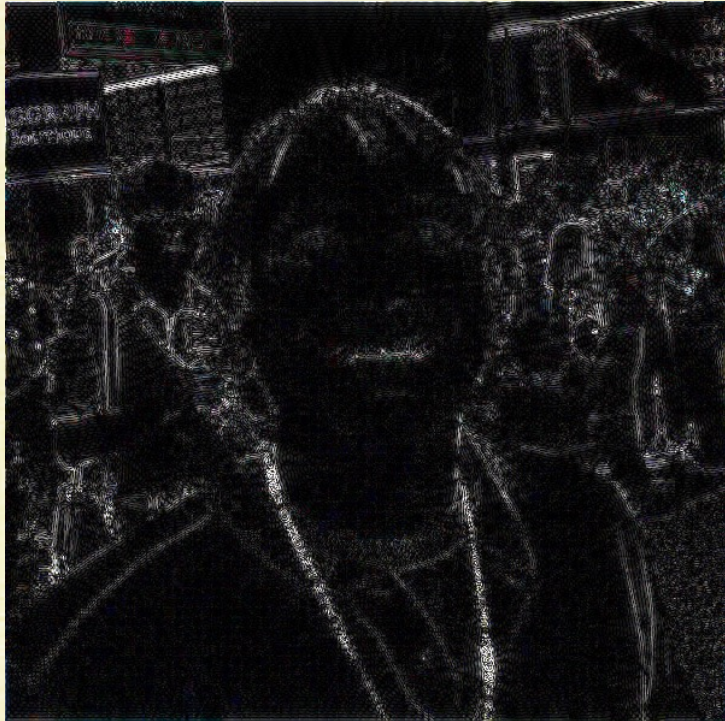
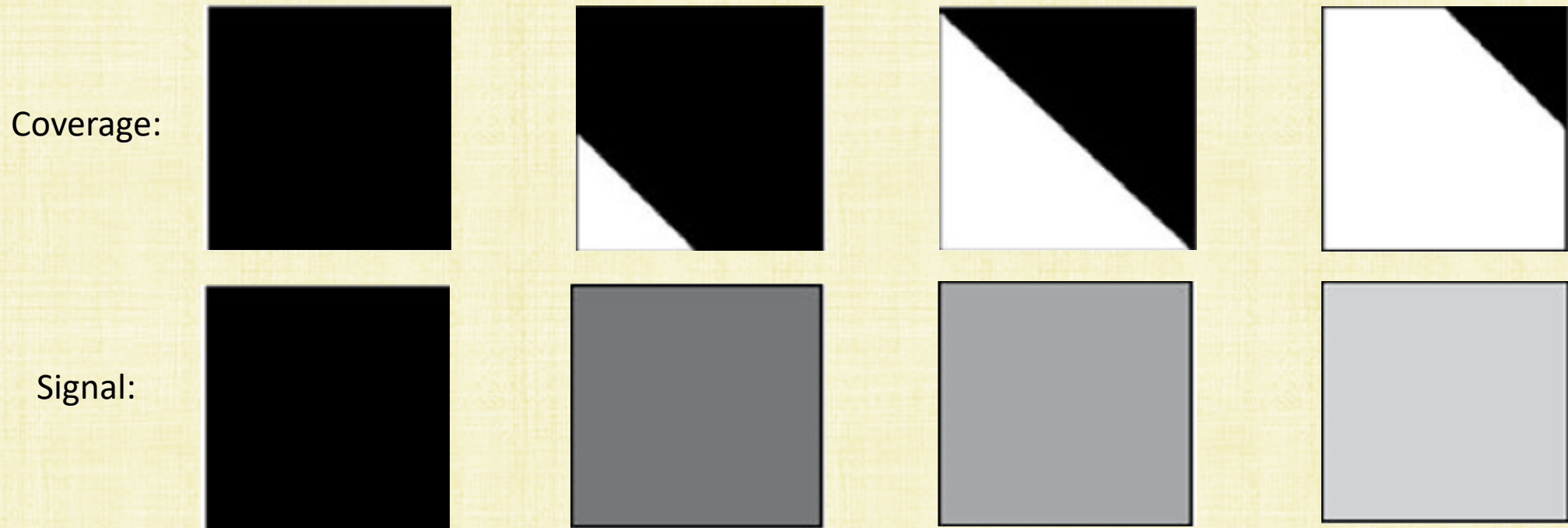


# Sampling



# Area-Coverage

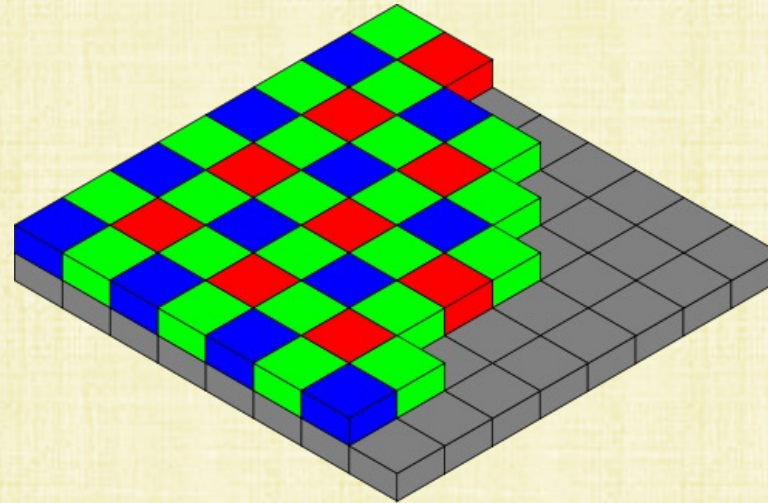
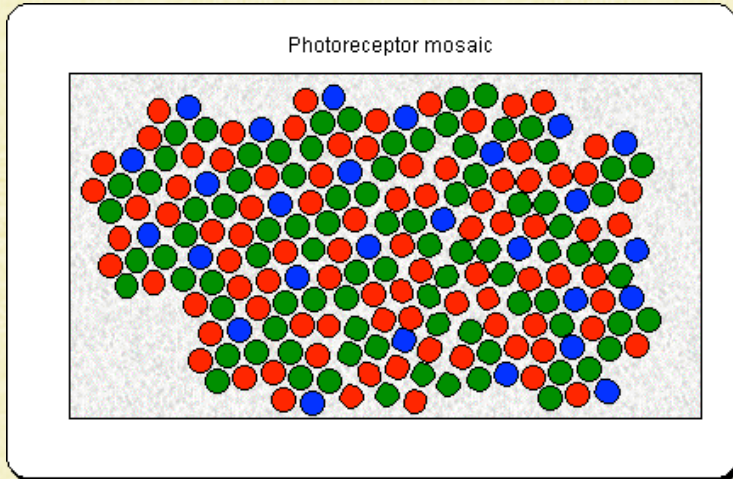
- Real-world sensors get a signal based on the area fraction of the sensor “covered” by objects



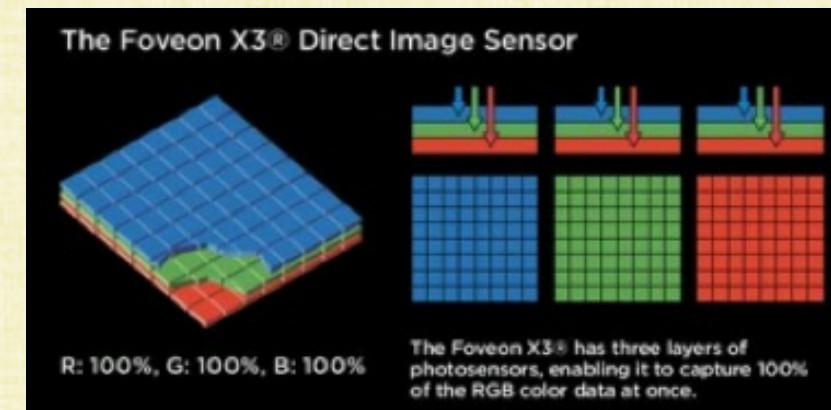
- A ray tracer **only** gets a sample of the geometry (using a ray-geometry intersection point)
- A scanline renderer projects the entire triangle onto the image plane
  - Testing pixel centers against triangles **only** uses sample information from the geometry
  - Computing area overlap between triangles and (square) pixels would better mimic real-world sensors

# Missing Information

- Eyes/cameras don't collect all of the information either
- The staggered spatial layout of real-world sensors means that large regions lack information for certain wavelengths (layered approaches can help to circumvent this)

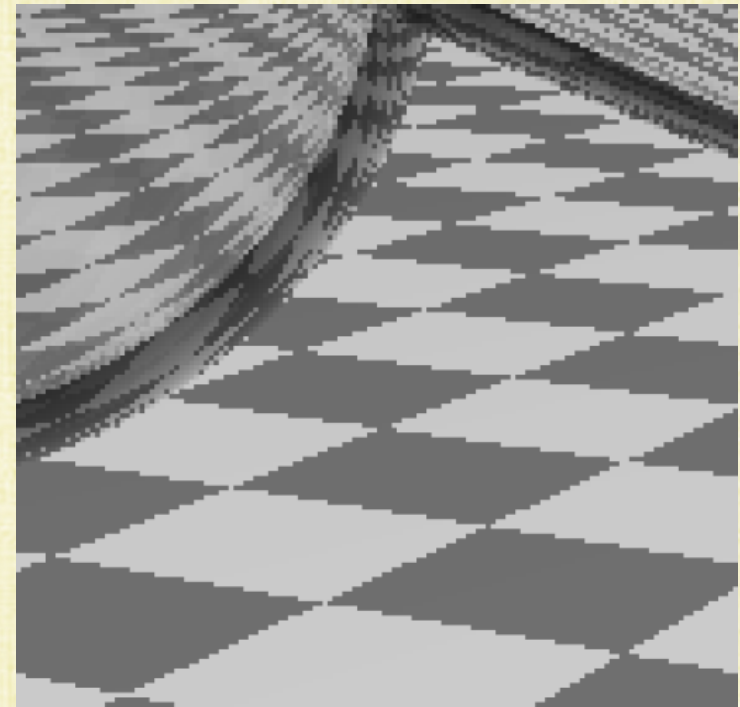
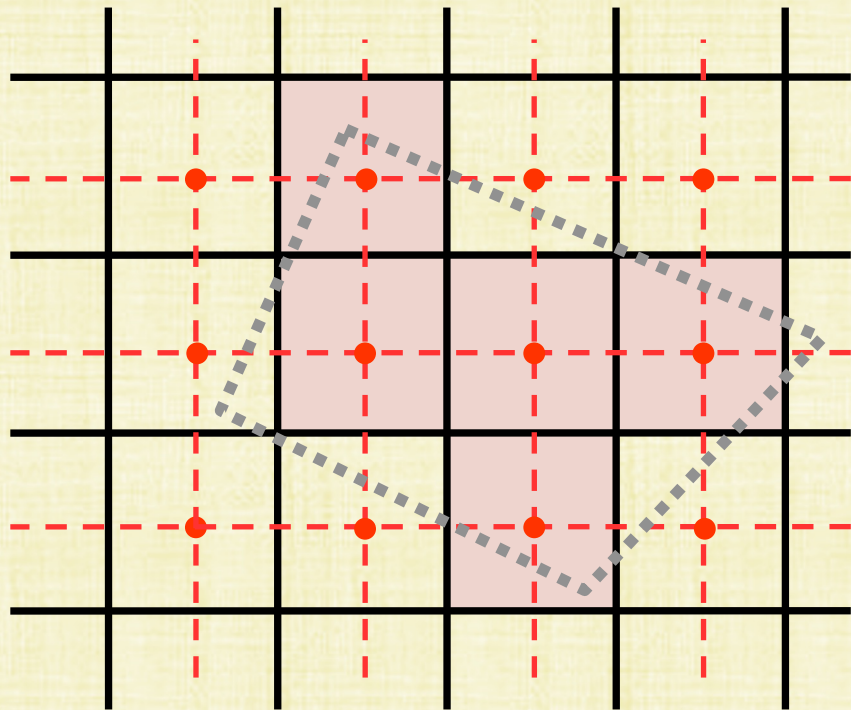


layered approaches can help to circumvent this:



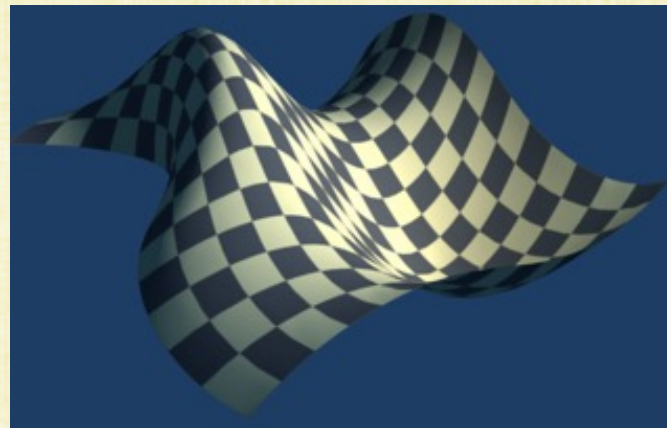
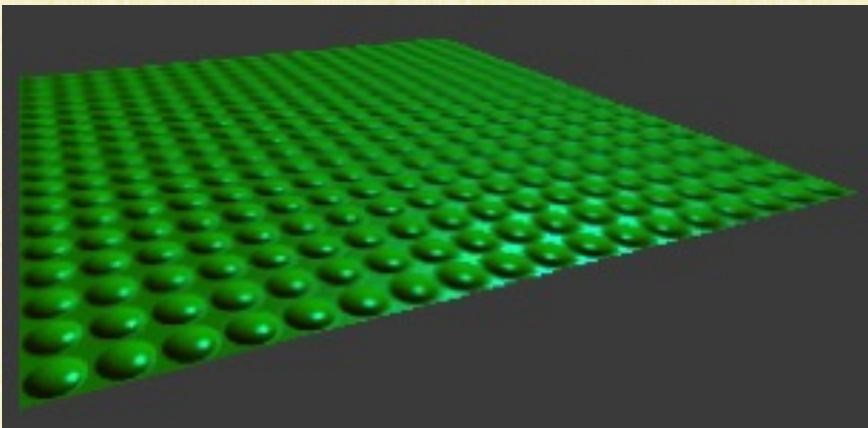
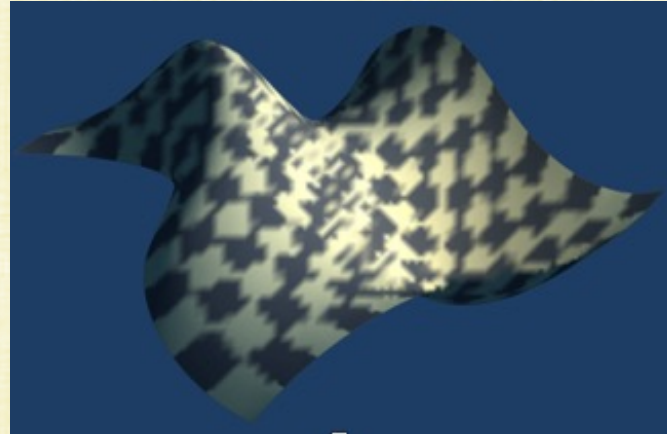
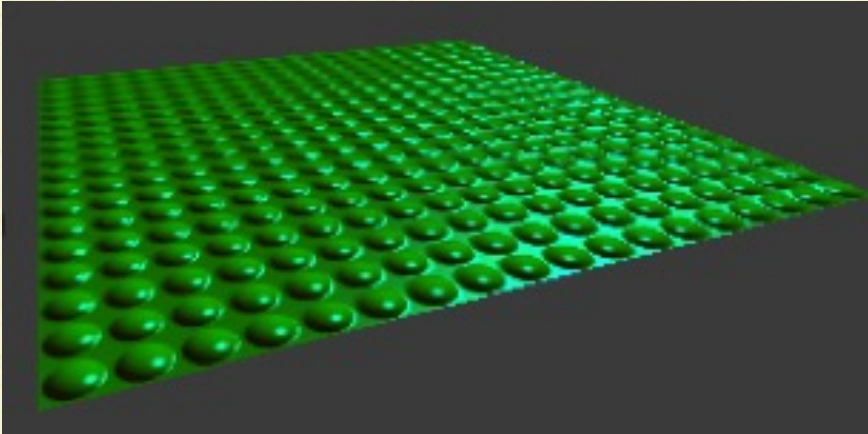
# Aliasing

- Testing **only** the pixel center (with ray-tracing or scanline rasterization) leads to jagged edges
- This causes aliasing artifacts (an alias/imposter takes the place of the correct feature)
- A jagged line appears instead of the correct straight line
- Anti-aliasing strategies aim to reduce aliasing artifacts (caused by sampling information)



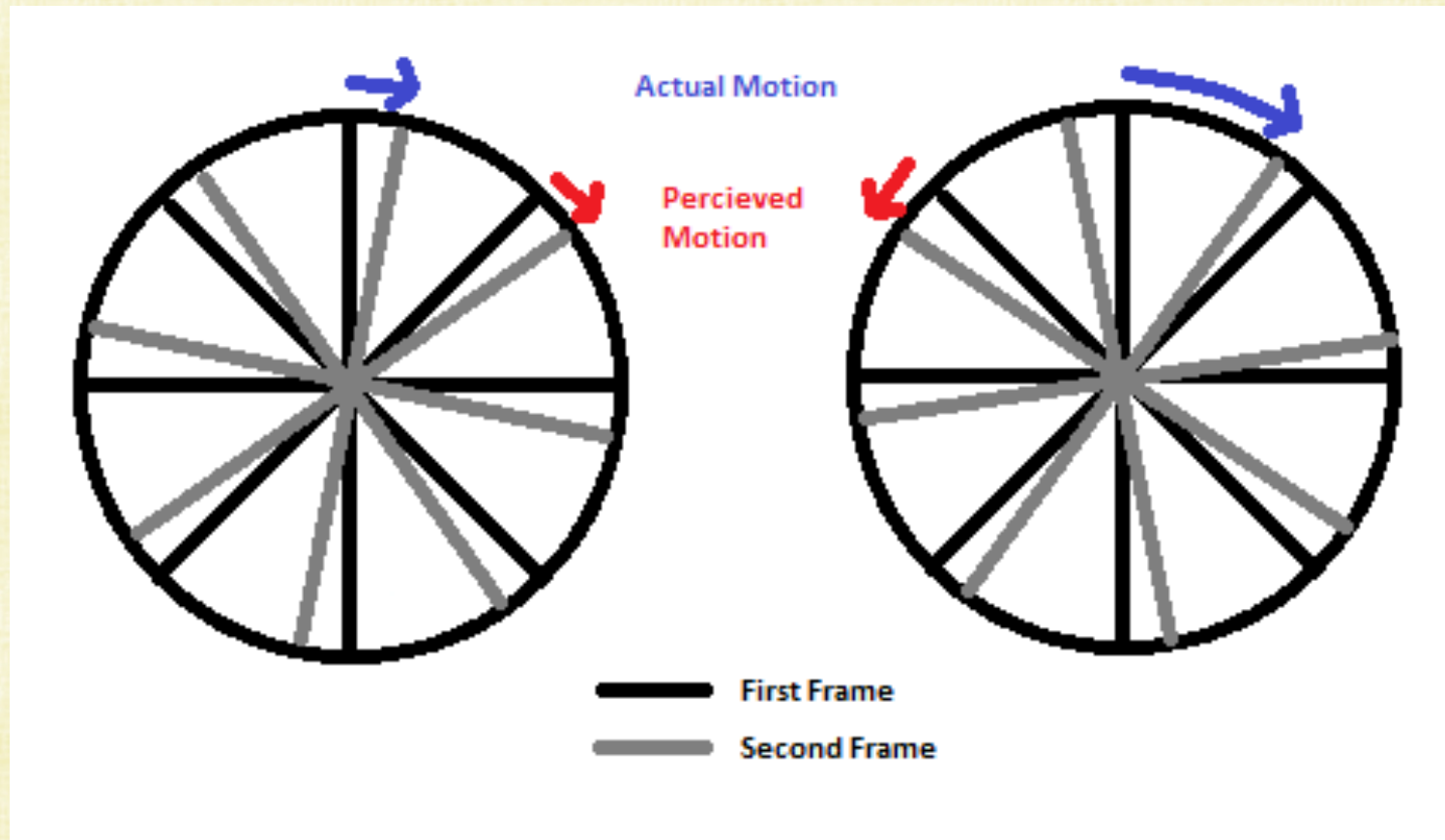
# Aliasing: Shaders & Textures

- Aliased normal vectors can cause erroneous sparkling highlights (top left)
- Aliasing can occur when texture mapping objects too (top right)



# Temporal Aliasing

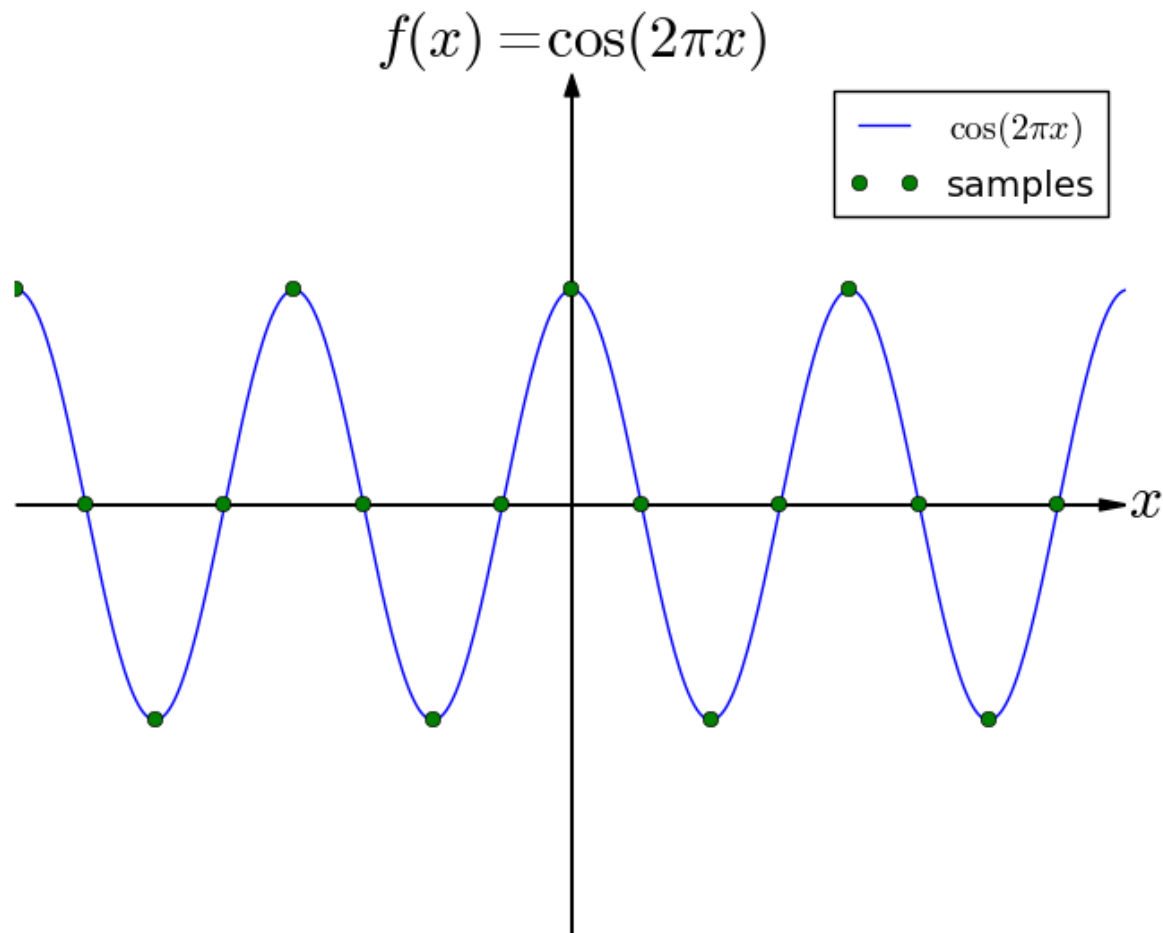
- A spinning wheel can appear to spin backwards, when the motion is insufficiently sampled in time (“wagon wheel” effect)



# Sampling Rate

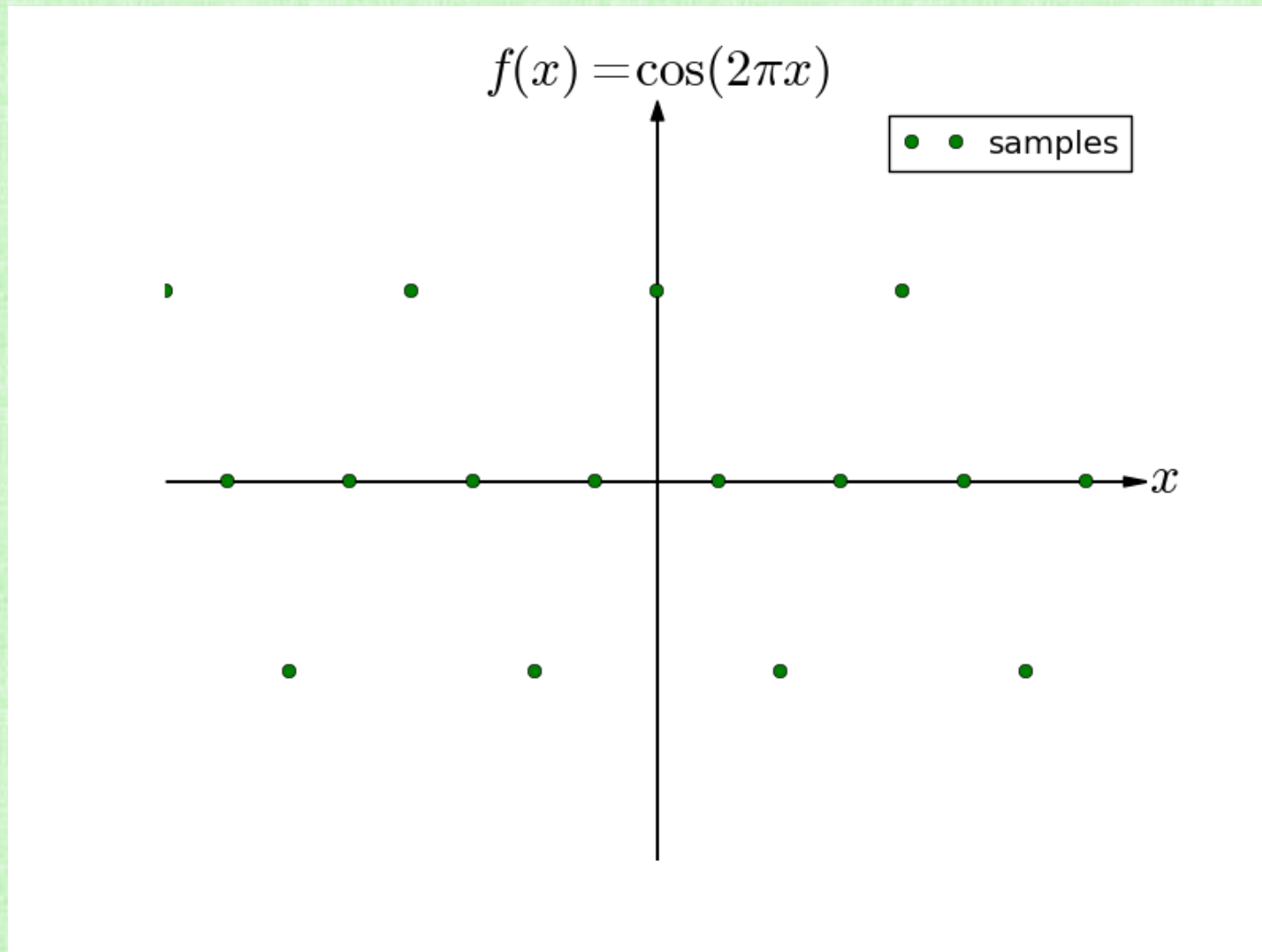
- Artifacts can be reduced by increasing the number of samples (per unit area)
- This can be accomplished by increasing the number of pixels in the image; but:
  - It takes longer to render the scene (because there are more pixels colors to determine)
  - Displaying higher-resolution images requires additional storage/computation
- **Instead: Optimize the Sample Rate!**
- Use the lowest possible sampling rate that does not result in “noticeable” artifacts
- What is the optimal sampling rate?

# 4 samples per period

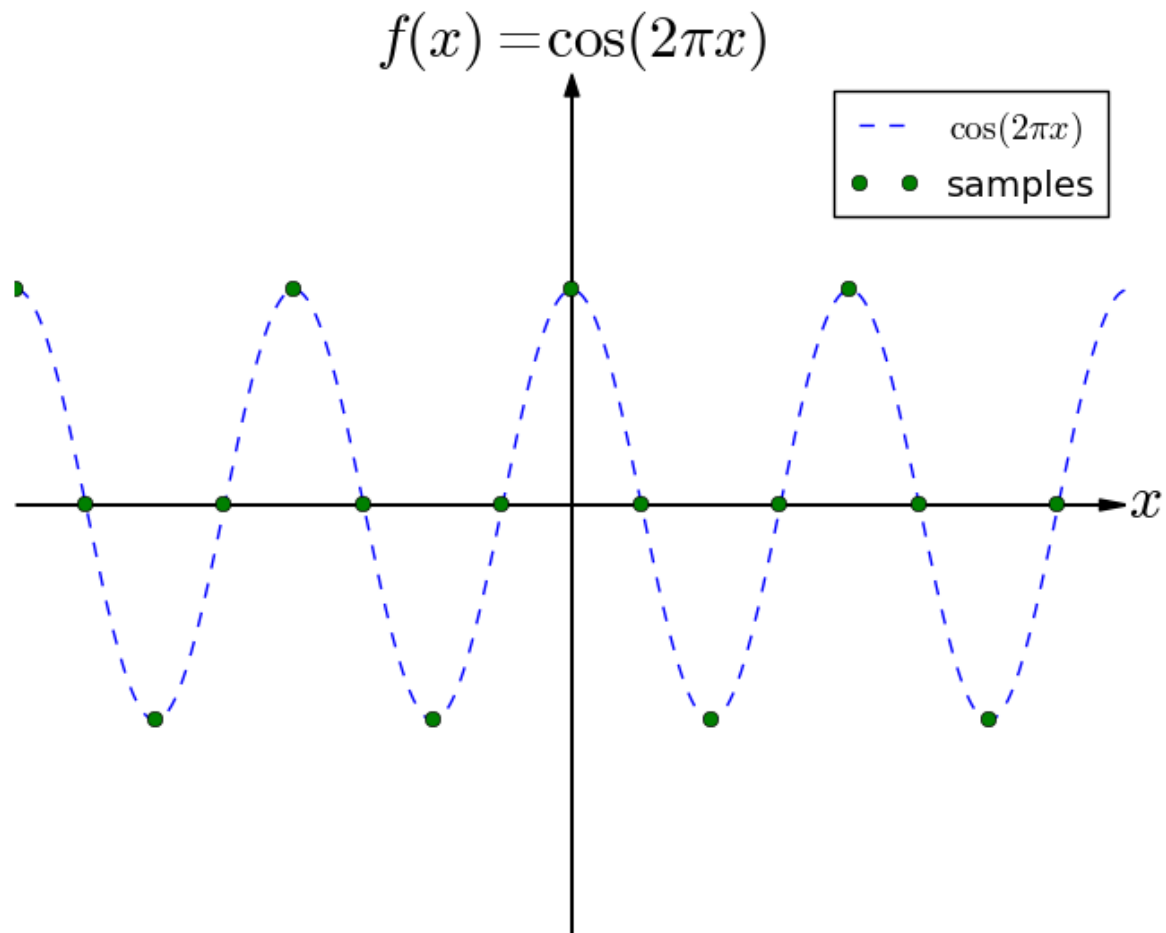




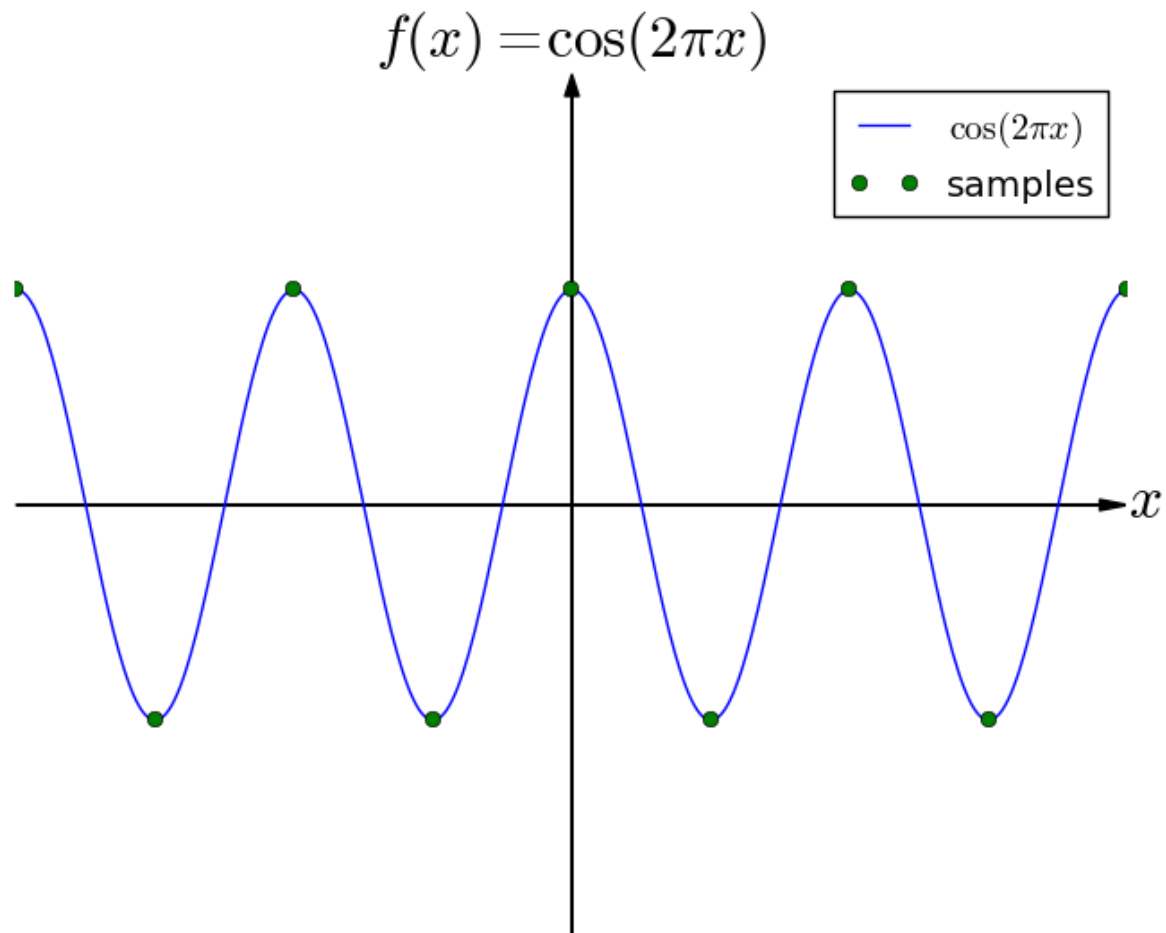
# samples



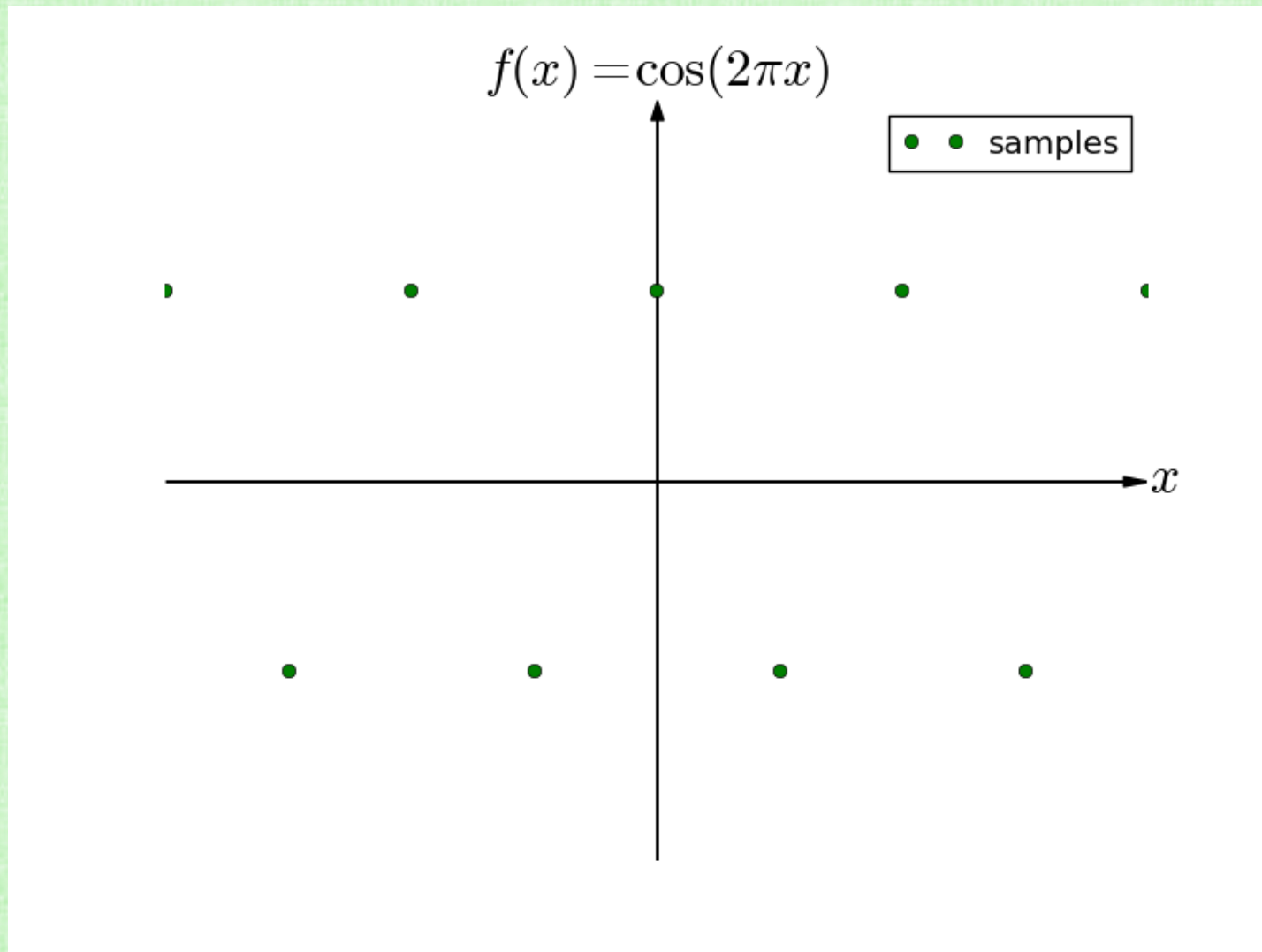
# reconstruction



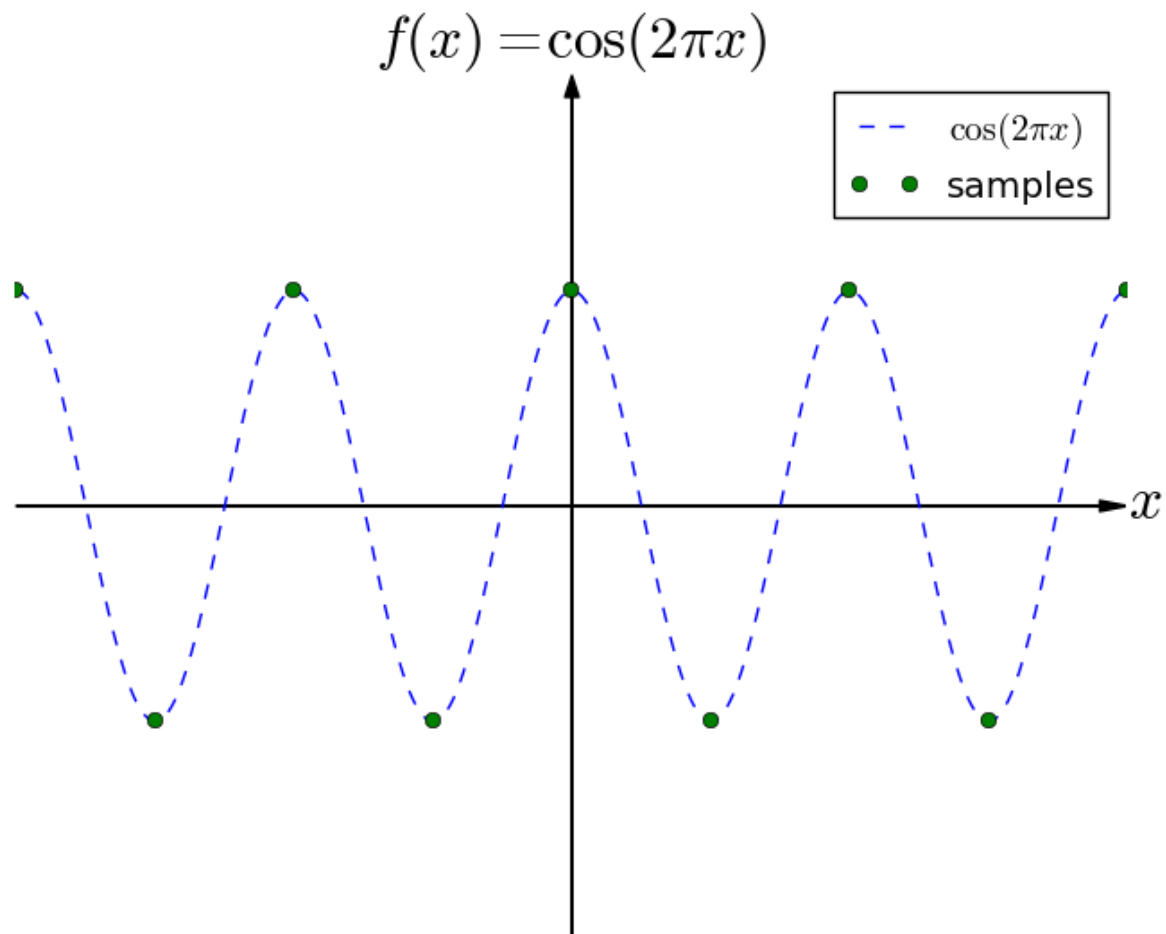
# 2 samples per period



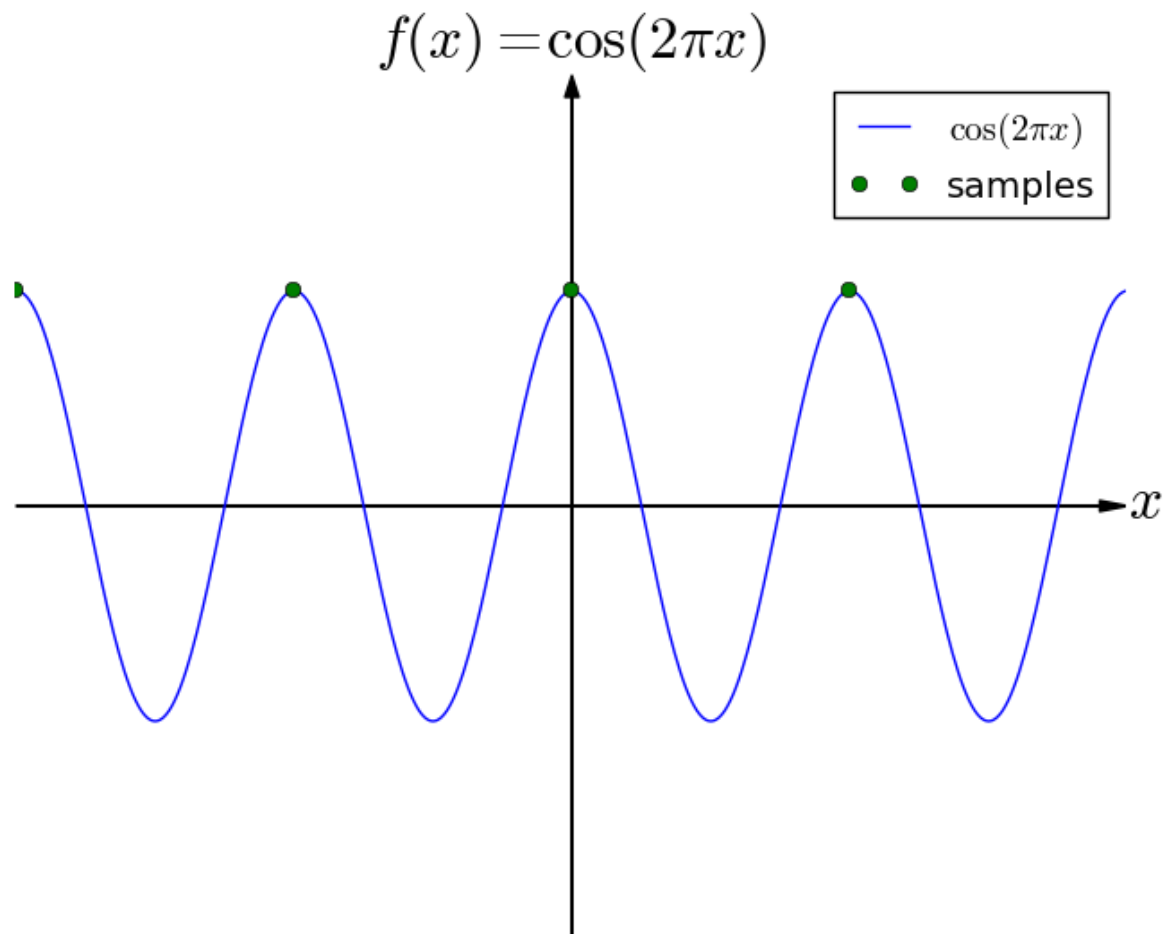
# samples



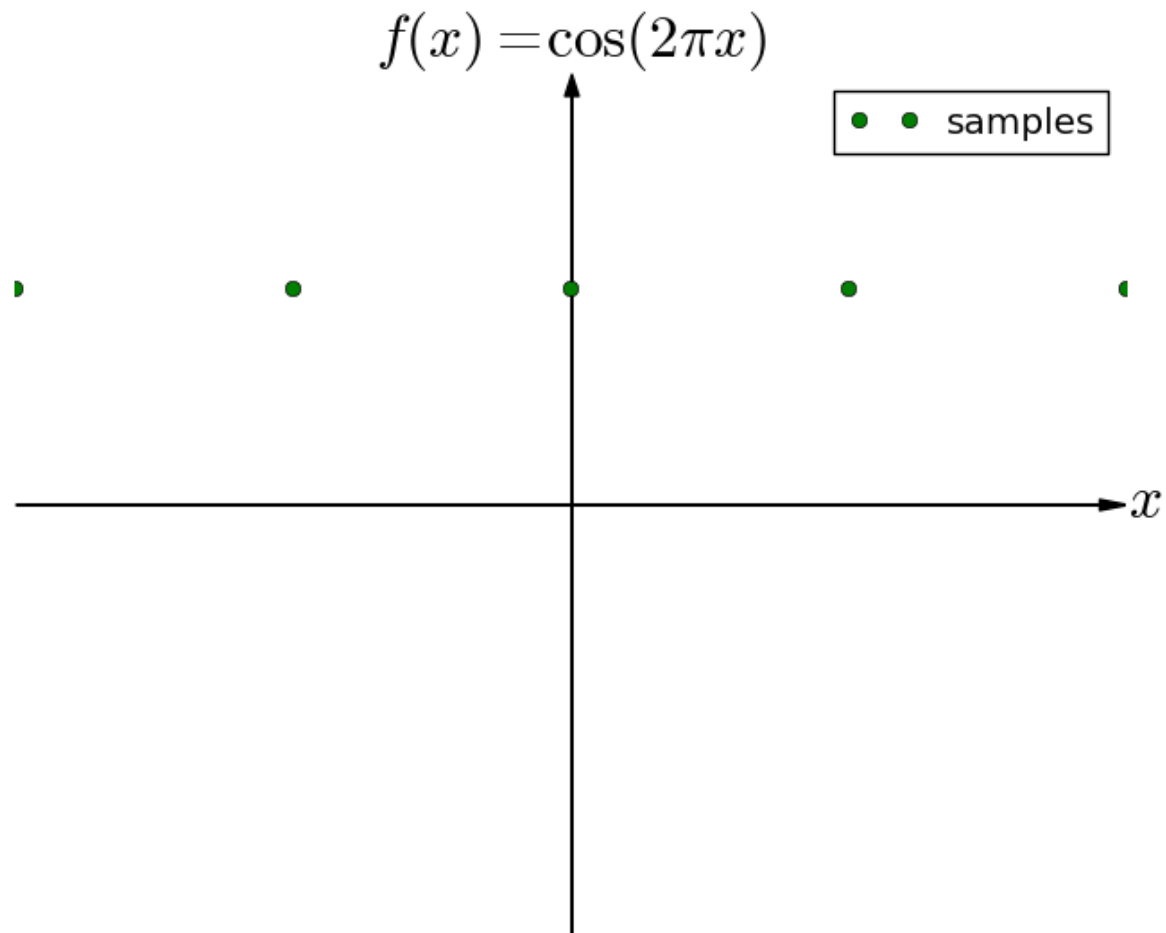
# reconstruction



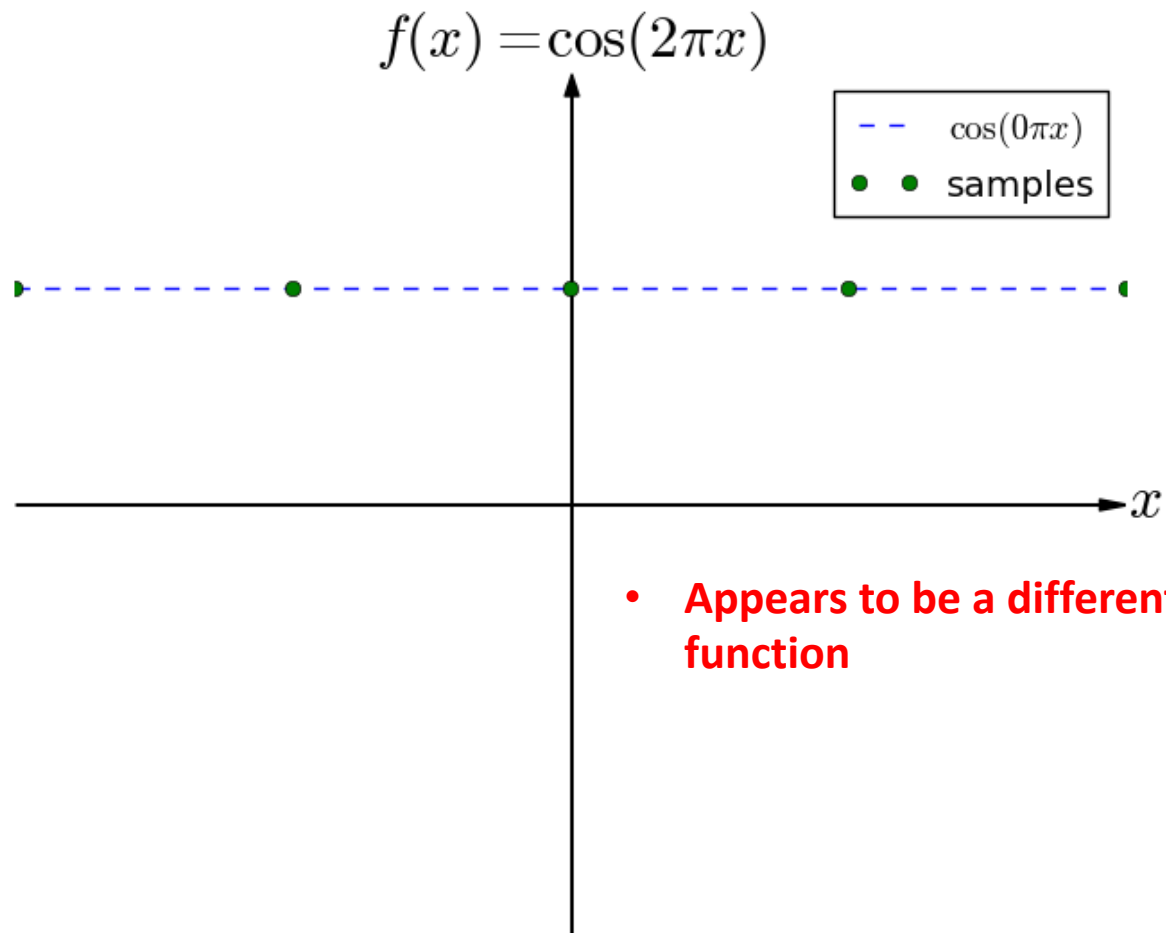
# 1 sample per period



# samples

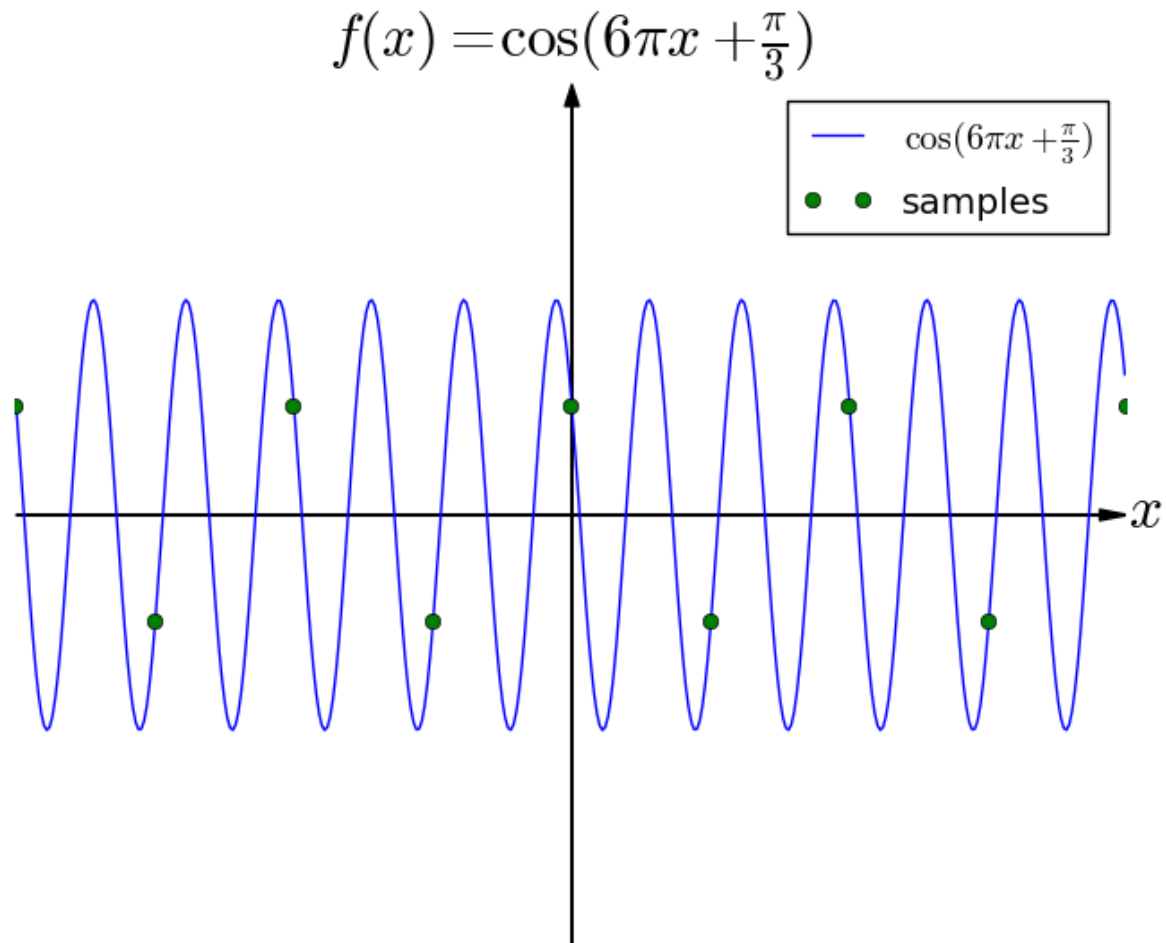


# reconstruction

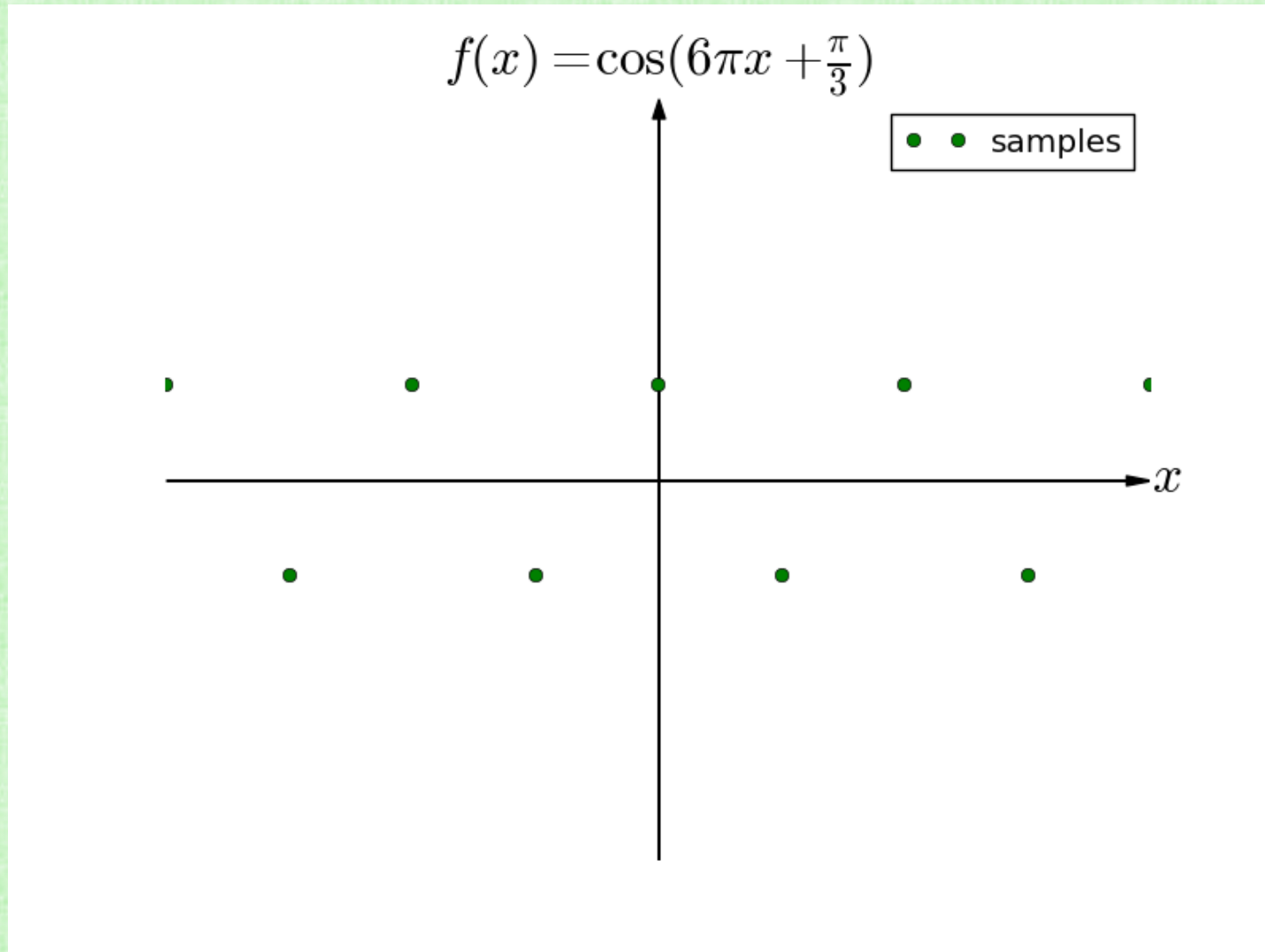




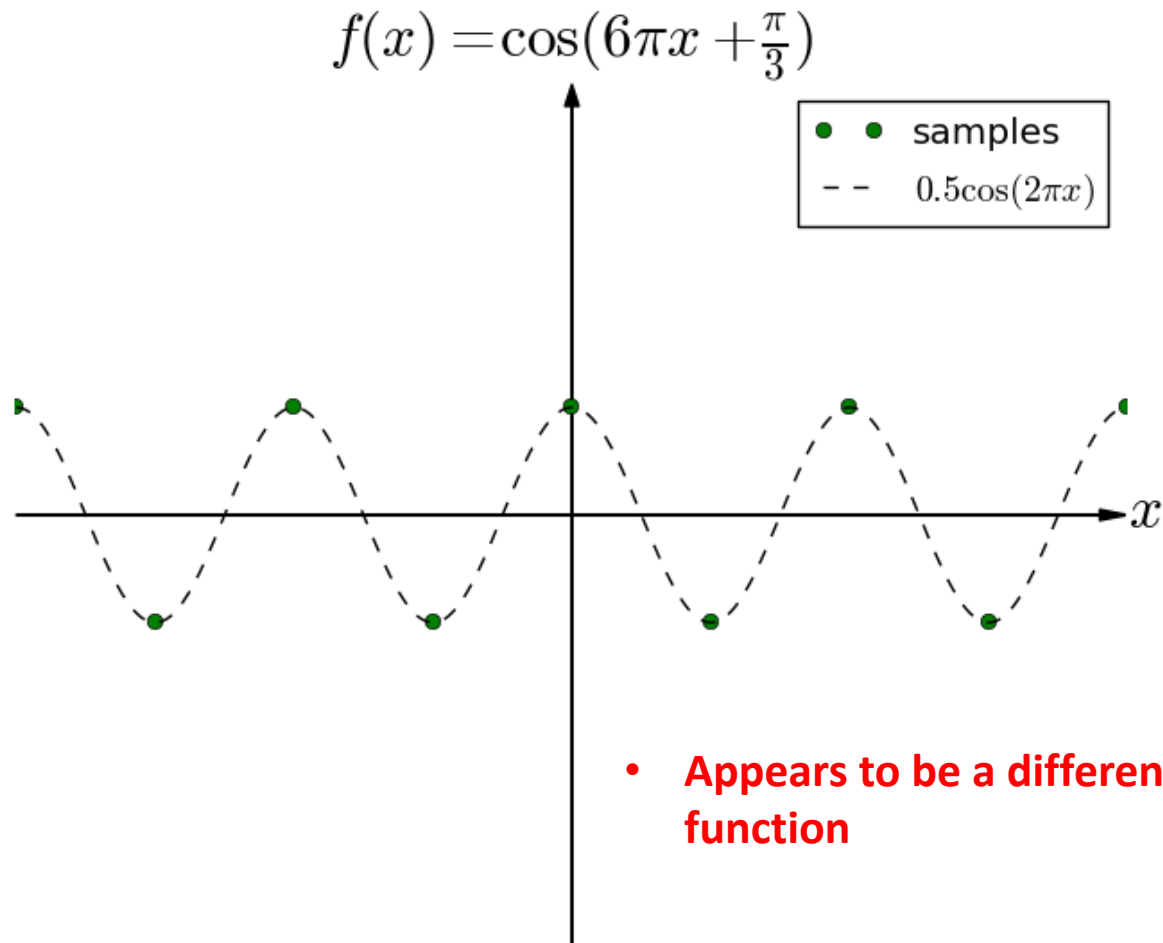
# 2/3 sample per period



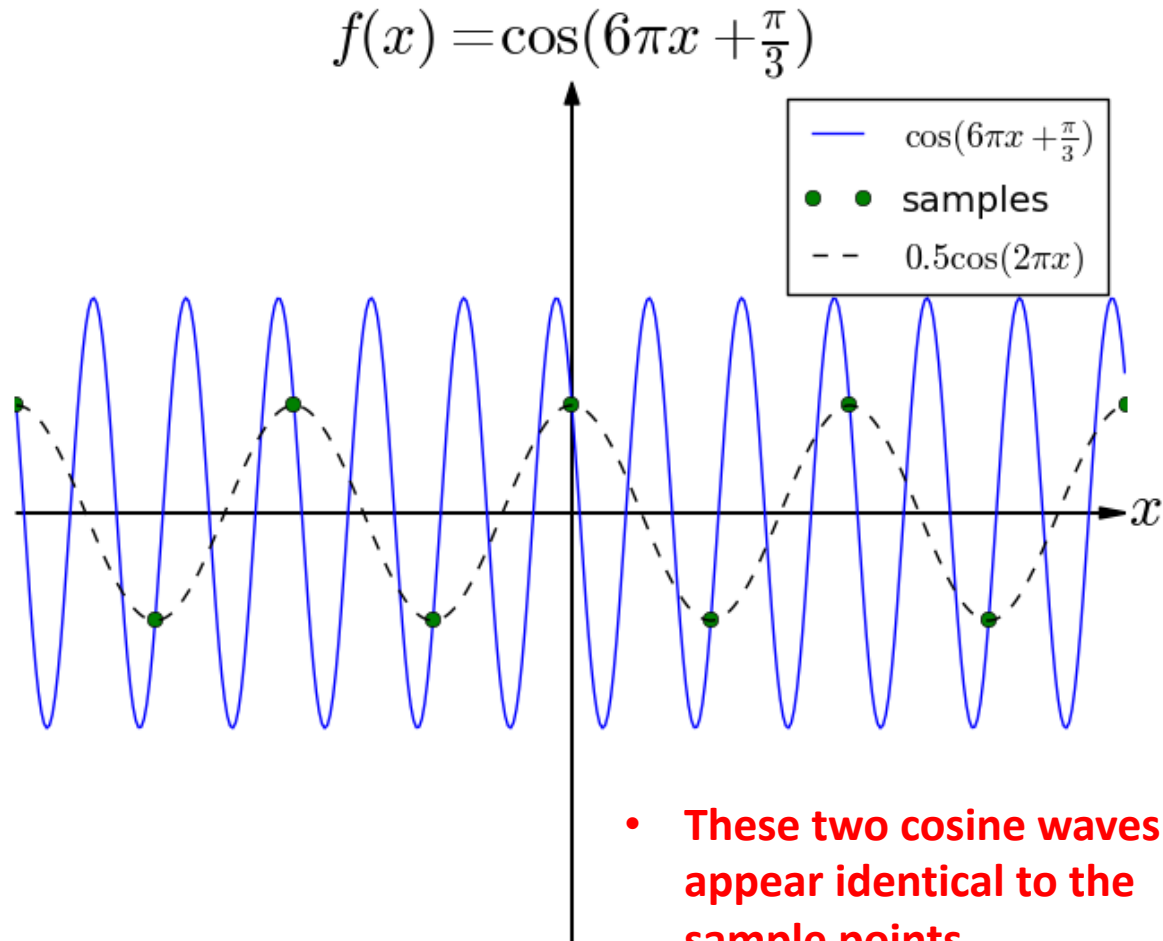
# samples



# reconstruction



# Aliasing



- **These two cosine waves appear identical to the sample points**

# Sampling Rate

- Sampling at too low a rate results in aliasing, where two different signals become indistinguishable (or aliased)
- Nyquist-Shannon Sampling Theorem
  - If  $f(t)$  contains no frequencies higher than  $W$  hertz, it can be completely determined by samples spaced  $1/(2W)$  seconds apart
  - That is, a minimum of 2 samples per period are required to prevent aliasing

# Anti-Aliasing

- The Nyquist frequency is defined as half the sampling frequency
- If the function being sampled has no frequencies above the Nyquist frequency, then no aliasing occurs
- *Real world frequencies above the Nyquist frequency appear as aliases to the sampler*
- **Before sampling, remove frequencies higher than the Nyquist frequency**

# Fourier Transform

- Transform between the spatial domain  $f(x)$  and the frequency domain  $F(k)$

$$\text{Frequency Domain: } F(k) = \int_{-\infty}^{\infty} f(x) e^{-2\pi i k x} dx$$

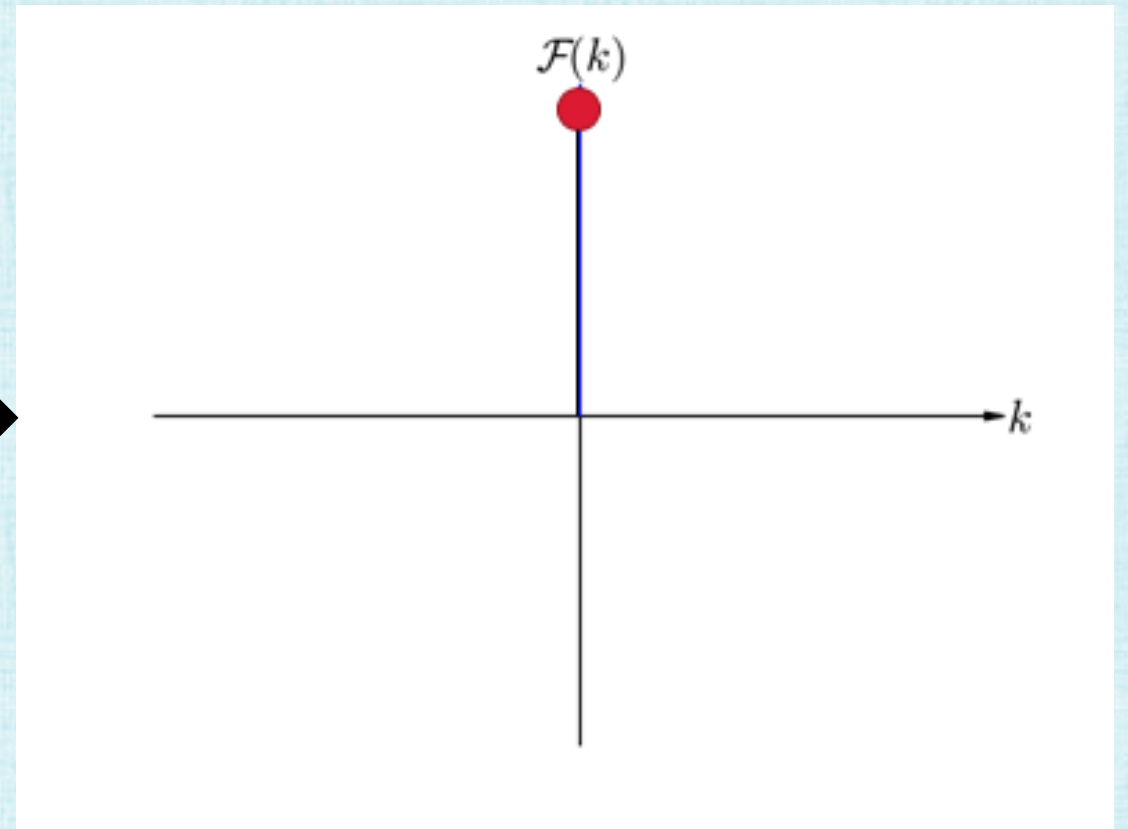
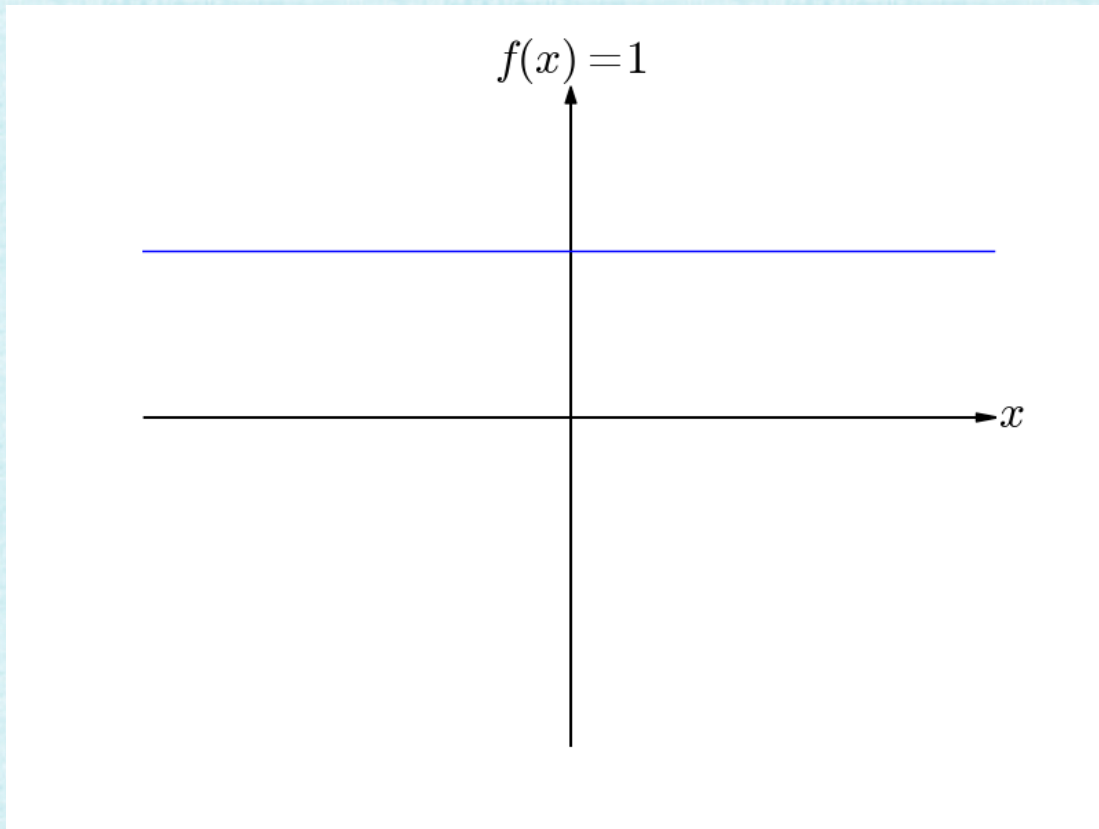
$$\text{Spatial Domain: } f(x) = \int_{-\infty}^{\infty} F(k) e^{2\pi i k x} dk$$

$$e^{i\theta} = \cos \theta + i \sin \theta$$

$$\cos \theta = \frac{e^{i\theta} + e^{-i\theta}}{2}$$

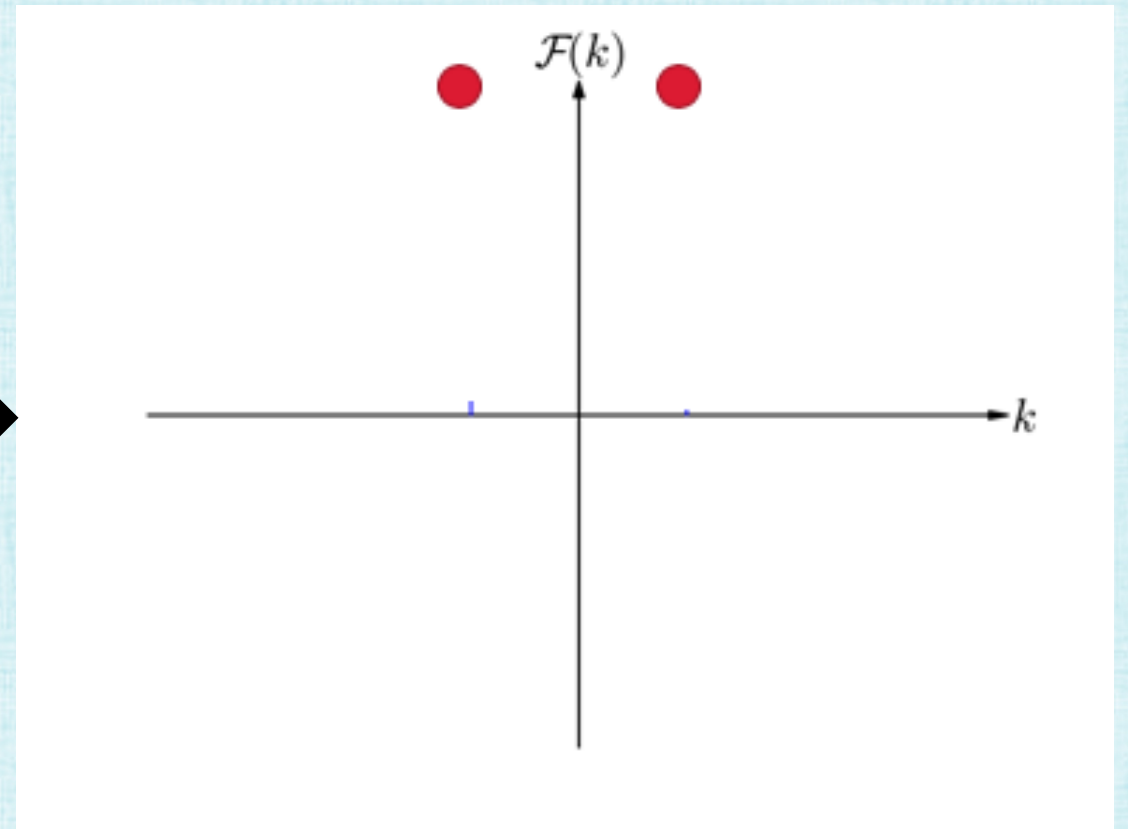
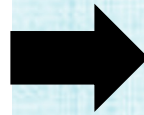
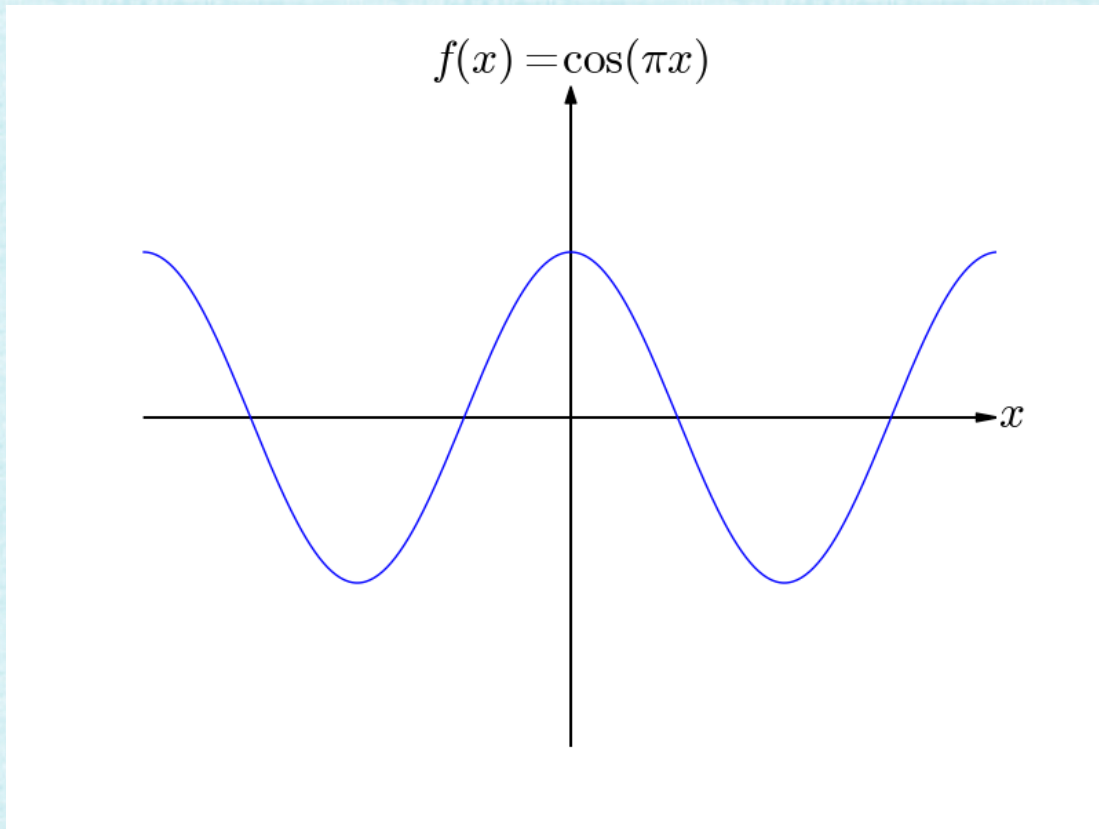
$$\sin \theta = \frac{e^{i\theta} - e^{-i\theta}}{2i}$$

# Constant Function

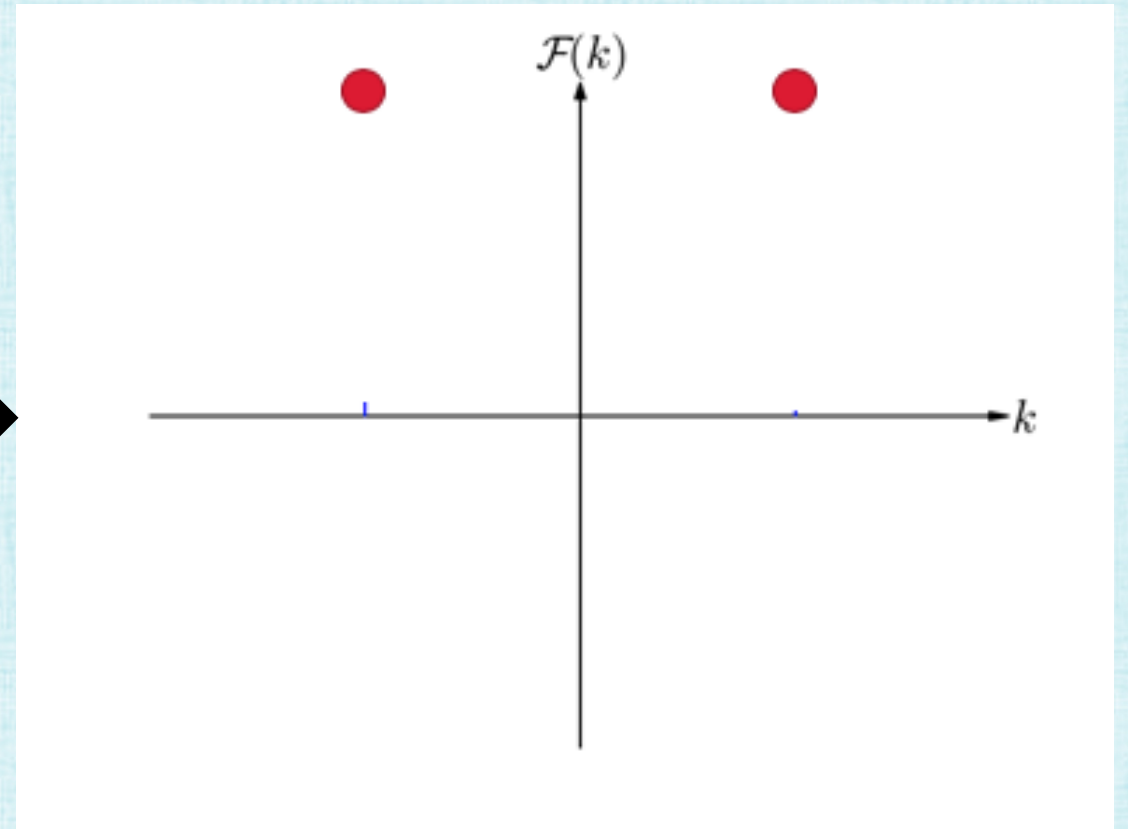
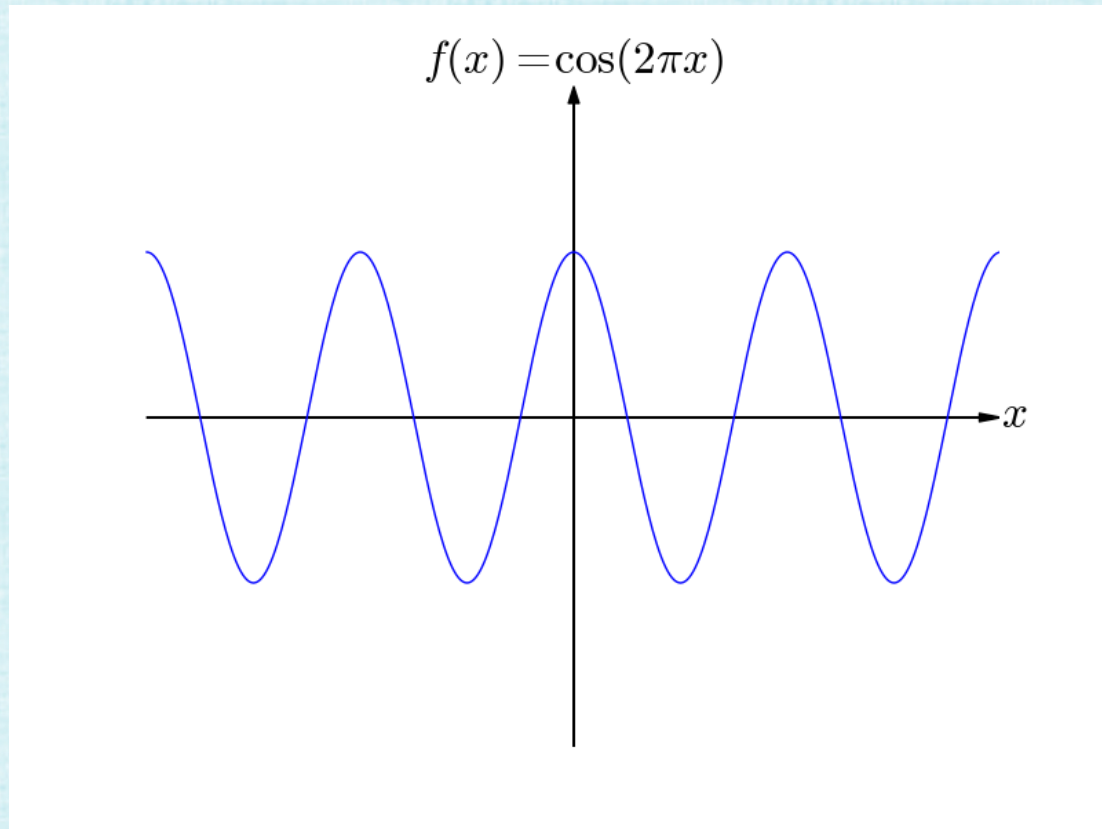




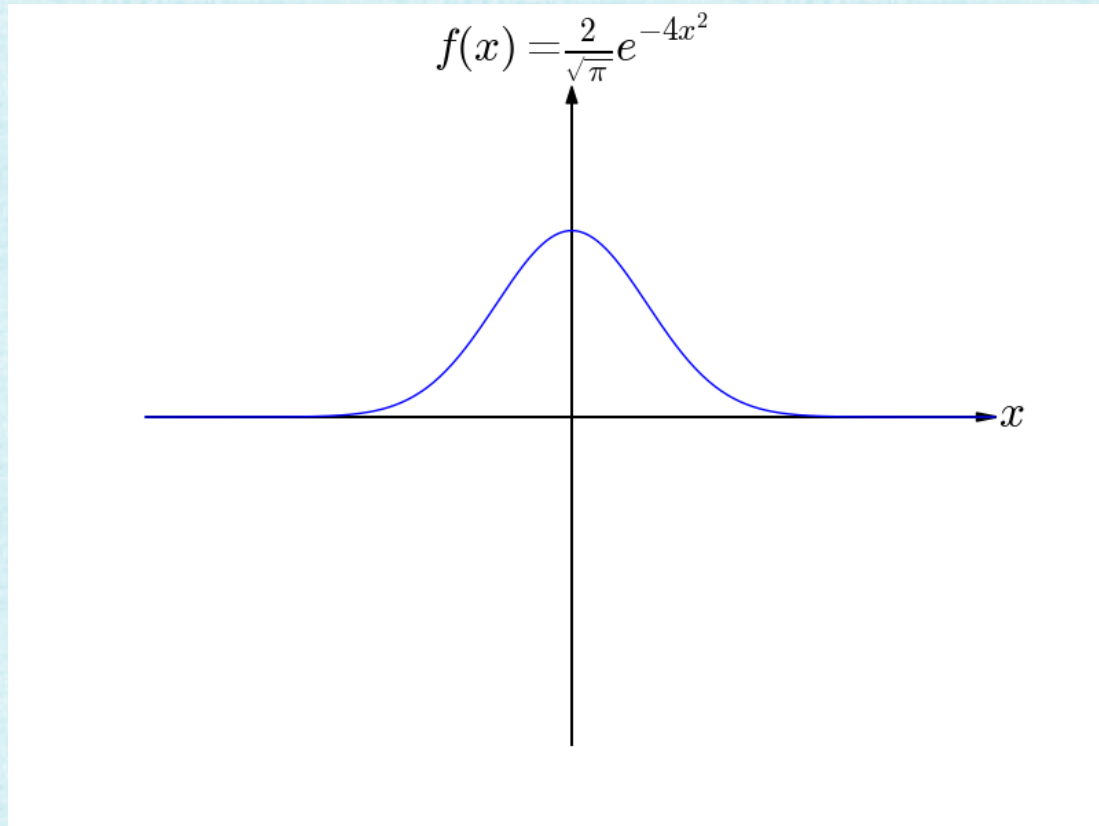
# Low Frequency Cosine



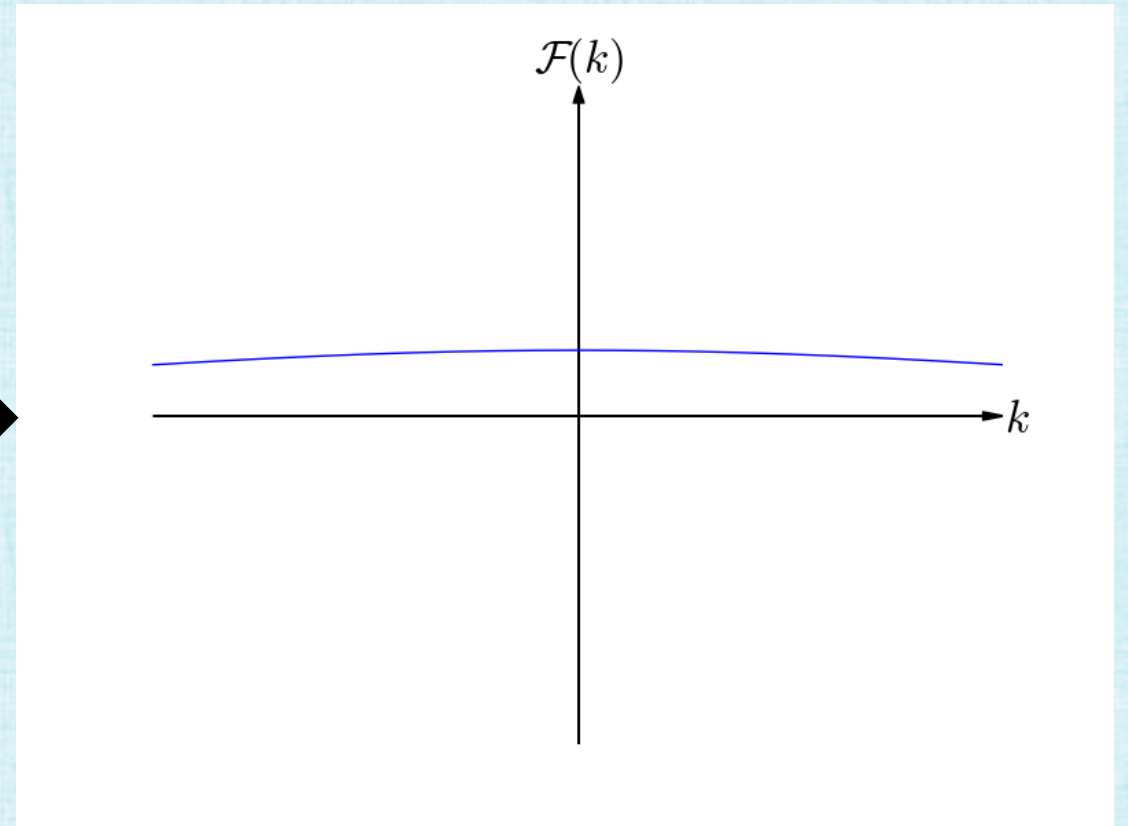
# High Frequency Cosine



# Narrow Gaussian

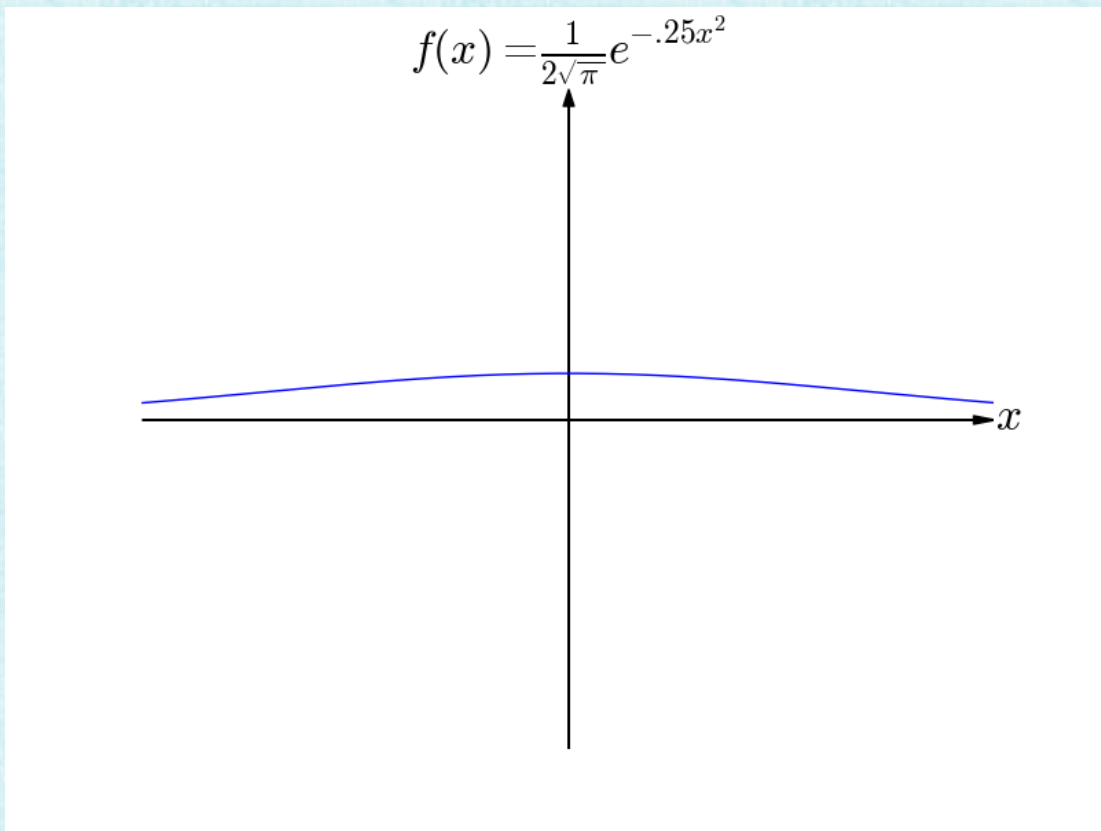


Narrow

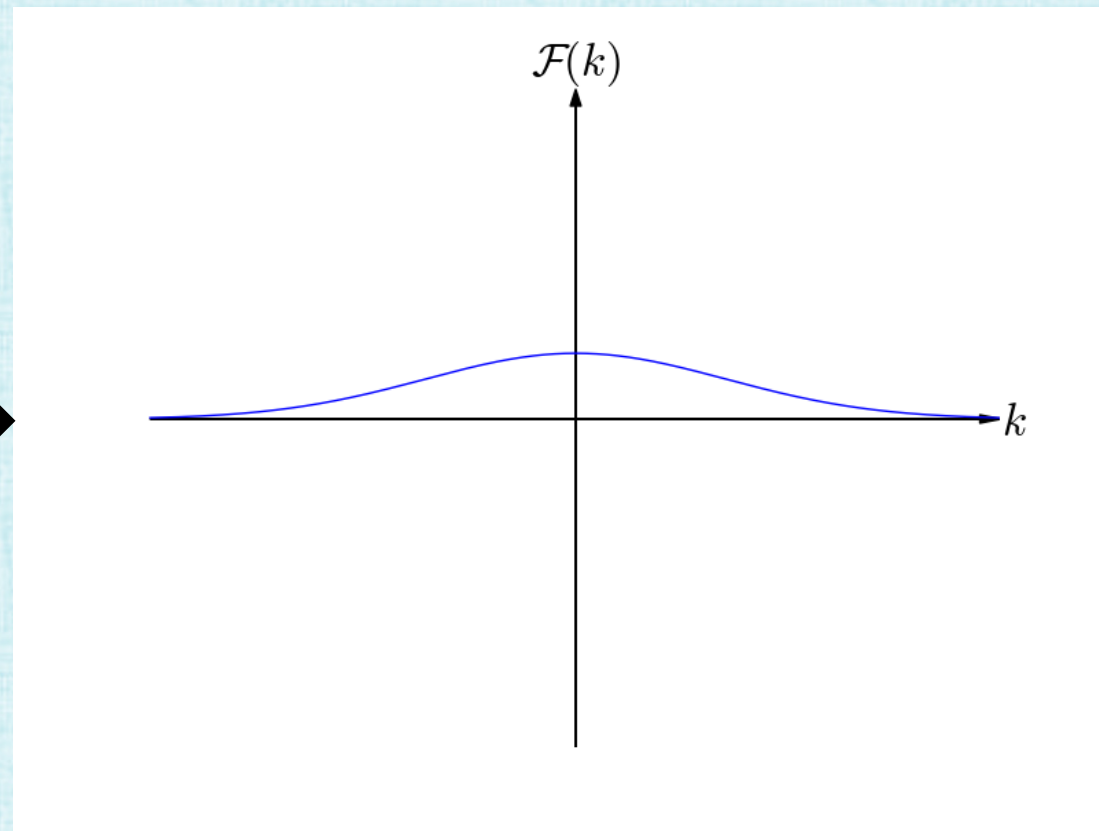


Wide

# Wider Gaussian

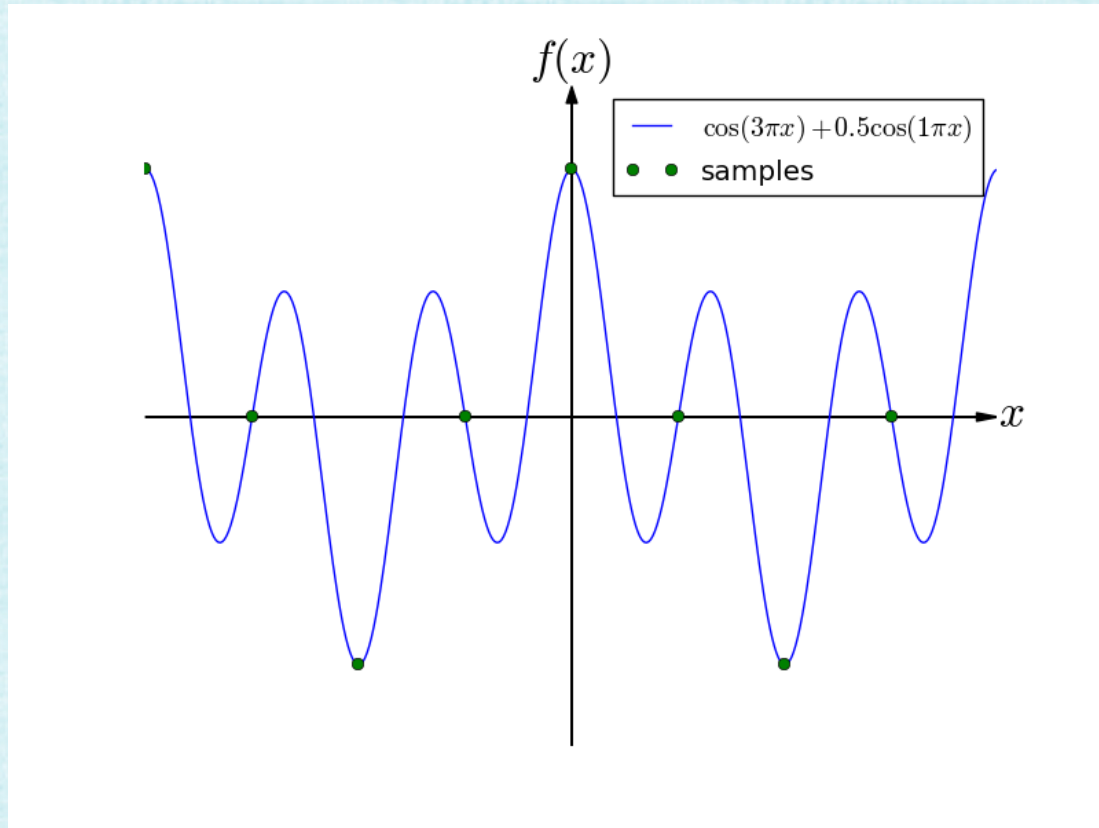


Wider

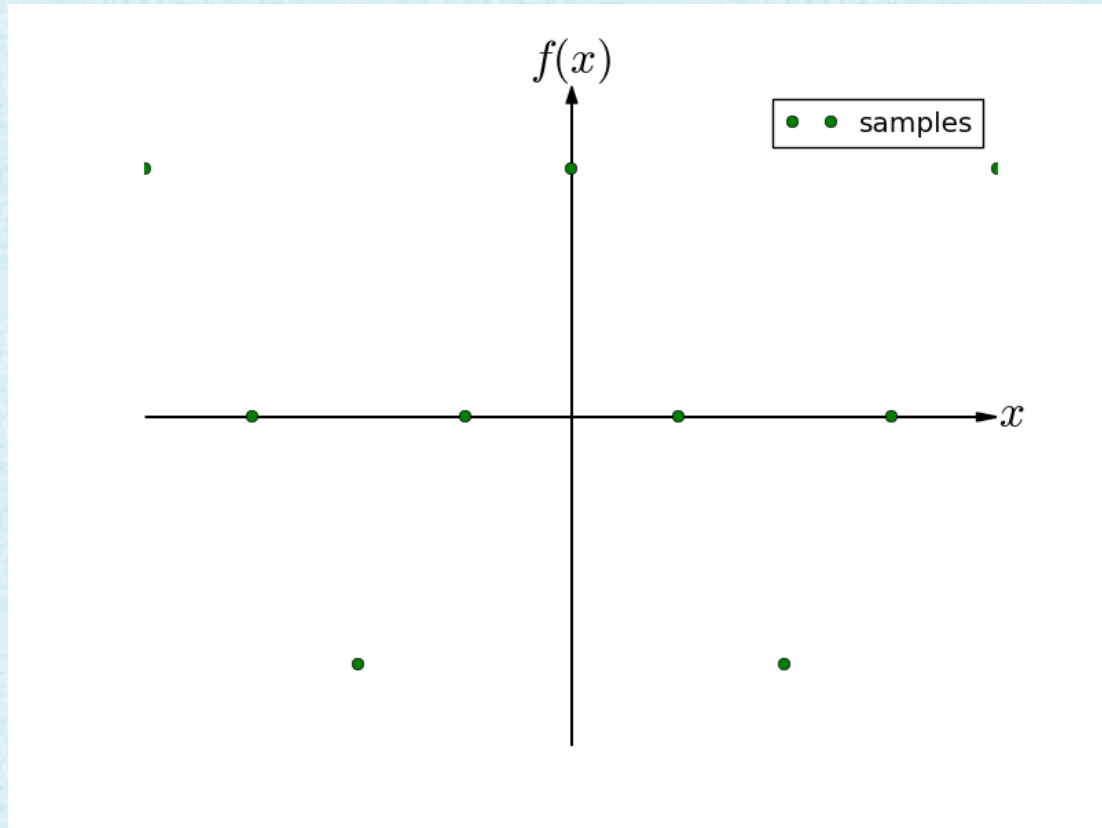


Narrower

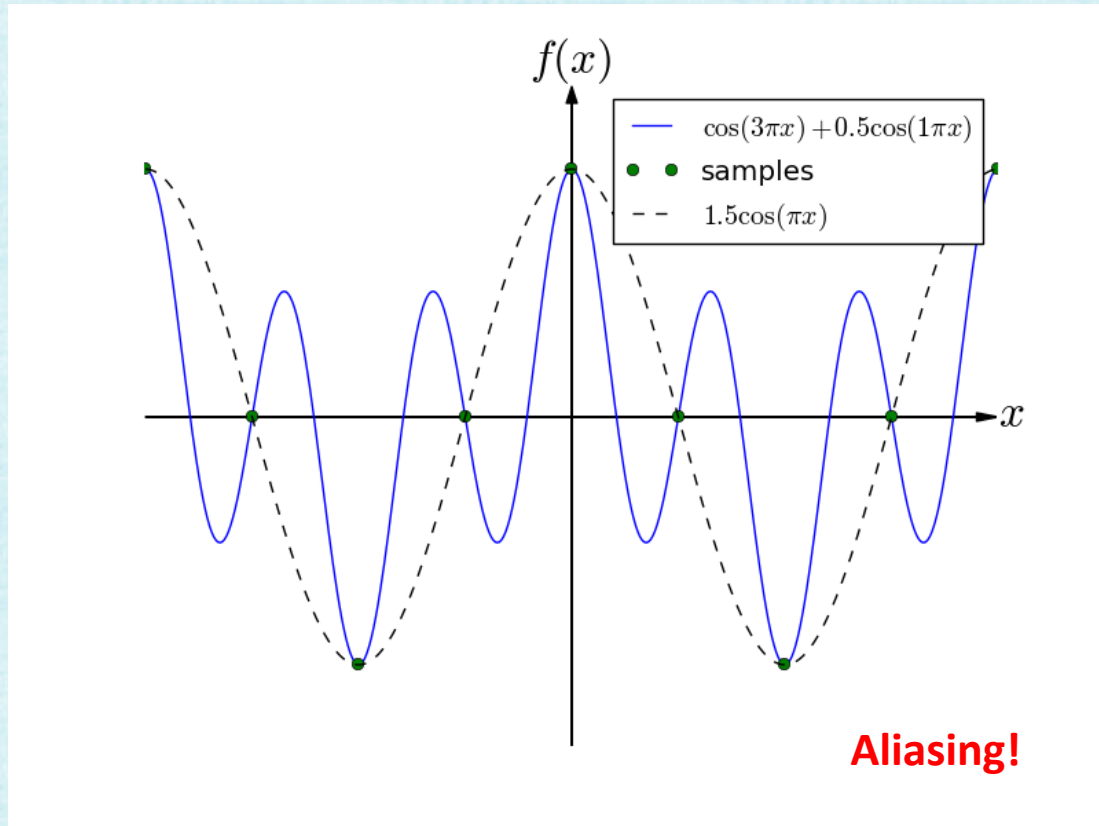
# sum of two different cosine functions



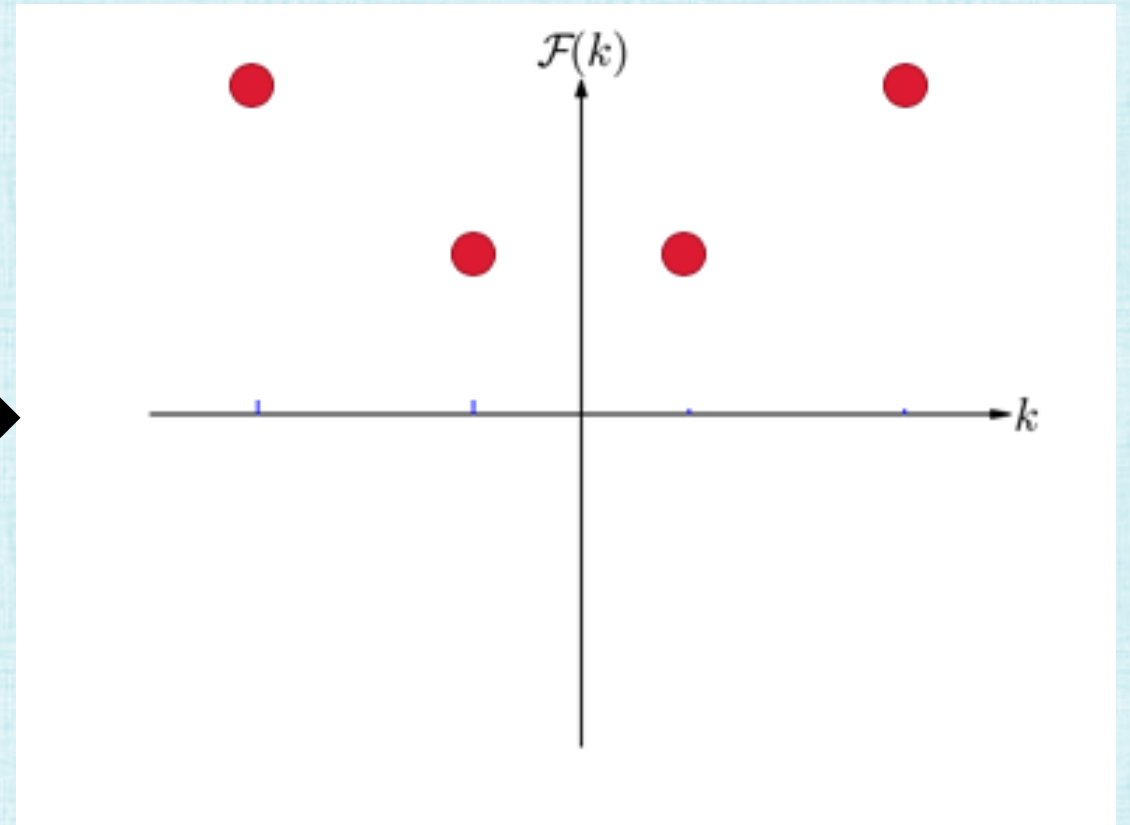
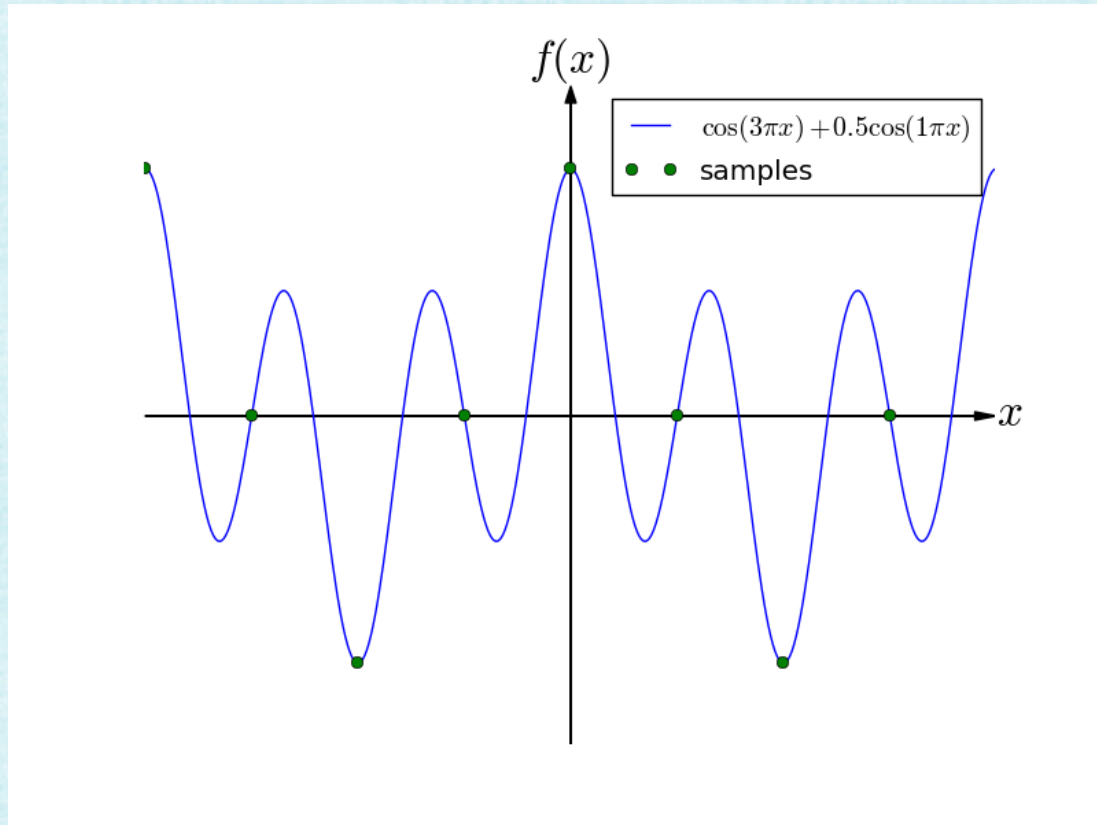
# samples



# reconstruction

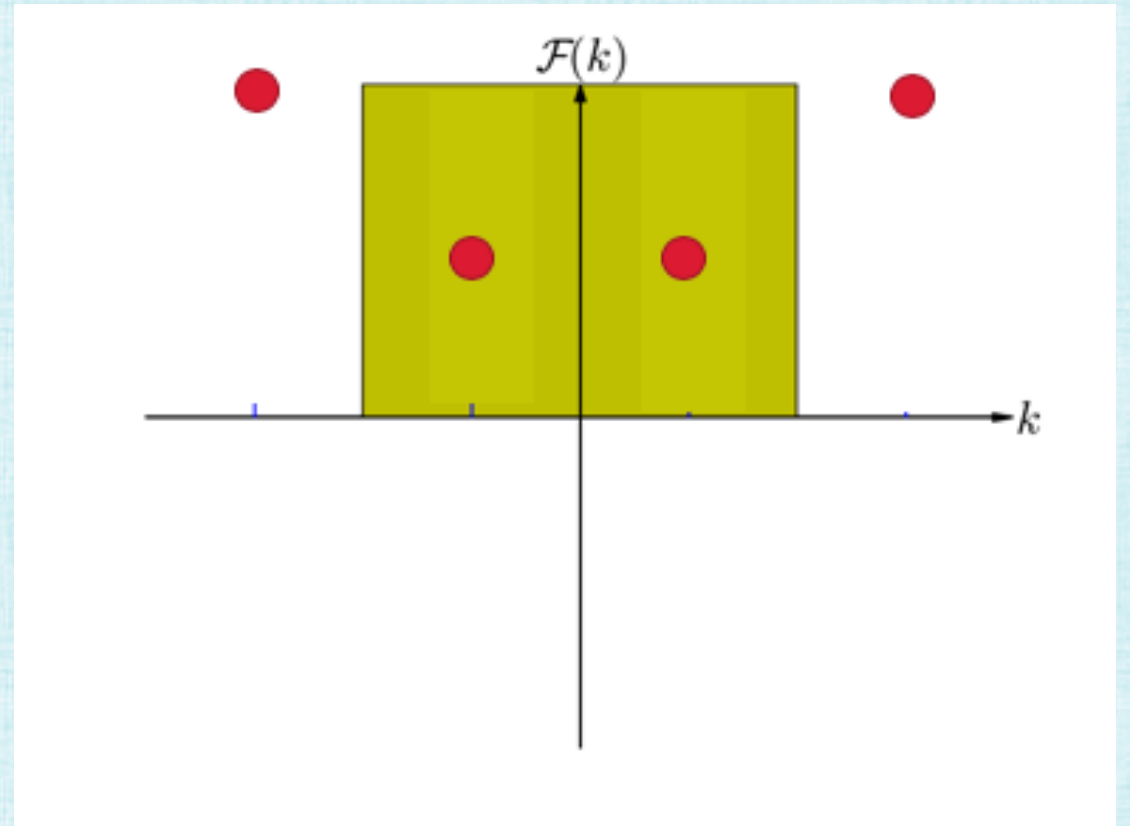


# Fourier transform

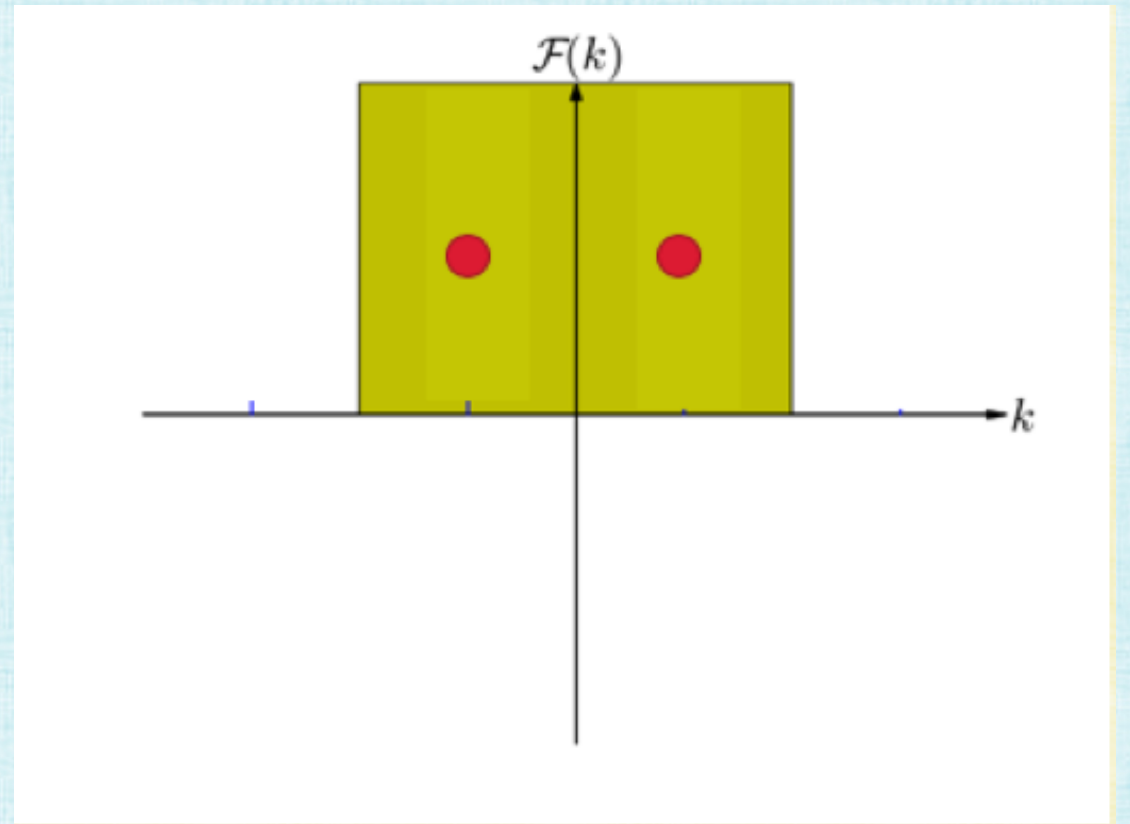




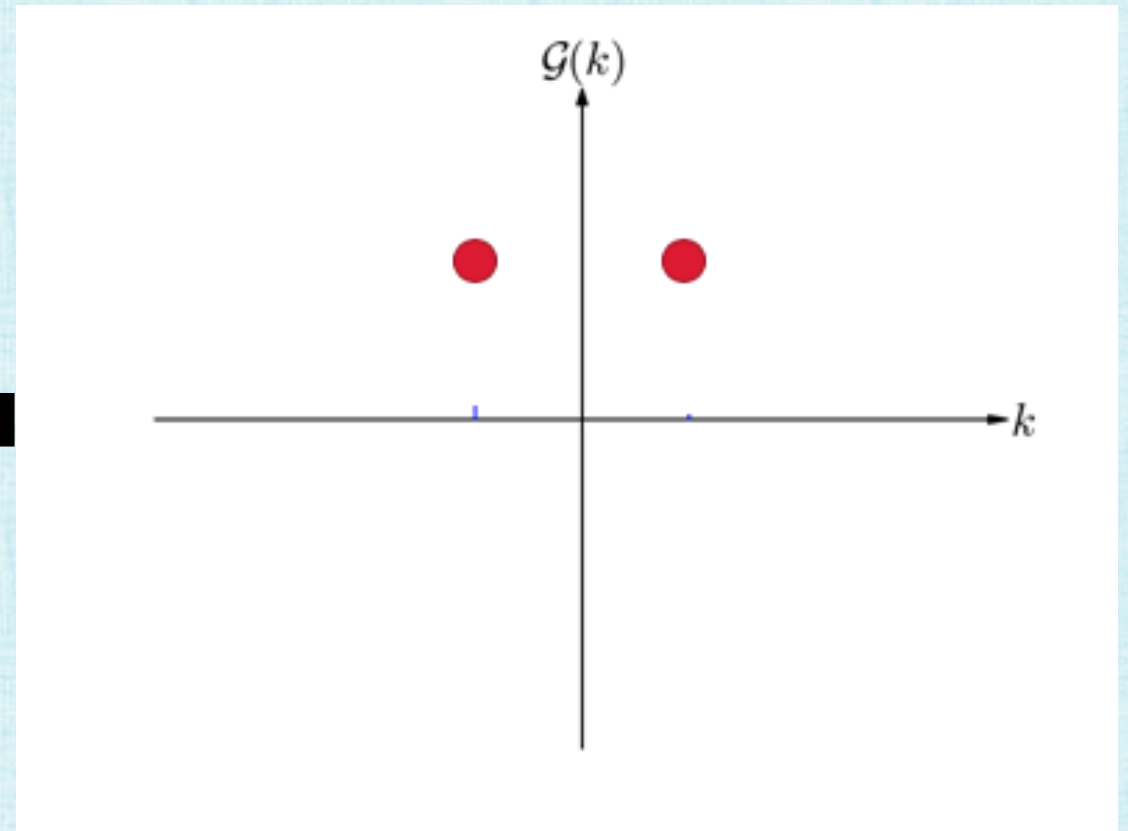
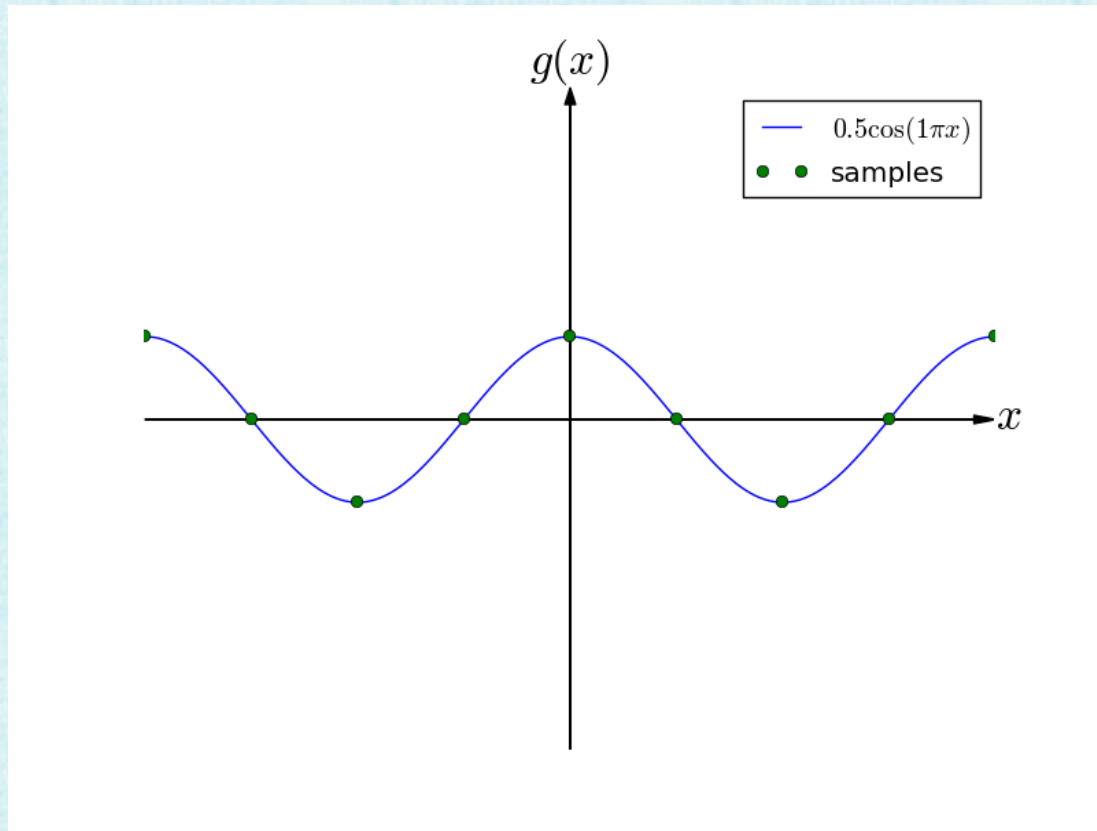
identify Nyquist frequency bounds



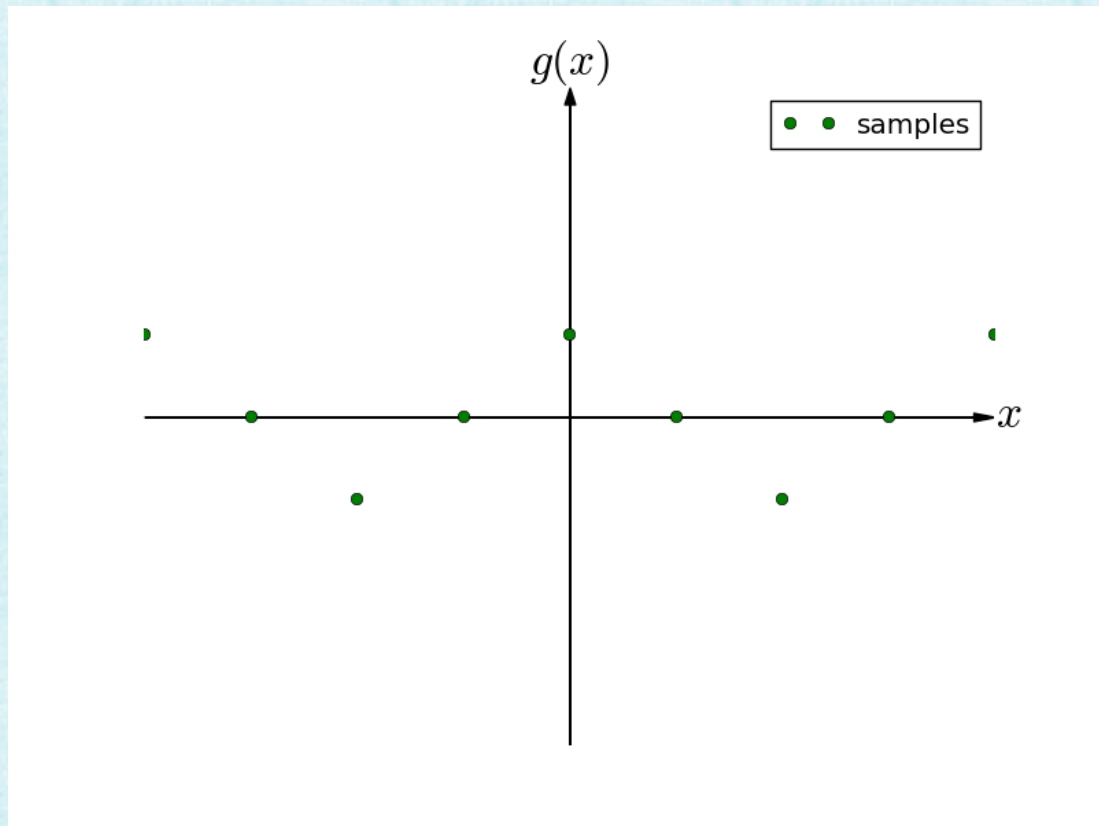
remove the high frequencies



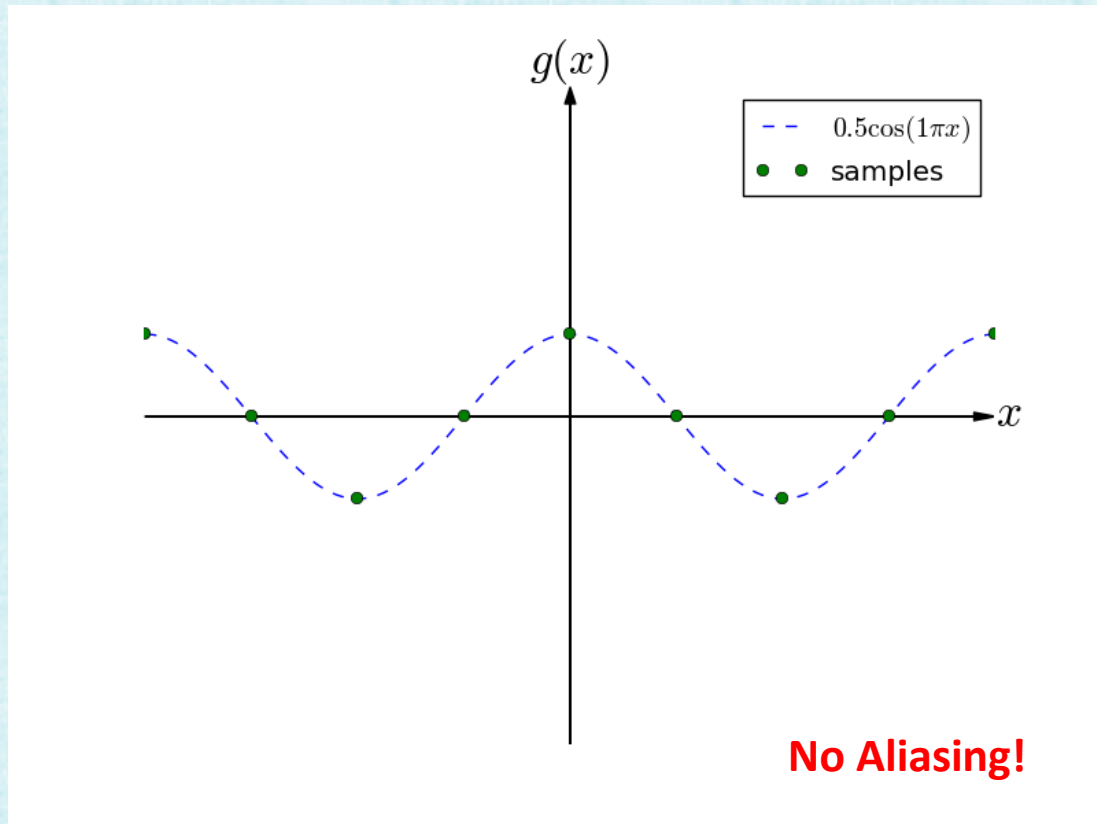
# inverse Fourier transform



# samples



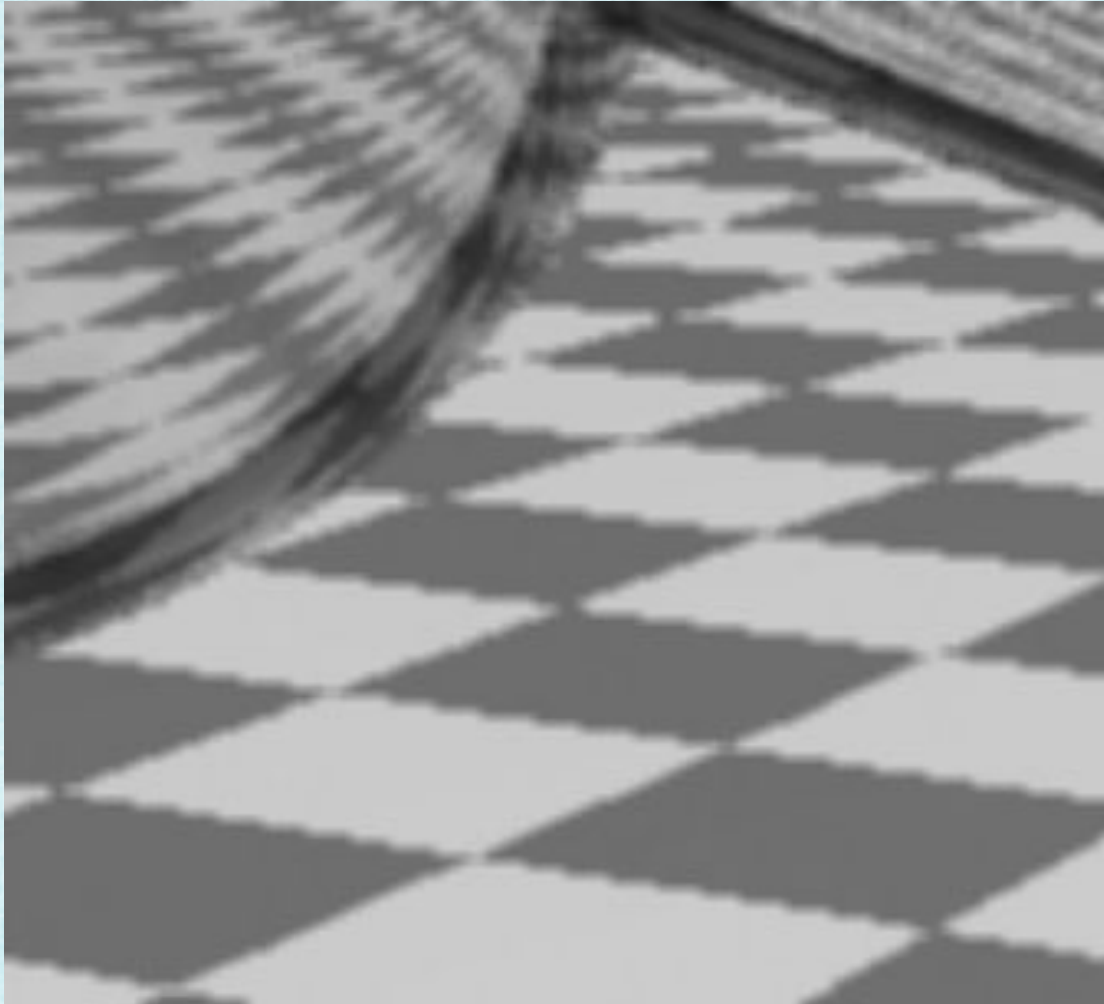
# reconstruction



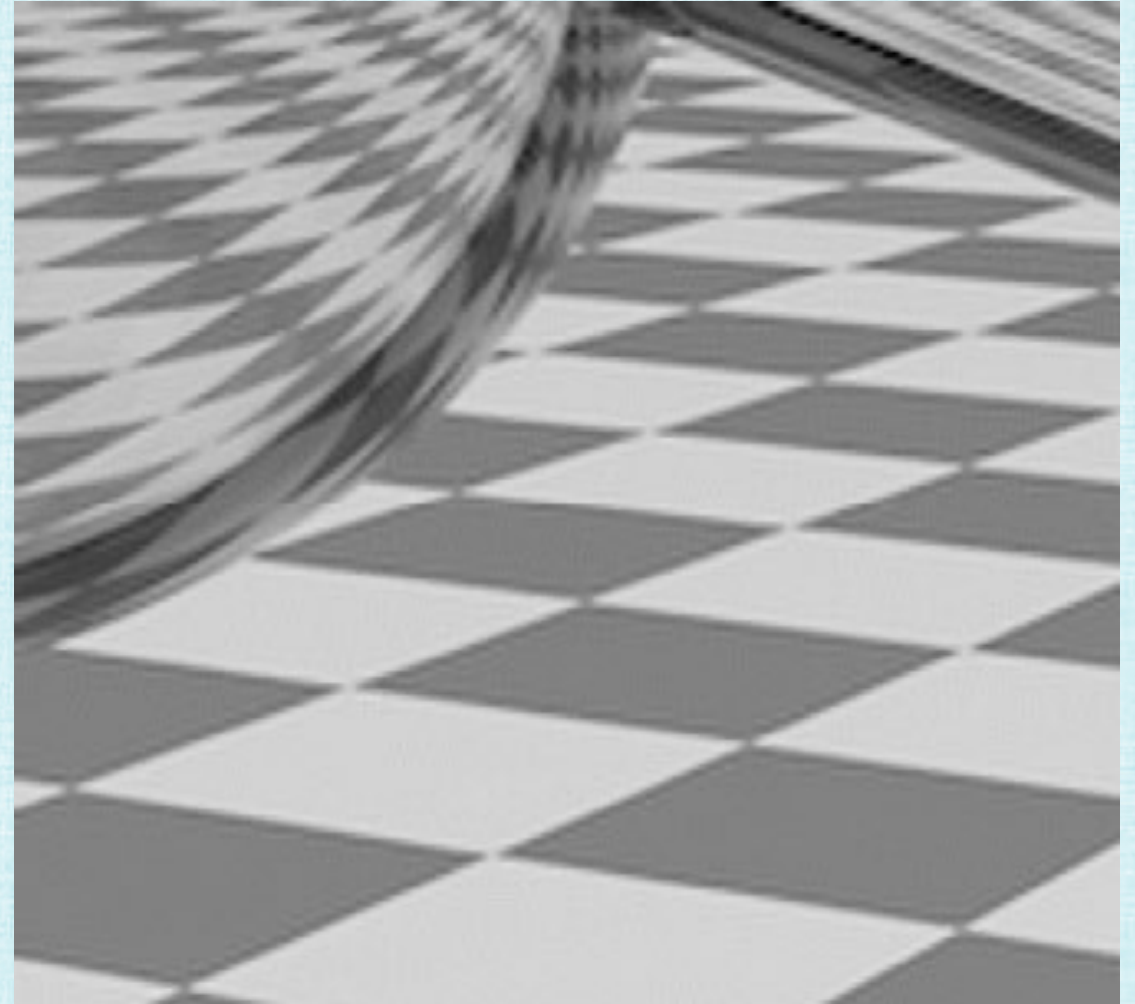
# Anti-Aliasing

- Sampling causes higher frequencies to masquerade as lower frequencies
- After sampling, can no longer untangle the mixed high/low frequencies
- Remove the high frequencies **before** sampling (in order to avoid aliasing)
- **Part of the signal is lost**
- **But, that part of the signal was not representable by the sampling rate anyways**

# Blurring vs. Anti-Aliasing



blurring jaggies after sampling



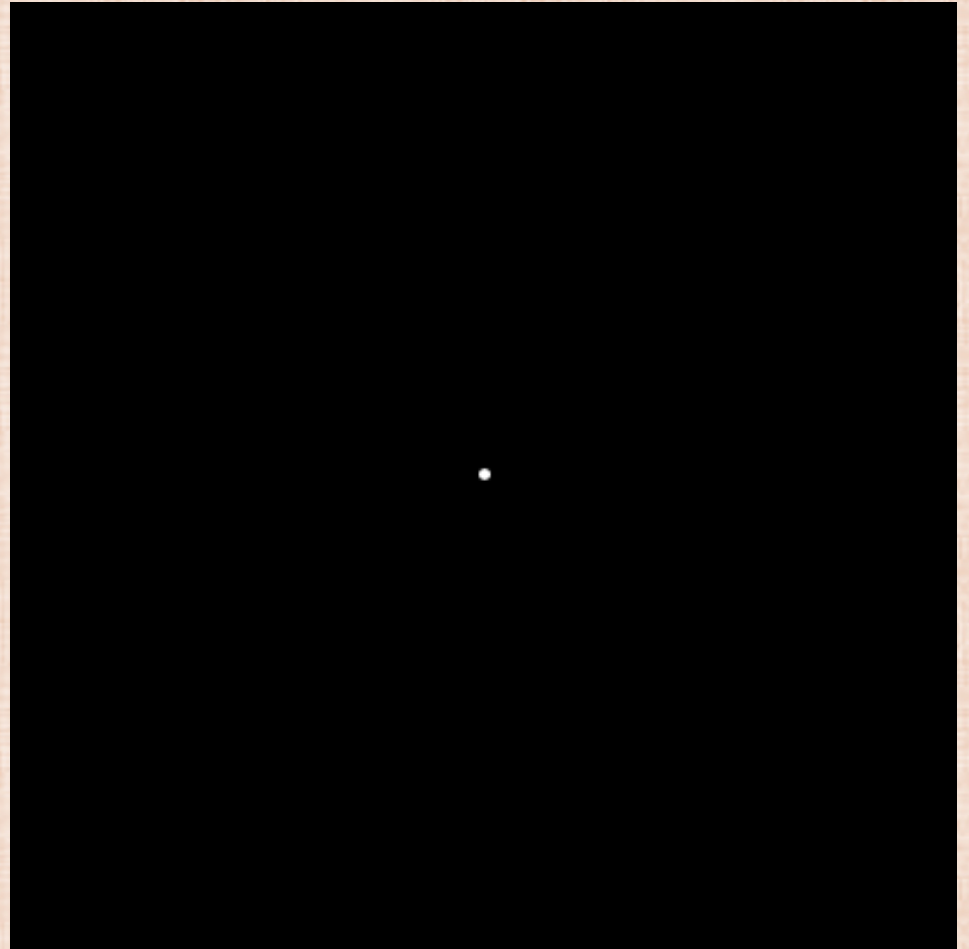
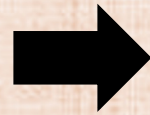
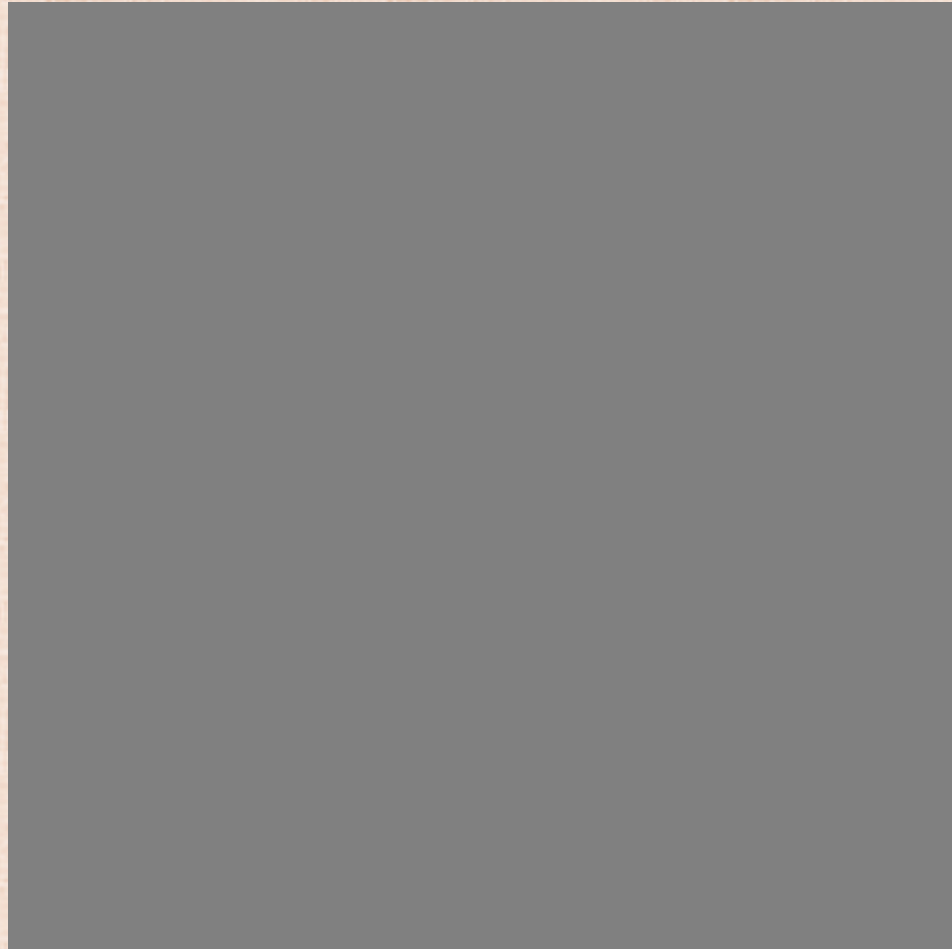
removing high frequencies before sampling

# Images

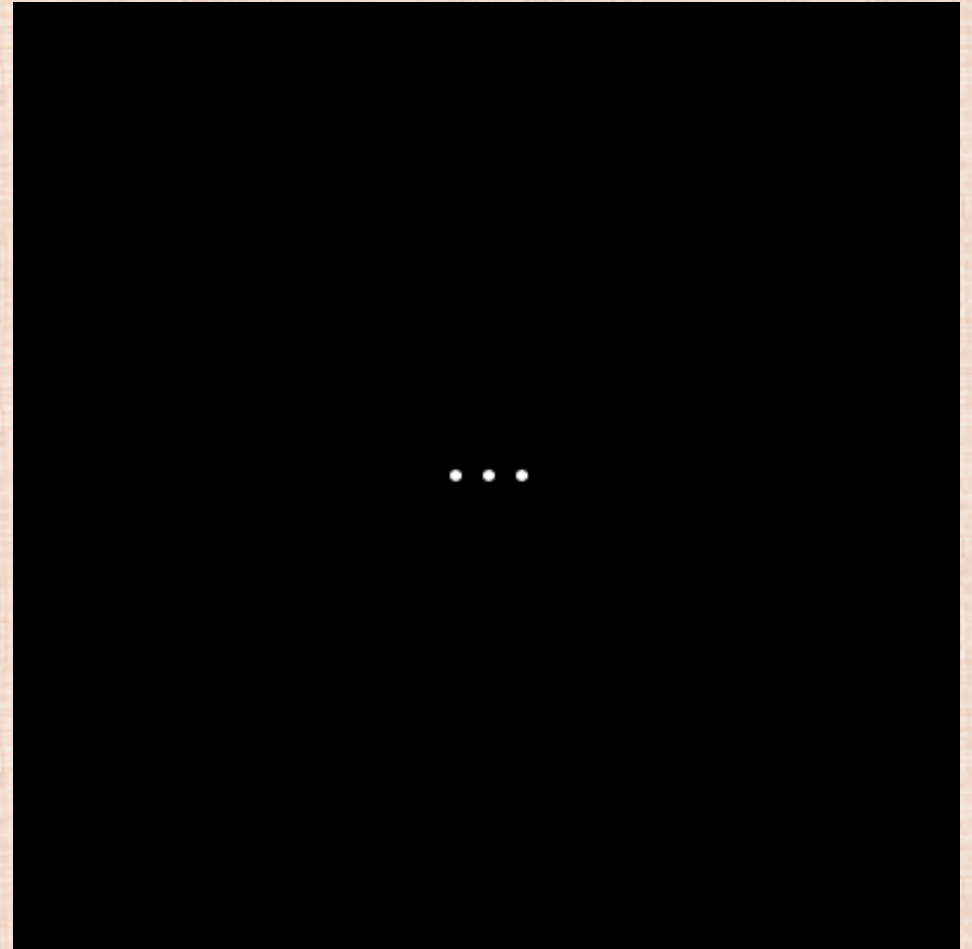
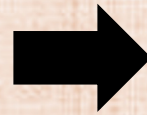
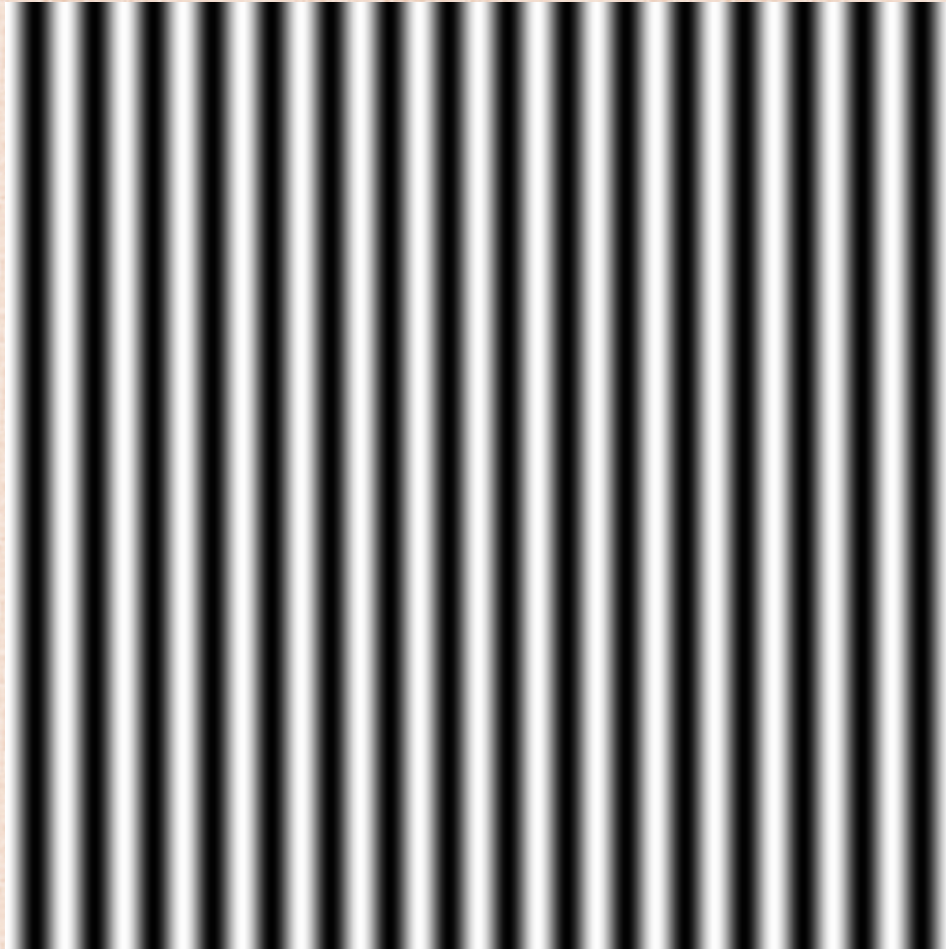
- Images have discrete values (and are not continuous functions)
    - Use a discrete version of the Fourier transform
    - The Fast Fourier Transform (FFT) computes the discrete Fourier transform (and its inverse) in  $O(n \log n)$  complexity (where  $n$  is the number of samples)
  - Images are 2D (not 1D)
    - A 2D discrete Fourier transform can be computed using 1D transforms along each dimension
1. Fourier transform (into the frequency domain)
    - Discrete image values are transformed into another array of discrete values
  2. Remove high frequencies
  3. Inverse Fourier transform (back out of the frequency domain)



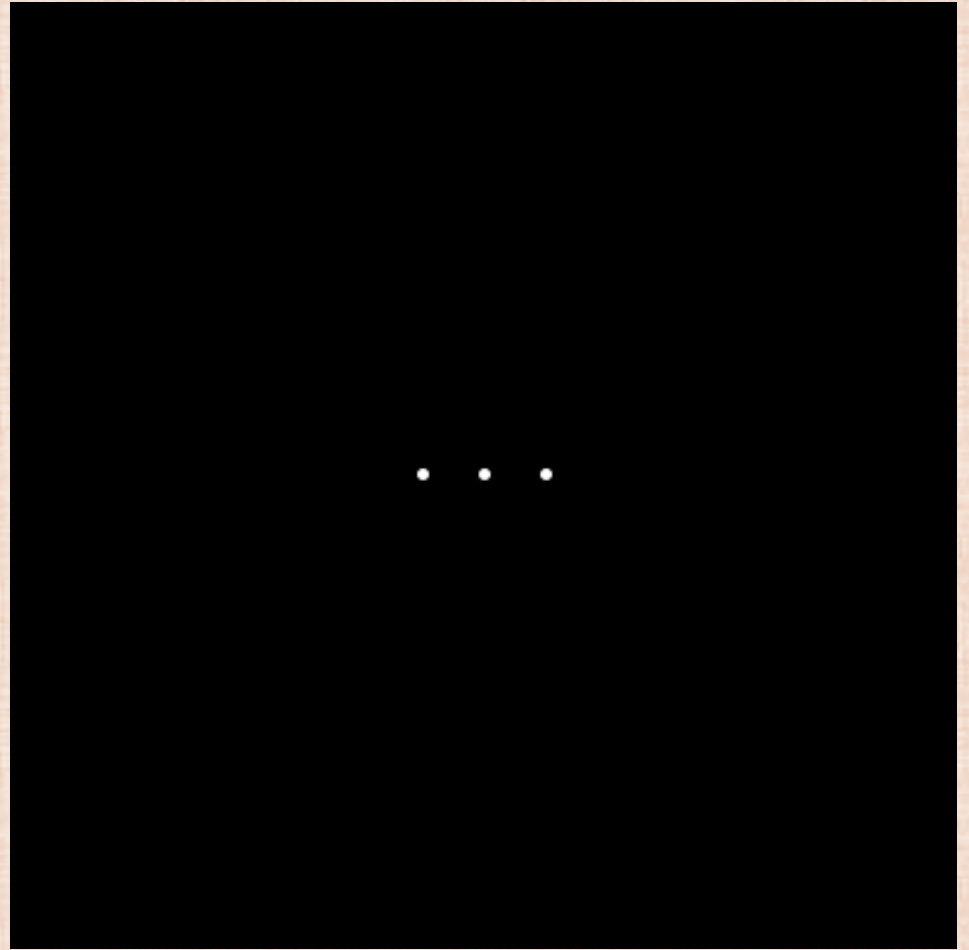
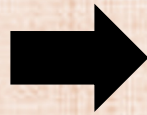
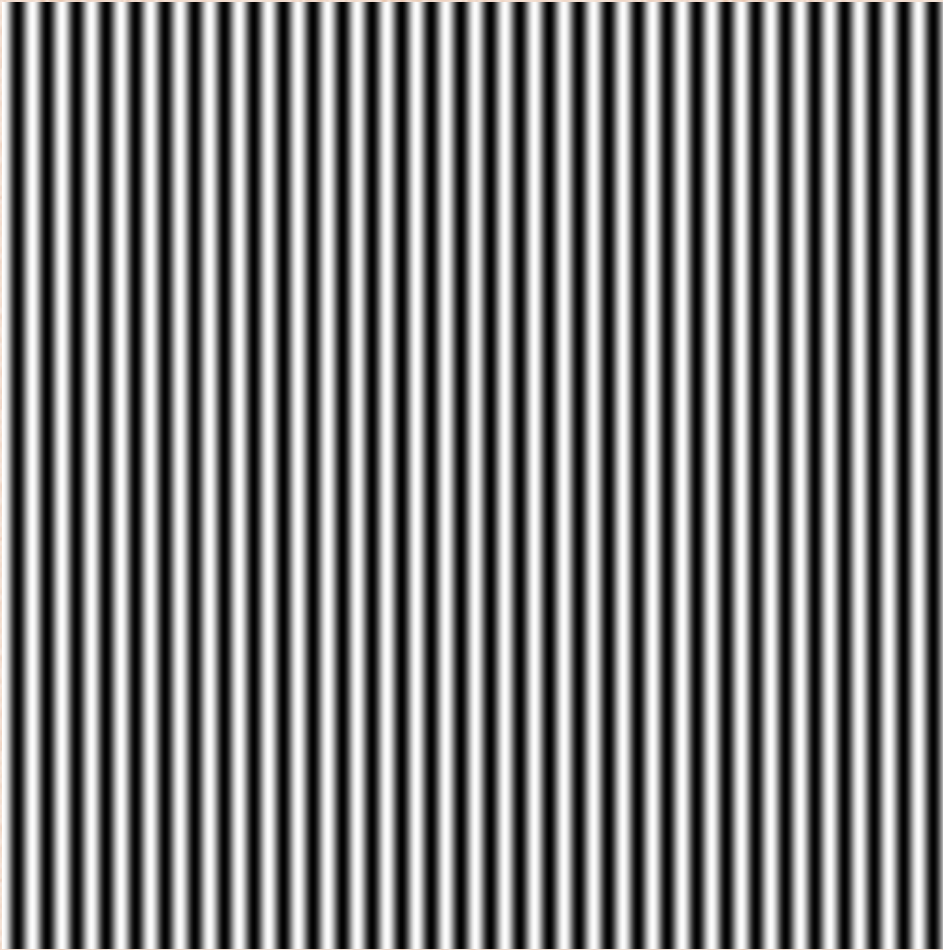
# Constant Function



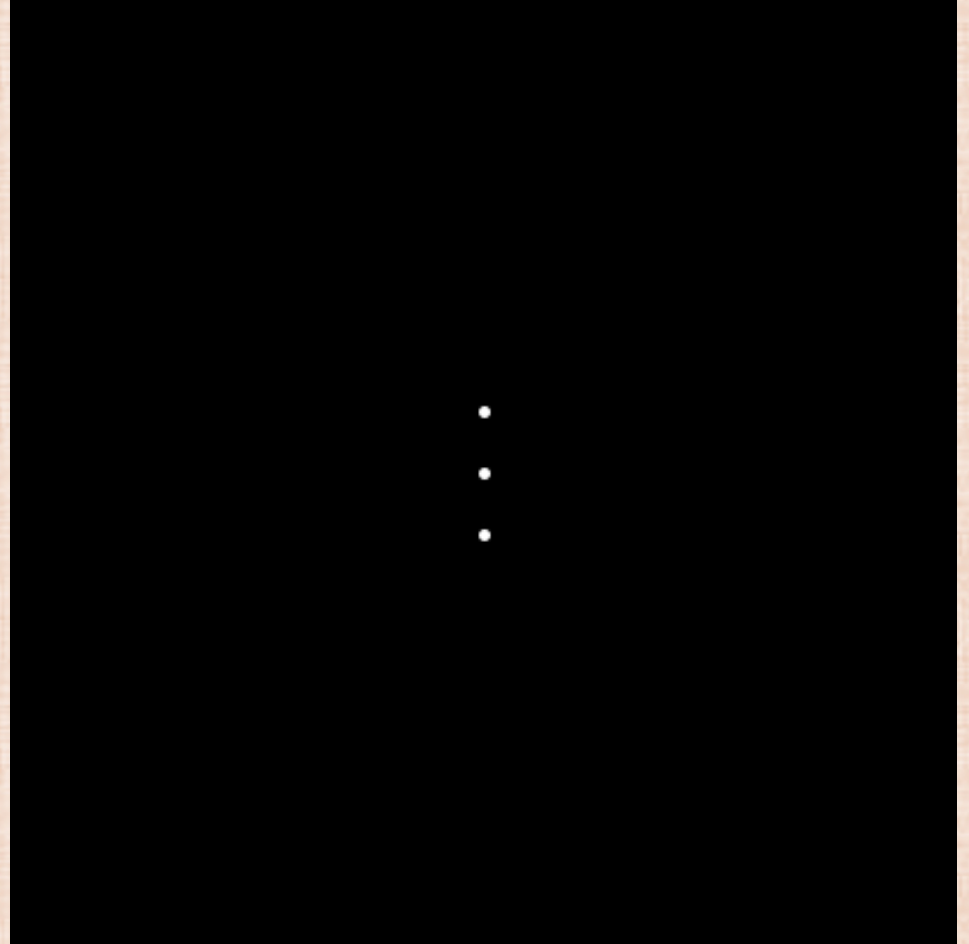
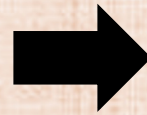
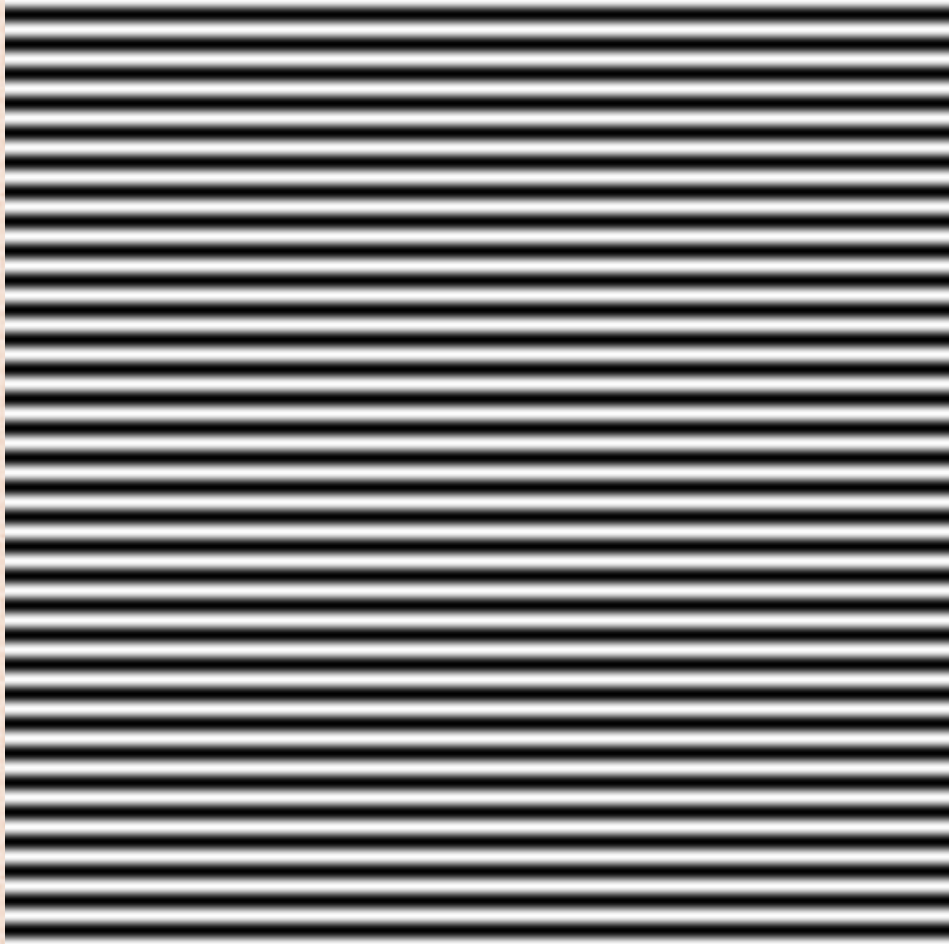
$$\sin(2\pi/32) x$$



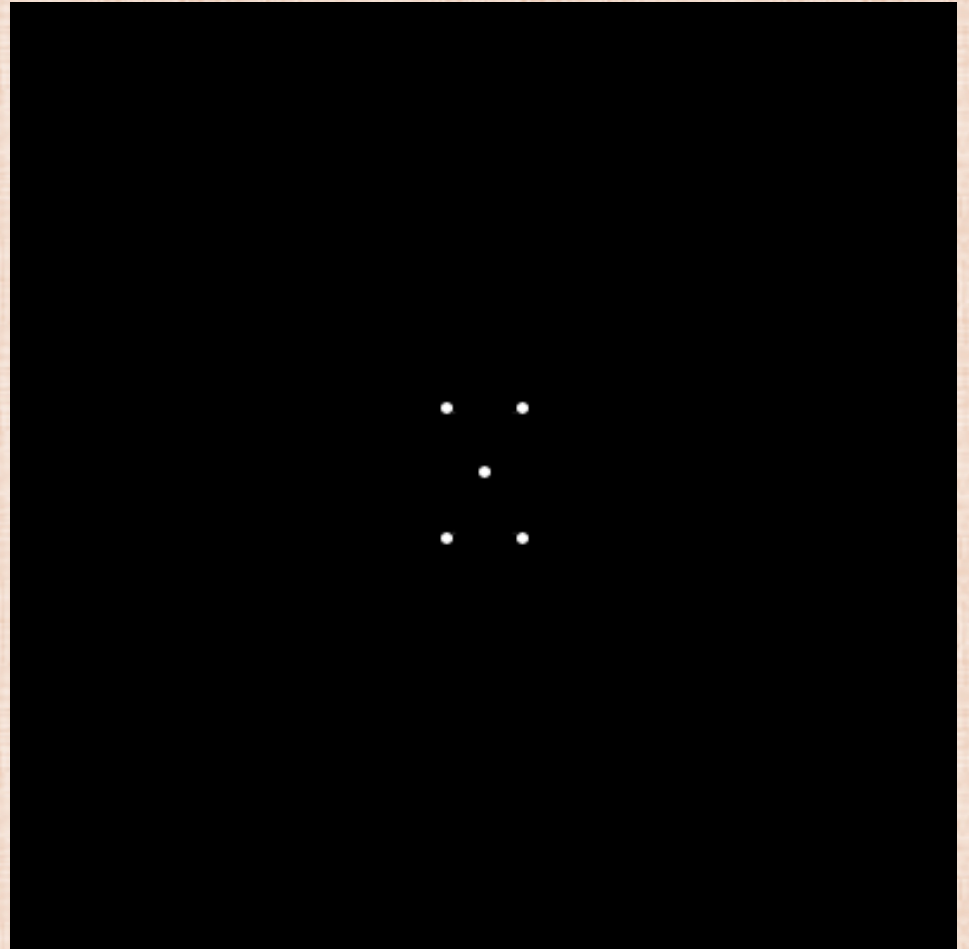
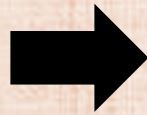
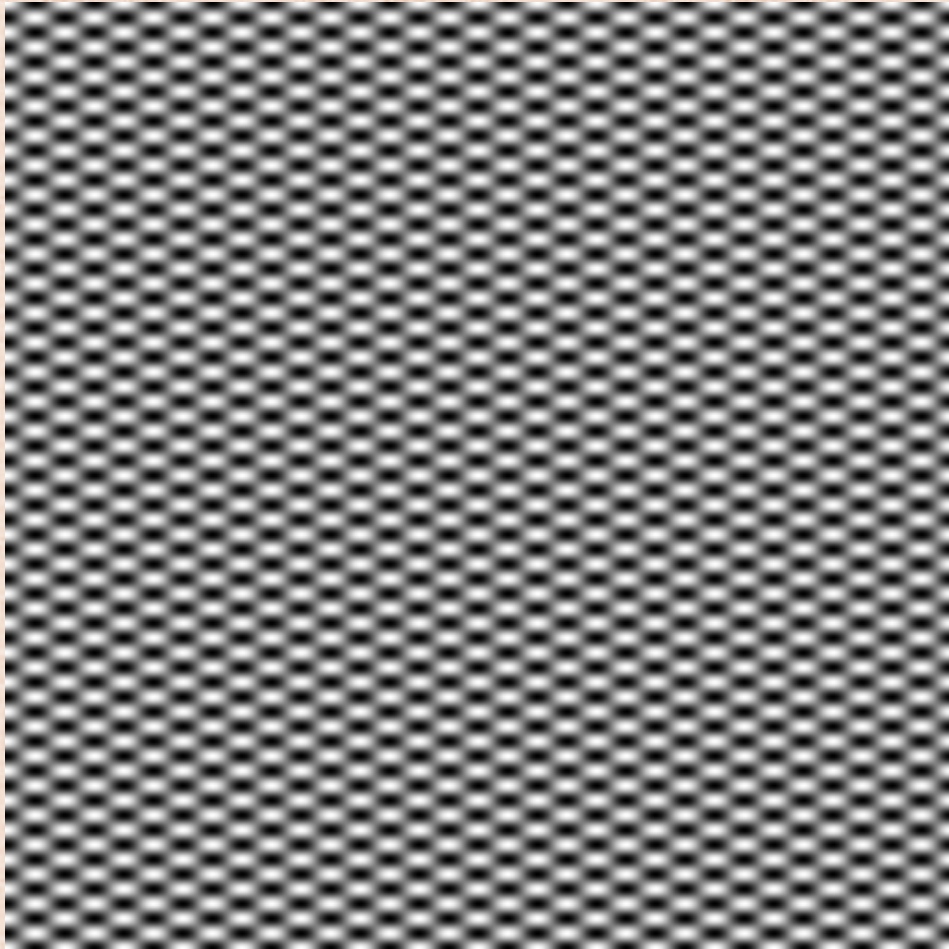
$$\sin(2\pi/16) x$$



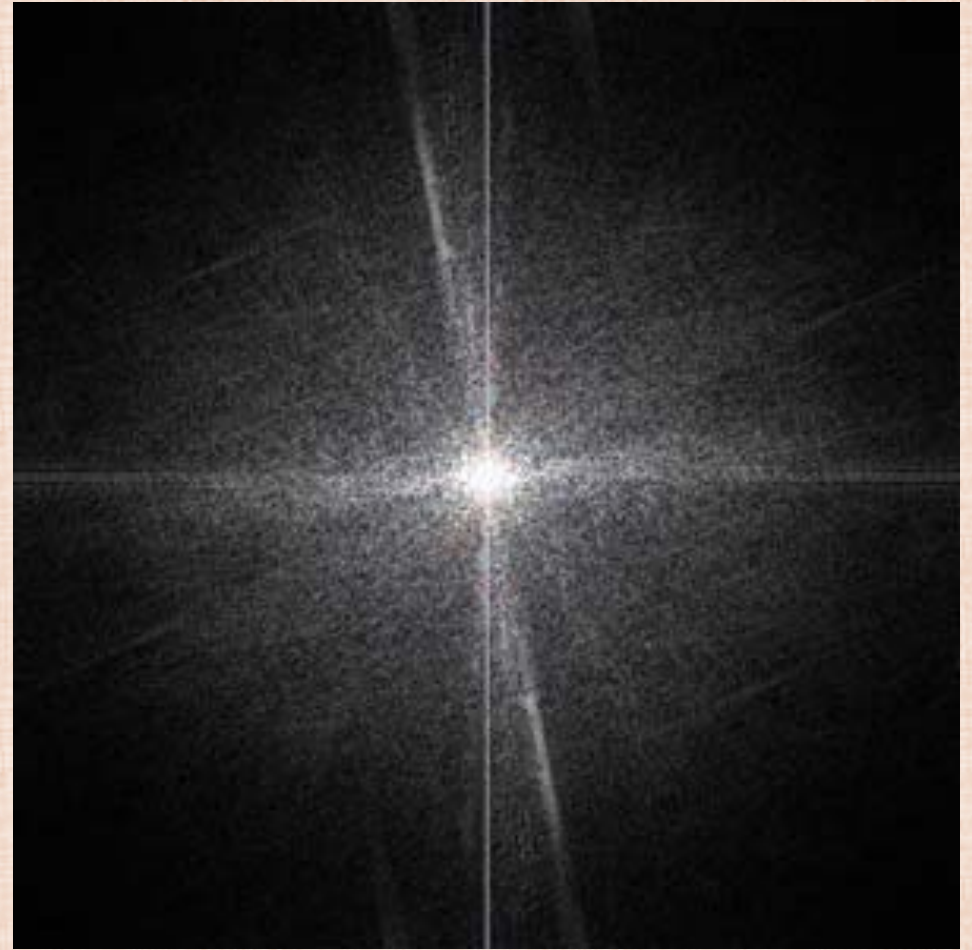
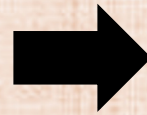
$$\sin(2\pi/16) y$$



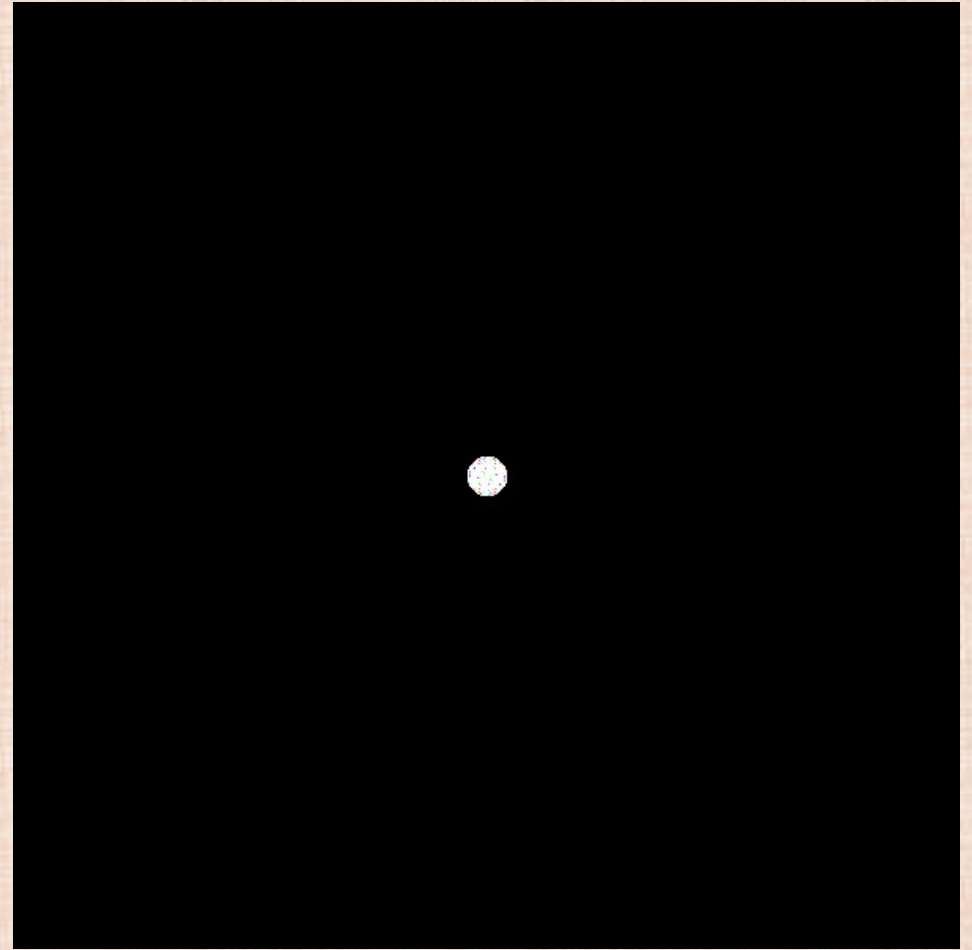
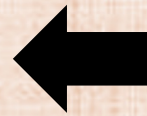
$$\sin(2\pi/32) x * \sin(2\pi/16) y$$



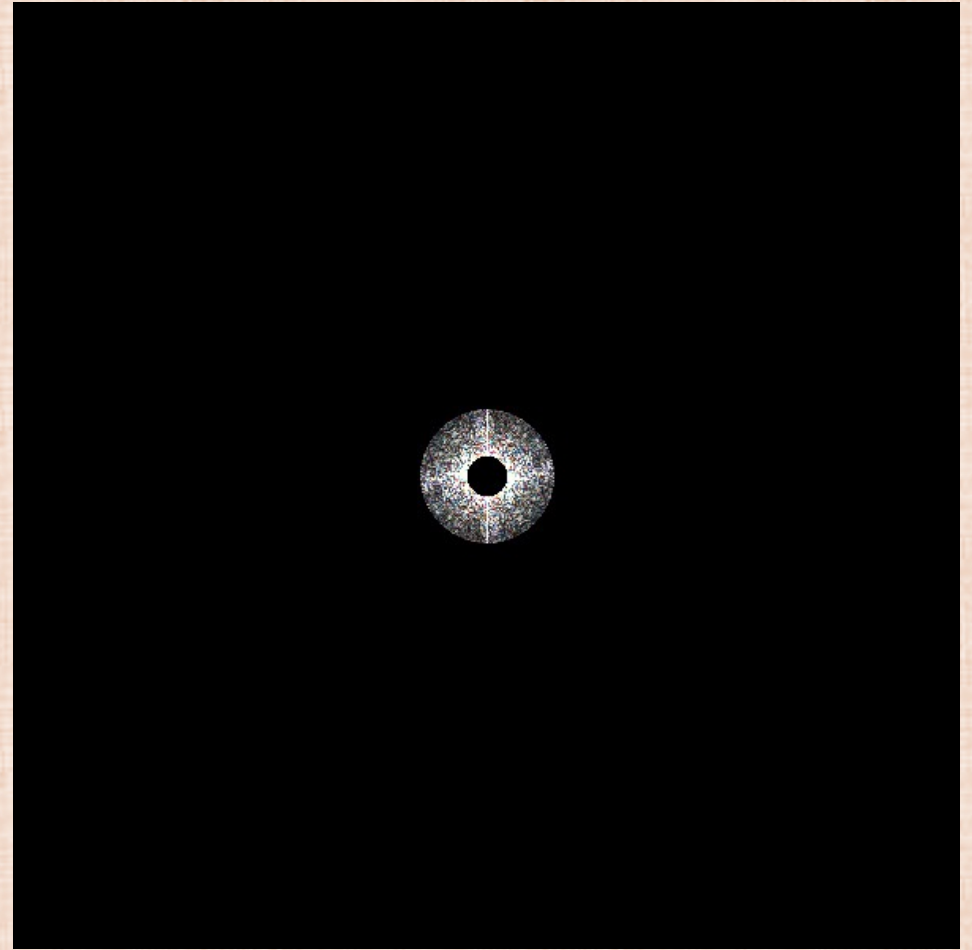
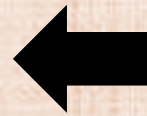
An obvious star!



lowest frequencies

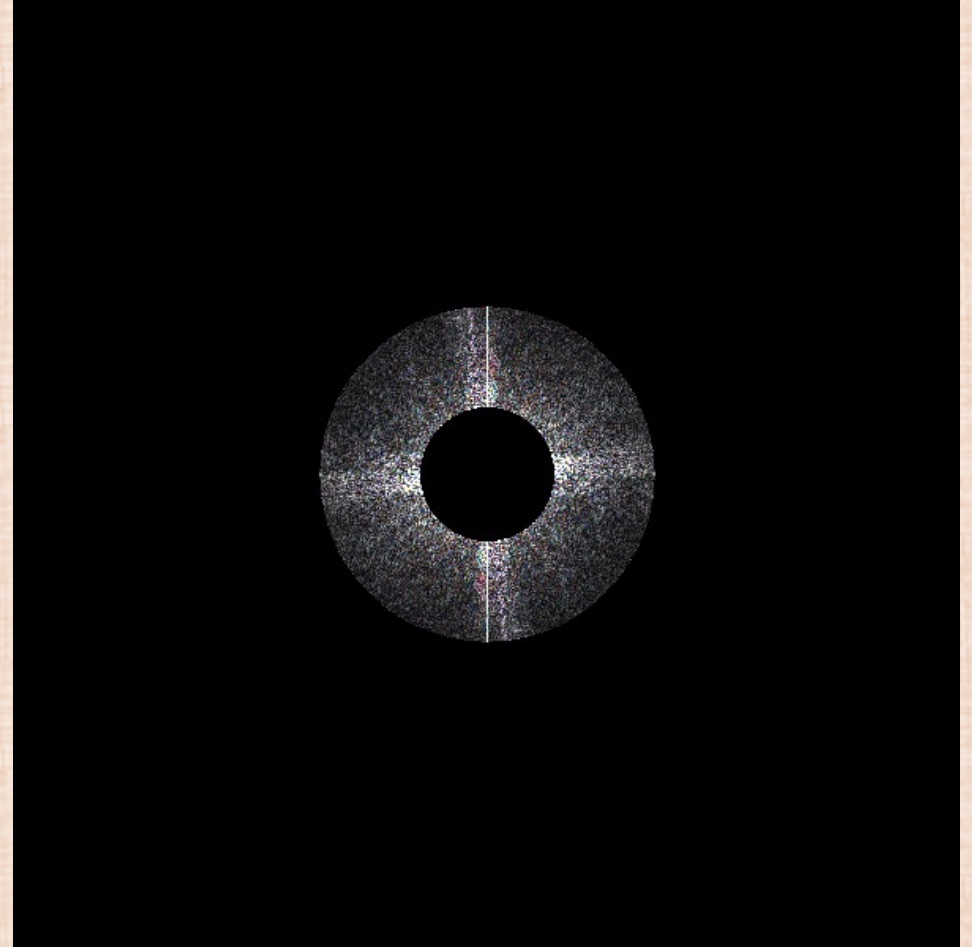
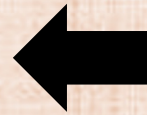


intermediate frequencies

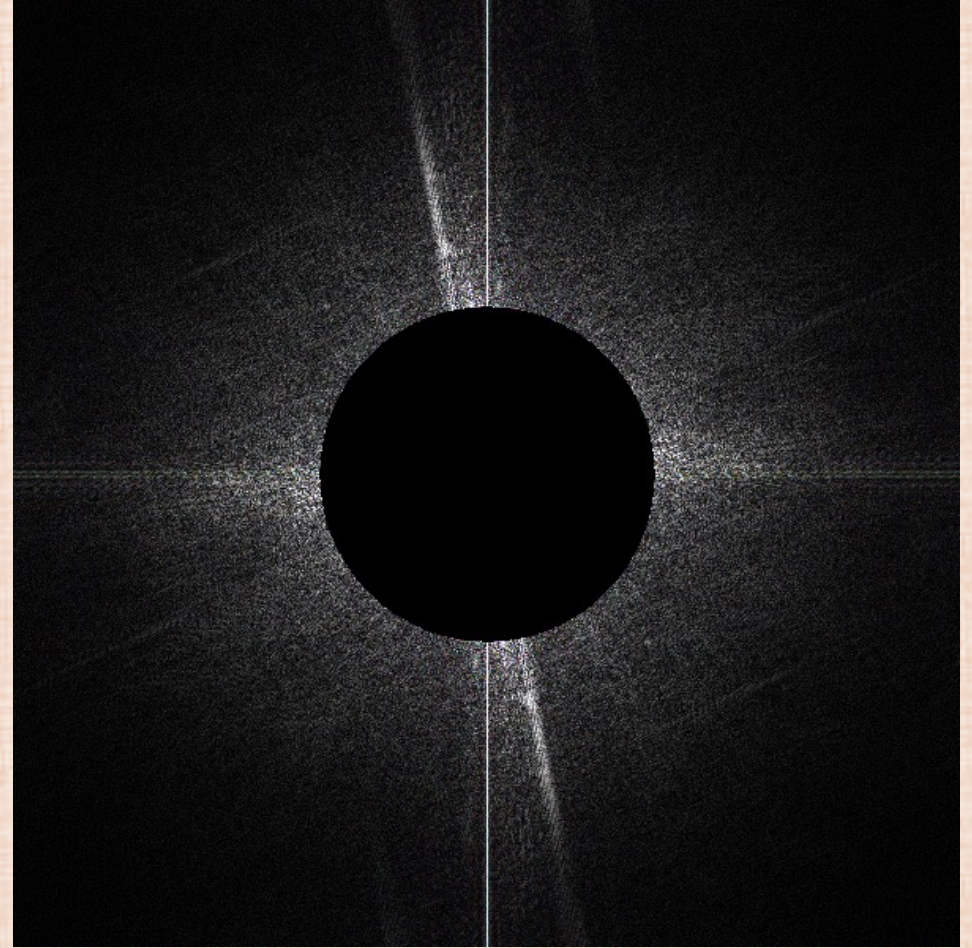
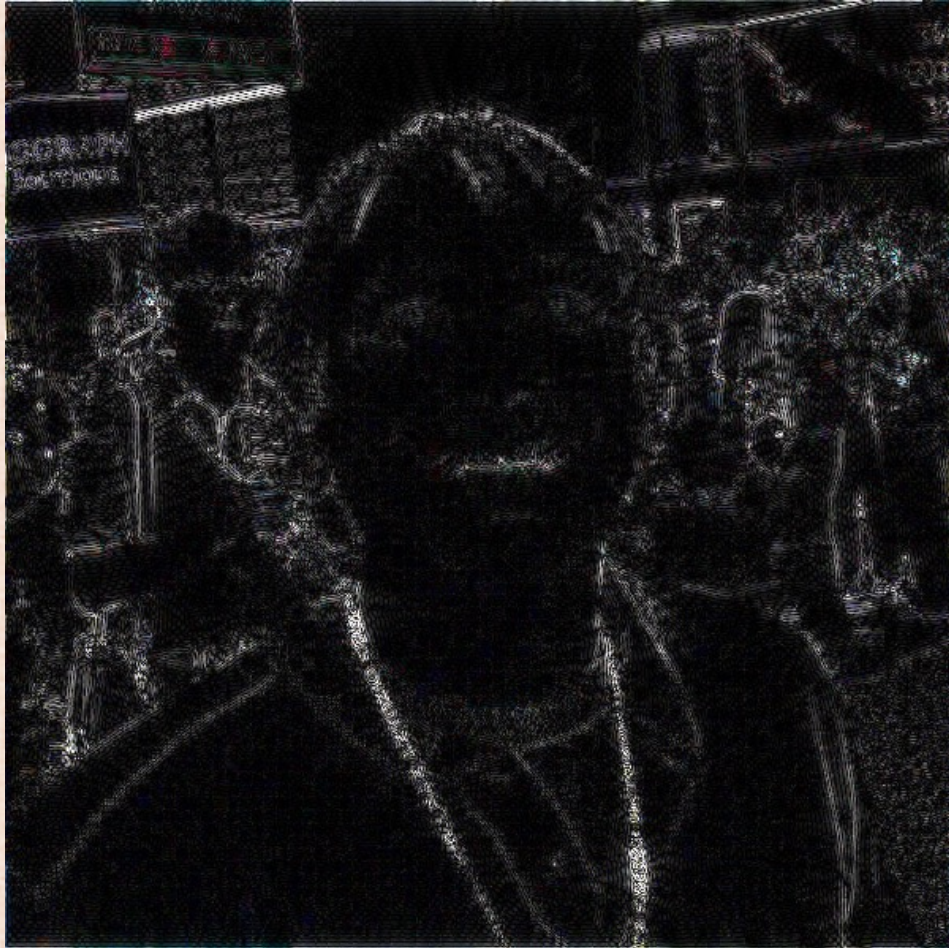




(larger) intermediate frequencies



highest frequencies (edges)



# Convolution

- Let  $f$  and  $g$  be functions in the spatial domain (e.g. images), and  $F(f)$  and  $F(g)$  be transformations of  $f$  and  $g$  into the frequency domain
  - In our prior examples:  $f$  was the image (to the left),  $F(f)$  was the frequency domain version of the image (to the right)
- Removing higher frequencies of  $F(f)$  is equivalent to multiplying by a Heaviside function  $F(g)$  (=1 for smaller frequencies, =0 for larger frequencies)
- Then, the inverse transform  $F^{-1}(F(f)F(g))$  gives the final result
- This entire process is called the **convolution** of  $f$  and  $g$ :
$$f * g = F^{-1}(F(f)F(g))$$

# Convolution Integral

- Convolution can be achieved without the Fourier Transform:

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t - \tau)d\tau = \int_{-\infty}^{\infty} f(t - \tau)g(\tau)d\tau$$

- A narrower  $g$  makes the integral more efficient to compute
- A narrower  $F(g)$  better removes high frequencies
- But, they can't both be narrow
  - Recall: the narrower Gaussian had wider frequencies, and the wider Gaussian had narrower frequencies

# Box Filter

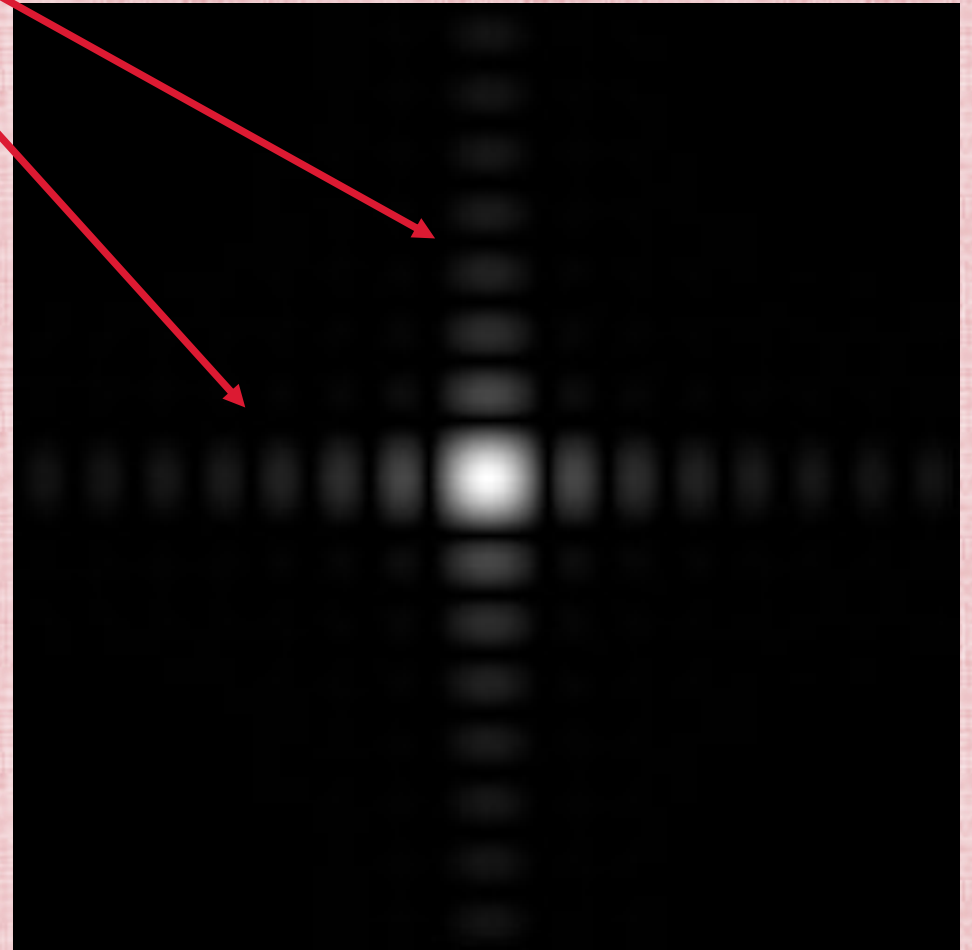
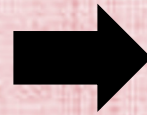
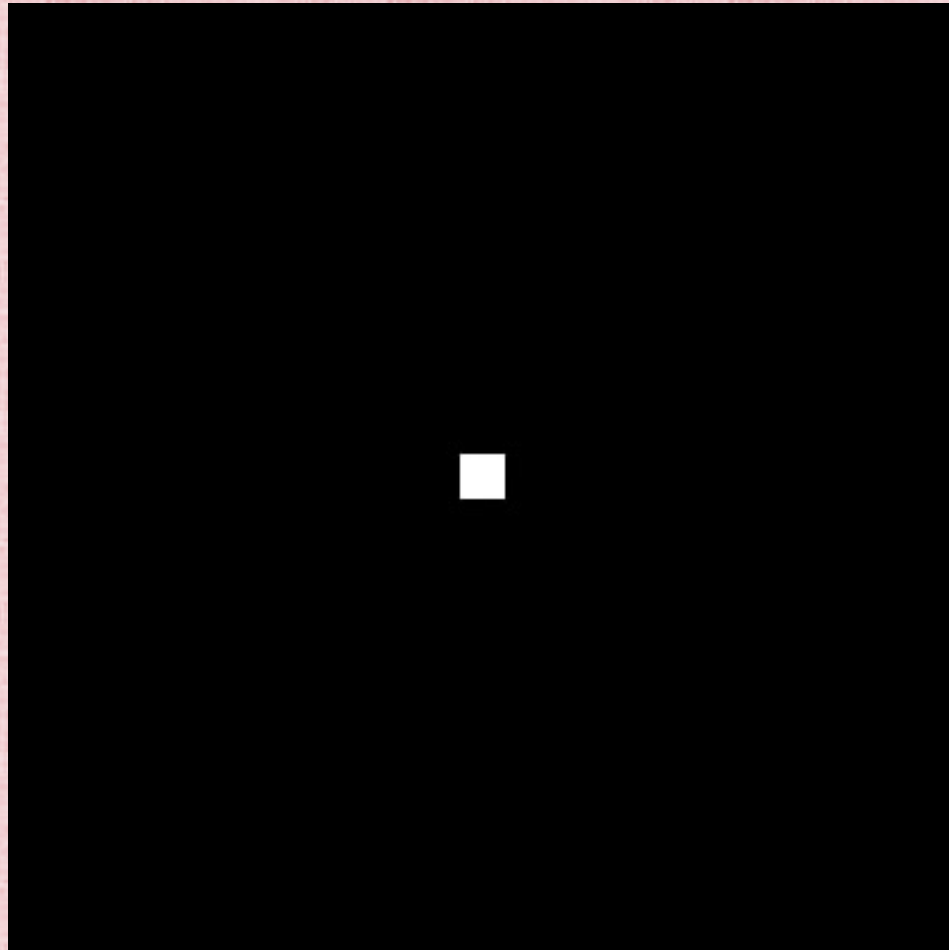
- Let  $g$  have nonzero values in an  $N \times N$  block of pixels (surrounding the origin), and be zero elsewhere
- The discrete convolution (integral) is computed via:
  - overlay the filter  $g$  on the image, multiply the corresponding entries, and sum the results
- The final result is (typically) defined at the center of the filter

$1/16$	$1/16$	$1/16$	$1/16$
$1/16$	$1/16$	$1/16$	$1/16$
$1/16$	$1/16$	$1/16$	$1/16$
$1/16$	$1/16$	$1/16$	$1/16$

# Filters Most (but not all) High Frequencies

$g$

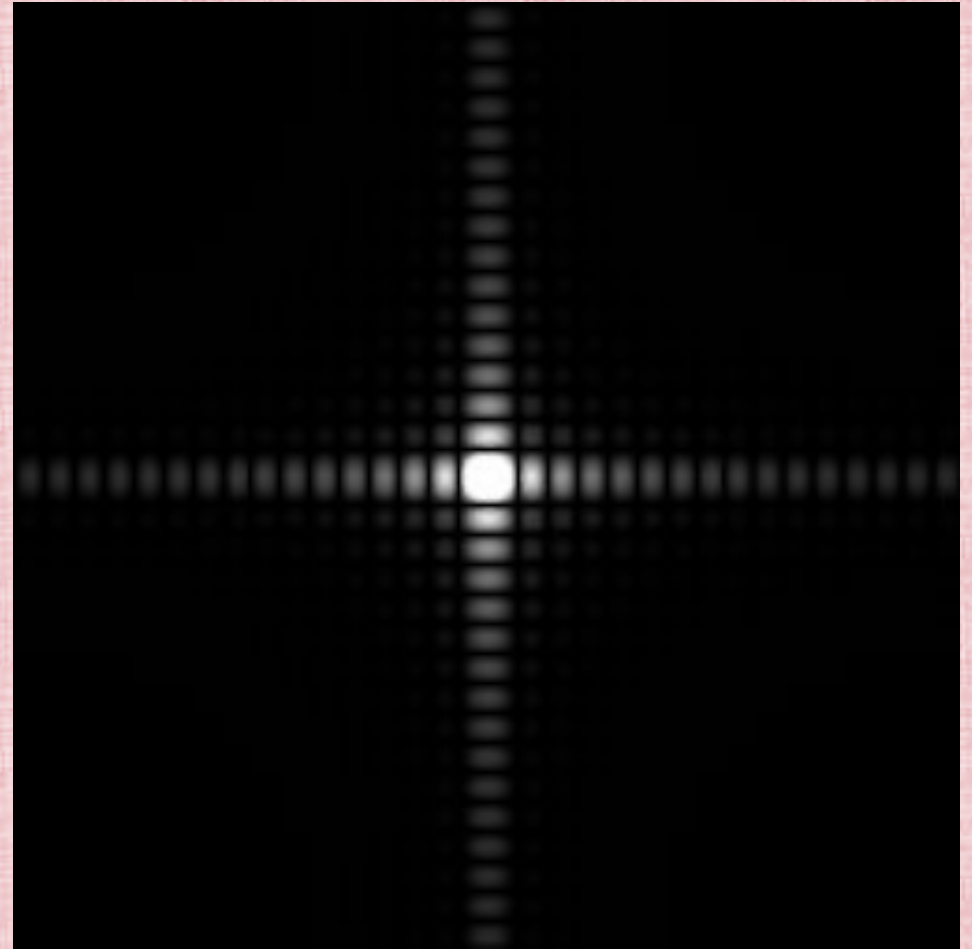
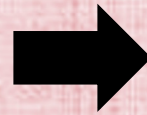
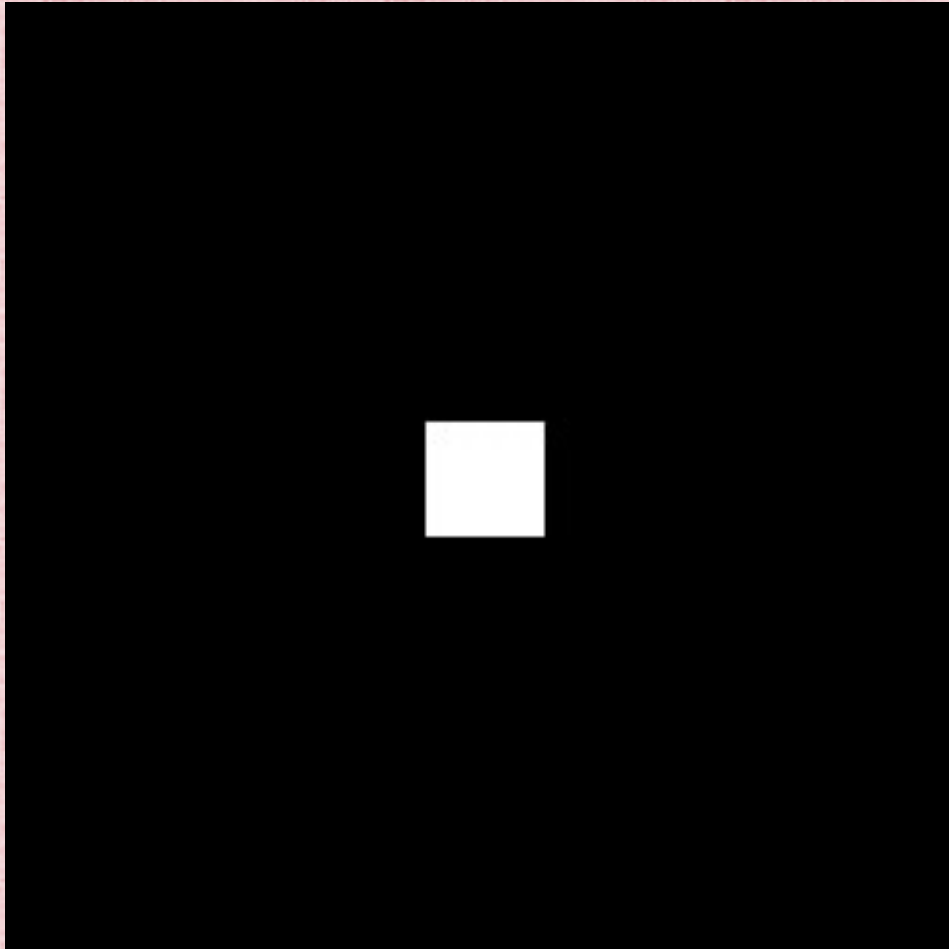
$F(g)$



# Wider Box Filter

$g$

$F(g)$

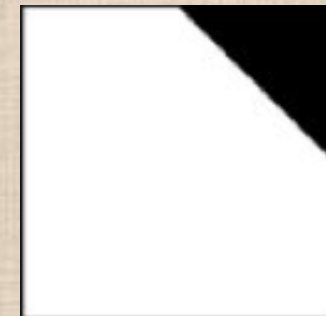
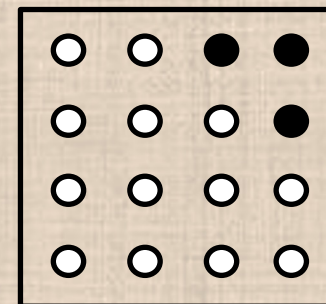
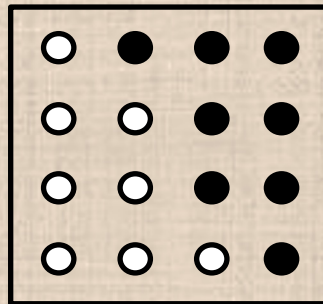
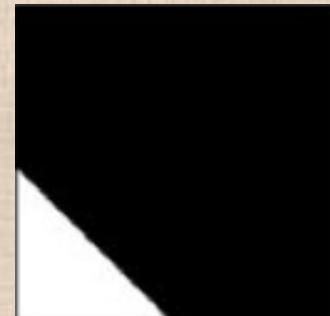
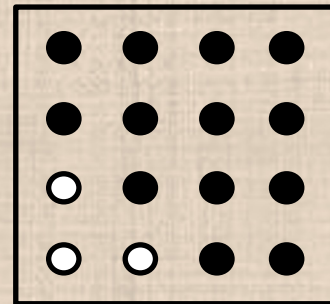
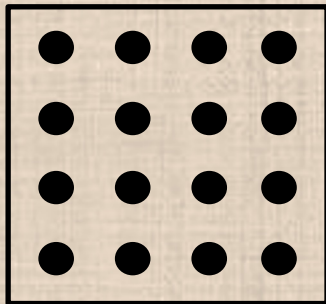


more expensive convolution integral

removes more of the high frequencies

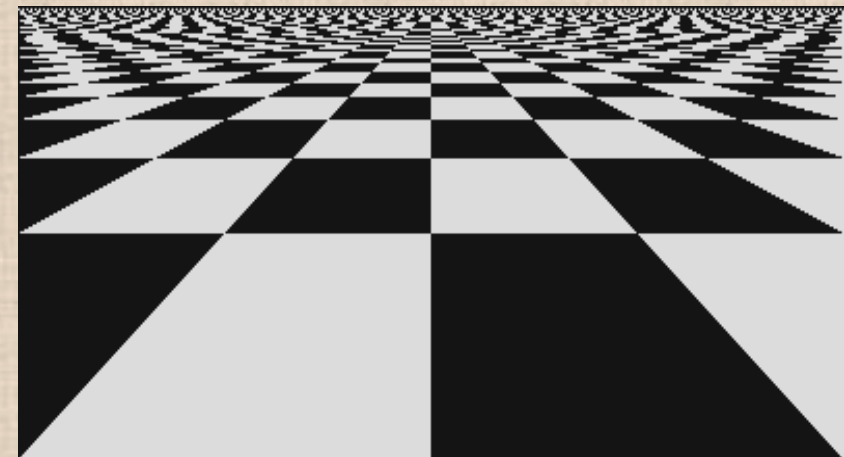
# Super-Sampling

- Collect extra information/samples (in each pixel), and average the result (e.g. with a box filter)
  - E.g. render a 100 by 100 image with 4 by 4 super-sampling (equivalent to rendering a 400 by 400 image)
  - This properly represents (without aliasing) frequencies up to 4 times higher (than the original image could)
  - Apply a 4 by 4 box filter aiming to remove as much of those extra frequencies as possible
- Converges to the area coverage integral, as the number samples per pixel increases
  - Efficiency: only super-sample pixels that have high frequencies (e.g. edges)
  - Better to use pseudo-random Monte-Carlo super-sampling strategies (instead of uniform super-sampling)

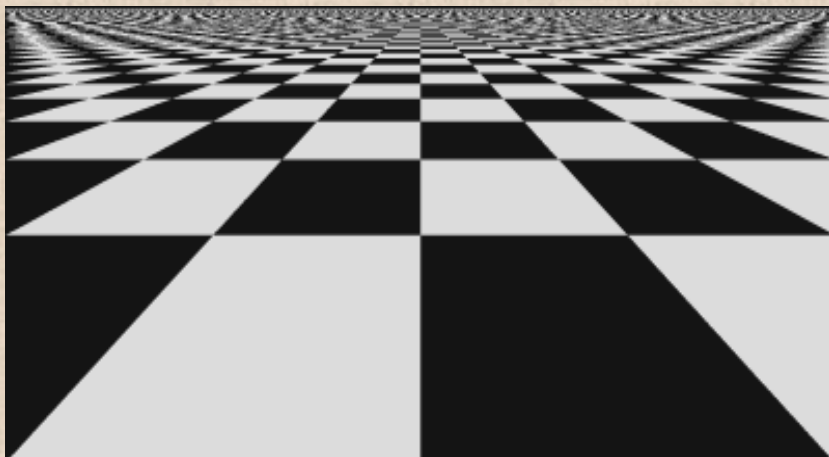




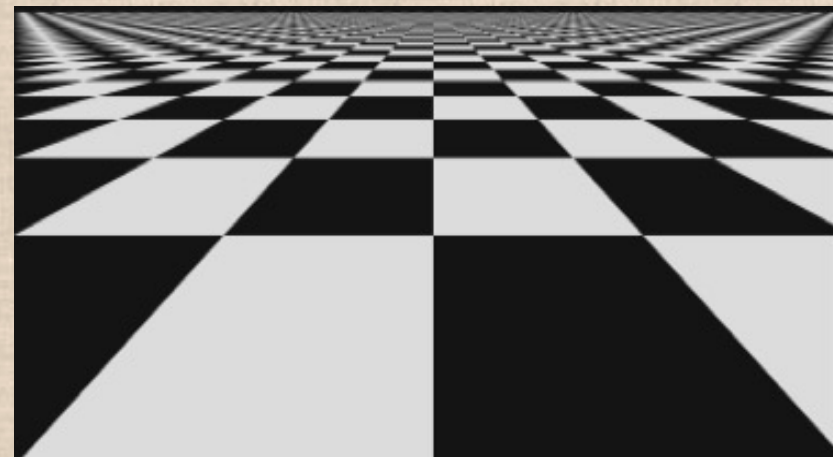
# Super-Sampling



Point Sampling

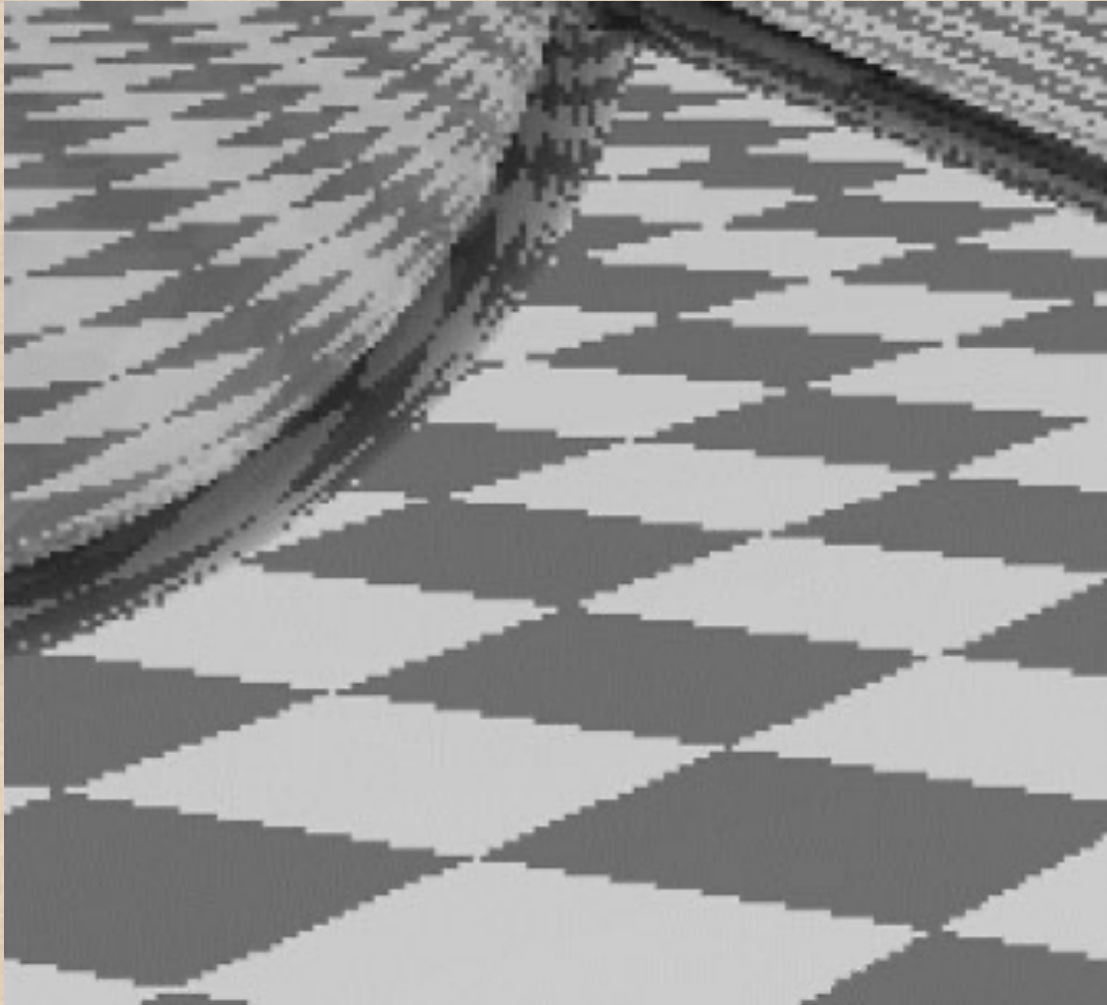


4 by 4 Super-Sampling

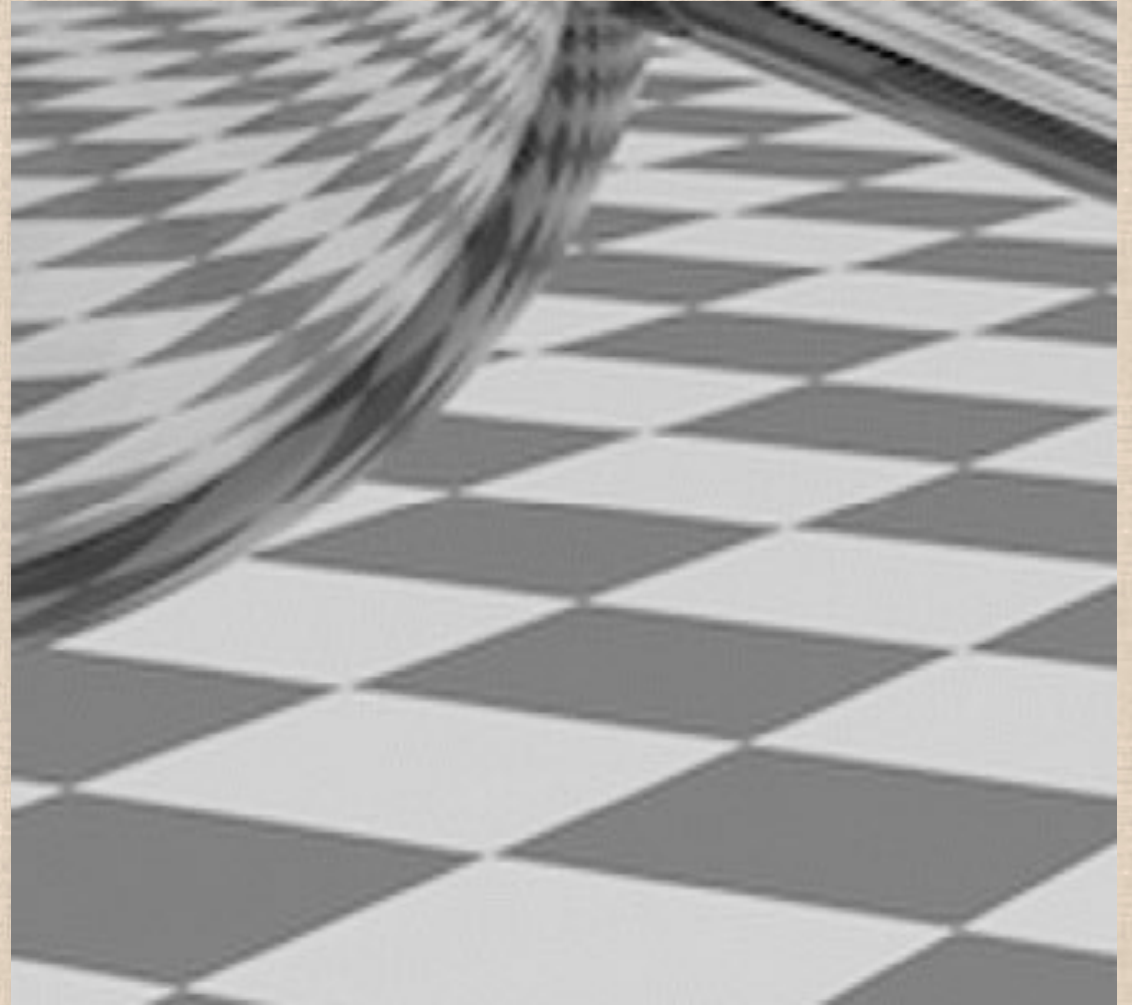


Exact Area Coverage

# Super-Sampling



Jaggies



Anti-Aliased