

# Sampling and Nyquist's theorem

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# Sampling in 2D

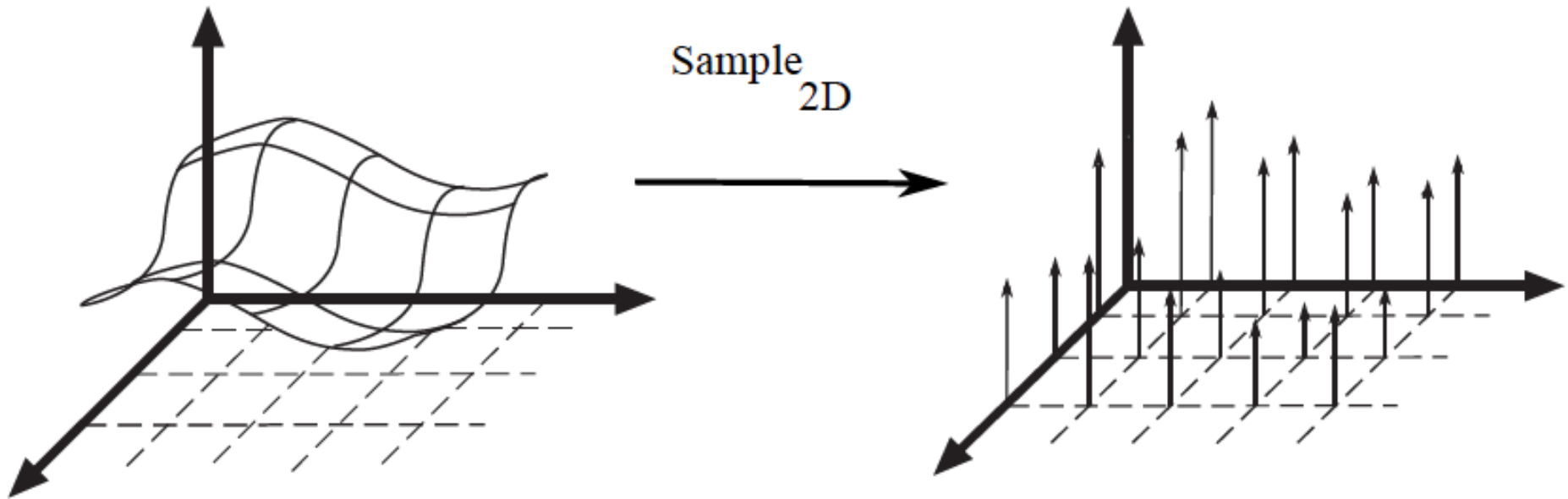


FIGURE 7.4: *Sampling in 2D takes a function and returns an array; again, we allow the array to be infinite dimensional and to have negative as well as positive indices.*

# Modelling a sampled function

## 12.2.1 Modelling a Sampled Function

A crucial step is a reasonable model of a sampled function. Passing from a continuous function—like the irradiance at the back of a camera system—to a collection of values on a discrete grid—like the pixel values reported by a camera—is referred to as *sampling*. Sampling must lose information about the original function (for example, see Figure 3.4). Accounting for what is lost requires building a model of the sampling process quite carefully.

Write

$$\text{sample}_{2D}(f)$$

for an operation that takes a continuous function in 2D and returns a sampled version. The sampled version should represent the values of  $f$  at all integer points (you can get any other uniform grid with a scale). It is highly desirable that  $\text{sample}_{2D}(f)$  produce a result that is compatible with integration. In particular, that

$$\int g(u, v) \text{sample}_{2D}(f) dudv \approx \int g(u, v) f(u, v) dudv$$

# Modelling a sampled function

to the extent possible for any  $g(u)$ . Recall the definition of the  $\delta$  function in 2D (Definition 11.3). It turns out that the right choice for  $\mathbf{sample}_{2D}(f)$  is

$$\mathbf{sample}_{2D}(f) = \sum_{ij} f(i, j)\delta(x - i, y - j)$$

The grid is infinite in each dimension to avoid having to write ranges, etc. (Figure 12.2). The  $\delta$  function is a conceptual device to make the mathematical plumbing work properly. There is no need to place one at each sample function in an array inside your programs (and you can't – you'd have to have an opinion about the value of  $\delta(0)$ , which isn't going to work out). This definition yields a model which behaves well for integrals. In particular,

$$\int g(u)\mathbf{sample}_{2D}(f)du = \sum_{ij} f(i, j)g(i, j)$$

# Interpolation is by convolution

Recall the interpolate of Section 3.1 had the form

$$\mathcal{I}(x, y) = \sum_{i,j} \mathcal{I}_{ij} b(x - i, y - j).$$

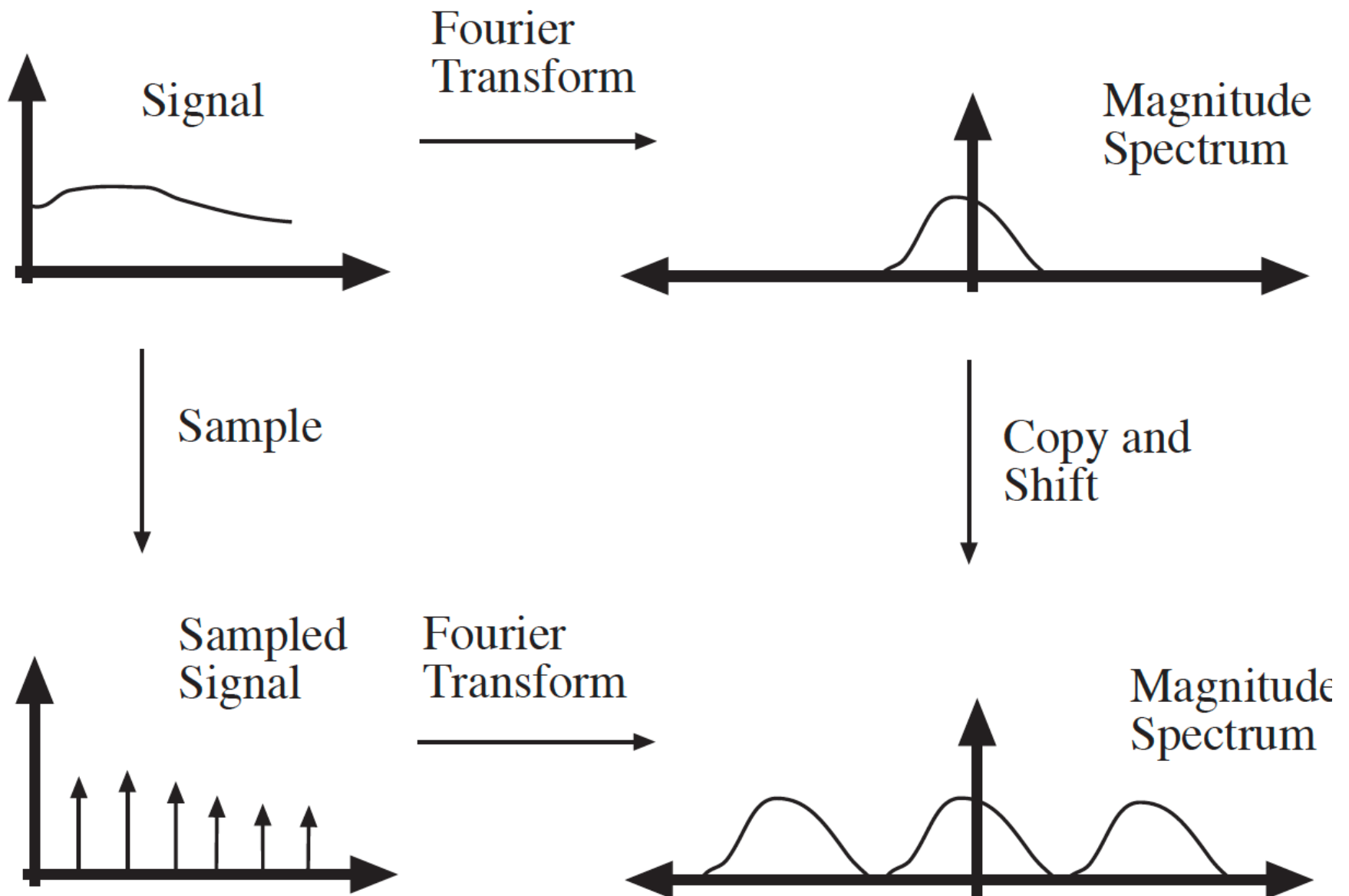
Here  $b$  is some function with the properties  $b(0, 0) = 1$  and  $b(u, v) = 0$  for  $u$  and  $v$  any other grid point. This is linear and shift invariant (**exercises**) so it must be a convolution. The way to see the convolution is to use the model of sampling, above. This exposes the convolution in interpolation. Check that

$$\begin{aligned} \text{sample}_{2D}(\mathcal{I}) * b &= \int \int \sum_{ij} \mathcal{I}_{ij} \delta(x - u - i, y - v - j) b(u, v) du dv \\ &= \sum_{ij} \mathcal{I}_{ij} \int \int \delta(x - u - i, y - v - j) b(u, v) du dv \\ &= \sum_{i,j} \mathcal{I}_{ij} b(x - i, y - j) \text{ from the property of a } \delta \text{ function} \end{aligned}$$

# The FT of a sampled signal

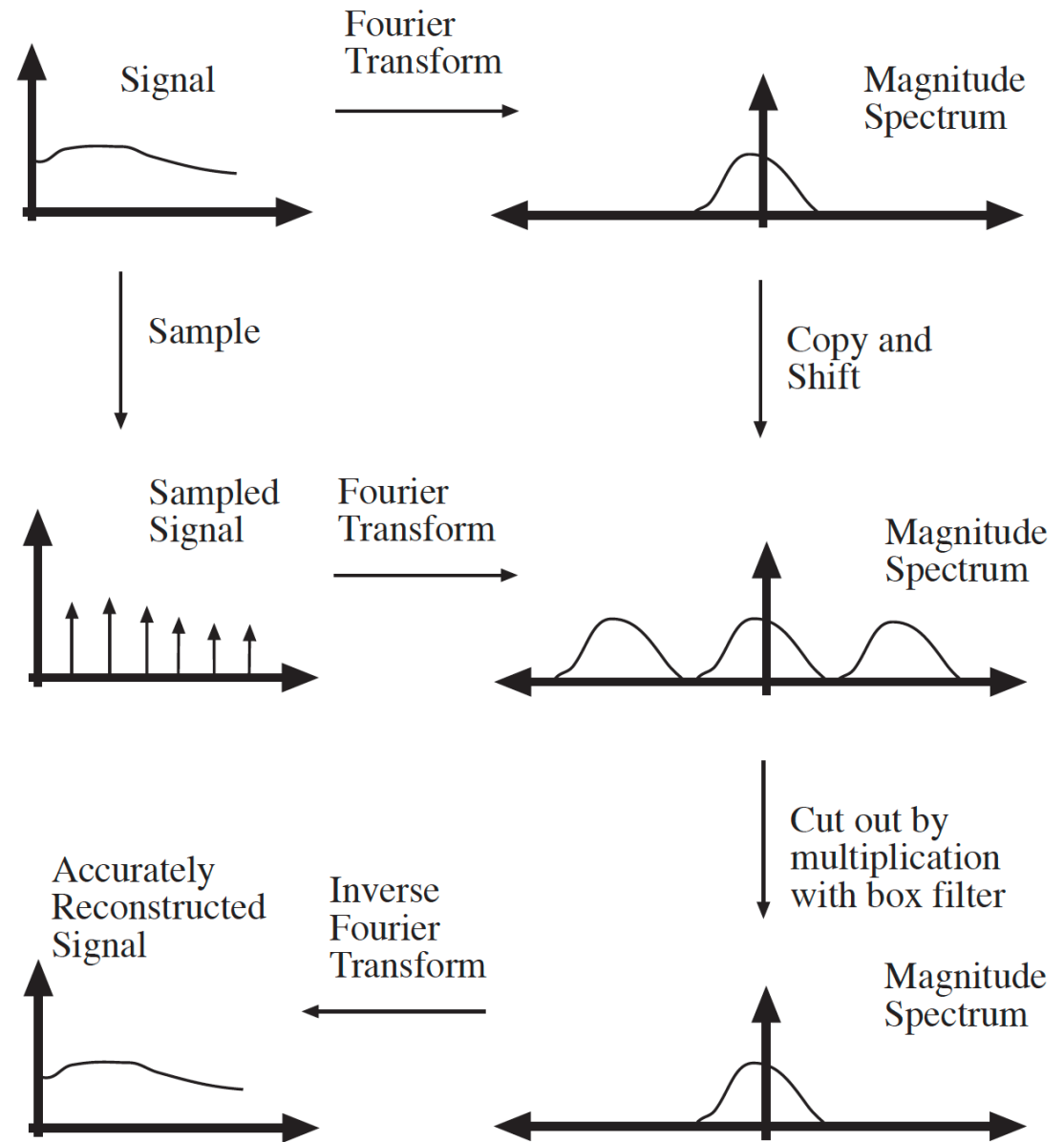
$$\begin{aligned}\mathcal{F}(\text{sample}_{2D}(f(x, y))) &= \mathcal{F}\left(f(x, y) \left\{ \sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} \delta(x - i, y - j) \right\}\right) \\ &= \mathcal{F}(f(x, y)) * \mathcal{F}\left(\left\{ \sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} \delta(x - i, y - j) \right\}\right) \\ &= \sum_{i=-\infty}^{\infty} \mathcal{F}(f)(u - i, v - j),\end{aligned}$$

# The FT of a sampled signal



# Sampling

- If the magnitude blobs don't overlap, you can reconstruct from samples
- Just cut out the blob in FT space with a box filter, inverse FT



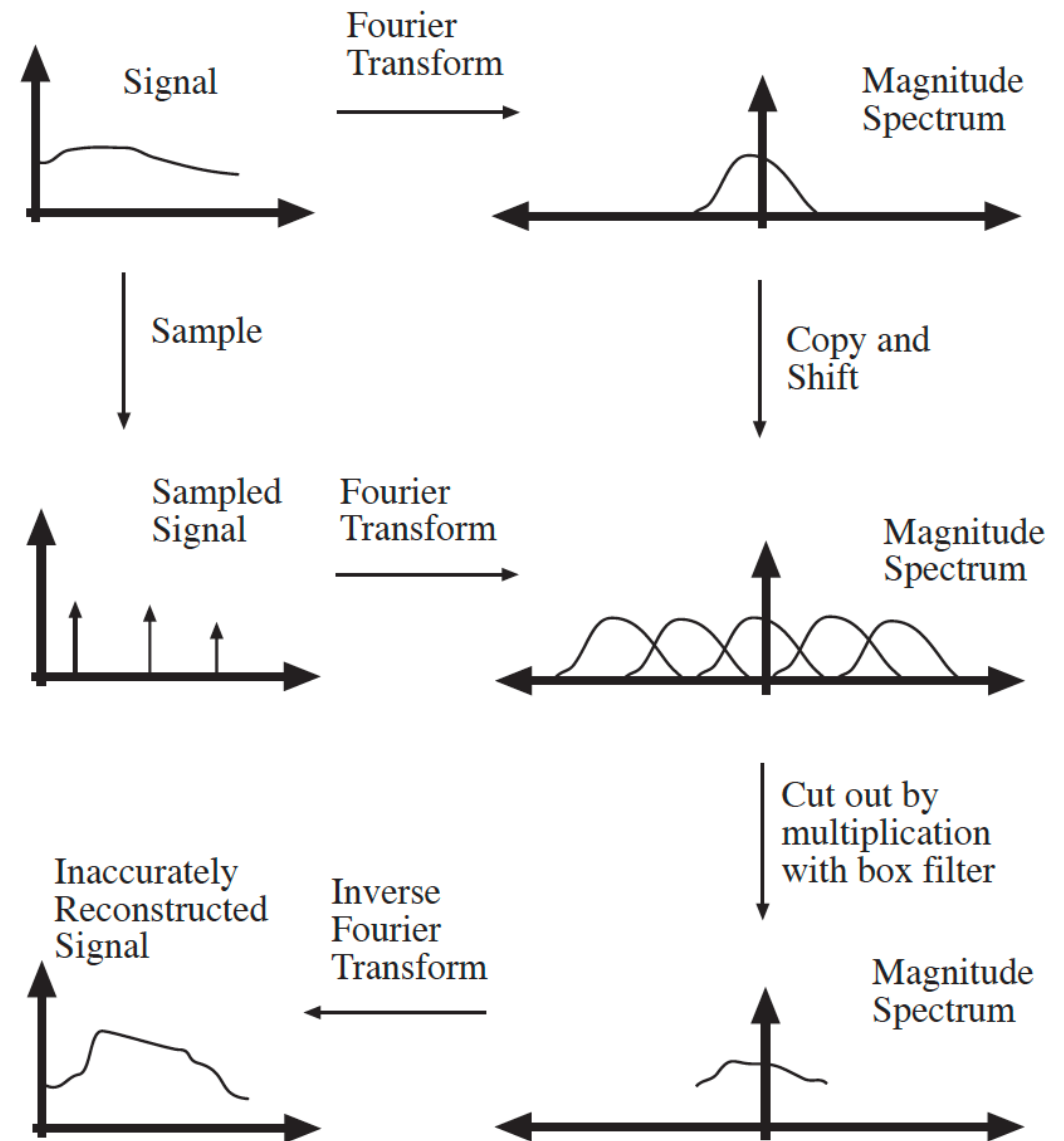


# Sampling

- If the magnitude blobs overlap, you can't reconstruct from samples

- Cutting out won't work – you'll get some information from a different frequency that aliases

- Nyquist's theorem



# Consequences

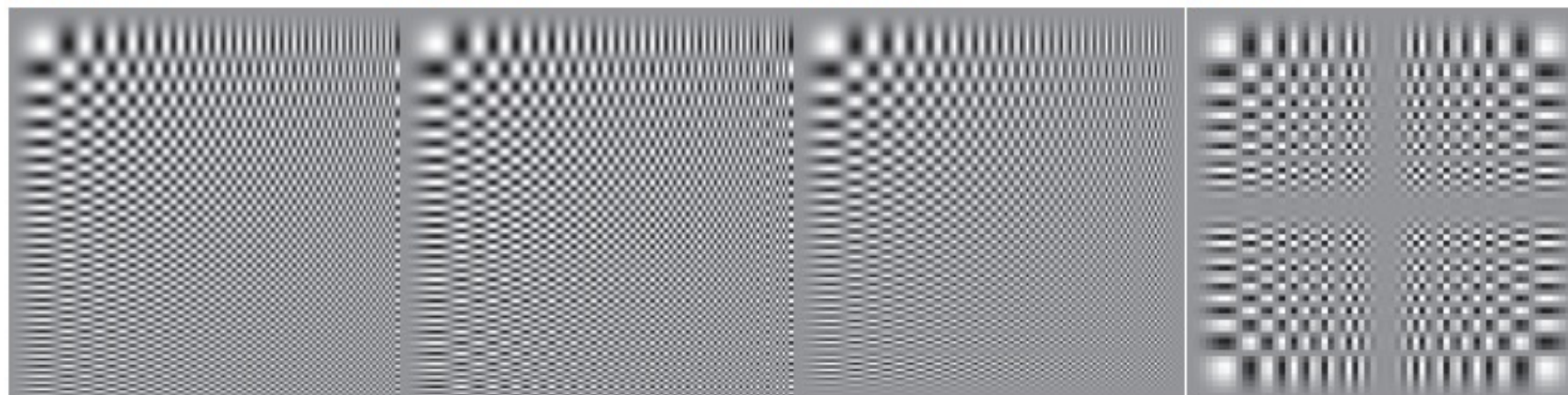
- Nyquist limits aren't really viable
  - Apply the convolution theorem
  - A box in FT magnitude space is a filter with infinite support (and you can't make one of those)
- You're forced to choose a filter that is low pass, but isn't perfect
  - the choice has consequences
  - Gaussian is such a filter

512x512

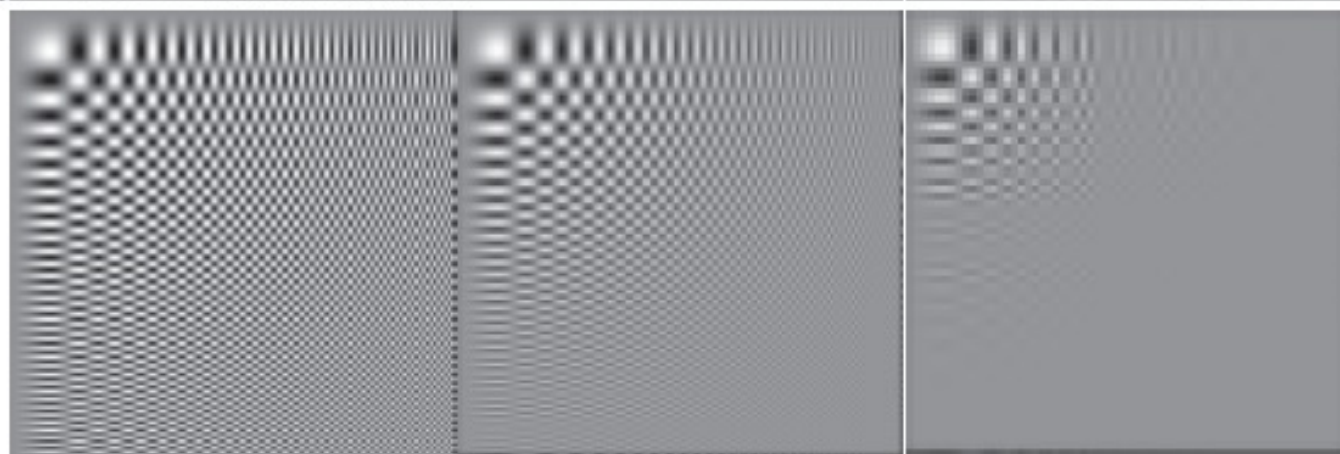
256x256

128x128

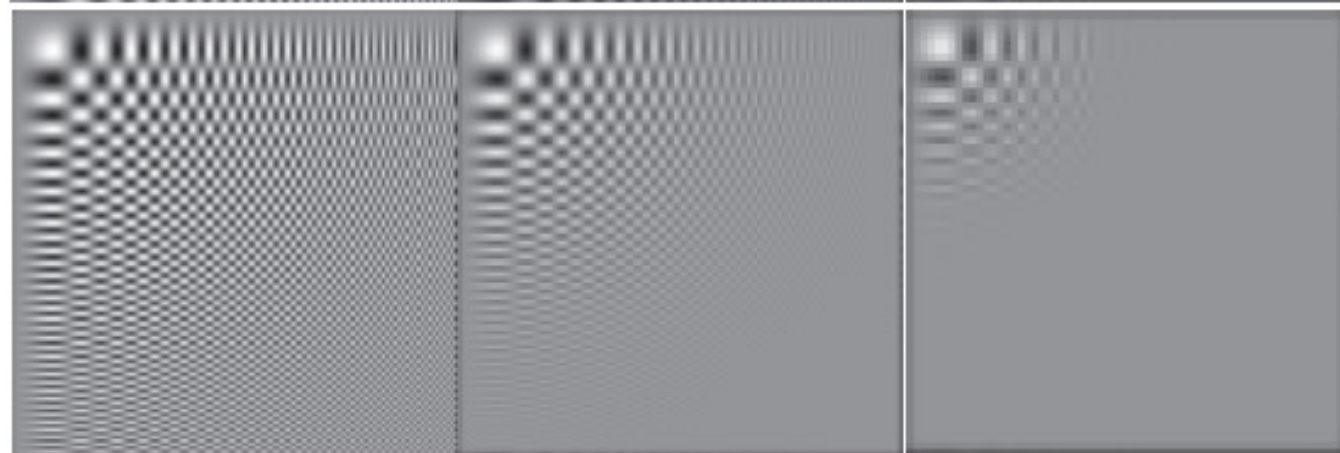
64x64

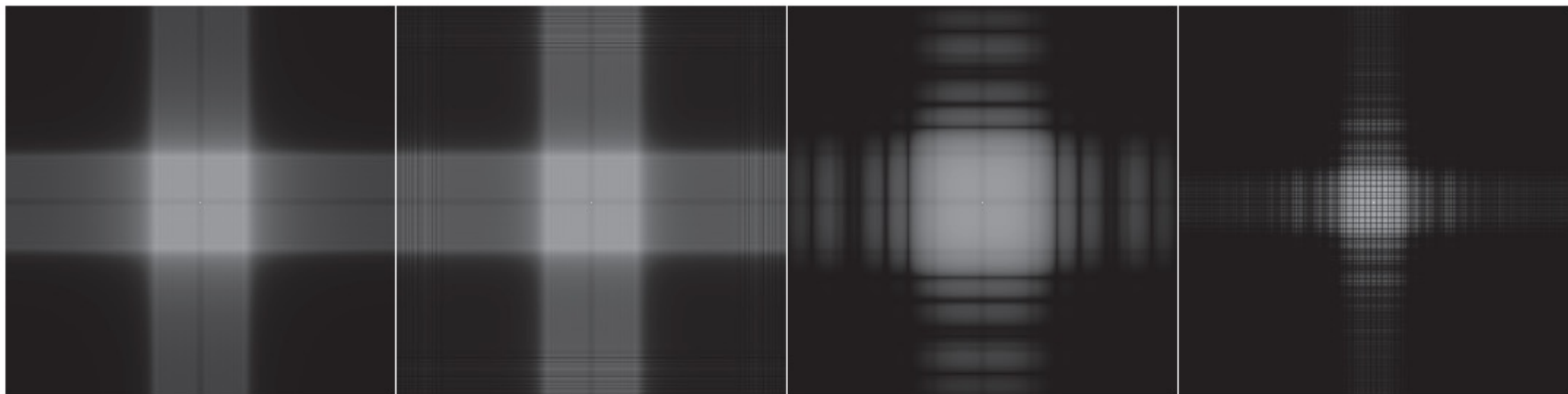


$\sigma=1$

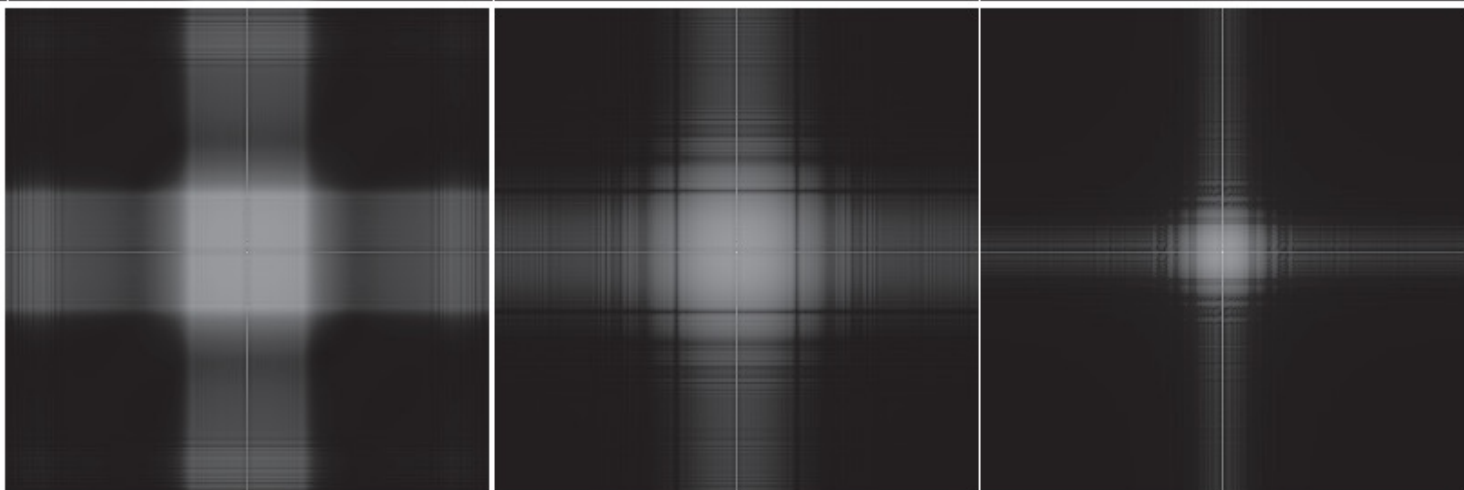


$\sigma=2$

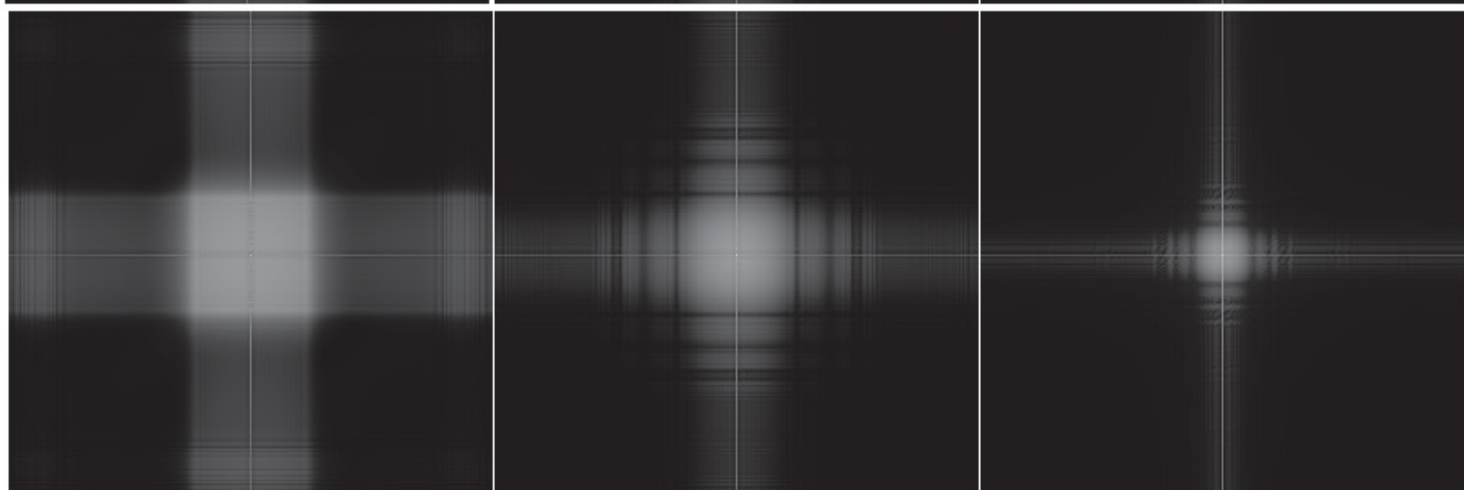




$\sigma=1$



$\sigma=2$



# Mystery 2

- Why can downsampling sometimes lead to aliasing?

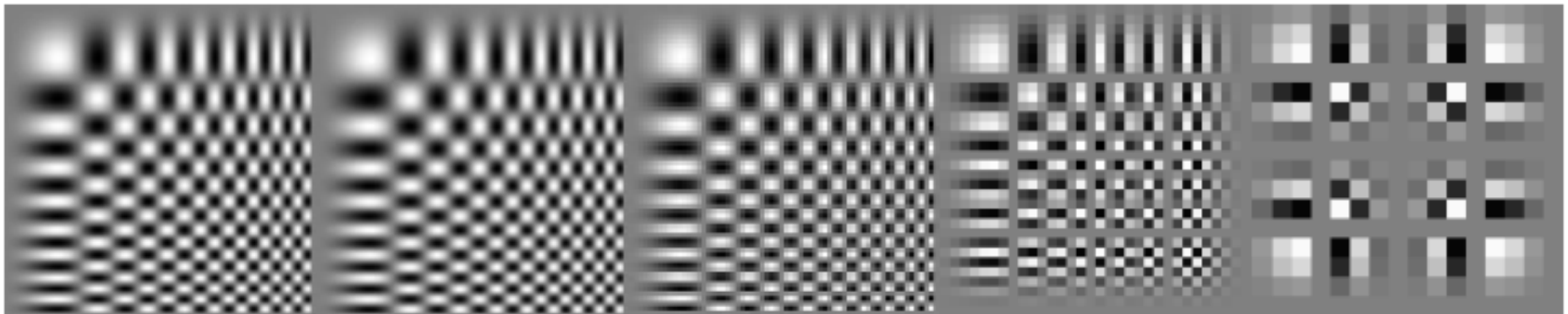
256x256

128x128

64x64

32x32

16x16



The downsampling mangles the Fourier Transform magnitude spectrum UNLESS you smooth by enough; and if you do, you lose some information

# Mystery 2 SOLVED

- Why can downsampling sometimes lead to aliasing?

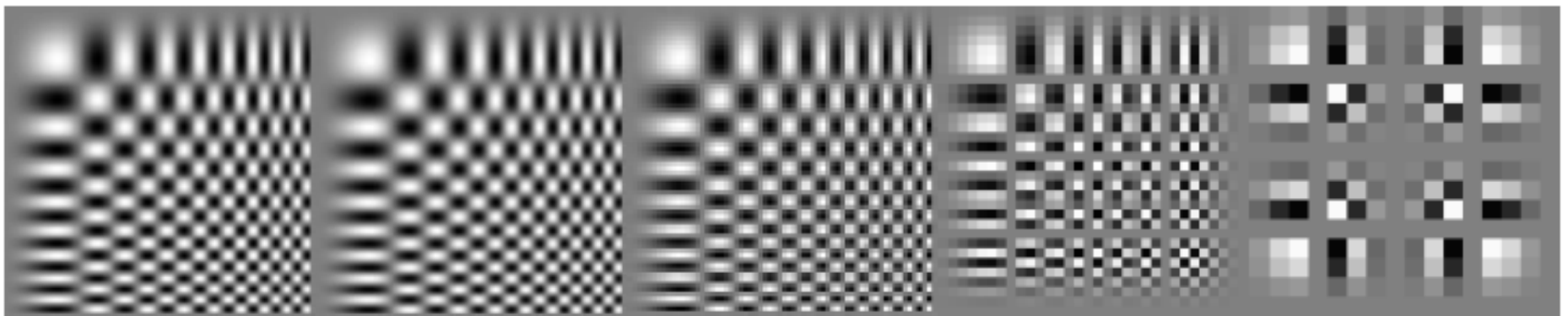
256x256

128x128

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32x32

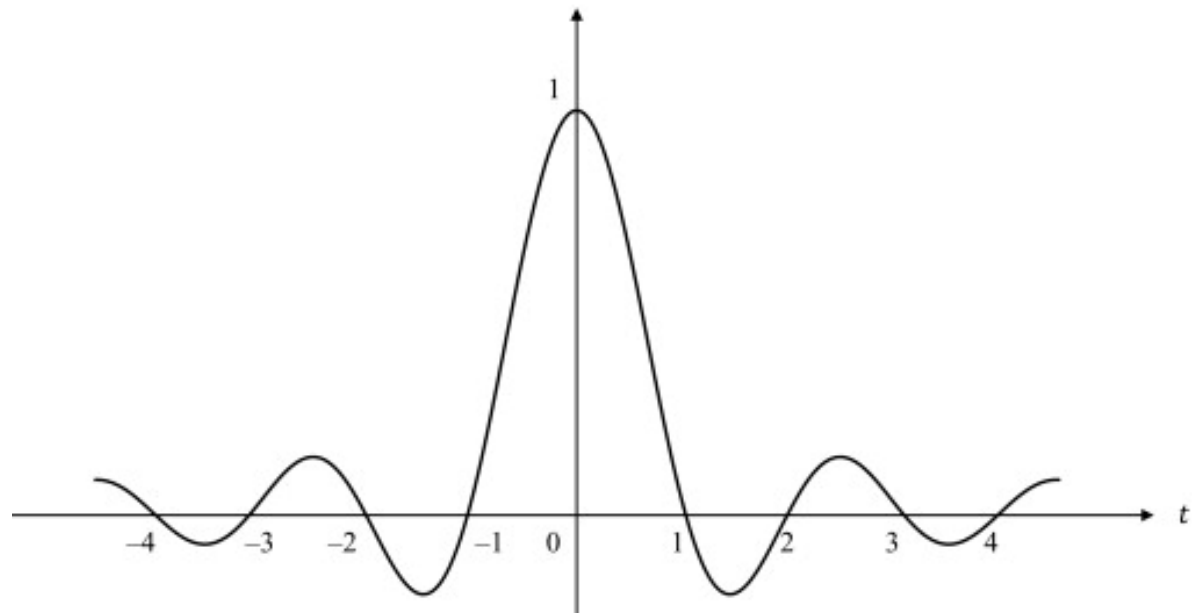
16x16



- The downsampling mangles the Fourier Transform magnitude spectrum UNLESS

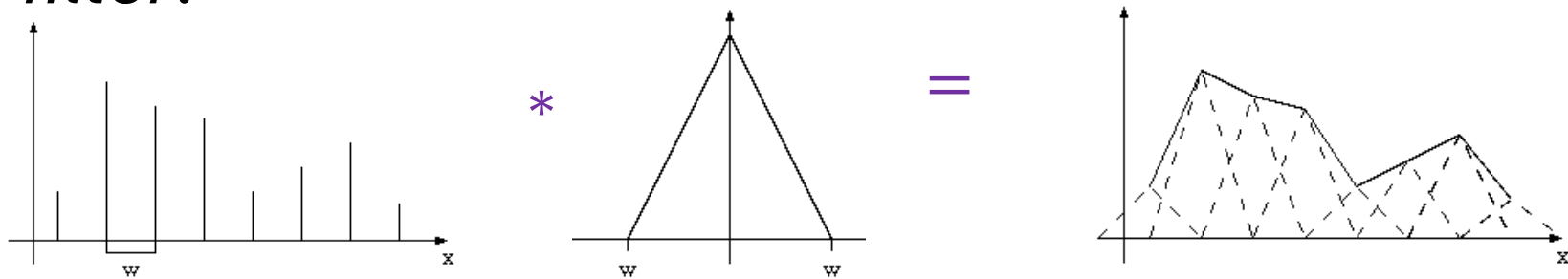
# Analyzing interpolation methods

- Perfect reconstruction requires convolution with a sinc filter in the spatial domain,
  - which is bad because sinc has infinite support
- Instead, simpler reconstruction (interpolation) methods are typically used

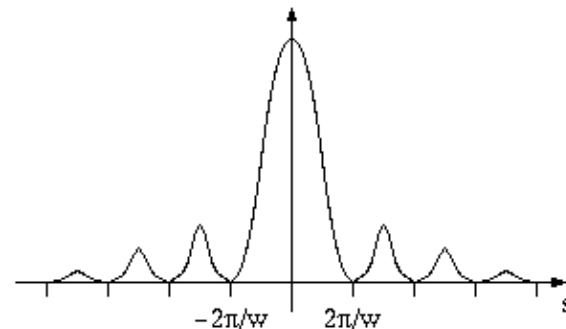


# Analyzing interpolation methods

- Linear reconstruction: convolve with *triangle filter*:



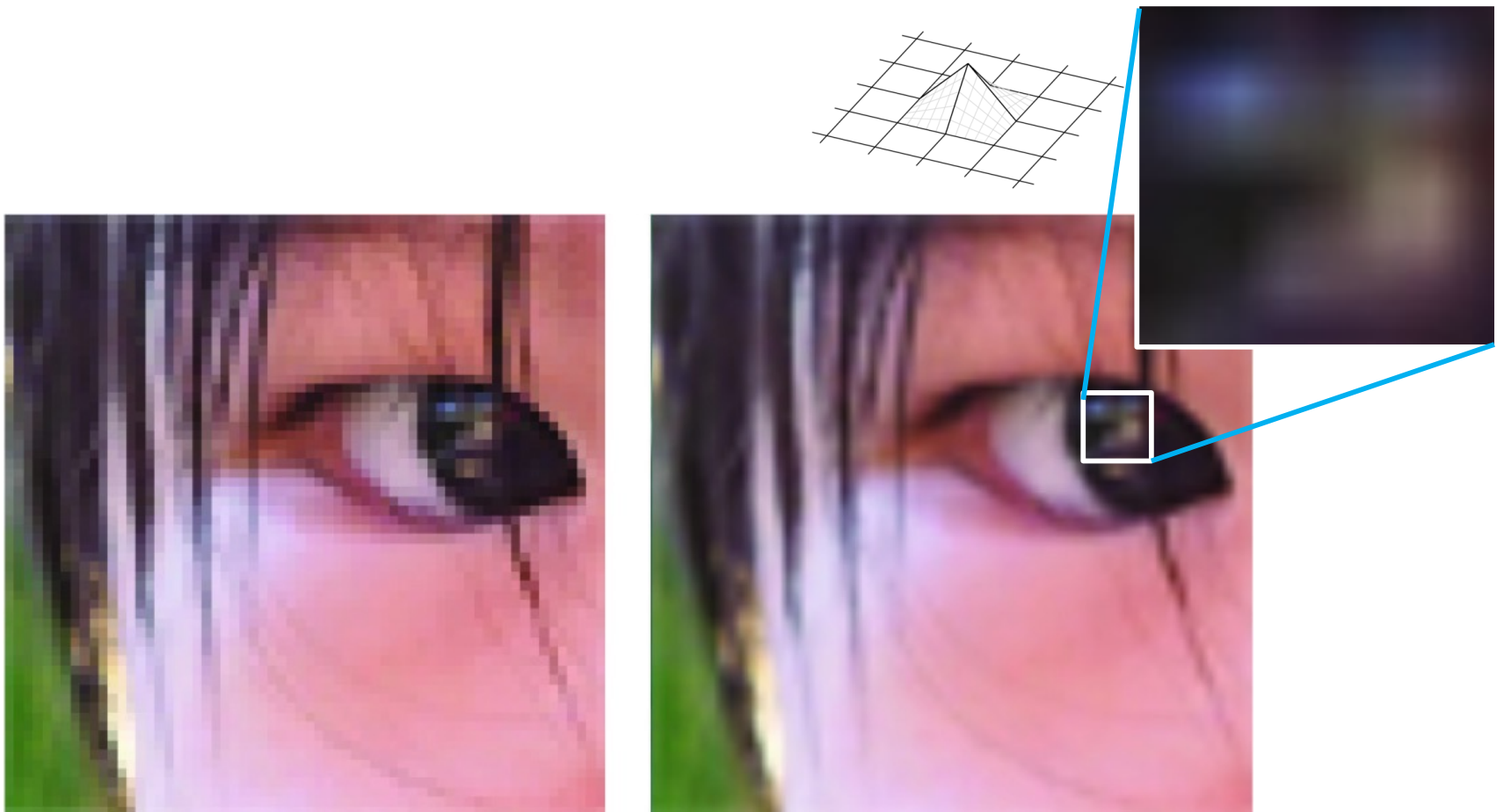
- Fourier transform of triangle filter is the  $\text{sinc}^2$  function,
  - so multiplying the signal's spectrum by it introduces high-frequency artifacts



[Image source](#)



# Bilinear interpolation closeup



[Image source](#)

# Why else should you care?

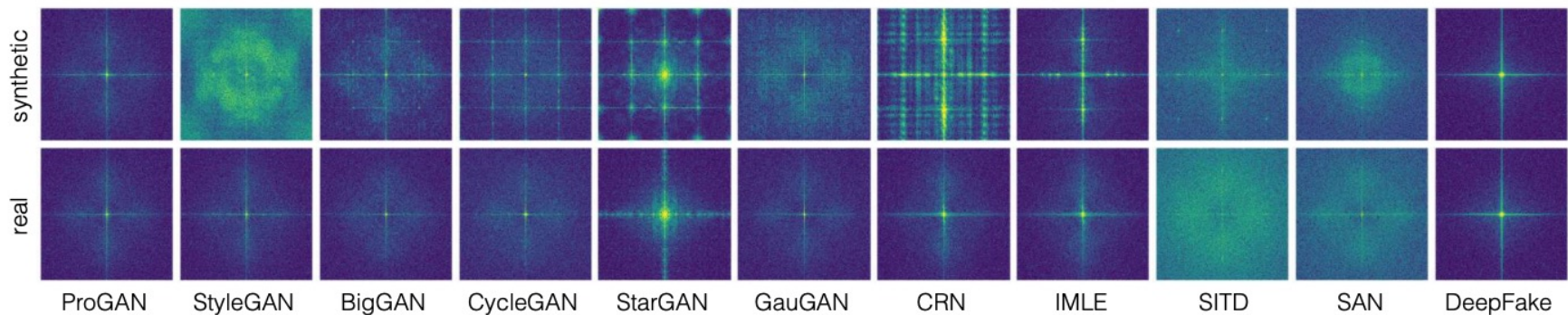
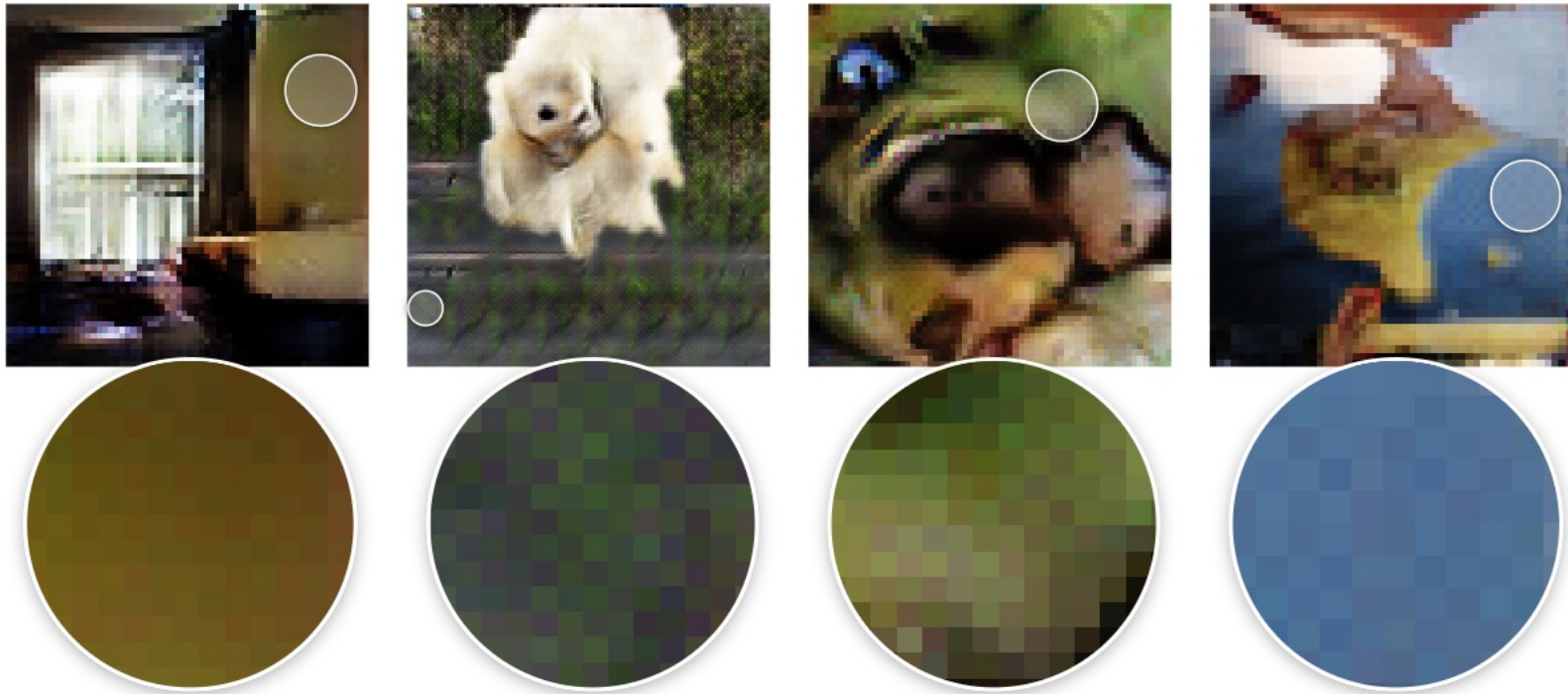


Figure 7: **Frequency analysis on each dataset.** We show the average spectra of each high-pass filtered image, for both the real and fake images, similar to Zhang *et al.* [50]. We observe periodic patterns (dots or lines) in most of the synthetic images, while BigGAN and ProGAN contains relatively few such artifacts.

# Why else should you care?

Checkerboard and repetition artifacts in GAN-generated images



Radford, et al., 2015 [1]

Salimans et al., 2016 [2]

Donahue, et al., 2016 [3]

Dumoulin, et al., 2016 [4]

<https://distill.pub/2016/deconv-checkerboard/>

# Things to think about...

**12.7.** Check that  $\int g(u) \text{sample}_{2D}(f) du = \sum_{ij} f(i, j)g(i, j)$ .

**12.8.** Section 22.6 has: "This definition yields a model which behaves well for integrals. In particular,

$$\int g(u) \text{sample}_{2D}(f) du = \sum_{ij} f(i, j)g(i, j)$$

which is the best approximation to the integral that you will get if you know  $f(u, v)$  only at integer points." Explain.

**12.9.** Write an expression for what you would get if you convolve  $\text{sample}_{2D}(\mathcal{I})$  with  $g(x, y)$ , then sample the result.

**12.10.** Write an expression for what you would get if you convolve  $\mathcal{I}$  with  $\text{sample}_{2D}(g)$ , then sample the result.

**12.11.** Section 12.2.3 has: "convolving a function with a shifted  $\delta$ -function merely shifts the function". Show this is true.

**12.12.** Section 12.2.4 has: "If the sampled image is downsampled by two, for example, the copies now have centers on the half-integer points in  $u, v$  space." Explain.