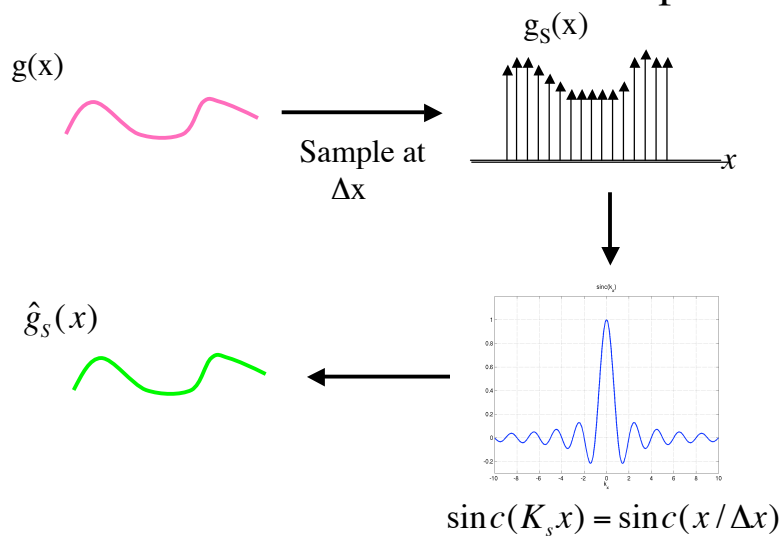
$$\hat{G}_S(k_x) = \frac{1}{K_S} G_S(k_x) \text{rect}(k_x / K_S) = G(k_x)$$

And the signal can be reconstructed by convolving the sample with a sinc function

$$\begin{aligned} \hat{g}_S(x) &= g_S(x) * \text{sinc}(K_S x) \\ &= \left(\sum_{n=-\infty}^{\infty} g(n\Delta X) \delta(x - n\Delta X) \right) * \text{sinc}(K_S x) \\ &= \sum_{n=-\infty}^{\infty} g(n\Delta X) \text{sinc}(K_S(x - n\Delta x)) \end{aligned}$$

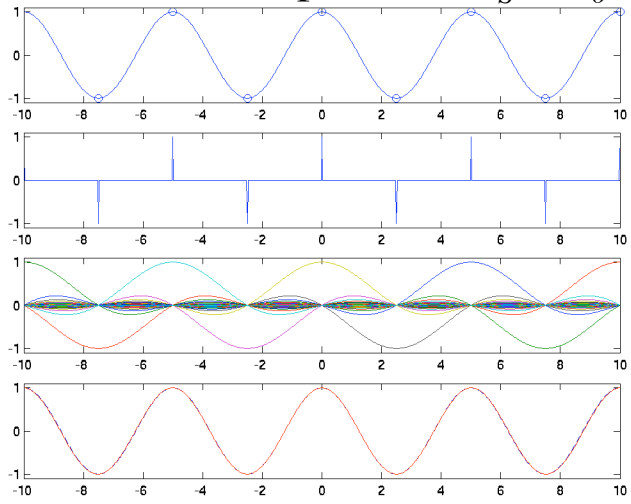
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Reconstruction from Samples



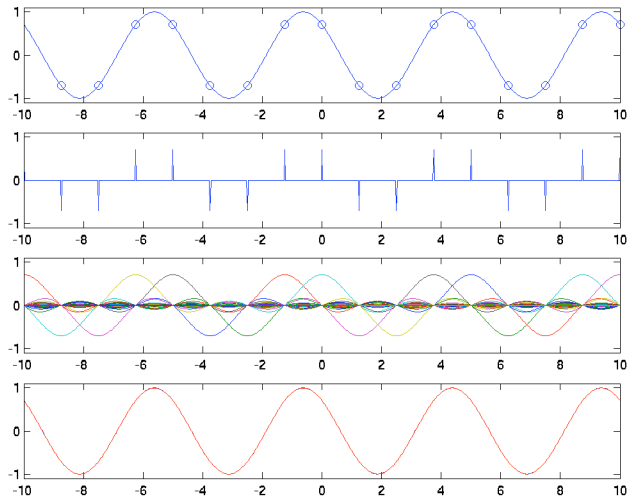
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Cosine Example with $K_s=2k_0$



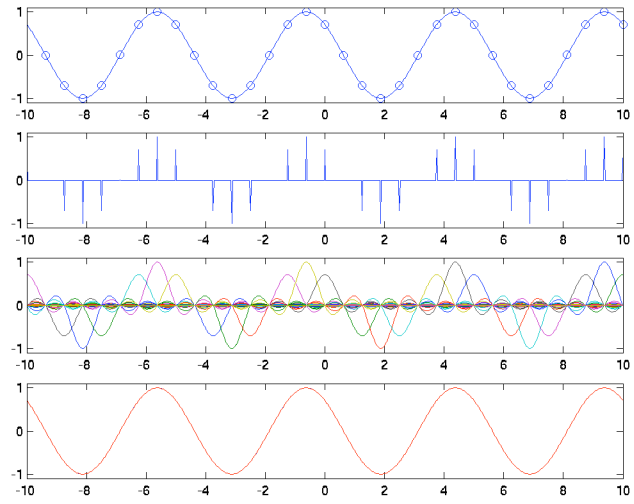
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Example with $K_s=4k_0$



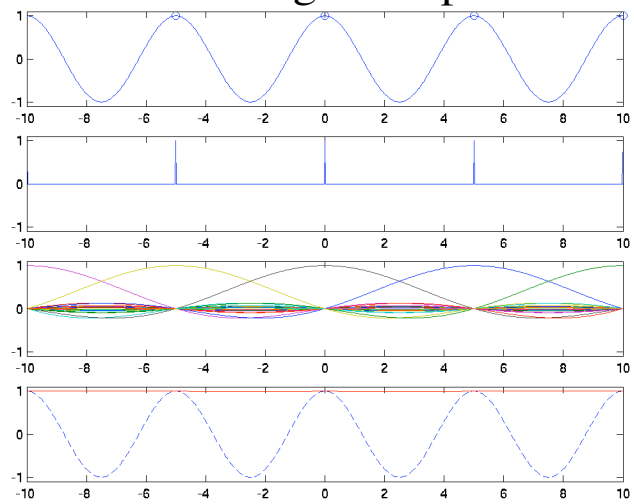
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Example with $K_s = 8k_0$



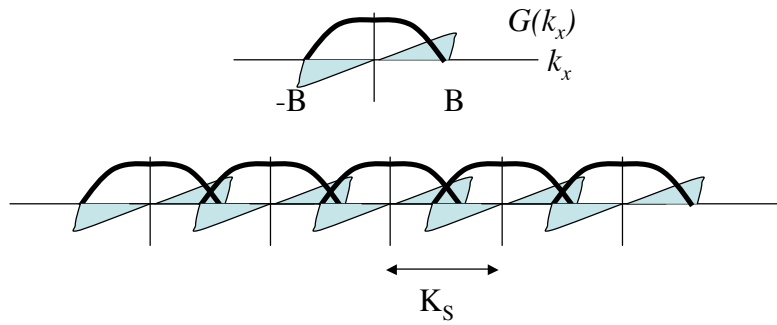
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Aliasing Example



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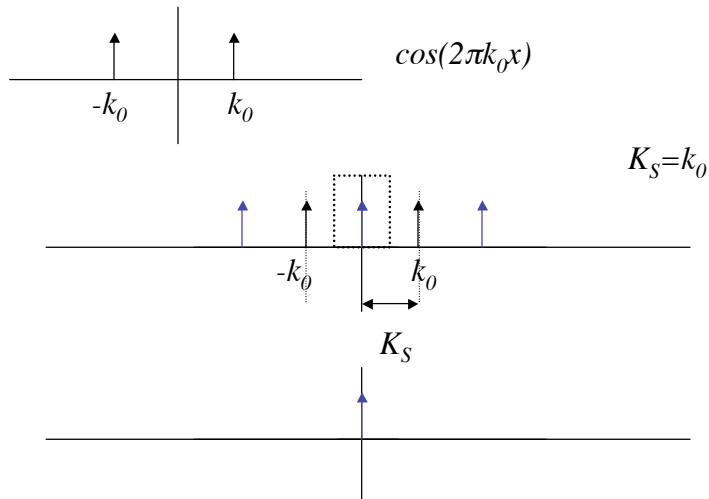
Aliasing



Aliasing occurs when the Nyquist condition is not satisfied.
This occurs for $K_S \leq 2B$

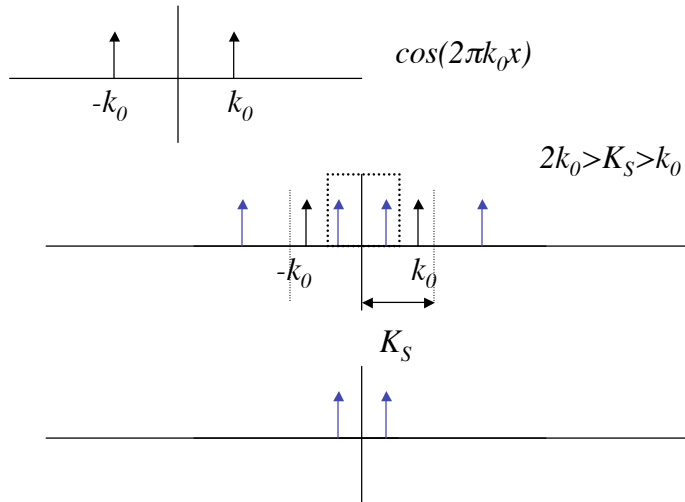
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Aliasing Example



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Aliasing Example

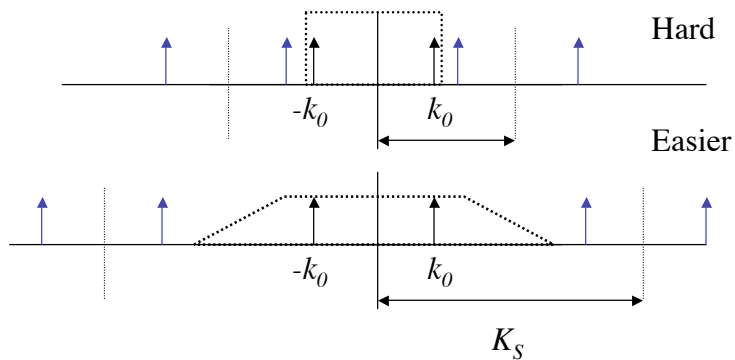


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Practical Considerations

Why sample higher than the Nyquist frequency?

- true sinc interpolation is not practical since the sinc function goes from $-\infty$ to ∞
- the requirements on the low-pass filter are reduced.



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