THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision

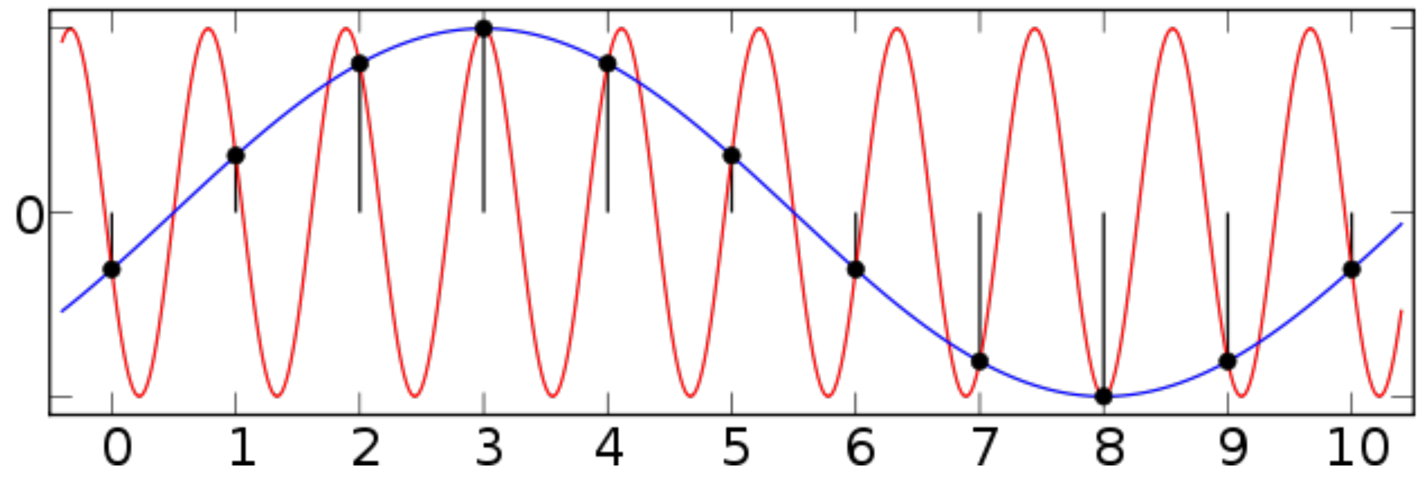


Image Credit: https://en.wikibooks.org/wiki/Analog_and_Digital_Conversion/Nyquist_Sampling_Rate

Lecture 6: Sampling

(unless otherwise stated slides are taken or adopted from **Bob Woodham, Jim Little** and **Fred Tung**)

Menu for Today

Topics:

- **Sampling** theory
- **Nyquist** rate
- Color **Filter Arrays**
- **Image** encoding

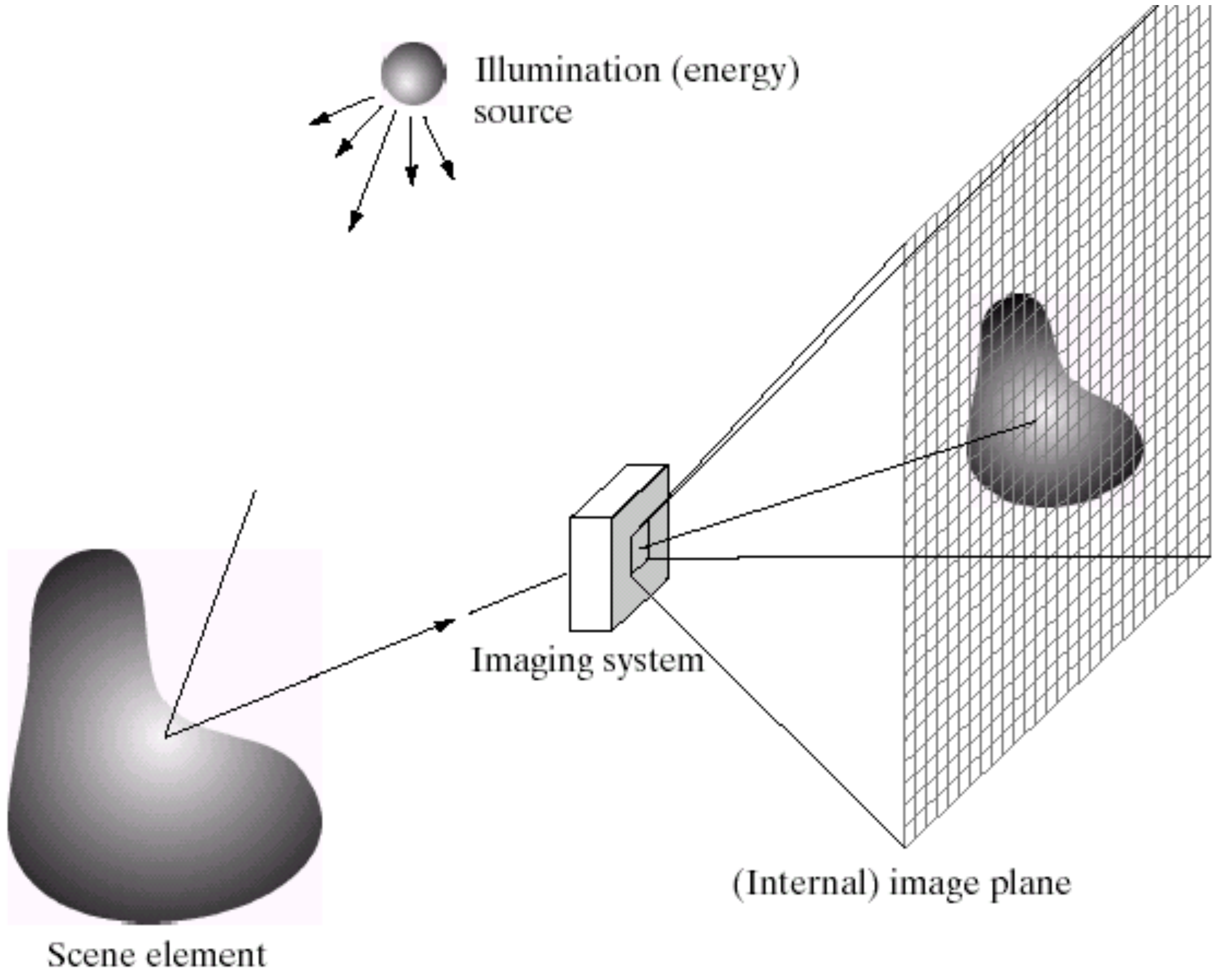
Readings:

- **Today's** Lecture: Szeliski 2.3, Forsyth & Ponce (2nd ed.) 4.5, 4.6

Reminders:

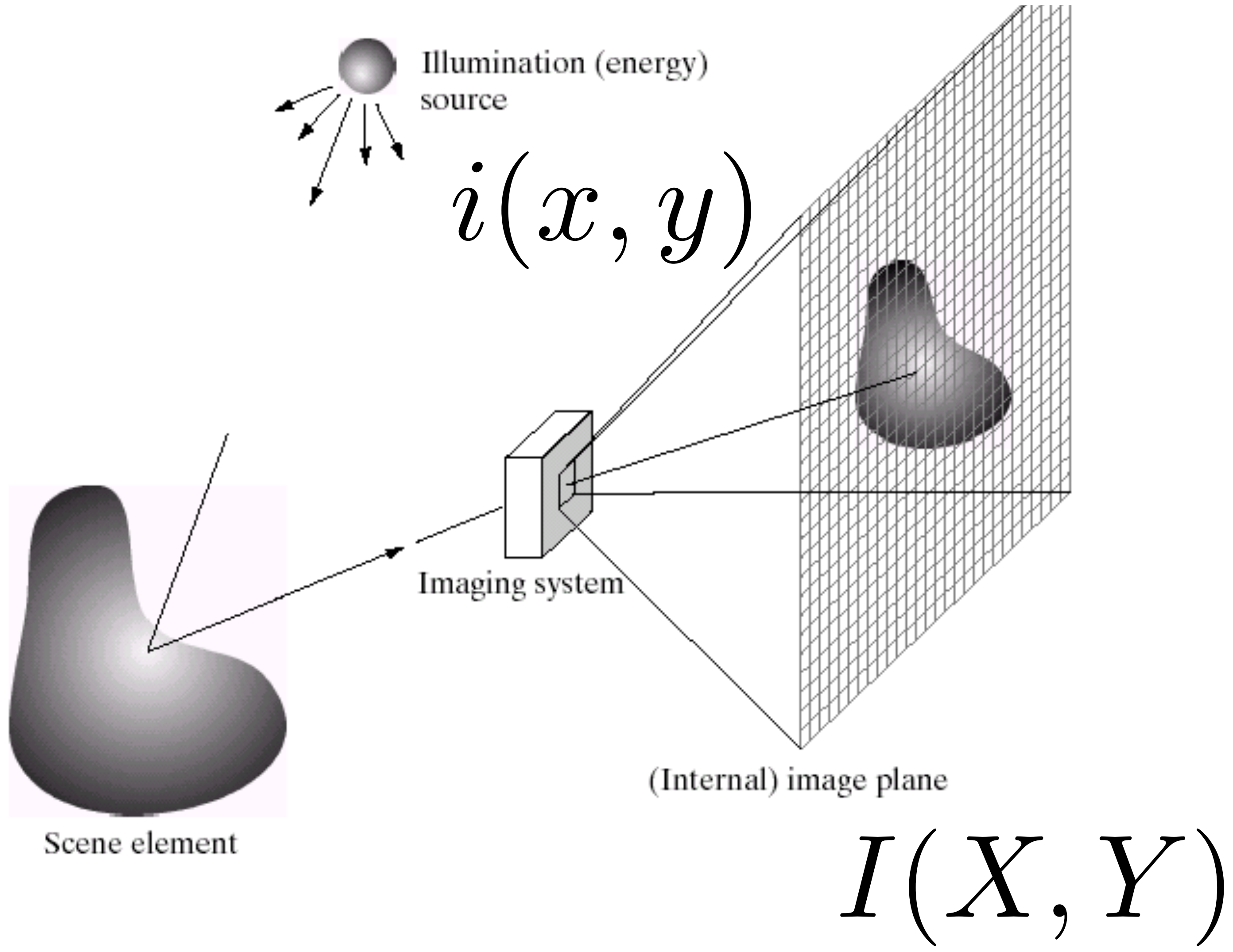
- **Assignment 1:** Image Filtering and Hybrid Images due **December 30th**

Reminder



Images are a **discrete**, or **sampled**, representation of a continuous world

What is **Sampling**?



A **continuous function** $i(x, y, \lambda)$ is presented at the image sensor at each time instant

How do we convert this to a **digital signal** (array of numbers) $I(x, y, \lambda)$?

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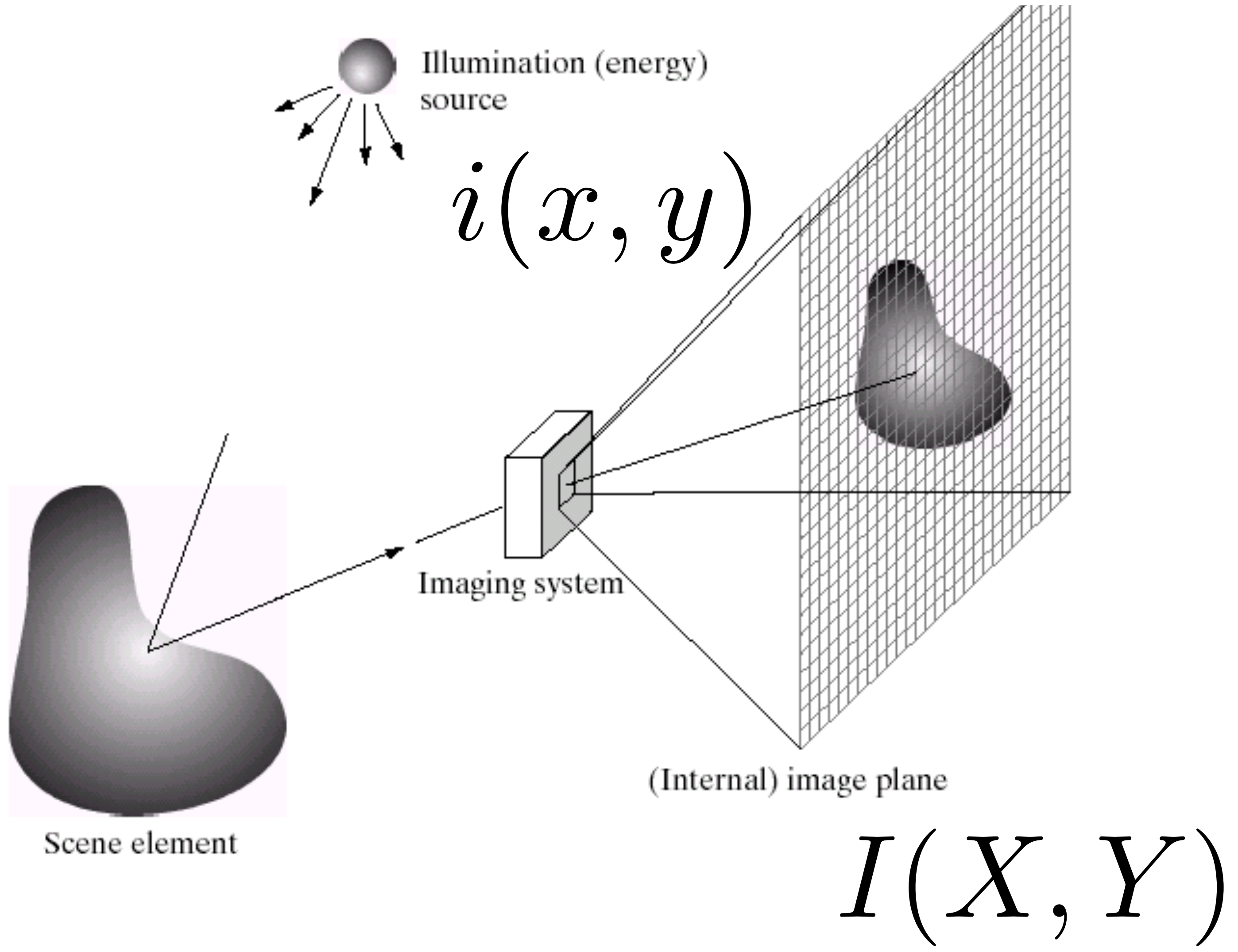


A **continuous function** $i(x, y, \lambda)$ is presented at the image sensor at each time instant

How do we convert this to a **digital signal** (array of numbers) $I(x, y, \lambda)$?

How can we **manipulate**, e.g., resample, this digital signal correctly?

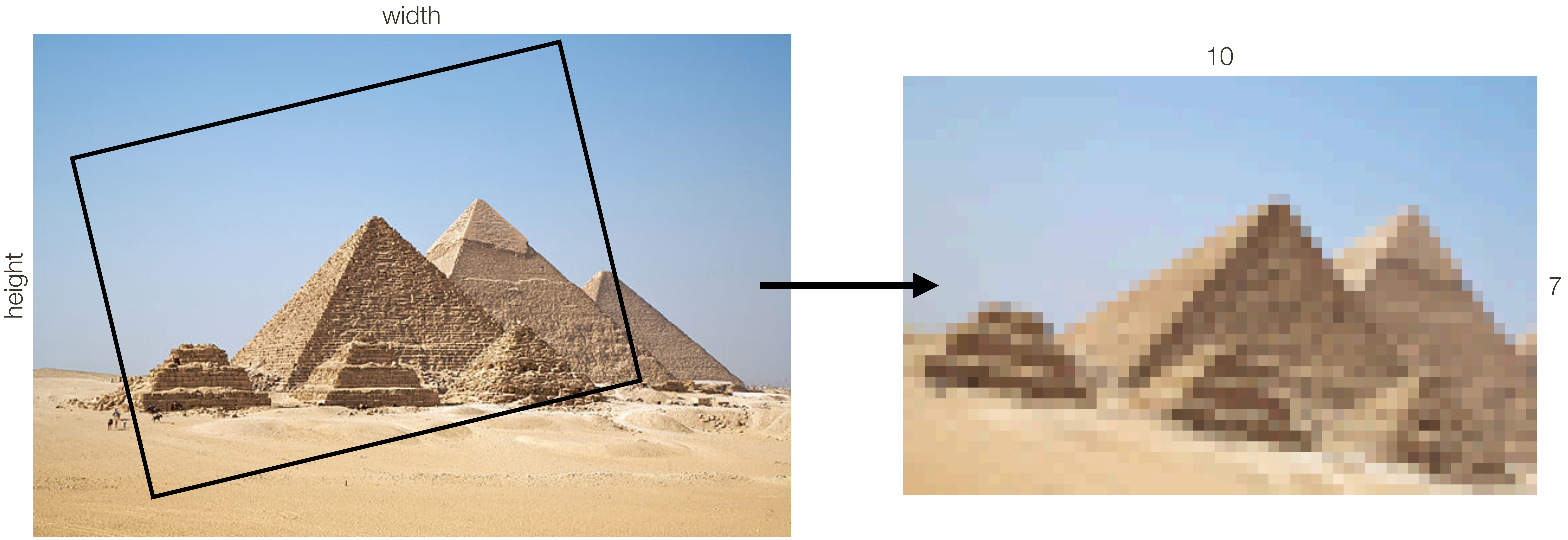
Resampling Images

width

height

Resampling Images

Resampling Images



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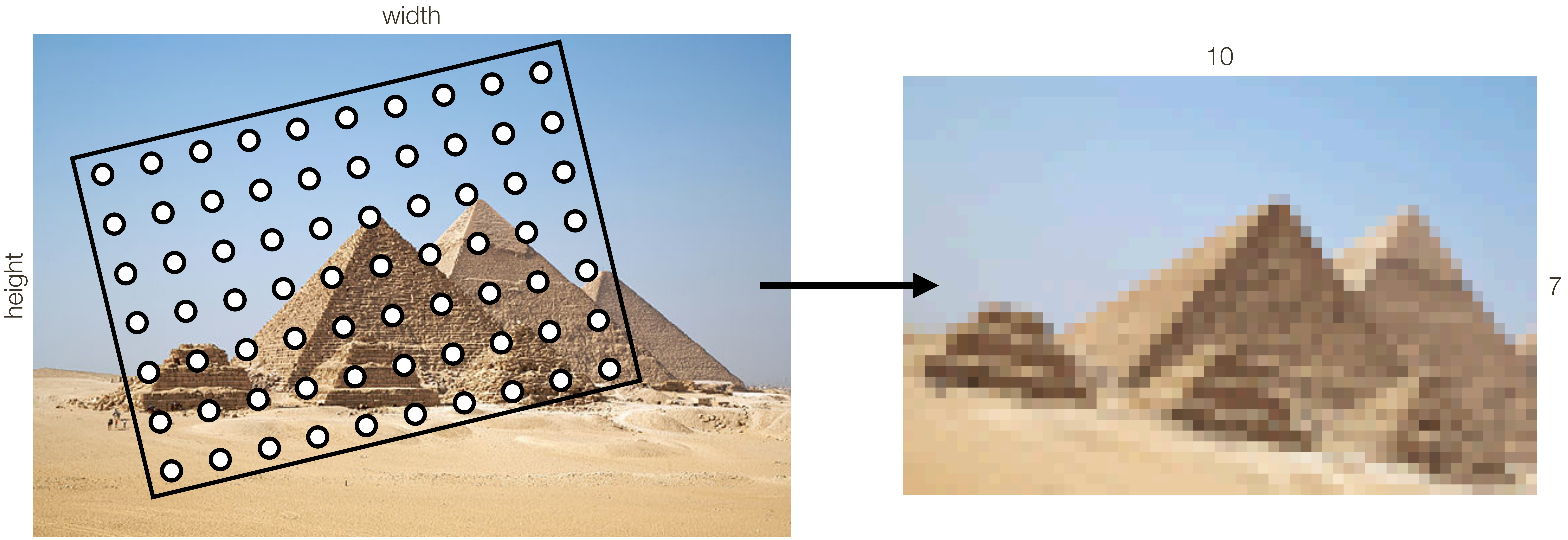

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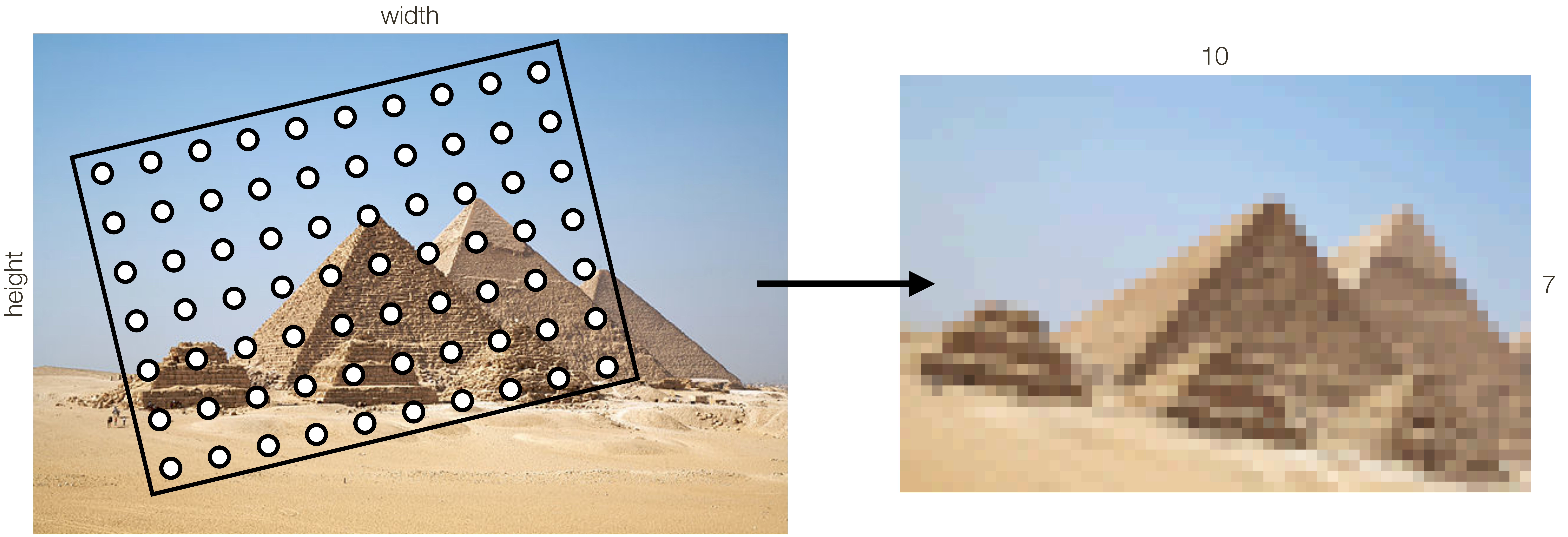
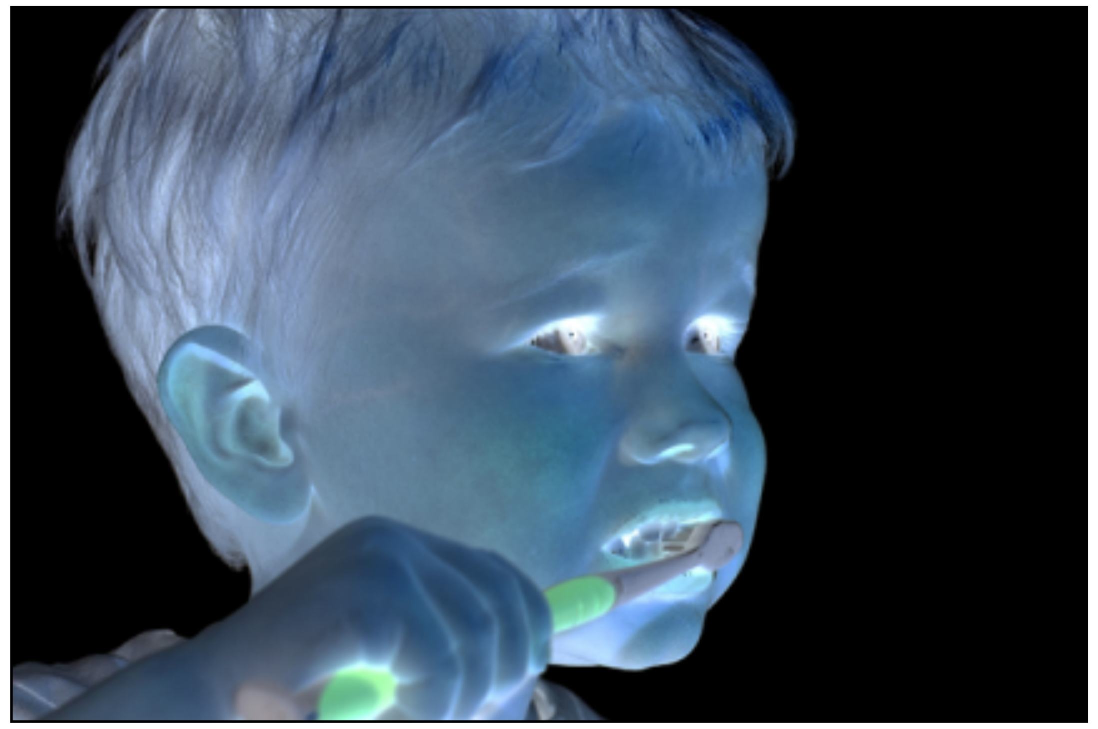


How do we correctly **generate samples** to resample or warp an image?

What types of **transformations** can we do?

$I(X, Y)$

Filtering

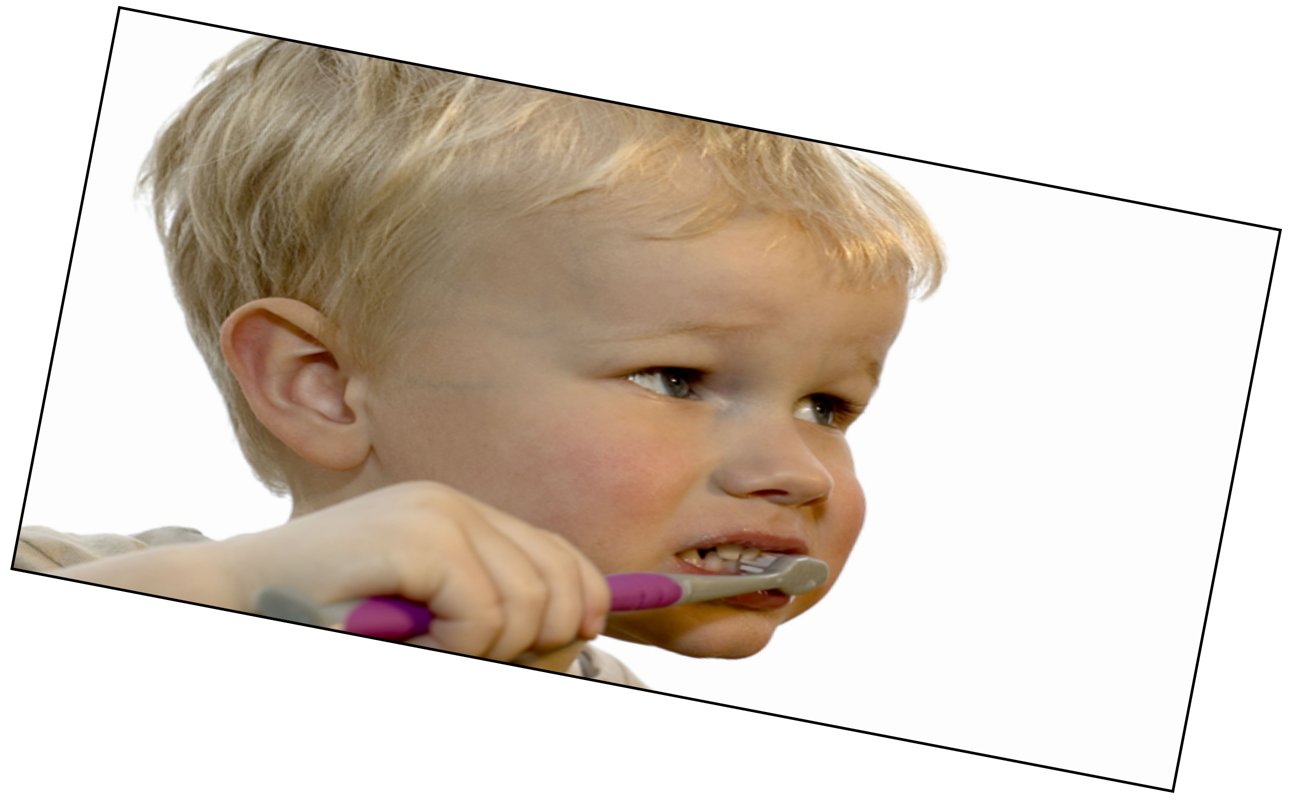


$I'(X, Y)$

changes range of image function

$I(X, Y)$

Warping



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Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

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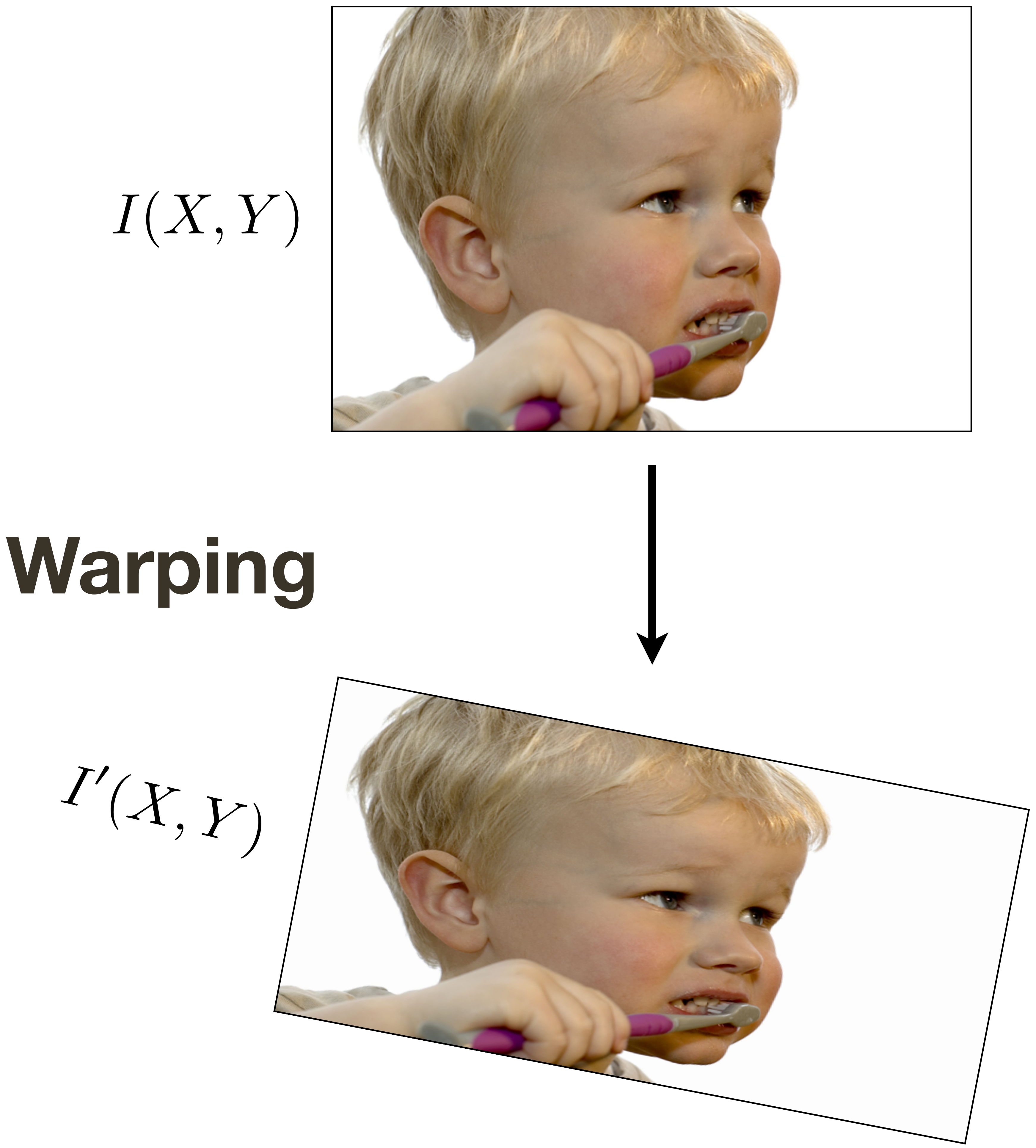

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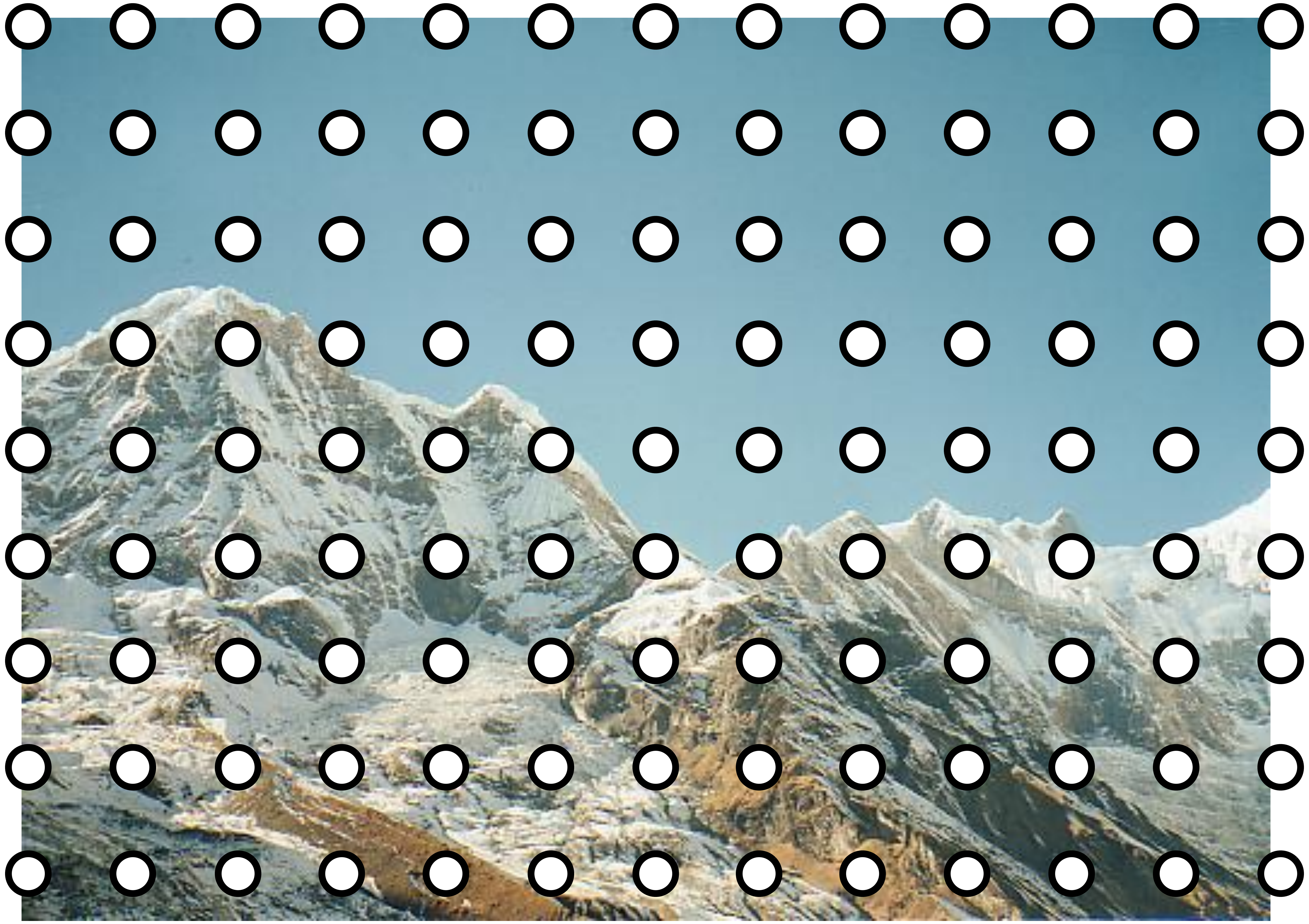
Resampling Images

Goal: Resample the image to get a lower resolution counterpart



What is the simplest way to do this (e.g., produce image 1/5 of original size)?

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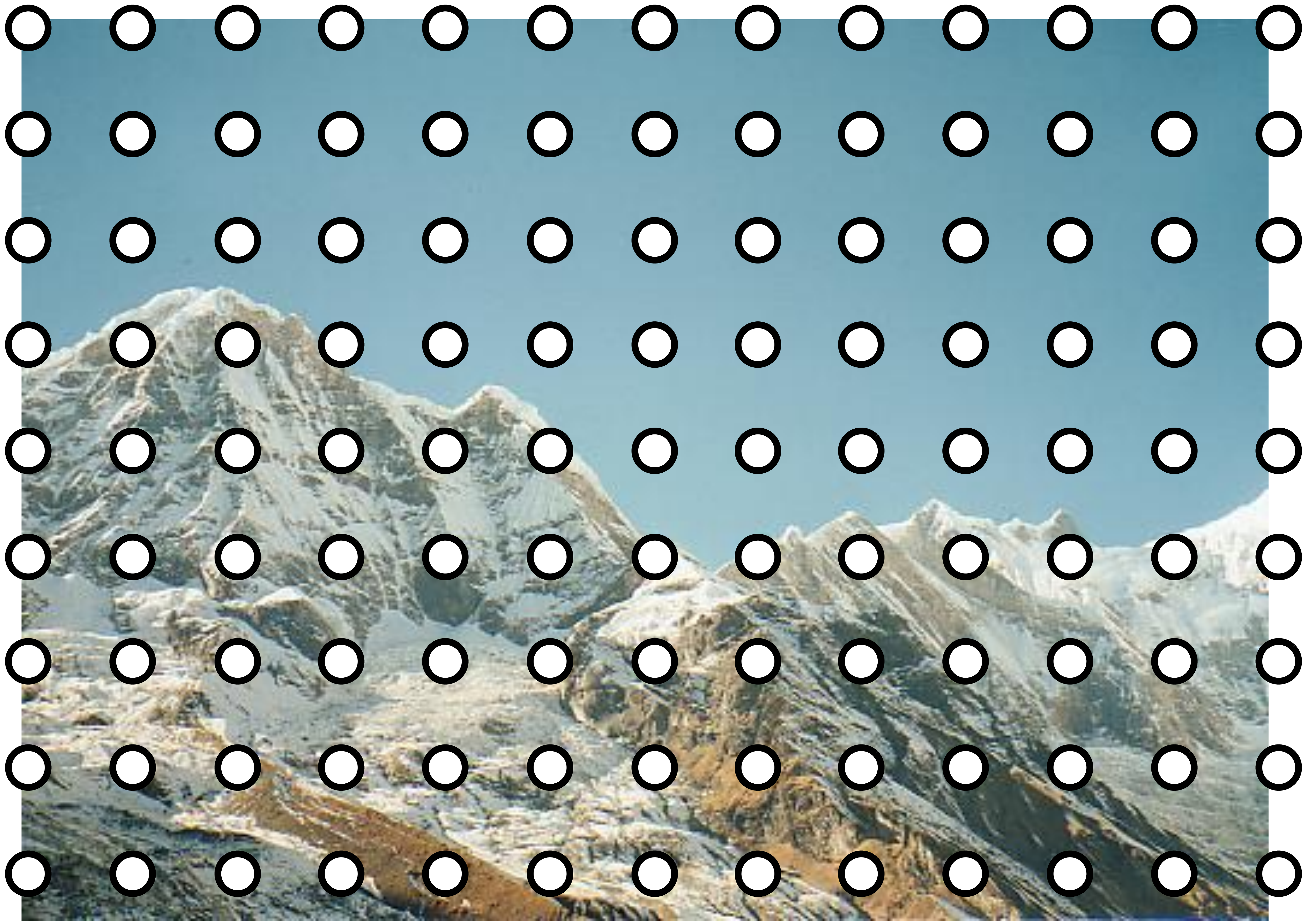

Naive Method: Form new image by taking every n-th pixel of the original image

Resampling Images

Sampling every 5-th pixel, while shifting rightwards one pixel at a time

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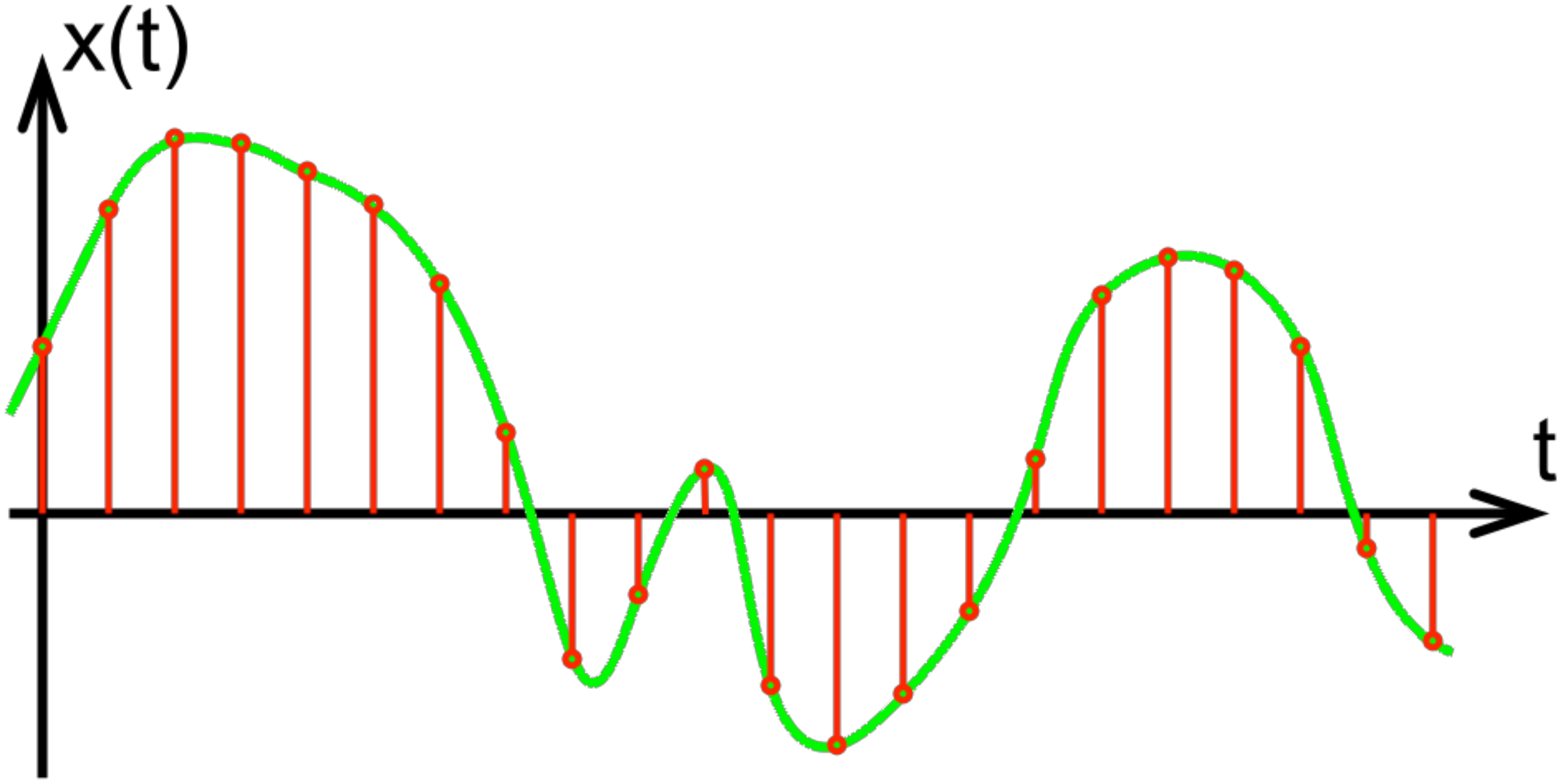
What's wrong with this method?

Example: Audio Sampling



Question: What choice/parameters do we have when sampling audio signal?

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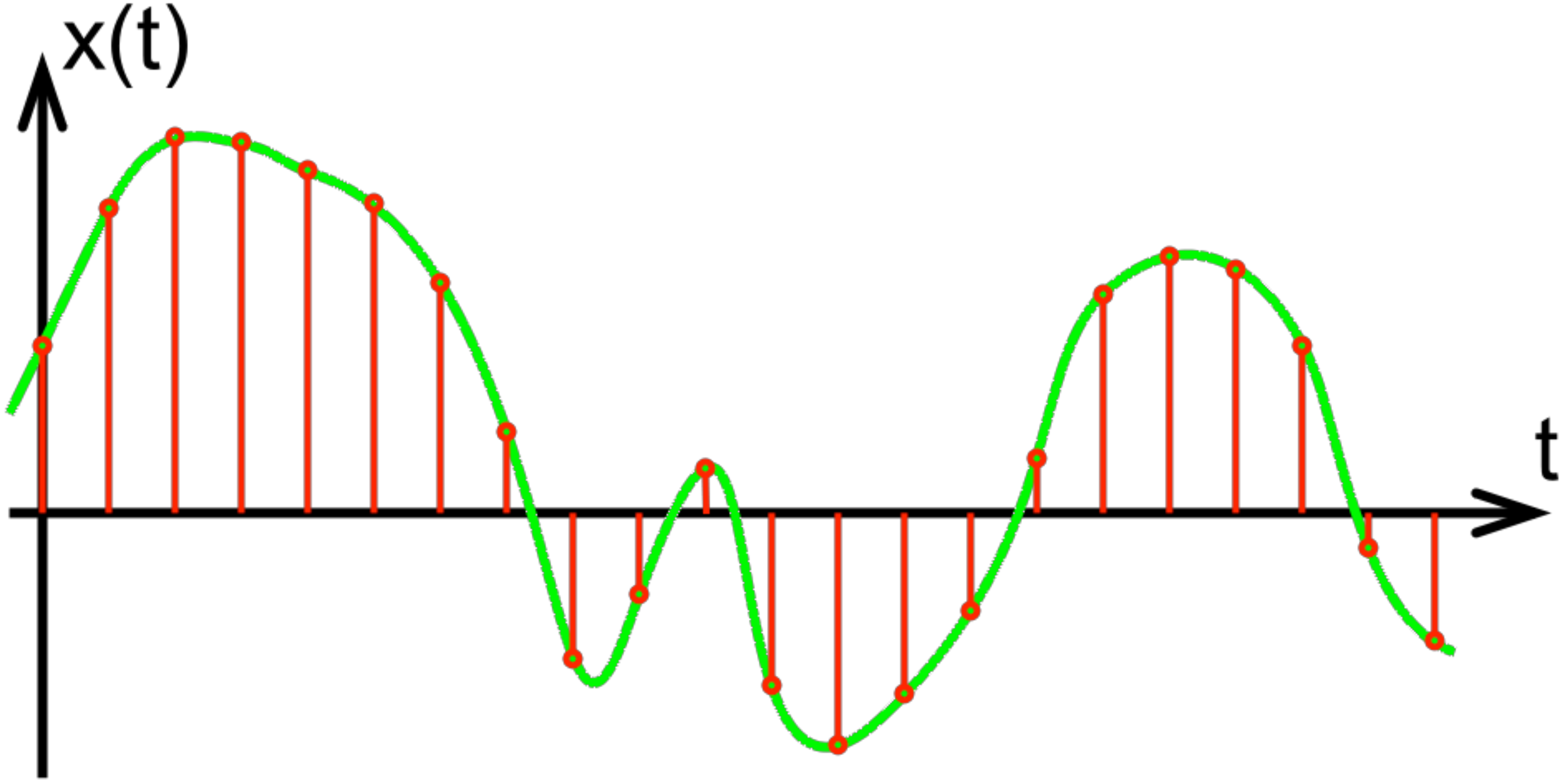
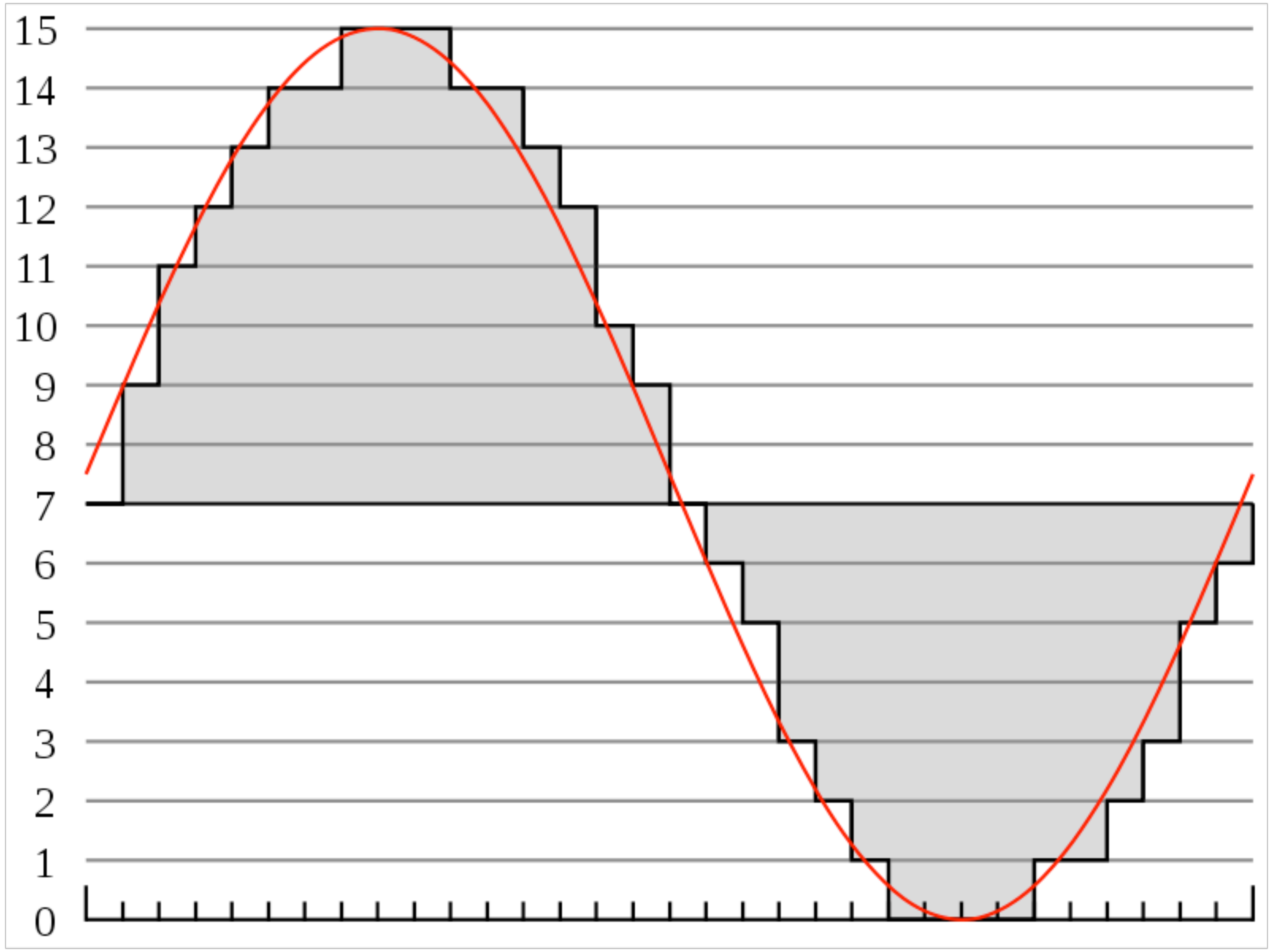


Question: What choice/parameters do we have when sampling audio signal?

Sampling rate and bit depth, e.g., 44.1 kHz (samples/second), 16 bits/sample

Example: Audio Sampling



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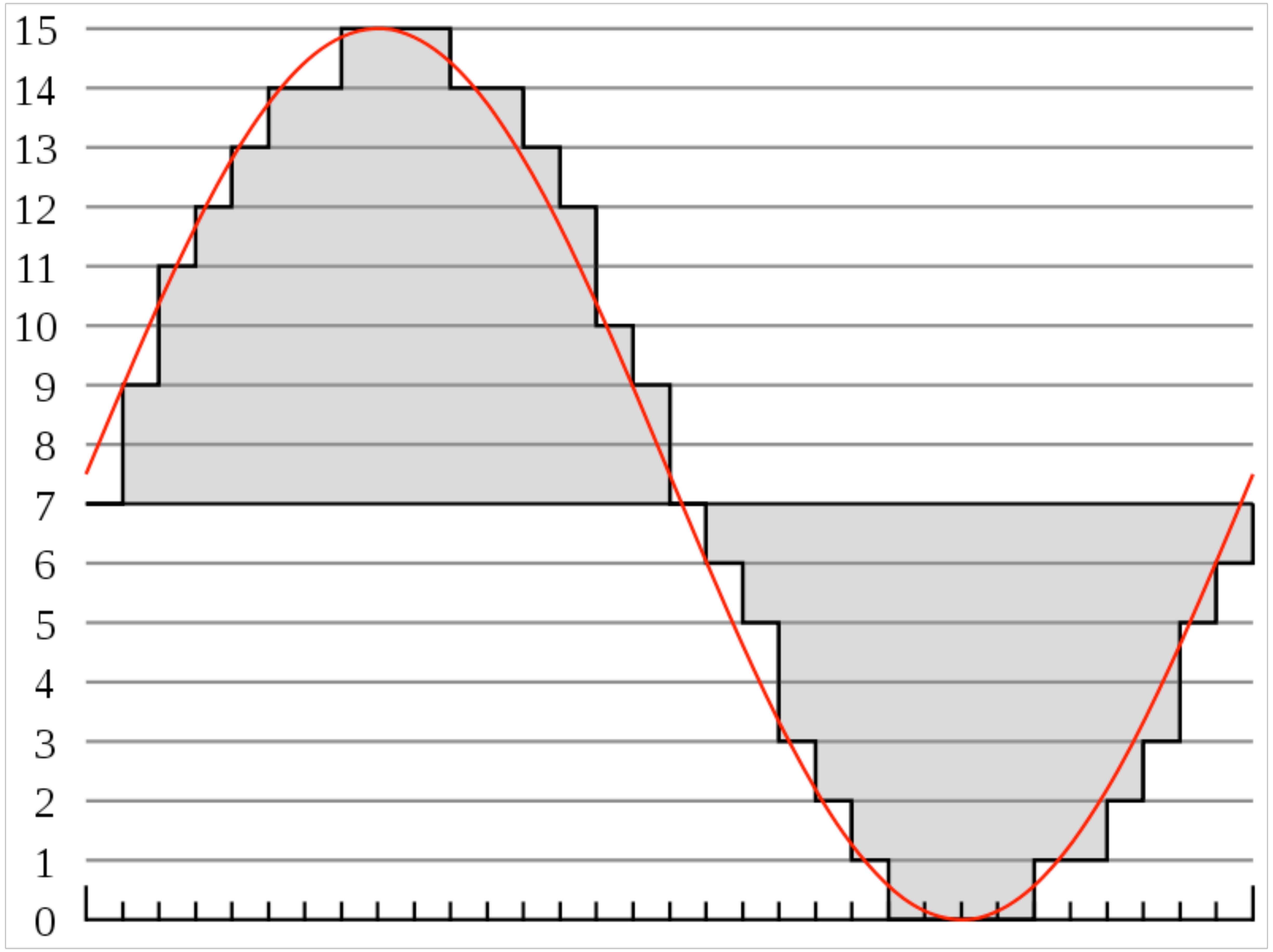

Quantization noise / error is the difference between black and red curves

Audio **Aliasing**

- Aliasing causes undesirable artifacts in audio reproduction
- e.g., if we take an audio signal and simply drop every second sample, the highest frequencies will be aliased… we hear robotic sounding distortion

```
import scipy.io.wavfile as wavfile

rate, signal = wavfile.read("stevie.wav")

data=signal[0:(rate*10),:] # 10 seconds of audio

data_2=data[0:-1:2,:] # select every 2nd sample
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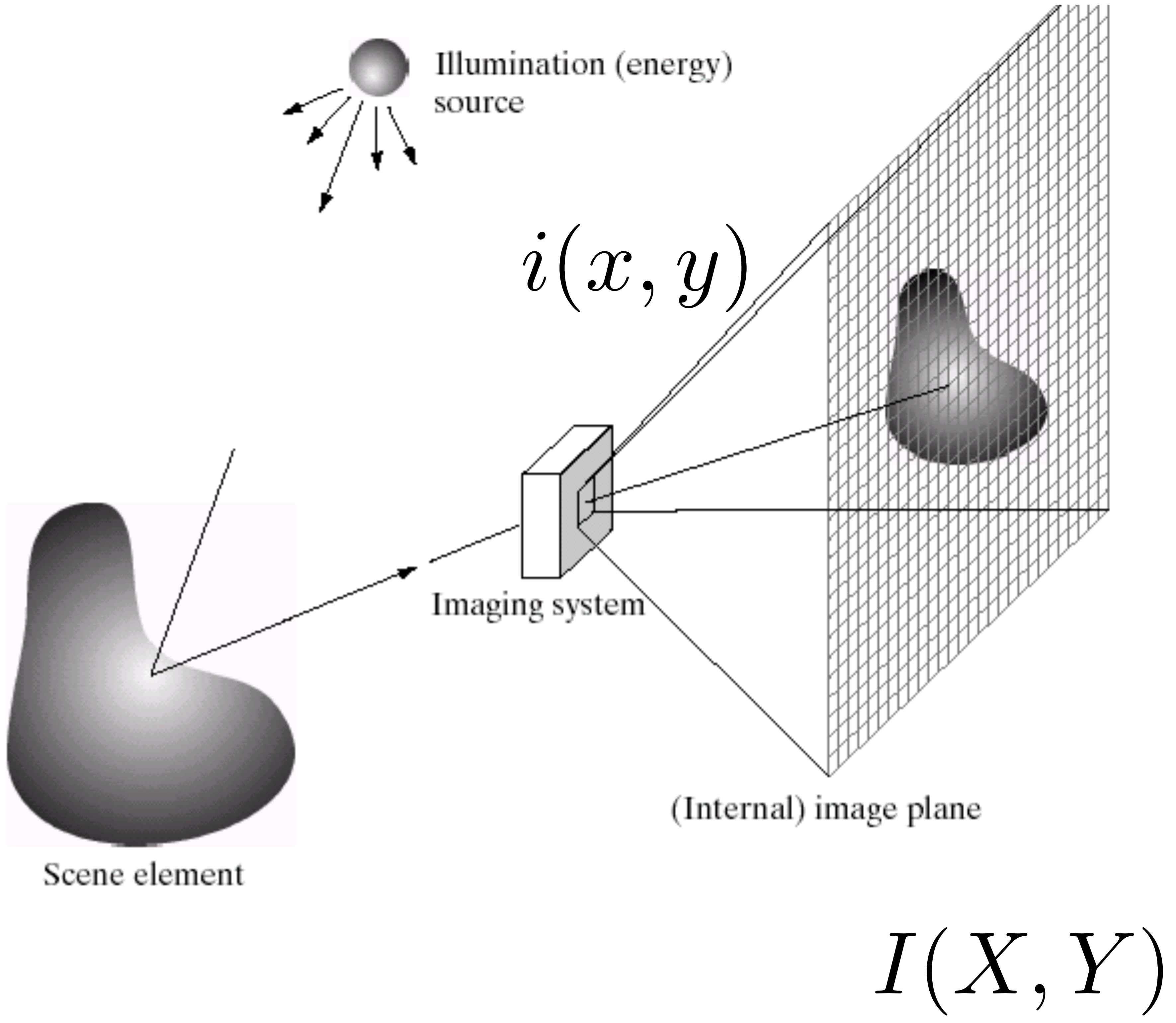
Example: Image Sampling



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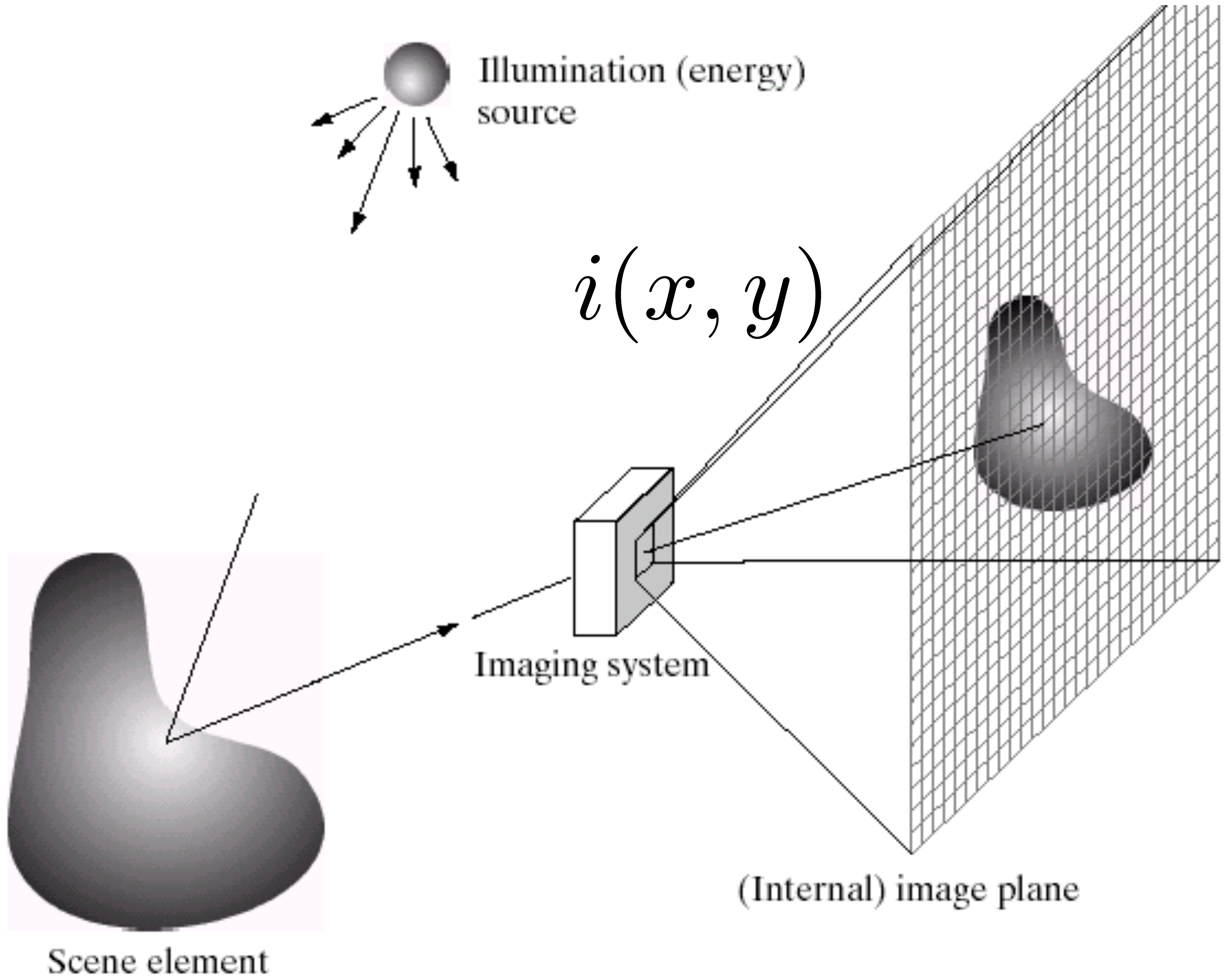

$I(X, Y)$

Sampling rate and bit depth (e.g., 8-bits)

Continuous Case: Observations

– $i(x, y)$ is a **real-valued function** of **real spatial variables**, x and y

– $i(x, y)$ is **bounded above and below**. That is

$$0 \leq i(x, y) \leq M$$

for some maximum brightness M

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- $i(x, y)$ is **bounded above and below**. That is

$$0 \leq i(x, y) \leq M$$

  for some maximum brightness M

- $i(x, y)$ is **bounded in extent**. That is, $i(x, y)$ is non-zero (i.e., strictly positive) over, at most, a bounded region

Pixel Bit Rate

Recall: $0 \leq i(x, y) \leq M$

We divide the range $[0, M]$ into a finite number of equivalence classes. This is called **quantization**.

The values are called **grey-levels**.

Suppose n bits-per-pixel are available. One can divide the range $[0, M]$ into evenly spaced intervals.

Typically $n = 8$ resulting in grey-levels in the range $[0, 255]$

Sampling Theory (informal)

Question: When is $I(X, Y)$ an exact characterization of $i(x, y)$?

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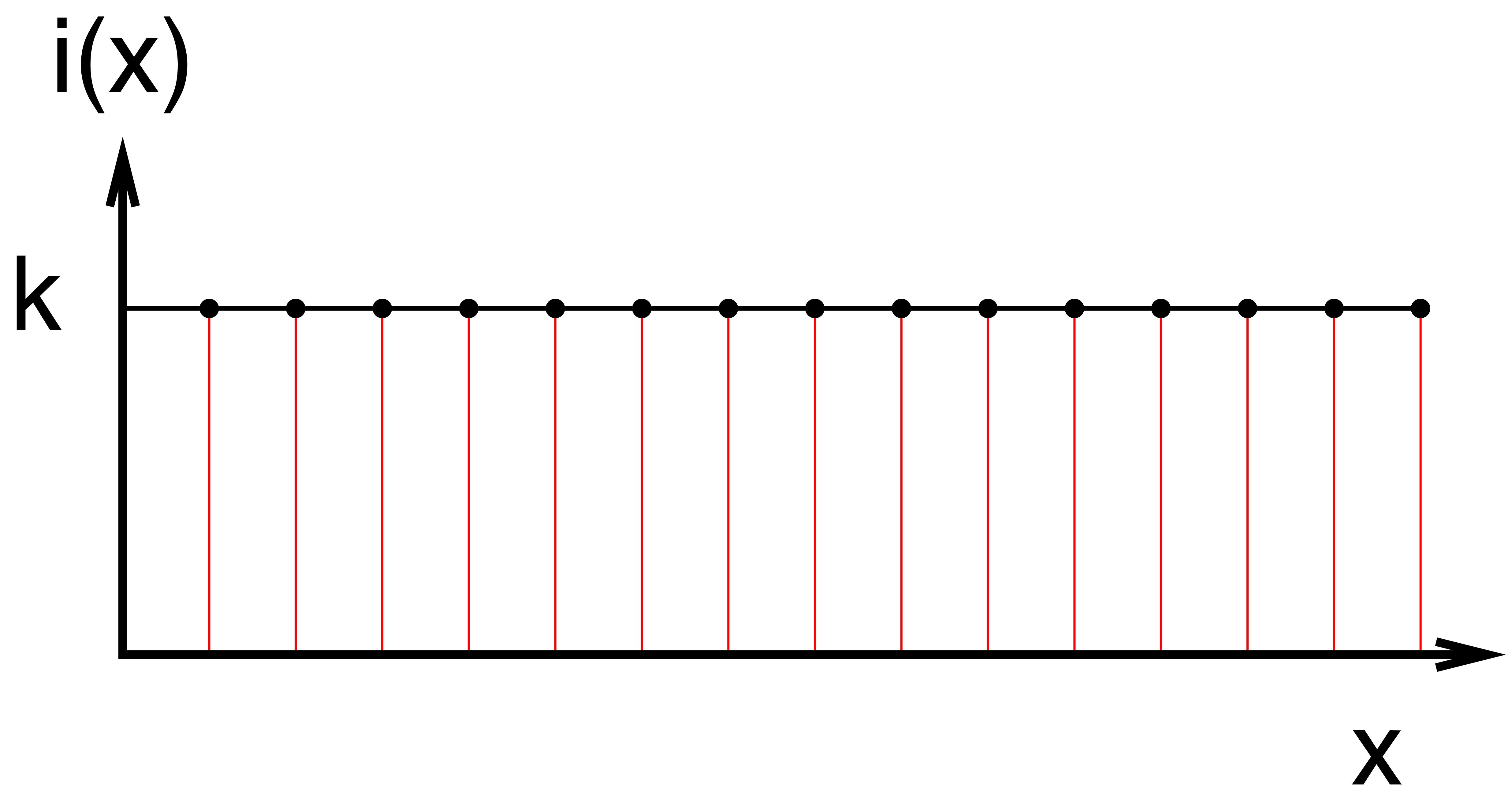
Intuition: Reconstruction involves some kind of **interpolation**

Heuristic: When in doubt, consider simple cases

Sampling Theory (informal)

Case 0: Suppose $i(x, y) = k$ (with k being one of our gray levels)

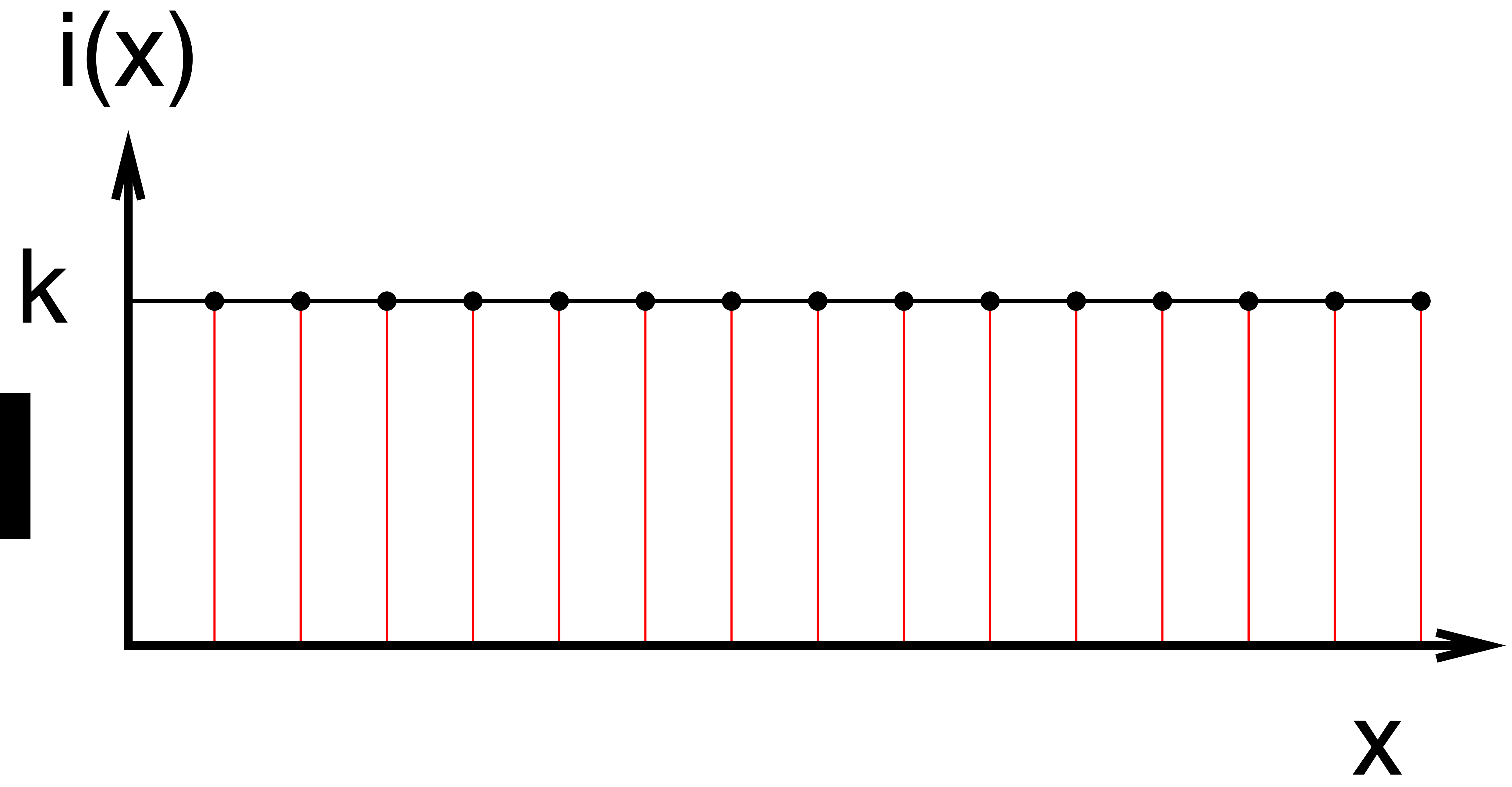


Note: we use equidistant sampling at integer values for convenience, in general, sampling doesn't need to be equidistant

Sampling Theory (informal)

Case 0: Suppose $i(x, y) = k$ (with k being one of our gray levels)

This is **easy**!



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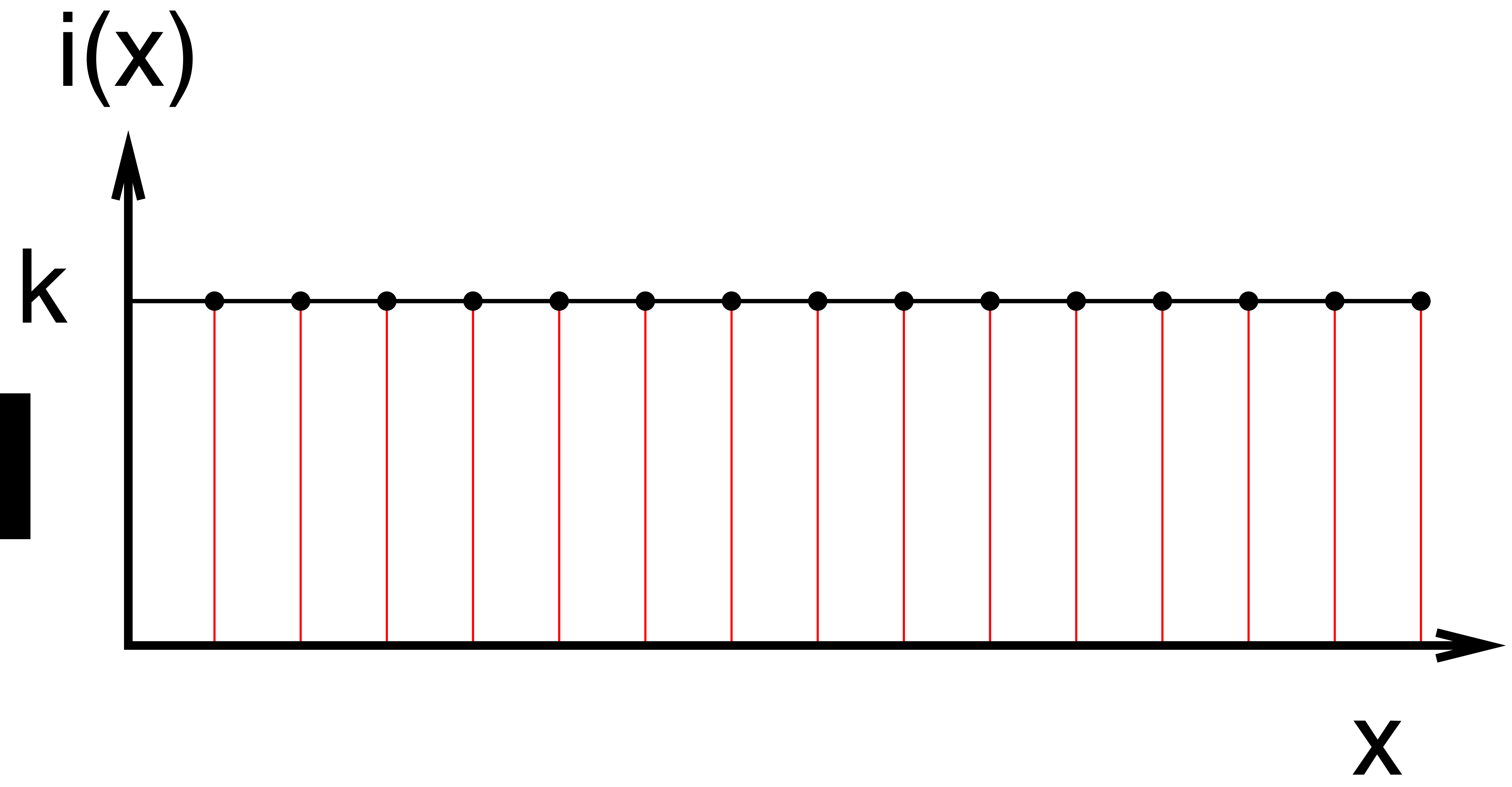
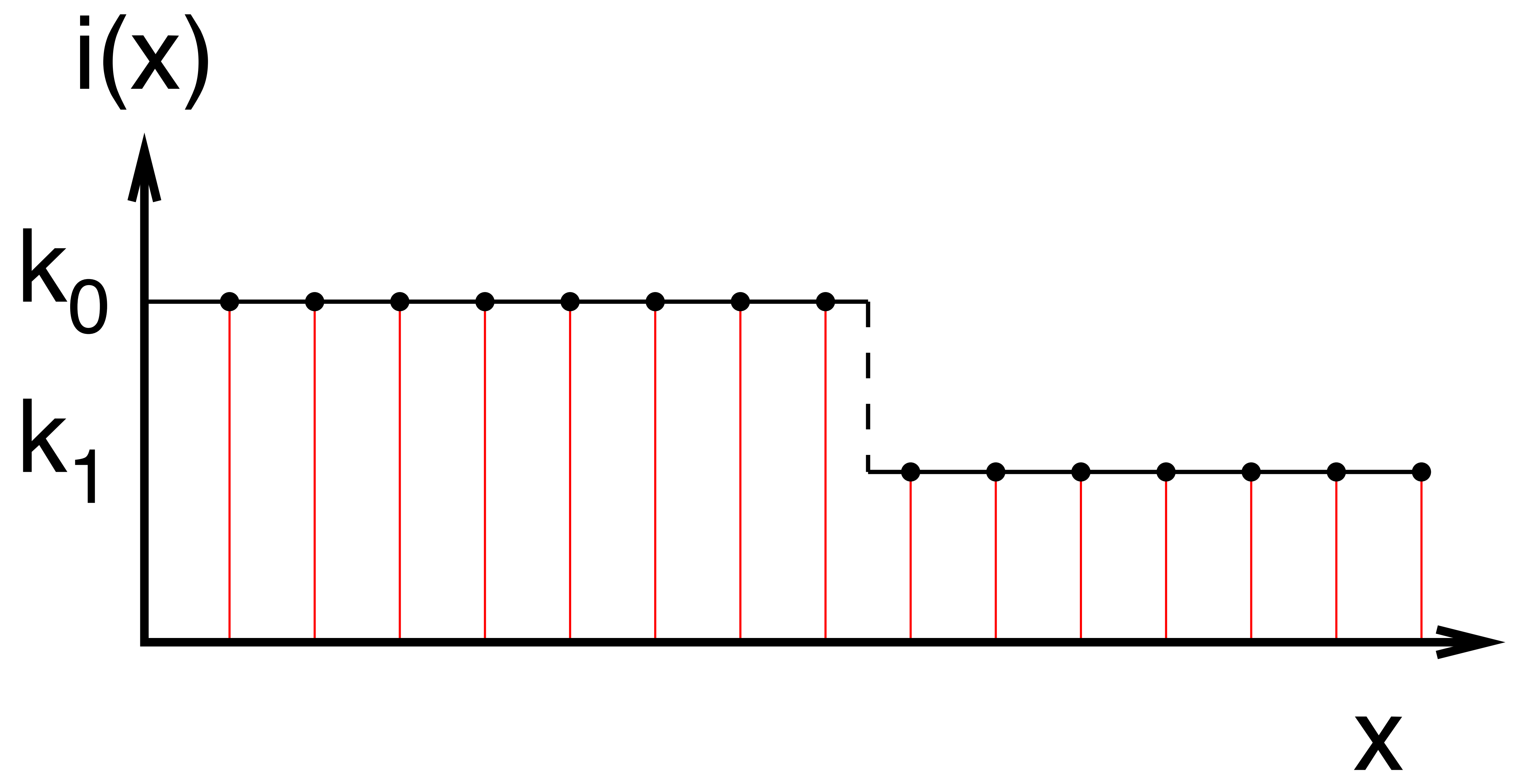


$I(X, Y) = k$. Any standard interpolation function would give $i(x, y) = k$ for non-integer x and y (irrespective oh how coarse the sampling is)

Sampling Theory (informal)

Case 1: Suppose $i(x, y)$ has a discontinuity not falling precisely at integer x, y



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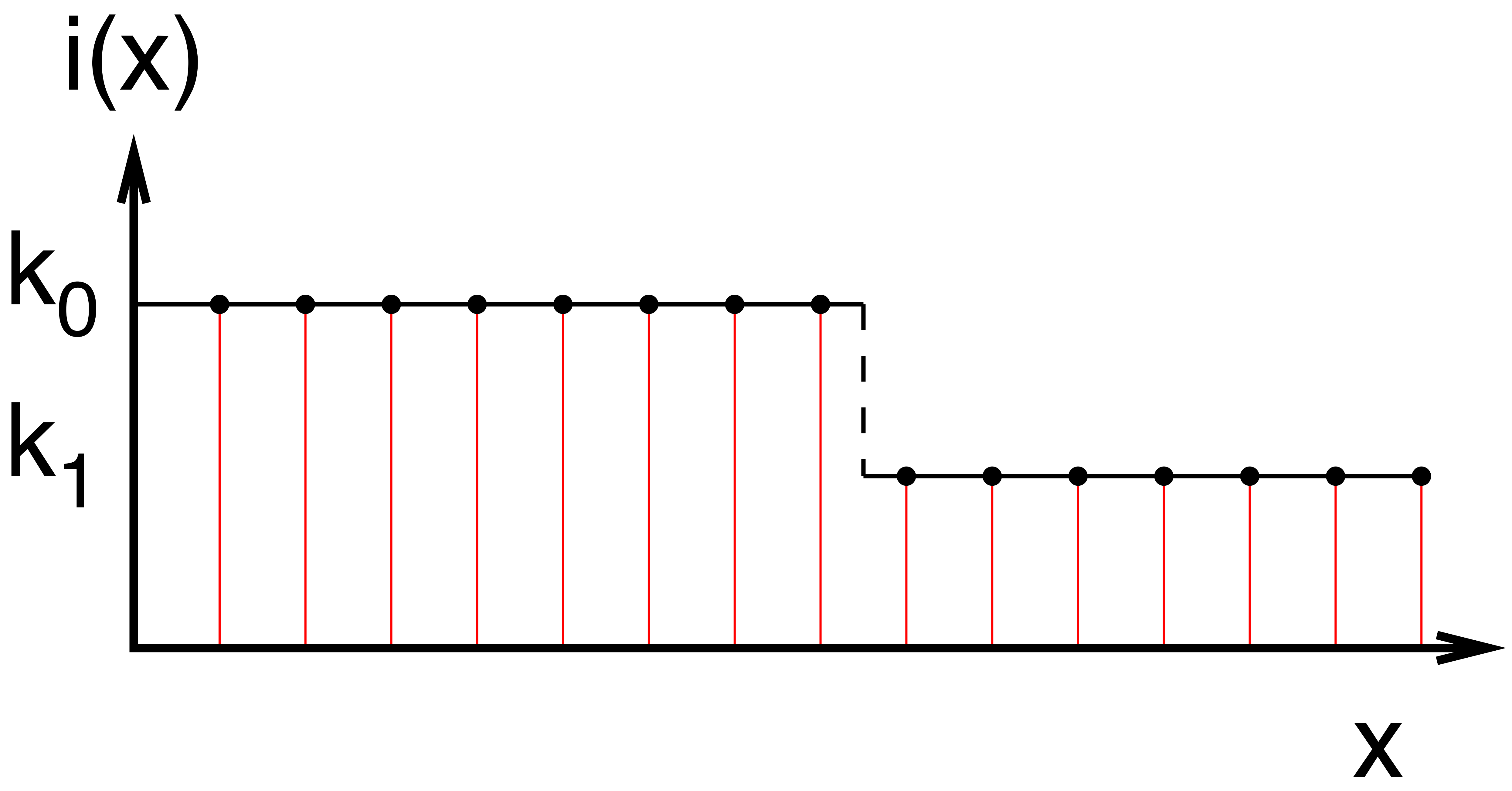

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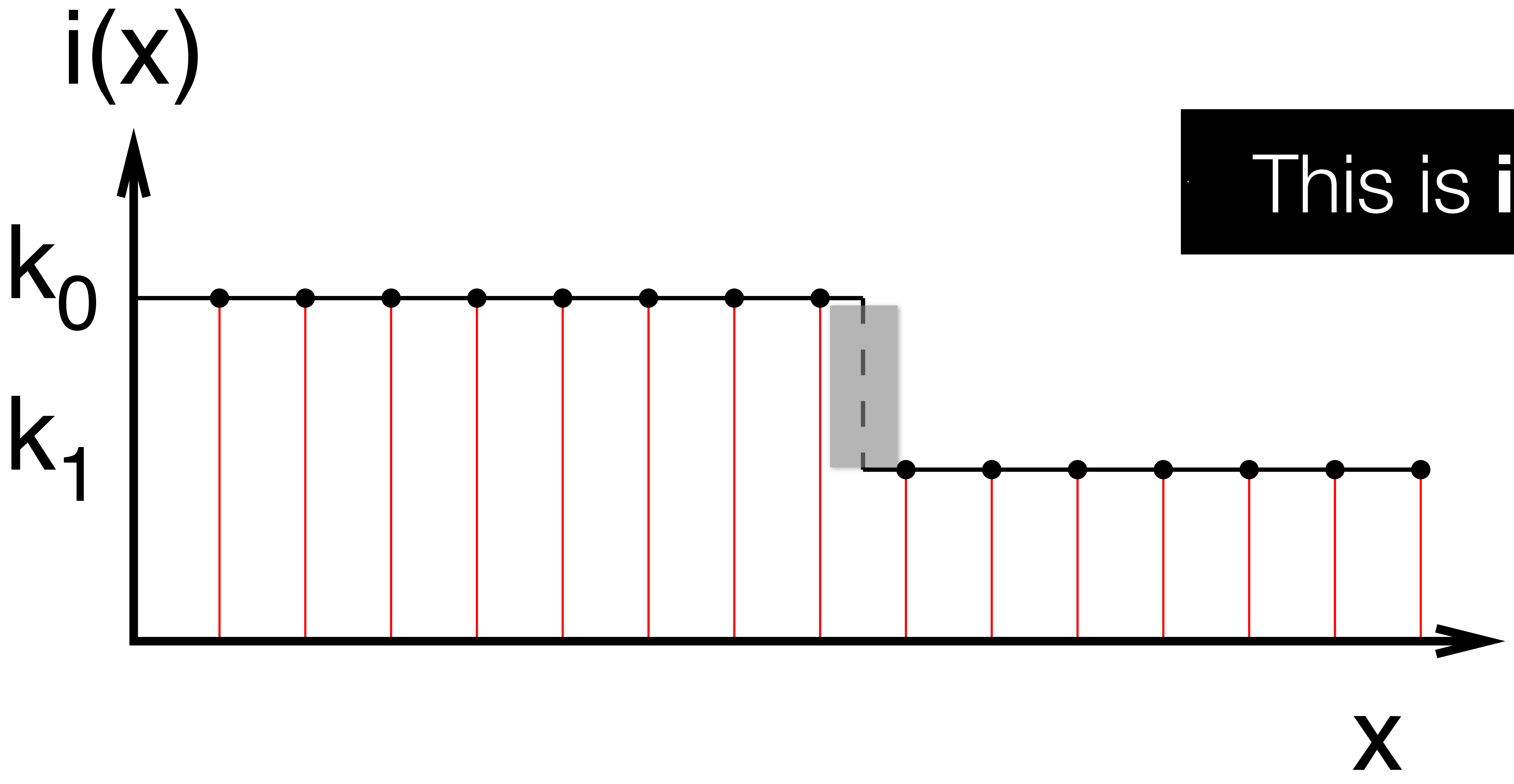


This is **impossible**!

We cannot reconstruct $i(x, y)$ exactly because we can never know exactly where the discontinuity lies

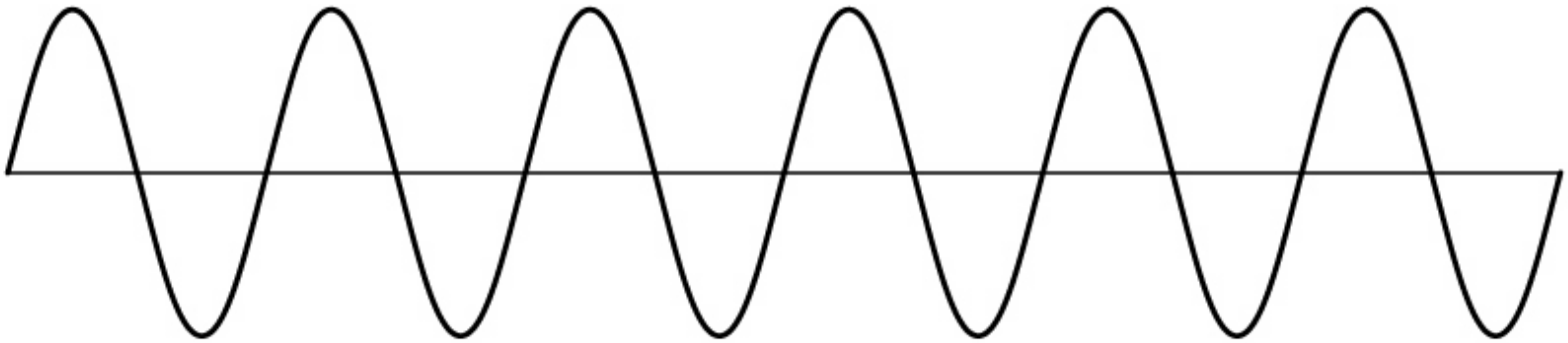
Sampling Theory (informal)

Question: How do we close the gap between “**easy**” and “**impossible**?”

Next, we build intuition based on informal argument

Example: A Simple Sine Wave

How do we discretize the signal?



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

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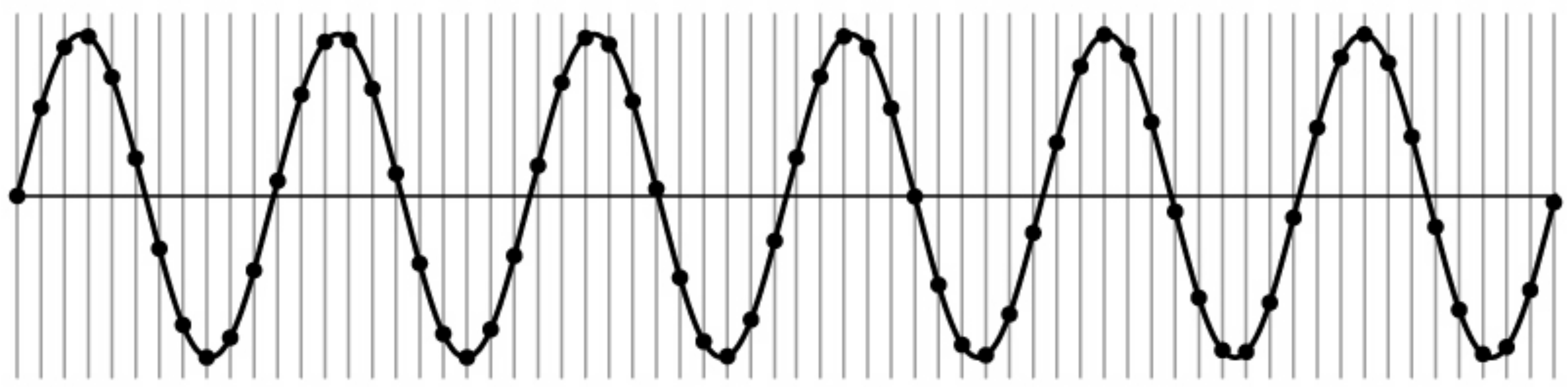

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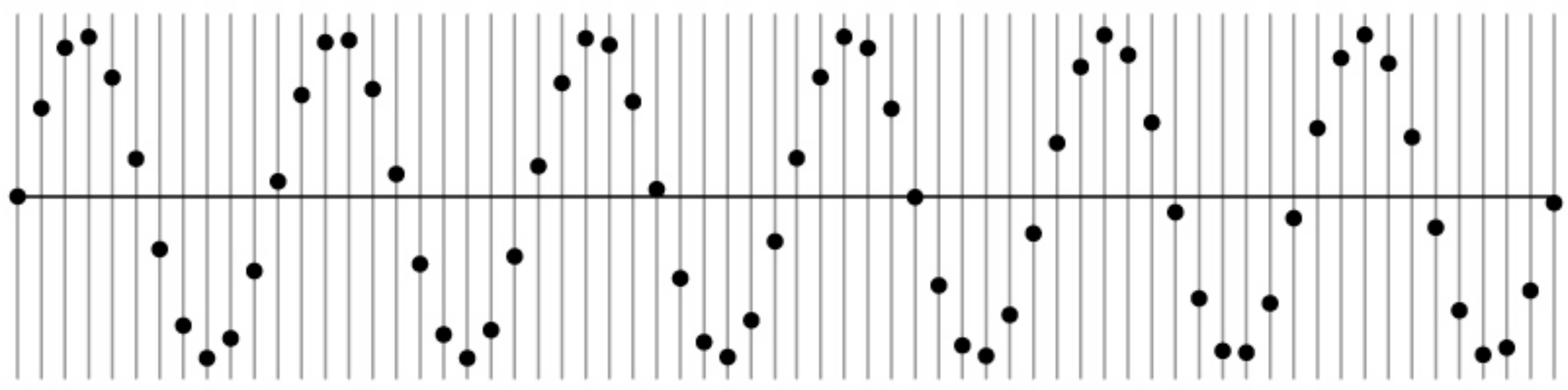

How many samples should I take?

Can I take as many samples as I want?

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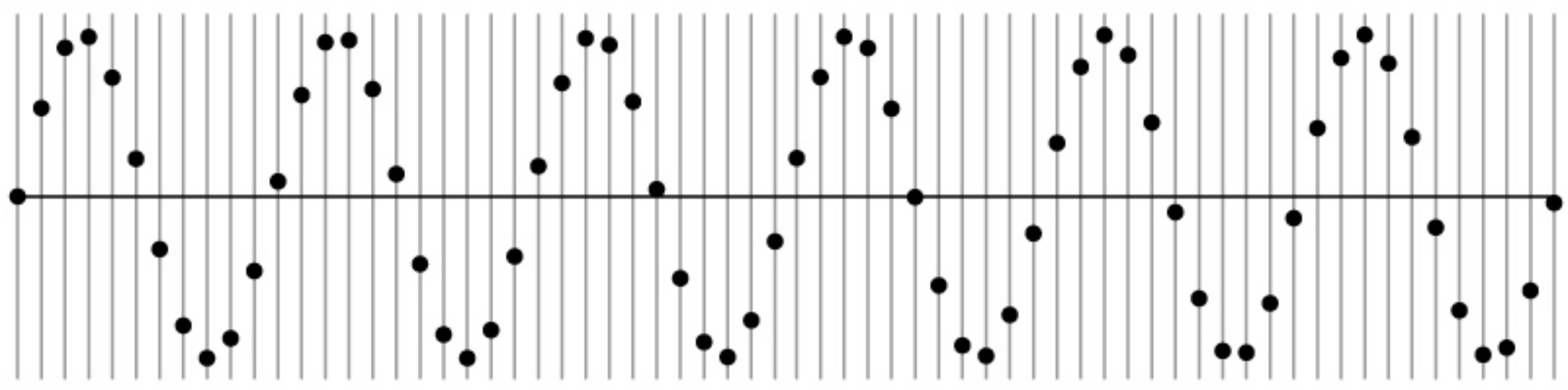

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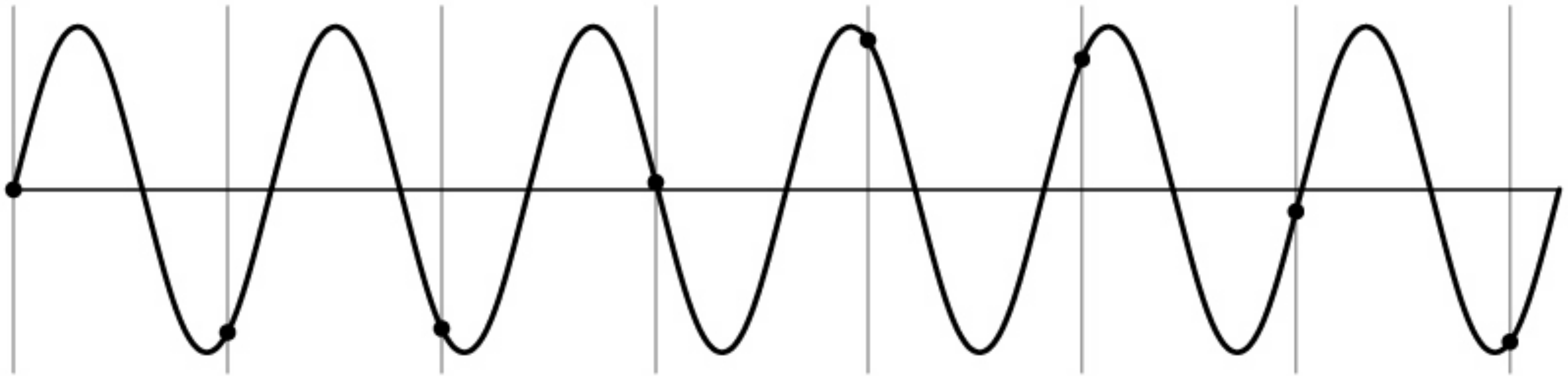

Signal can be confused with one at lower frequency

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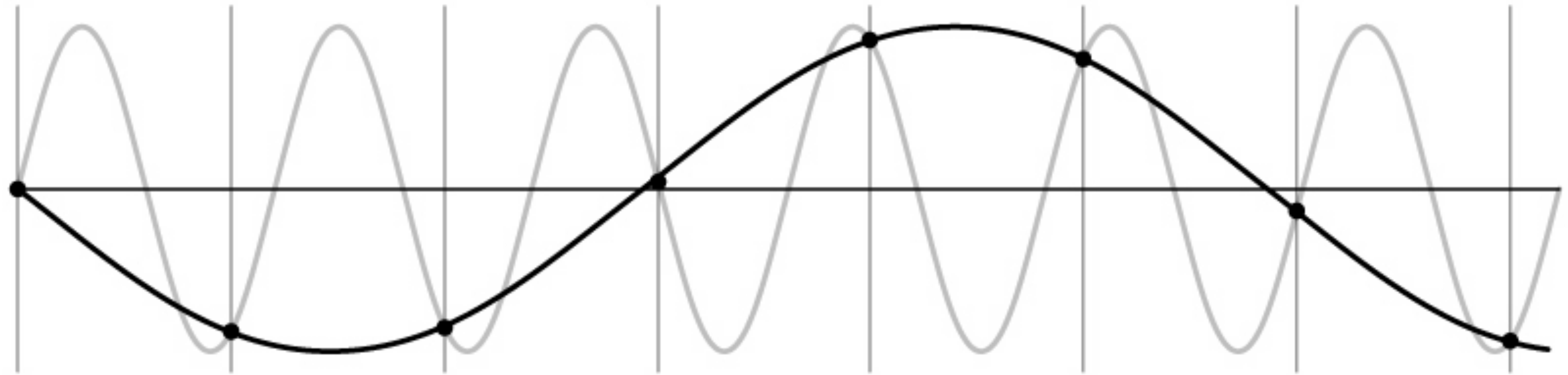

Signal can be confused with one at lower frequency
— This is called “Aliasing”

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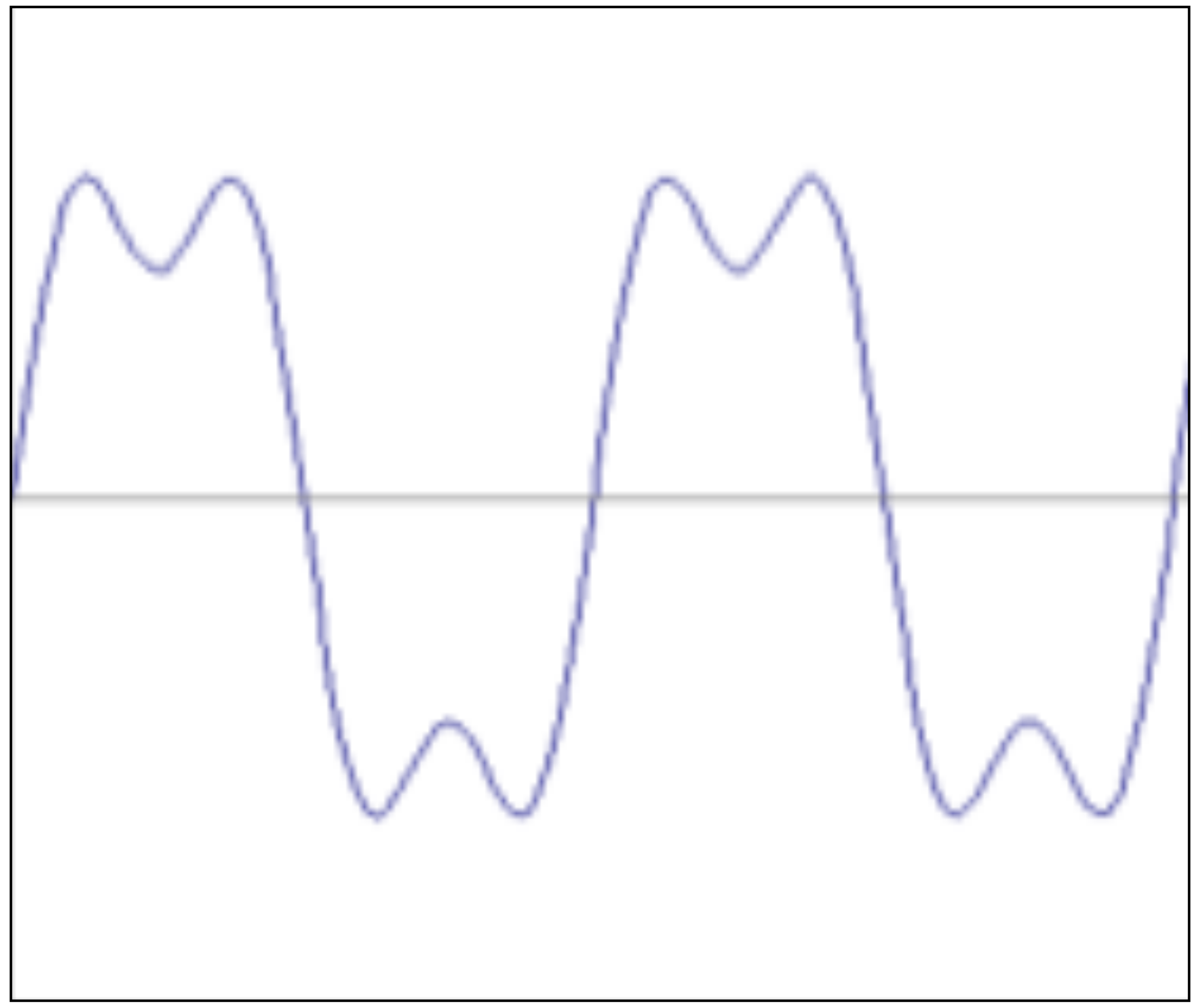
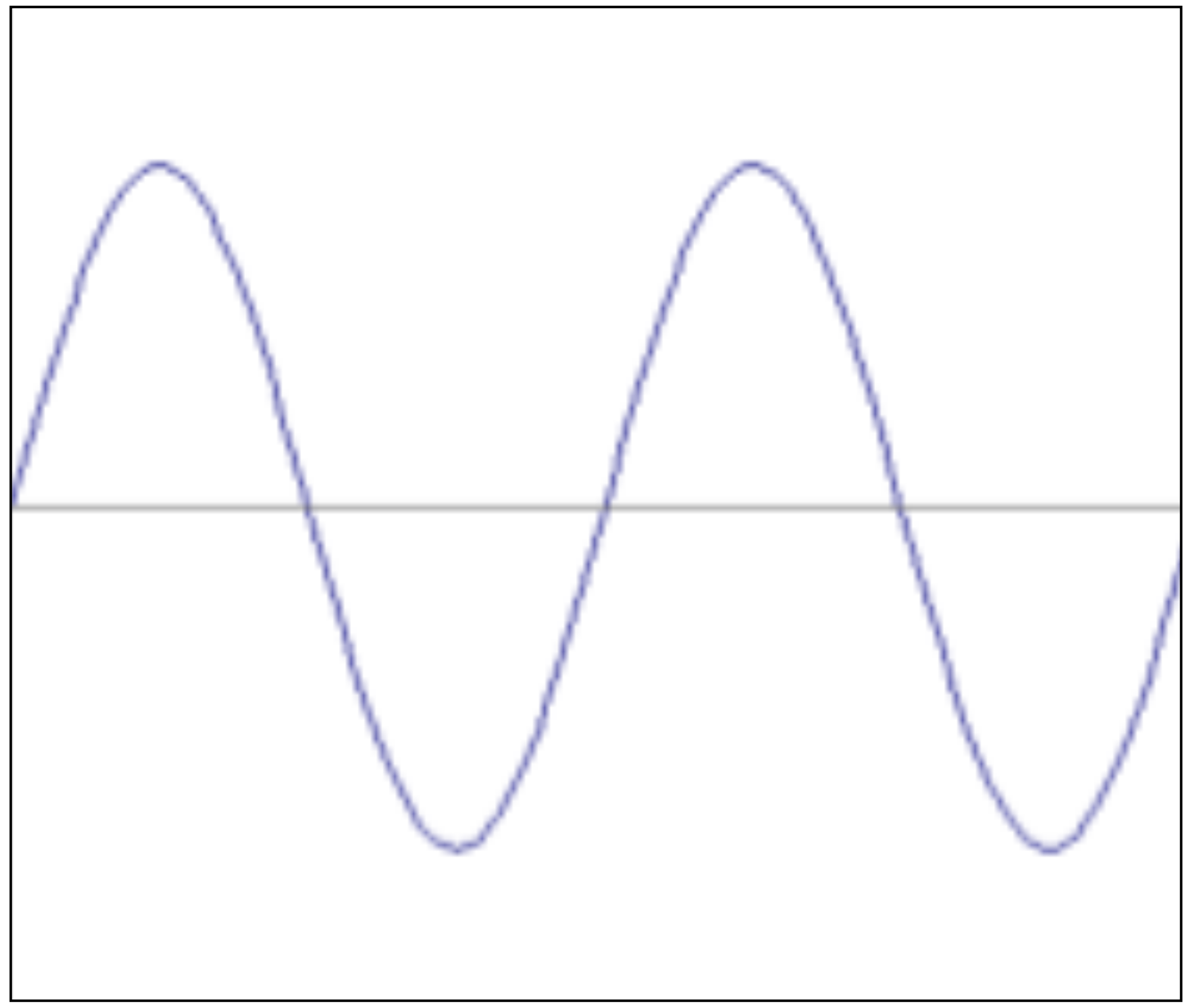
Recall: **Fourier** Representation

Any signal can be written as a sum of sinusoidal functions



$$f(x) = \sin(2\pi x) + \frac{1}{3}\sin(2\pi 3x)$$

=



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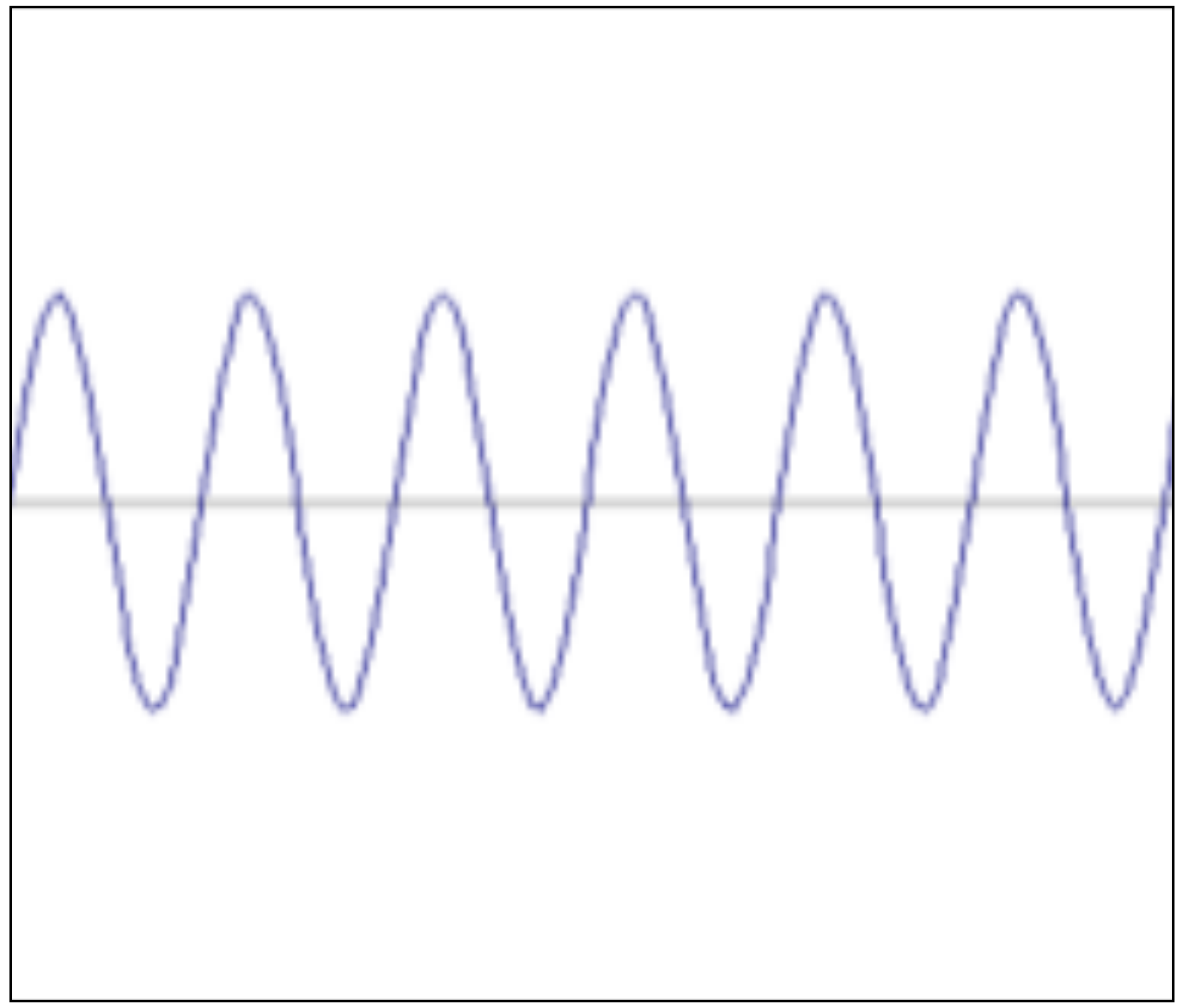

$$\frac{1}{3}\sin(2\pi 3x)$$

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Nyquist Sampling Theorem

To avoid aliasing a signal must be sampled at twice the maximum frequency:

$$f_s > 2 \times f_{max}$$

where f_s is the sampling frequency, and f_{max} is the maximum frequency present in the signal

Futhermore, Nyquist’s theorem states that a signal is **exactly recoverable** from its **samples** if sampled at the **Nyquist rate** (or higher)

Note: that a signal must be **bandlimited** for this to apply (i.e., it has a maximum frequency)

Sampling Theory (informal)

Exact reconstruction requires constraint on the rate at which i(x,y) can change between samples

— “rate of change” means derivative

— the formal concept is **bandlimited signal**

— “bandlimit” and “constraint on derivative” are linked

Think of music

— bandlimited if it has some maximum **temporal frequency**

— the upper limit of human hearing is about 20 kHz

Think of imaging systems. Resolving power is measured in

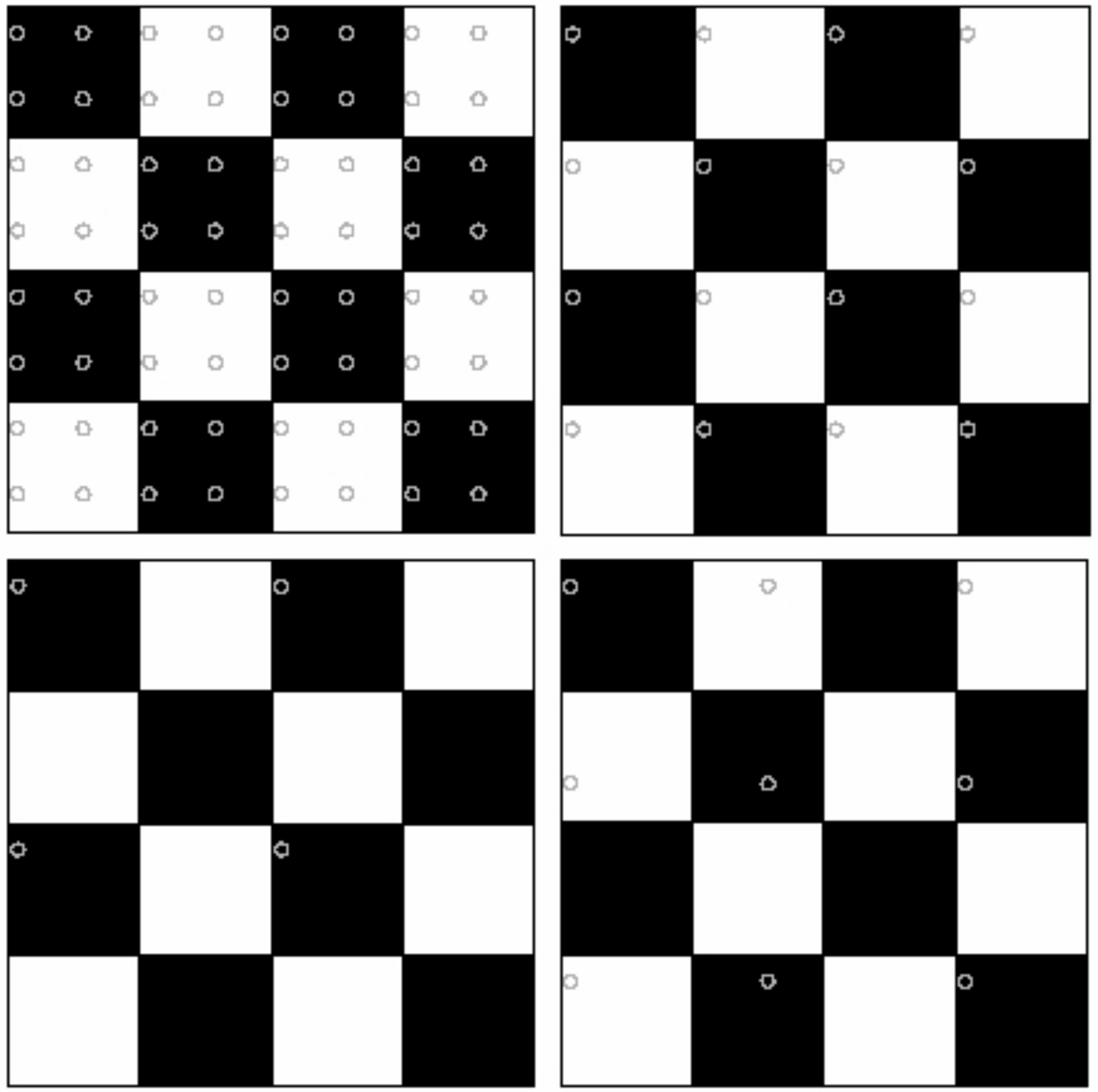
— “line pairs per mm” (for a bar test pattern)

— “cycles per mm” (for a sine wave test pattern)

An image is bandlimited if it has some maximum **spatial frequency**

Sampling

It is clear that *some* information may be lost when we work on a discrete pixel grid.



Forsyth & Ponce (2nd ed.) Figure 4.7

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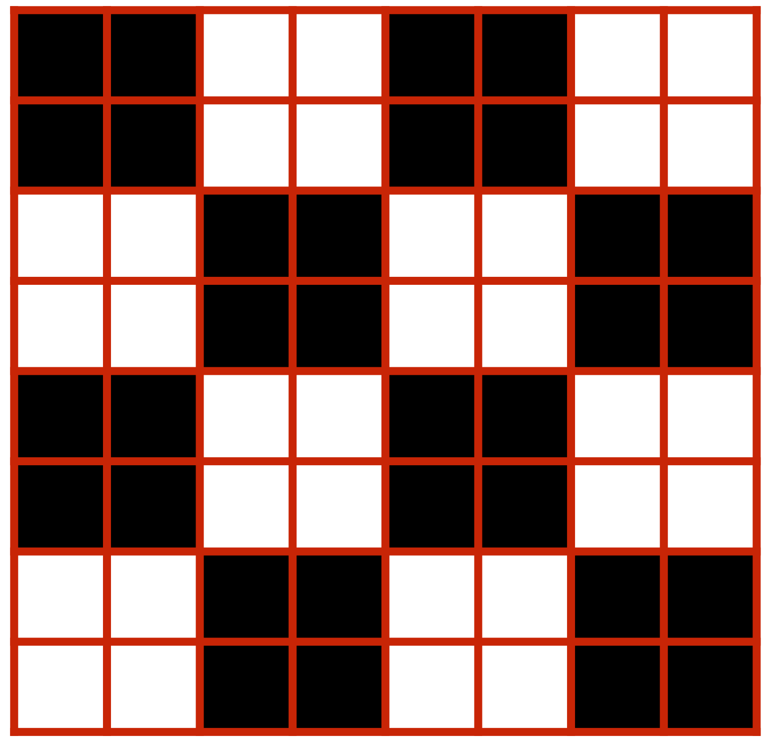

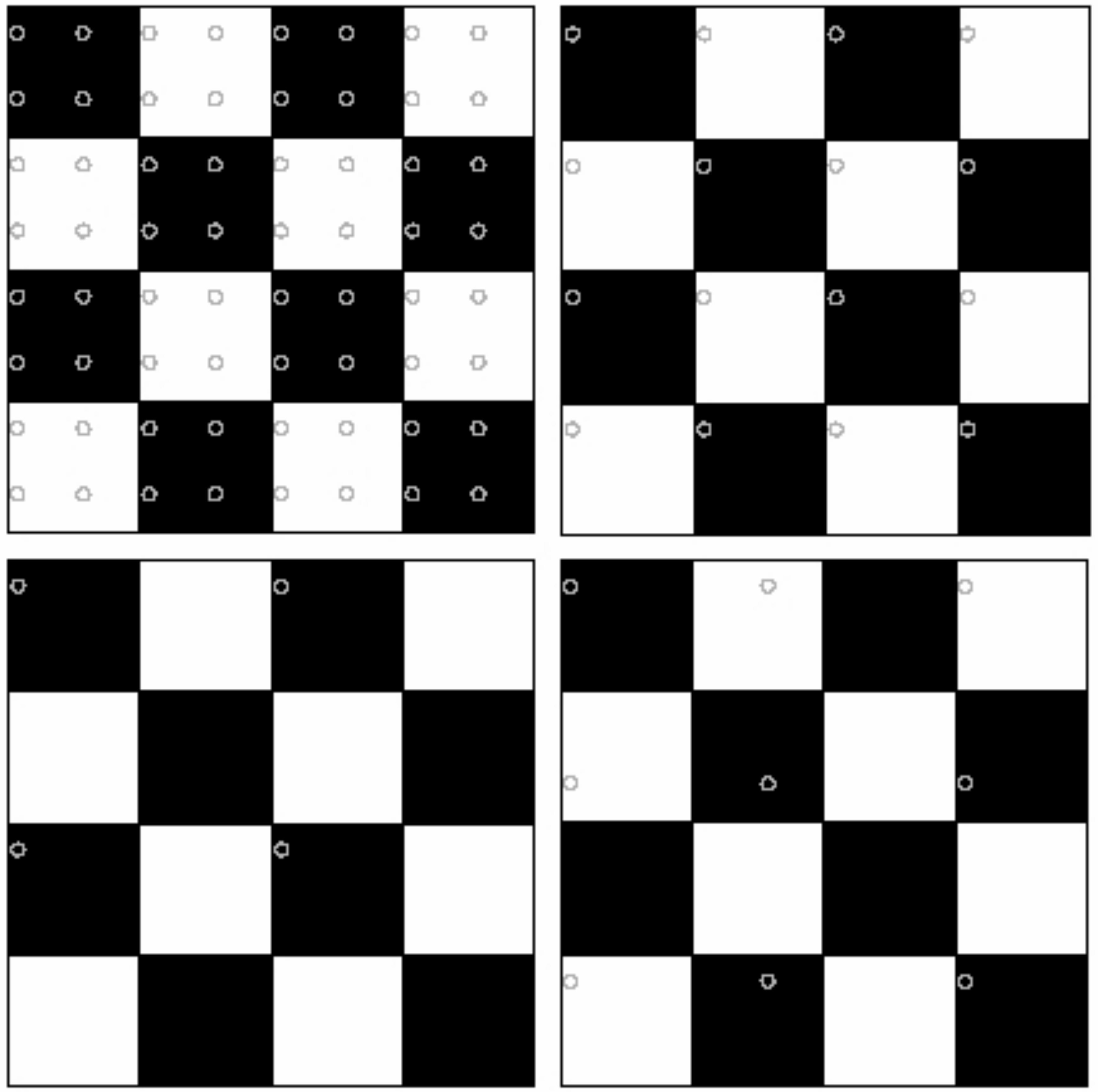

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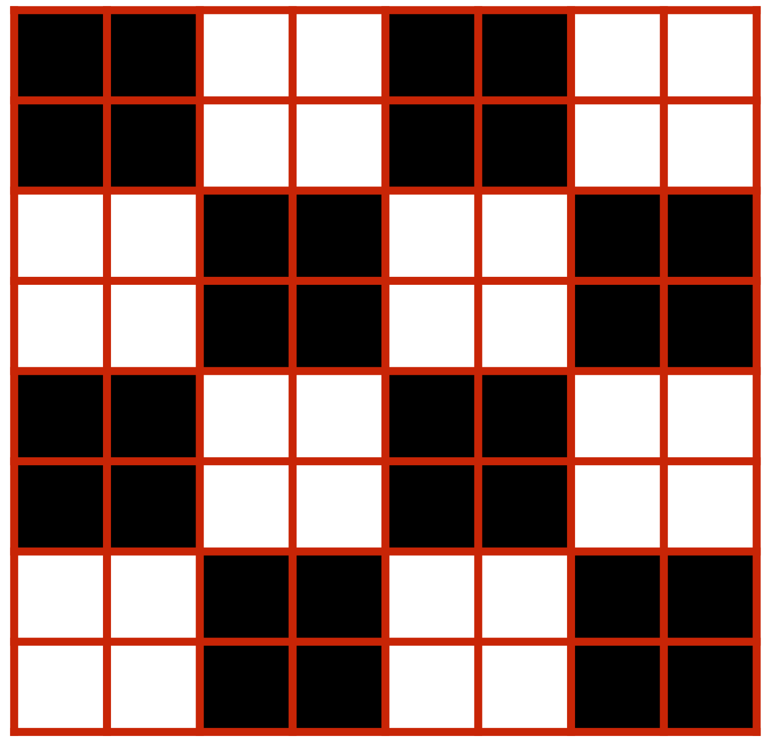

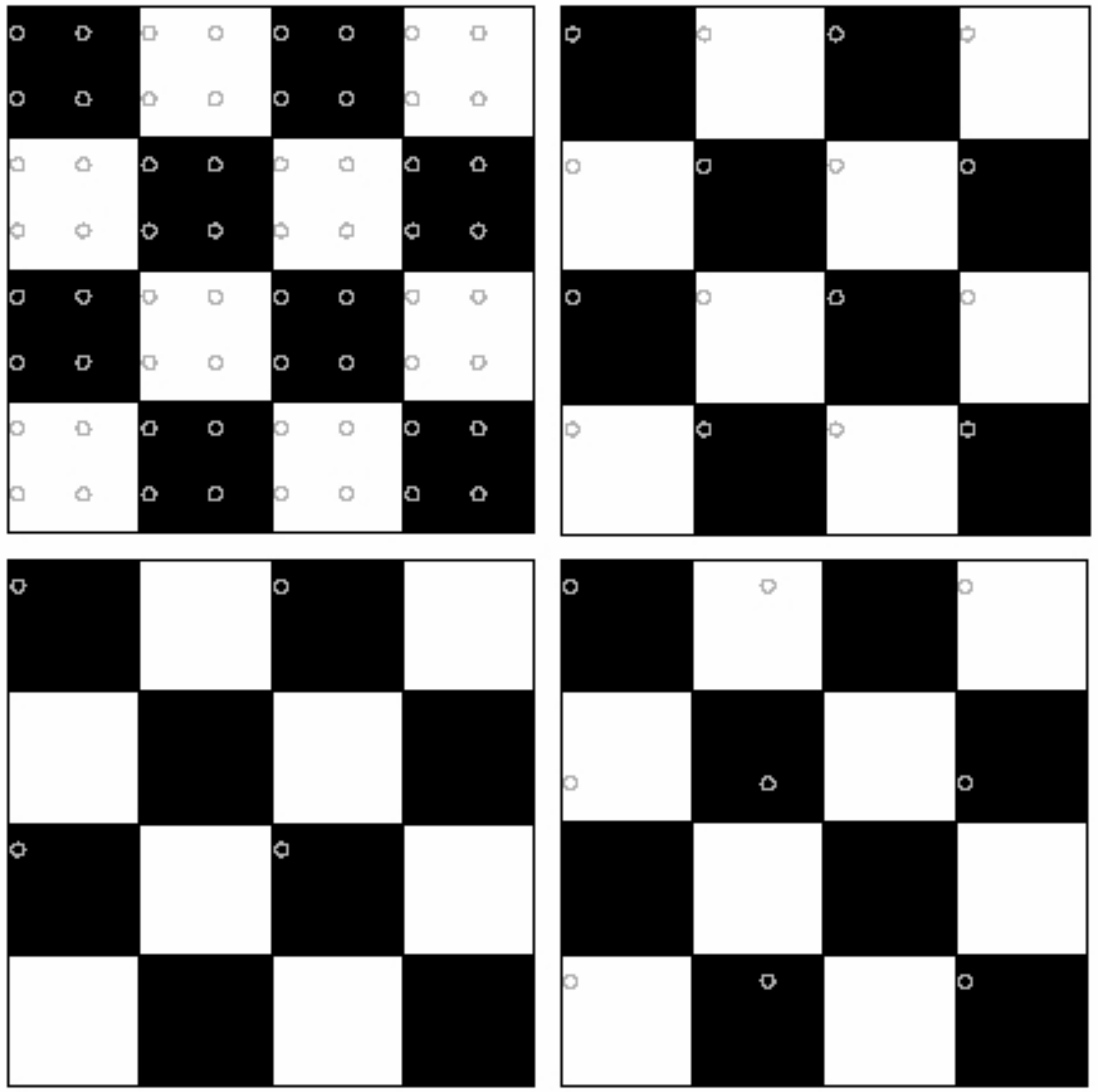

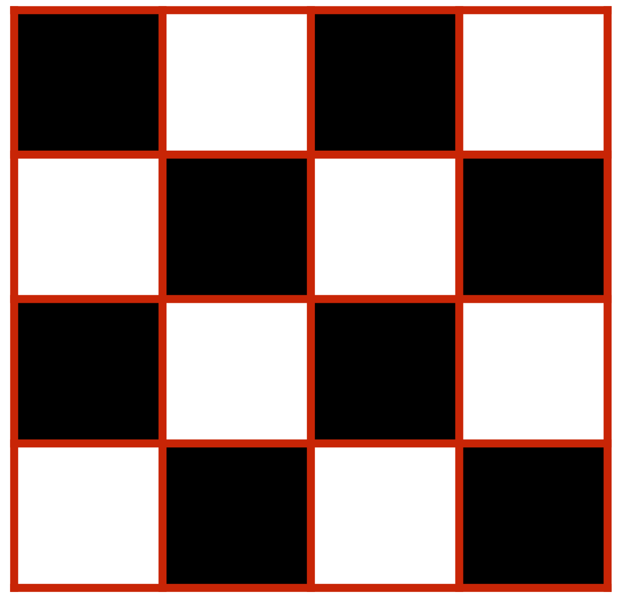

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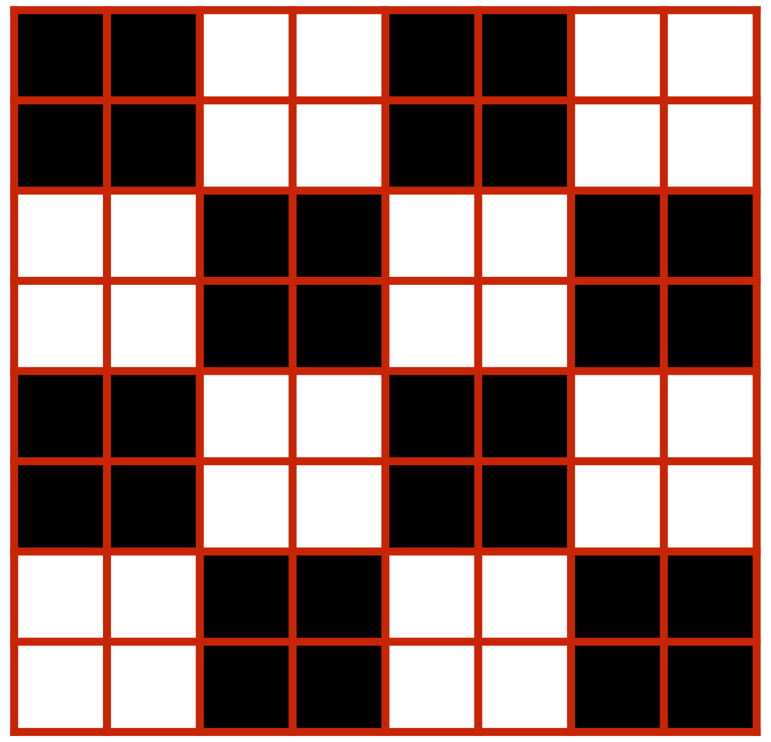
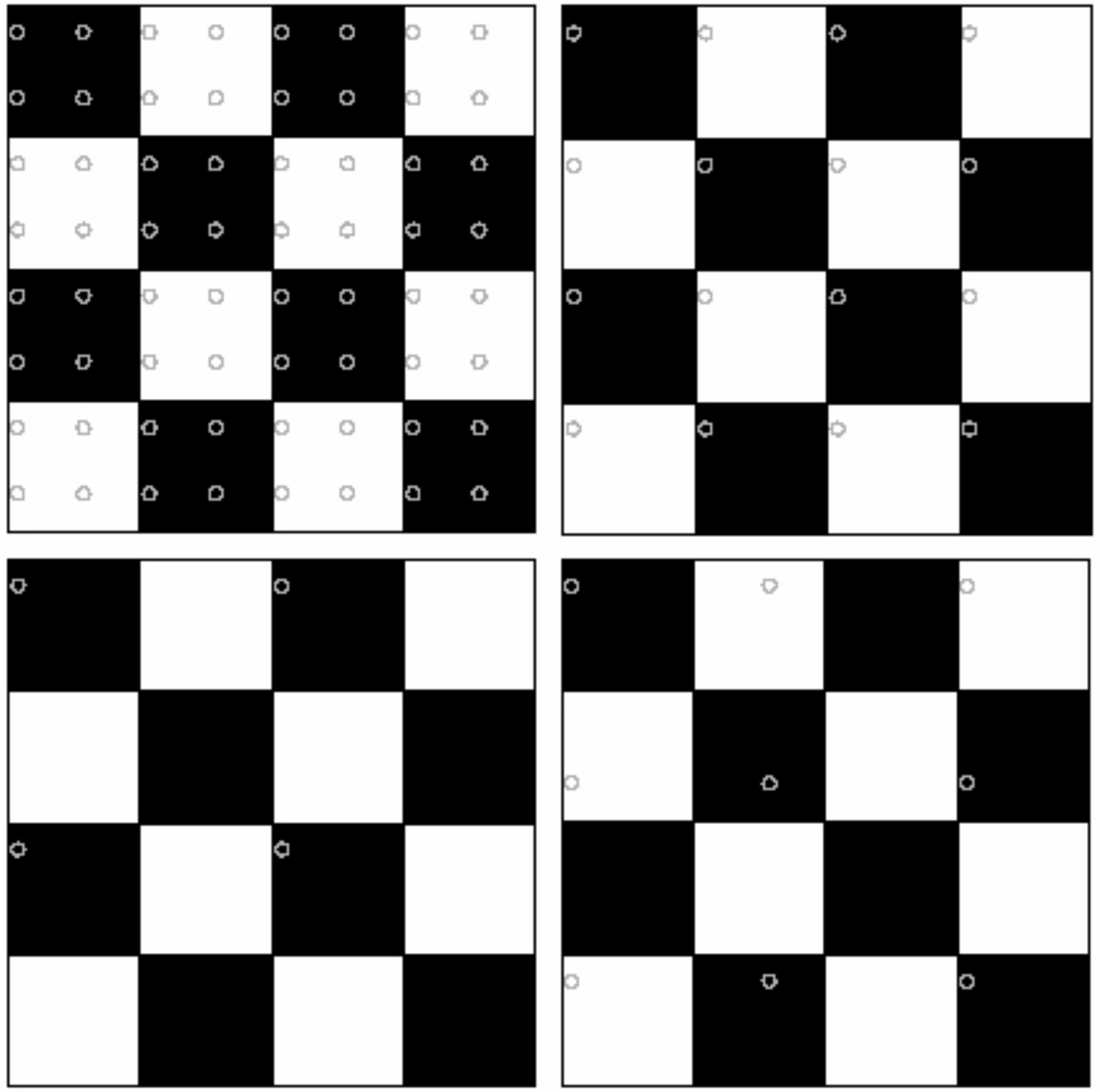
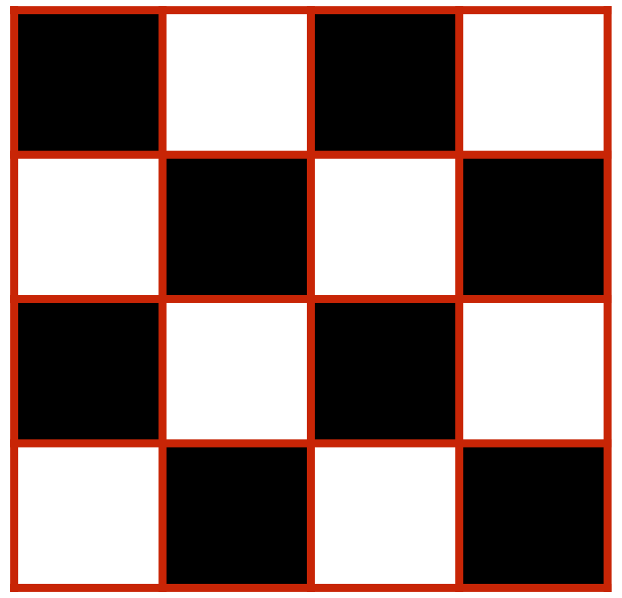
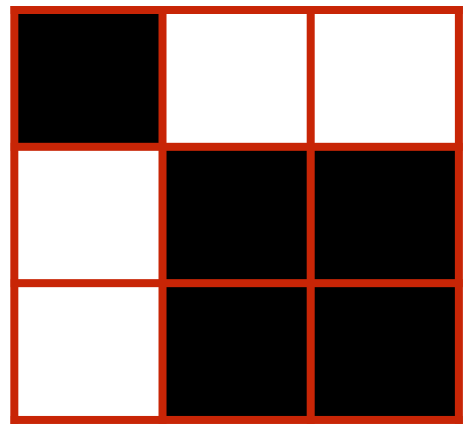




Forsyth & Ponce (2nd ed.) Figure 4.7





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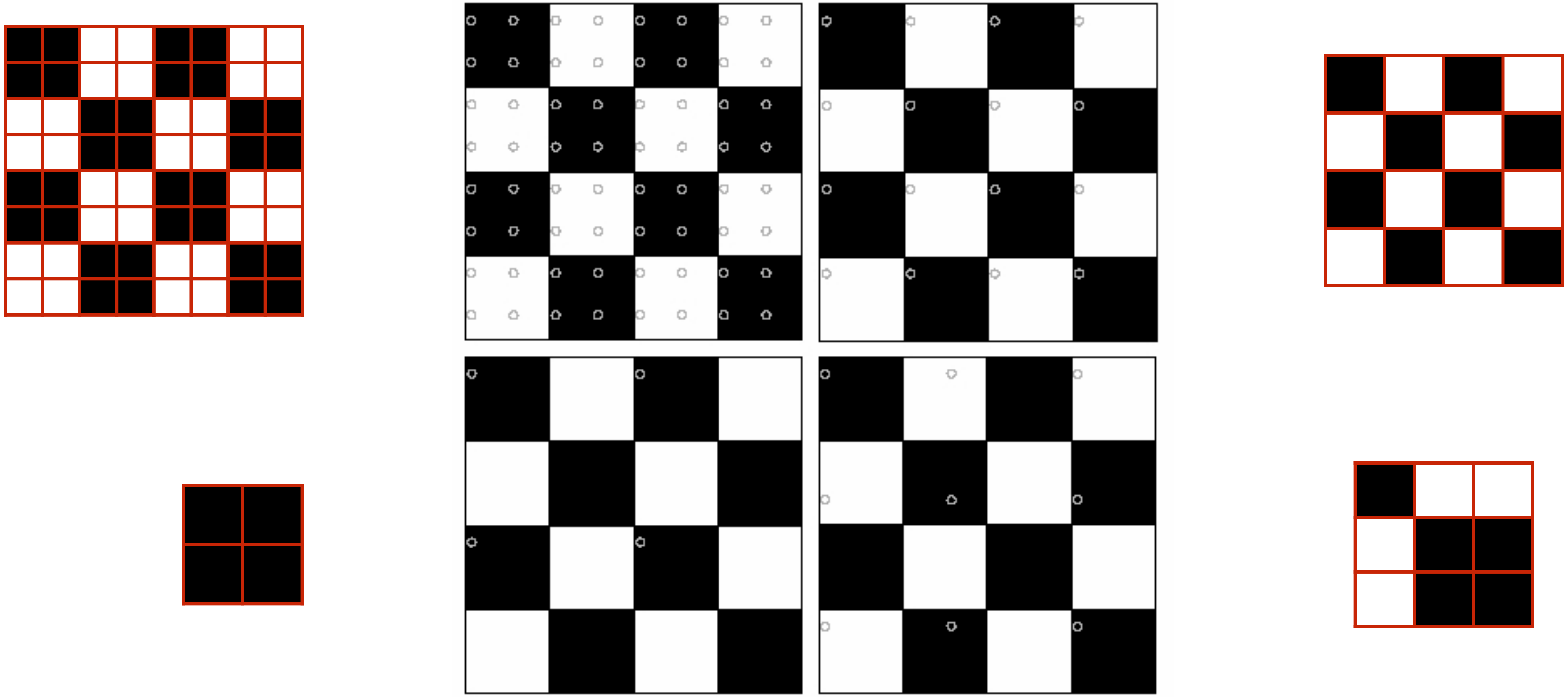

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Resampling Images

Goal: Resample the image to get a lower resolution counterpart

Naive Method: Form new image by taking every n-th pixel of the original image

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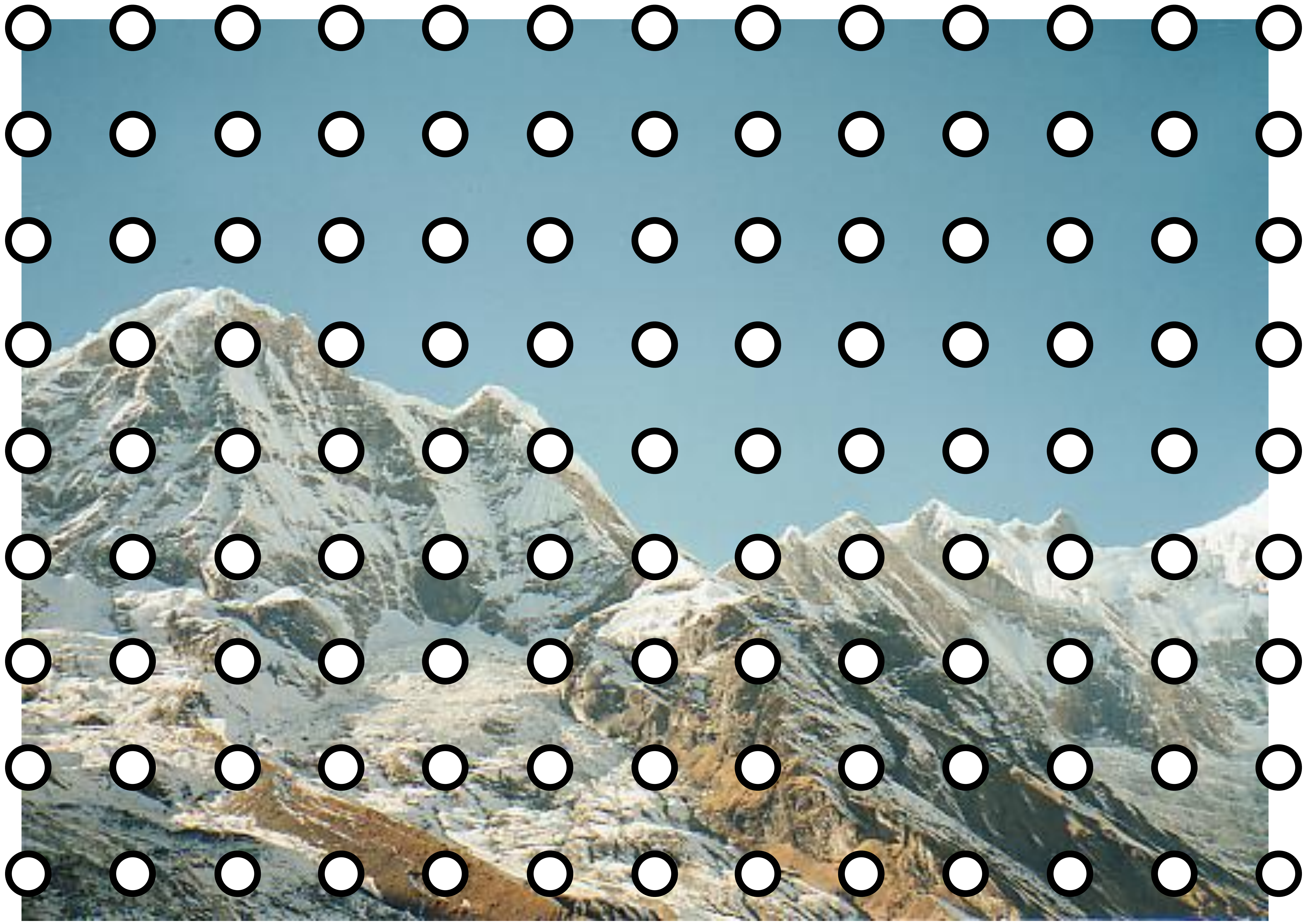

Naive Method: Form new image by taking every n-th pixel of the original image

Resampling Images

With correct sigma value for a Gaussian, no <u>information</u> is lost

Improved Method: First blur the image (with low-pass) then take n-th pixel

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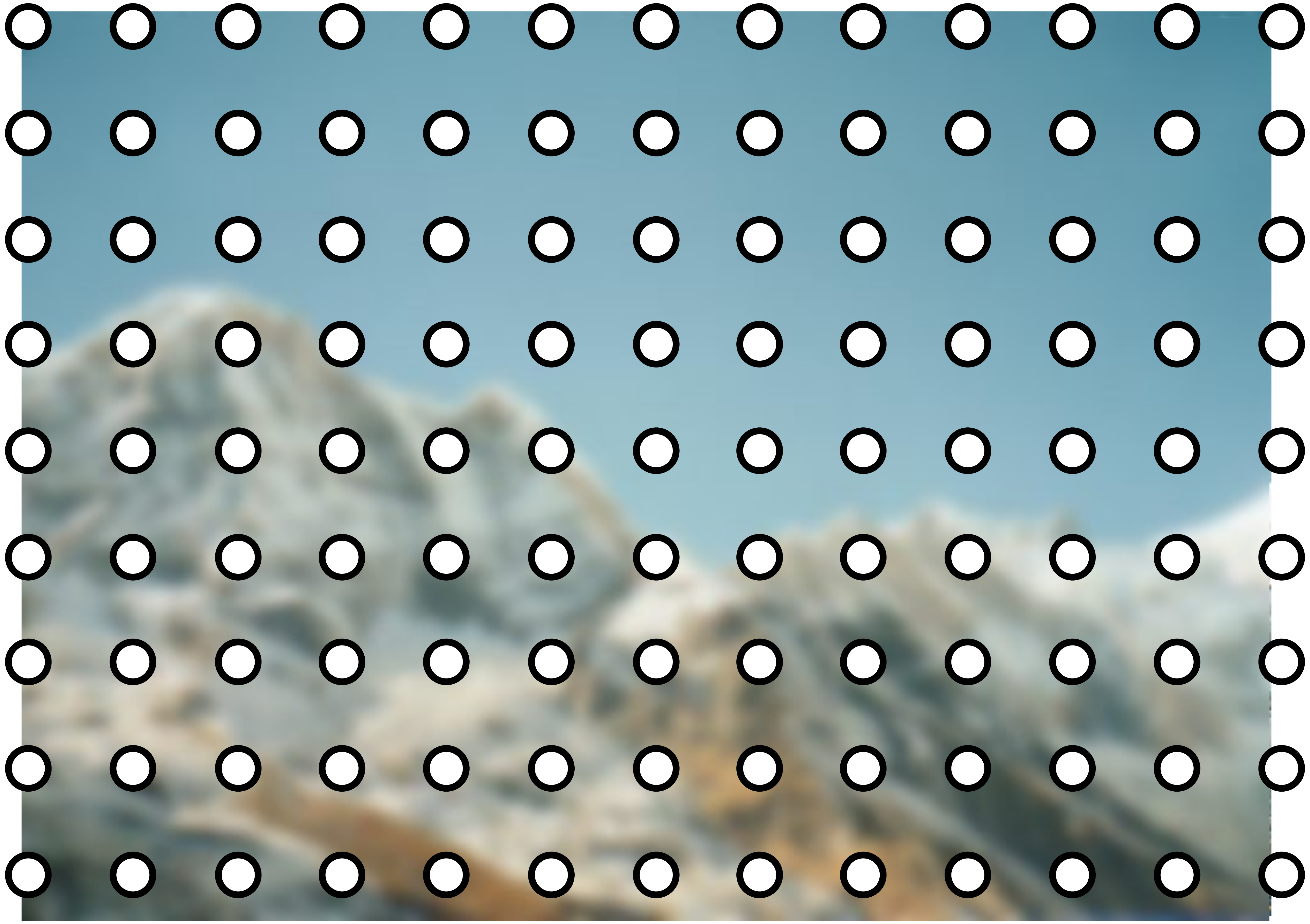

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Aliasing Example

Sampling every 5th pixel with and without low-pass blur

No filtering

Gaussian Blur $\sigma = 3.0$

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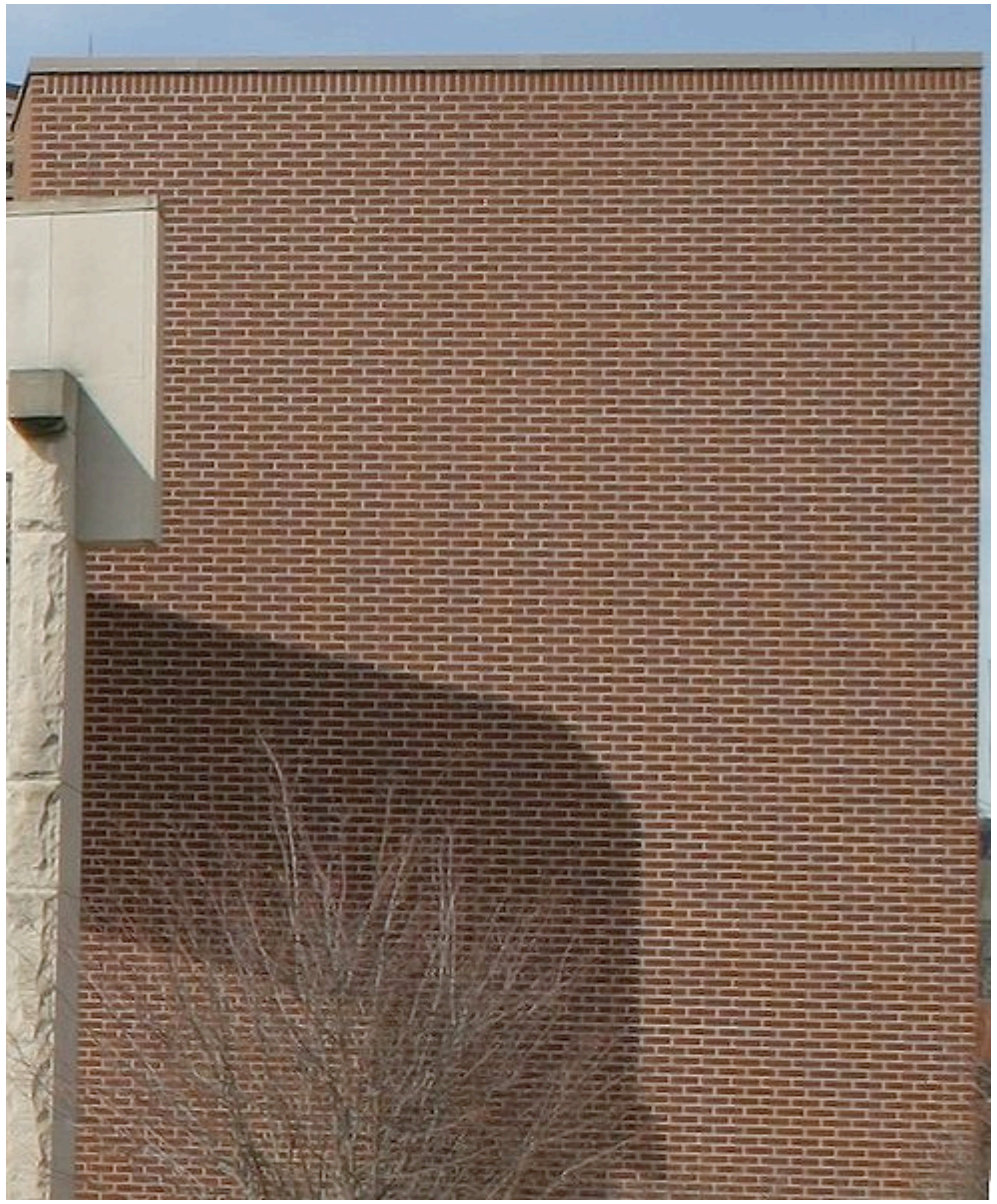
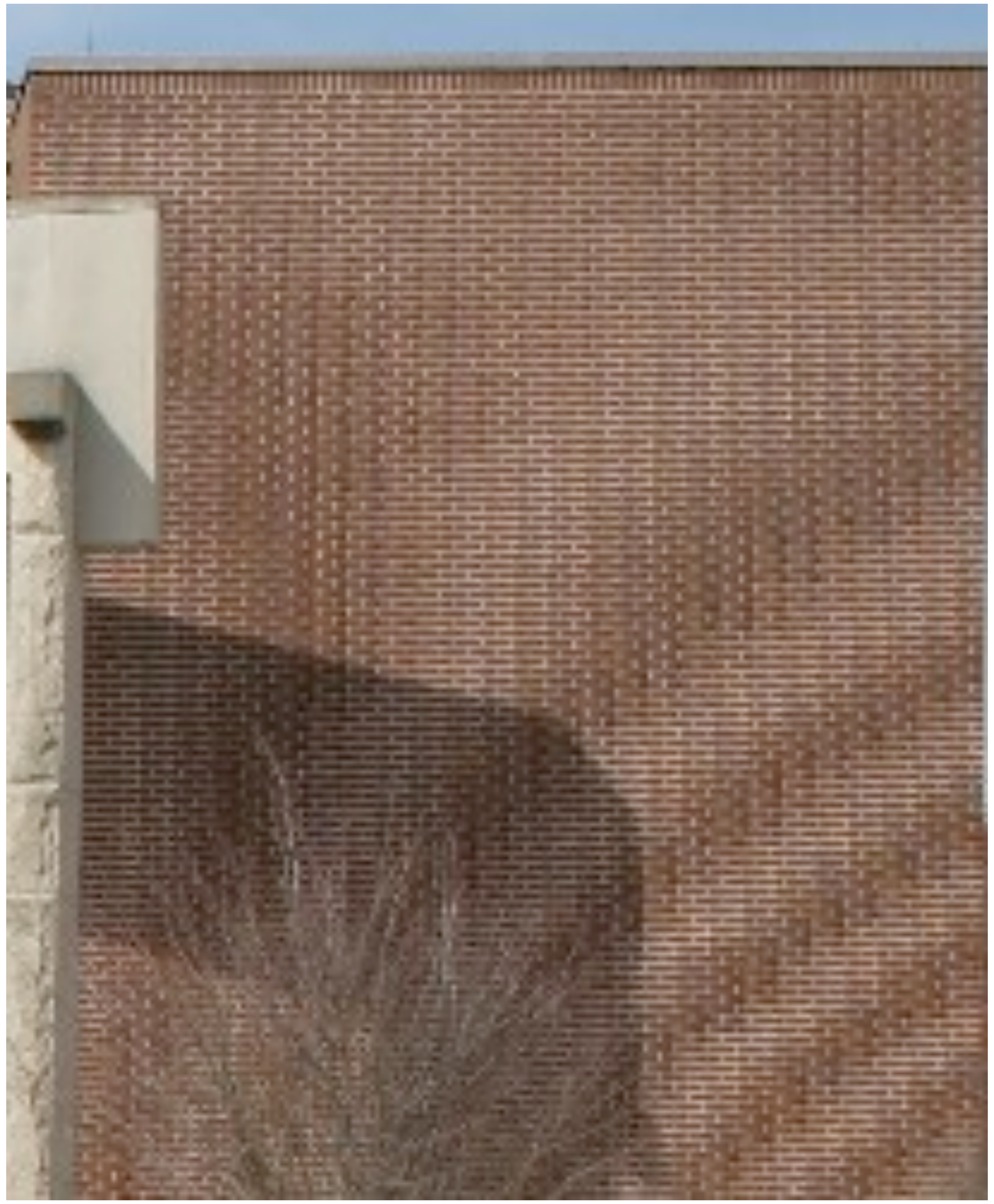
Image Sampling and Aliasing



$f_s > 2 \times f_{max}$



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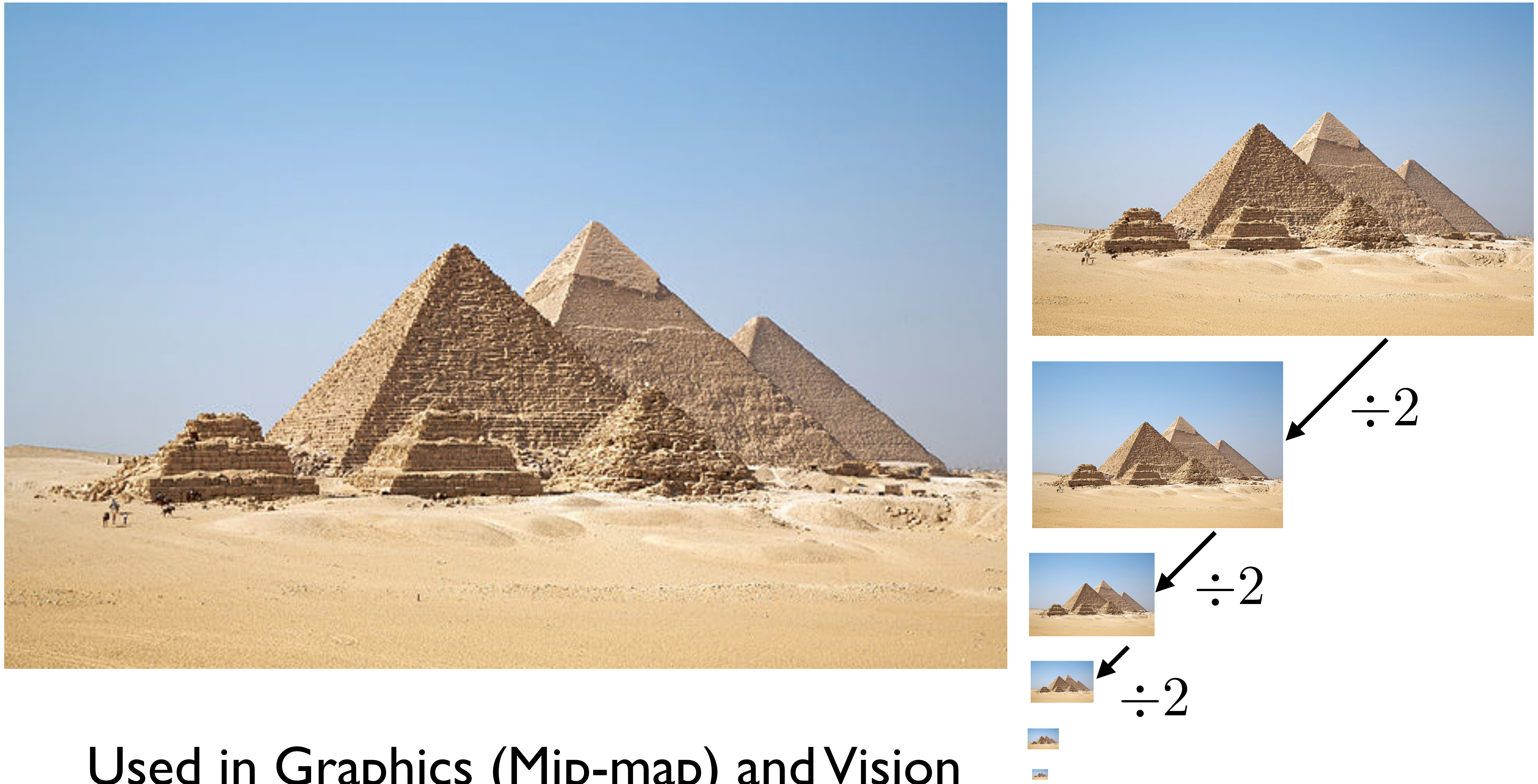
Aliasing in Photographs

This is also known as “moire”

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Image Pyramids



Used in Graphics (Mip-map) and Vision
(for **multi-scale** processing)

$G1$ 

Blur with a Gaussian kernel, then select every 2nd pixel

$$I_s(x,y) = I(x,y) * g_\sigma(x,y)$$

Often approximations to the Gaussian kernel are used, e.g.,

$$\frac{1}{16}\begin{bmatrix}1 & 4 & 6 & 4 & 1\end{bmatrix}$$

[Assignment 2]

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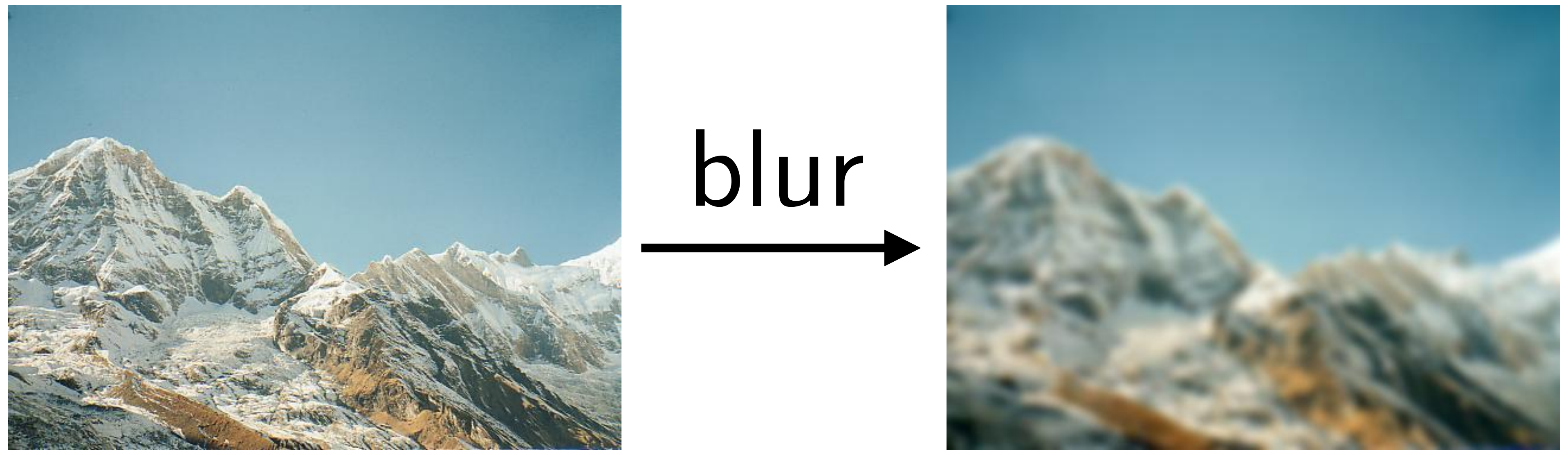

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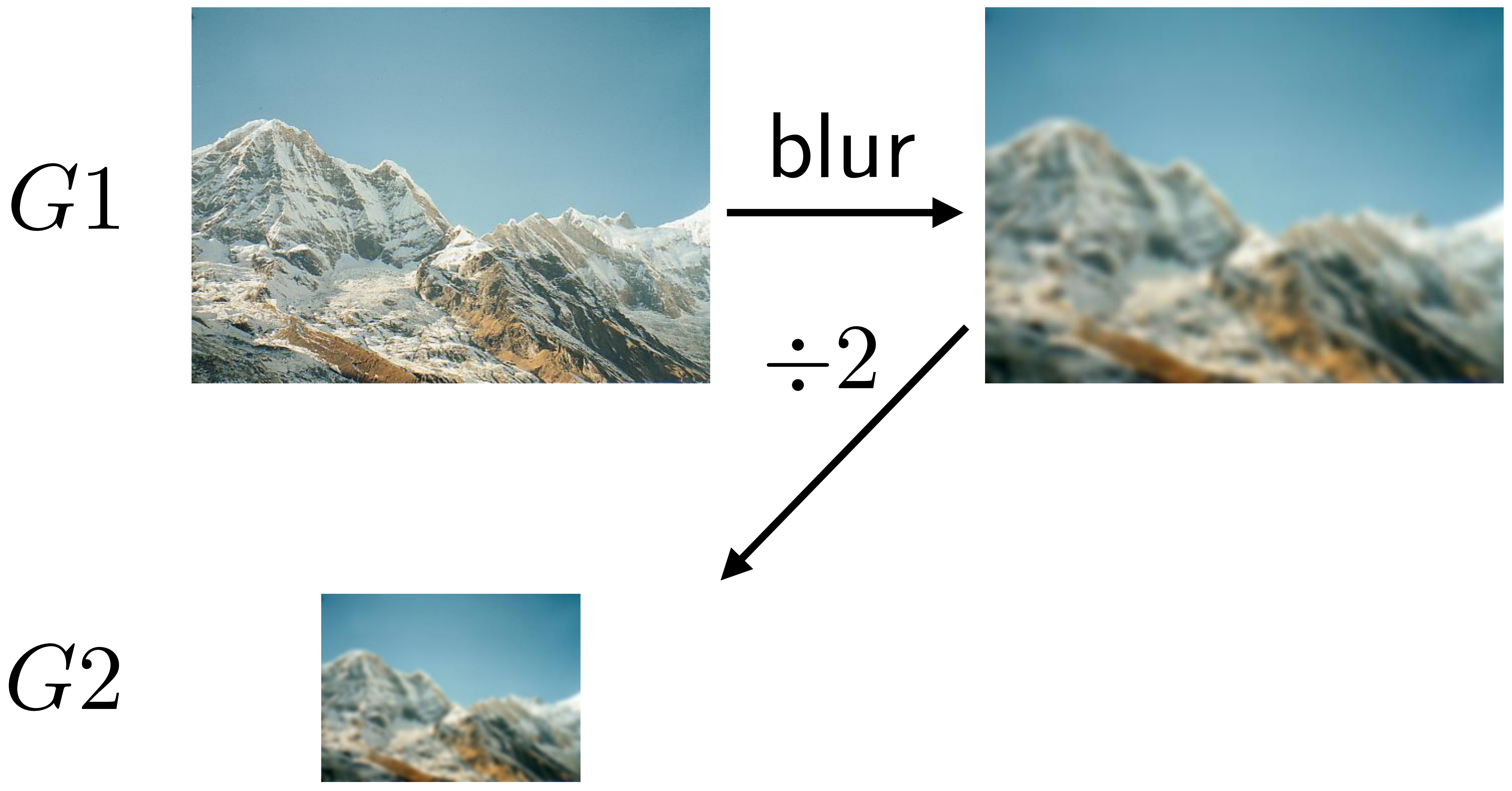

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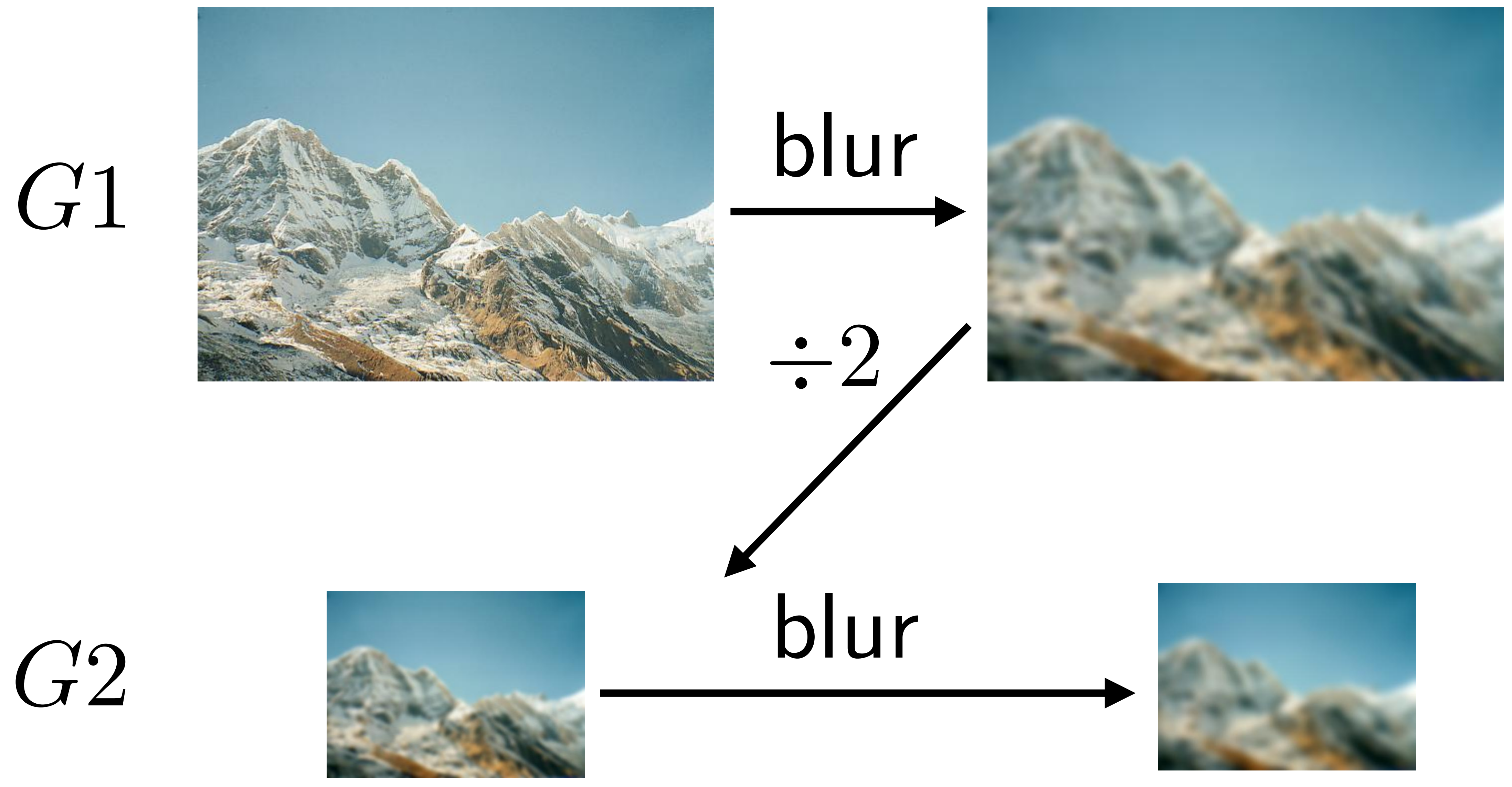

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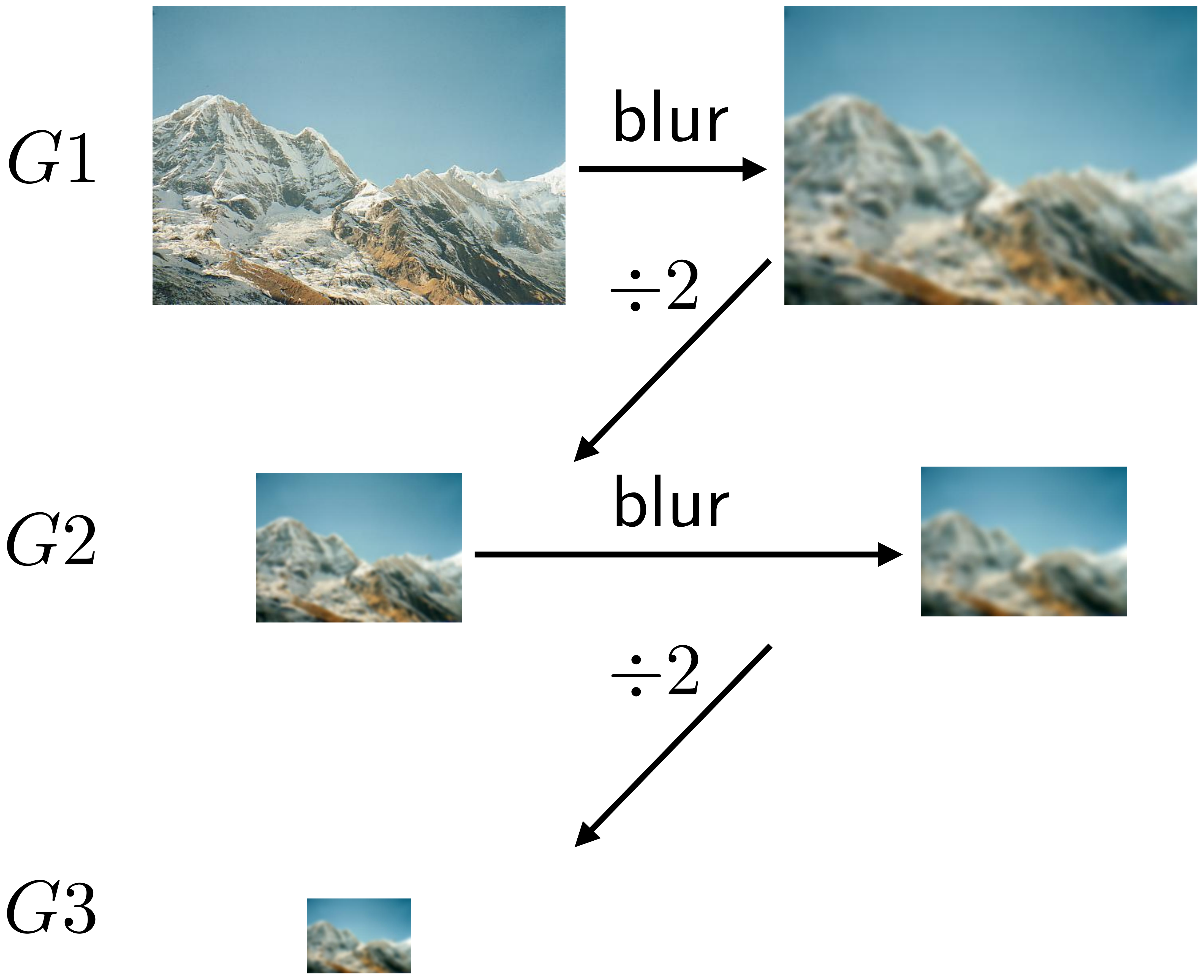

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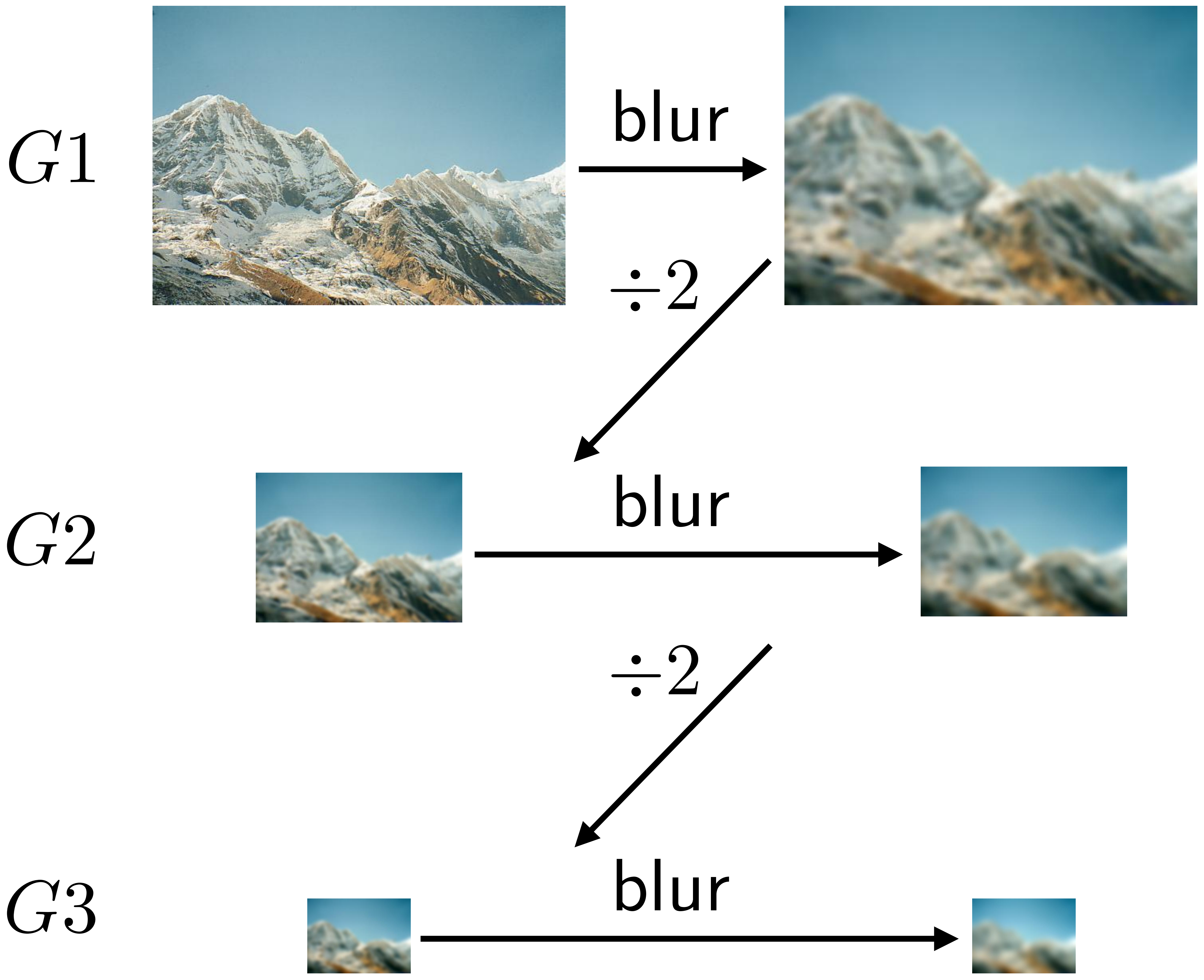

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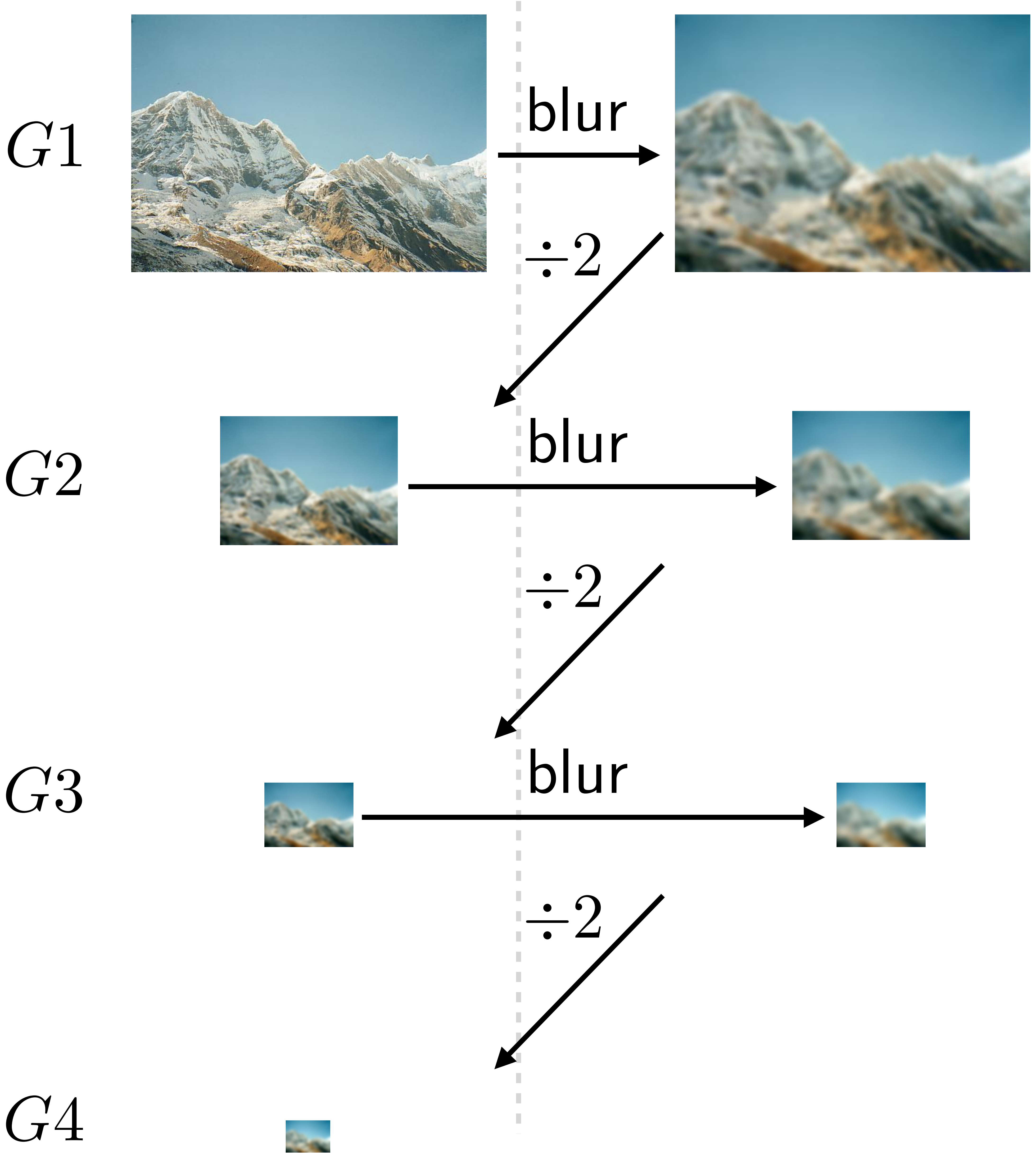

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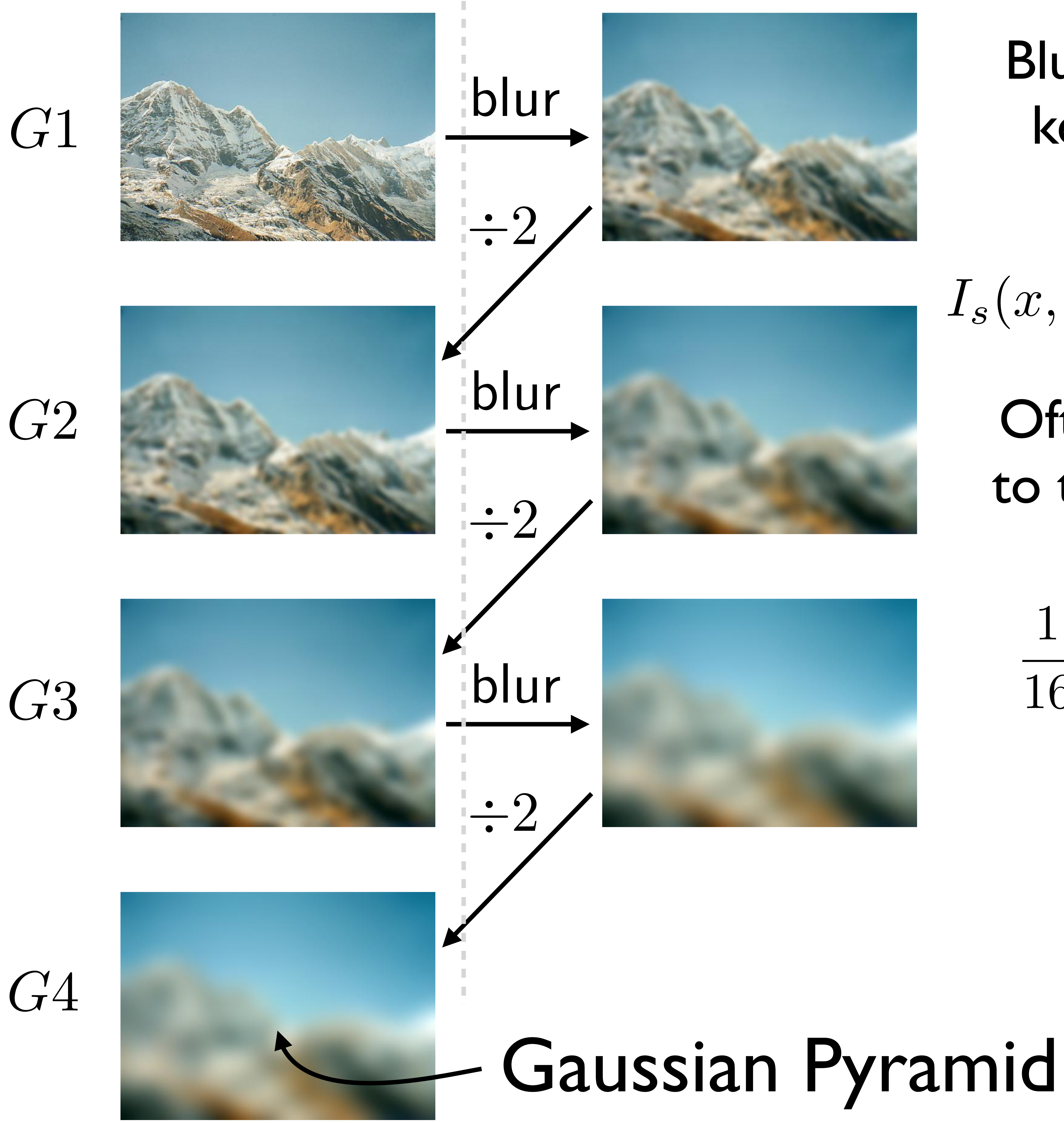

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Sampling Theory (informal)

Question: For a bandlimited signal, what if you **oversample** (i.e., sample at greater than the Nyquist rate)

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Question: For a bandlimited signal, what if you **undersample** (i.e., sample at less than the Nyquist rate)

Answer: Two bad things happen! Things are missing (i.e., things that should be there aren’t). There are artifacts (i.e., things that shouldn’t be there are)

How to Prevent **Aliasing?**

1. **Reduce the maximum frequency**, by low pass filtering i.e., **Smoothing** before sampling.

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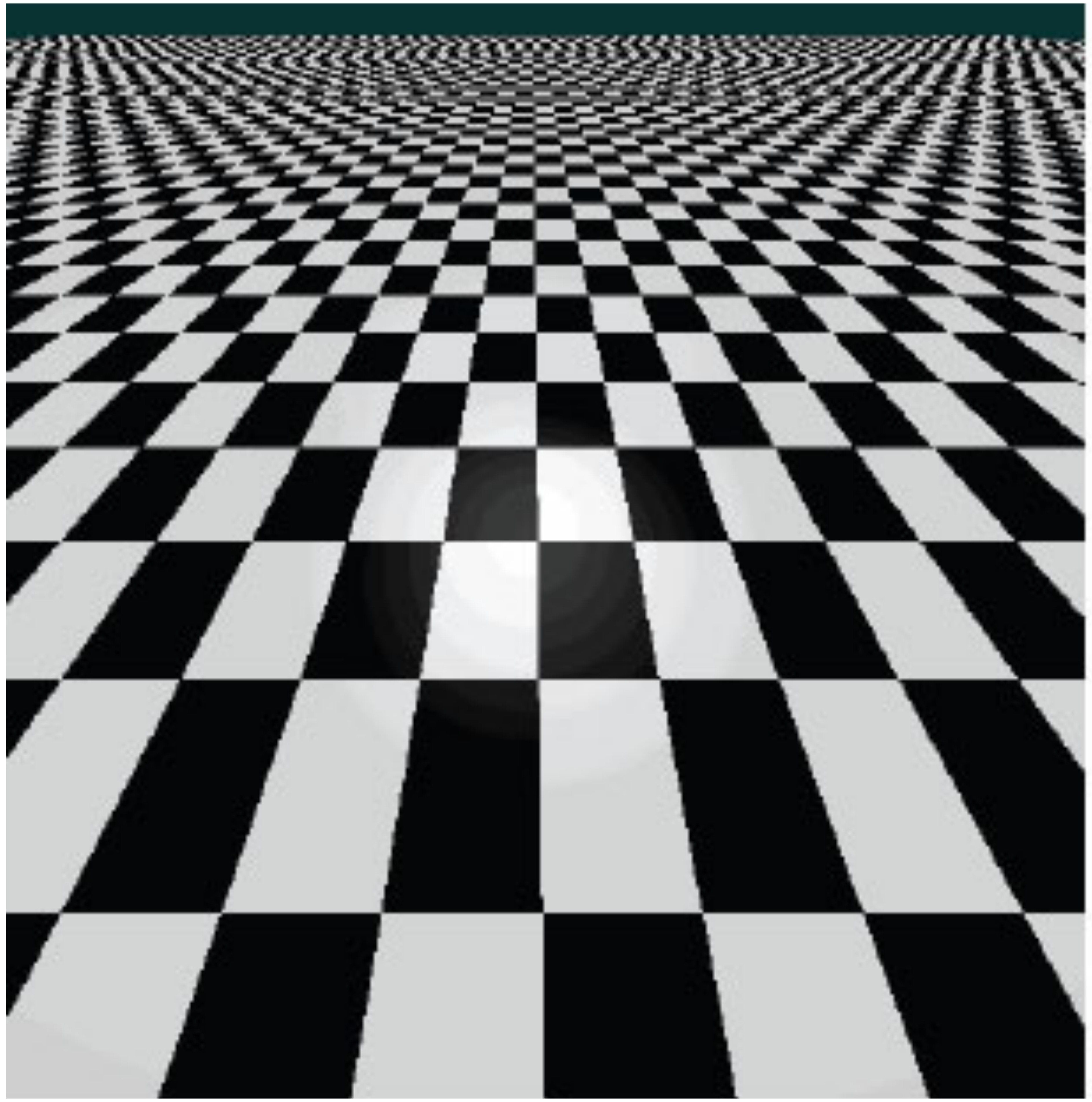
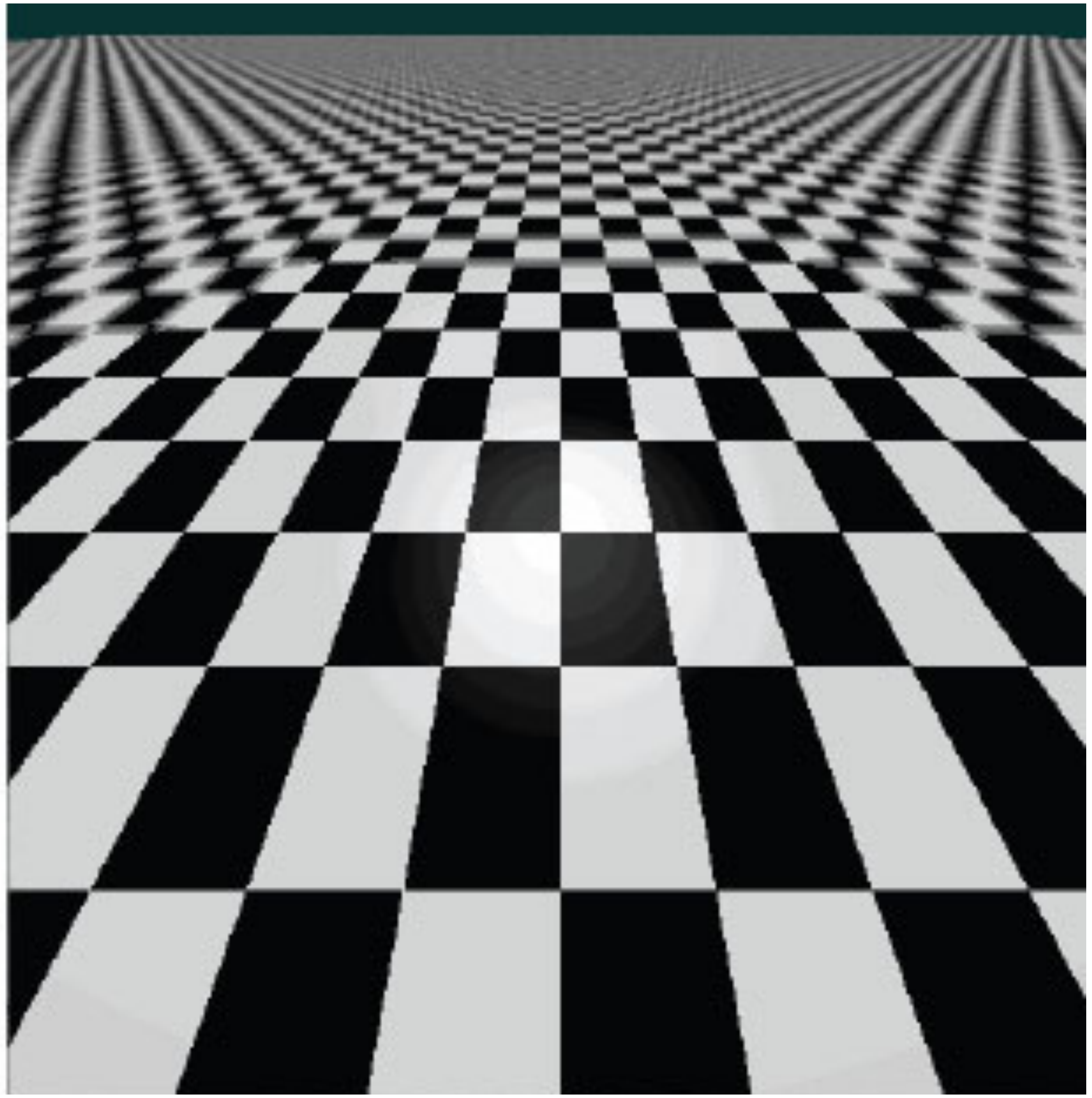
2. **Sample more frequently** i.e., oversampling — sample more than you think you need and average (i.e., area sampling)

Aliasing



aliasing artifacts



anti-aliasing by oversampling

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Temporal Aliasing

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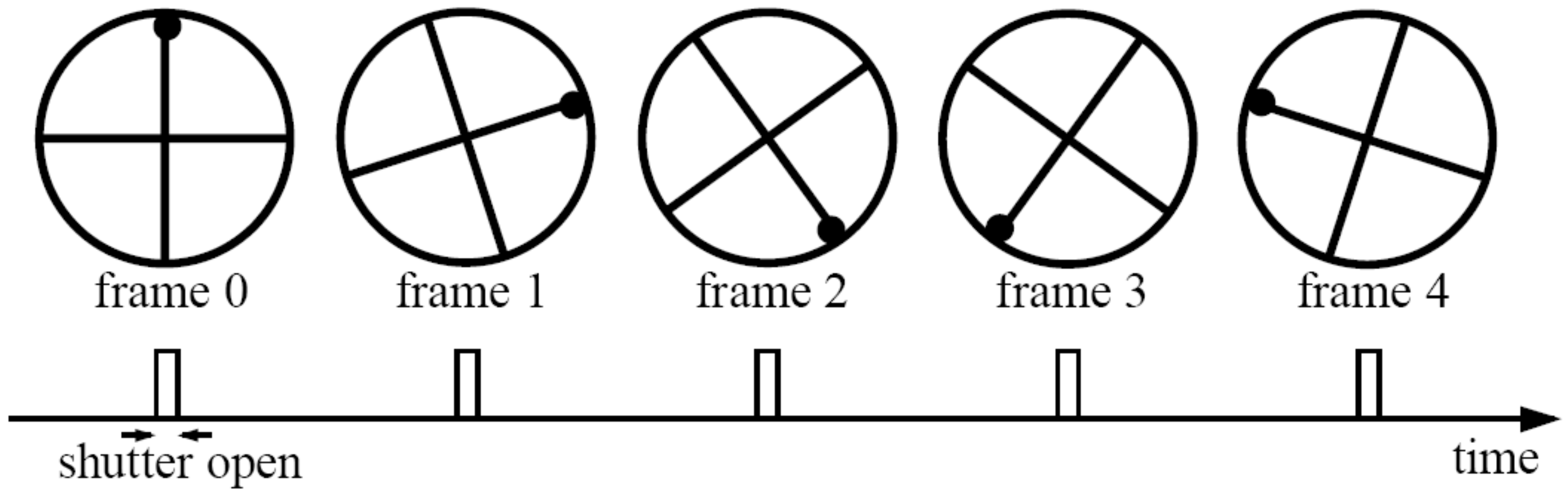
Temporal Aliasing

Imagine a spoked wheel moving to the right (rotating clockwise). Mark wheel with dot so we can see what's happening.

If camera shutter is only open for a fraction of a frame time (frame time = 1/30 sec. for video, 1/24 sec. for film):



Without dot, wheel appears to be rotating slowly backwards! (counterclockwise)

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Sampling Theory (informal)

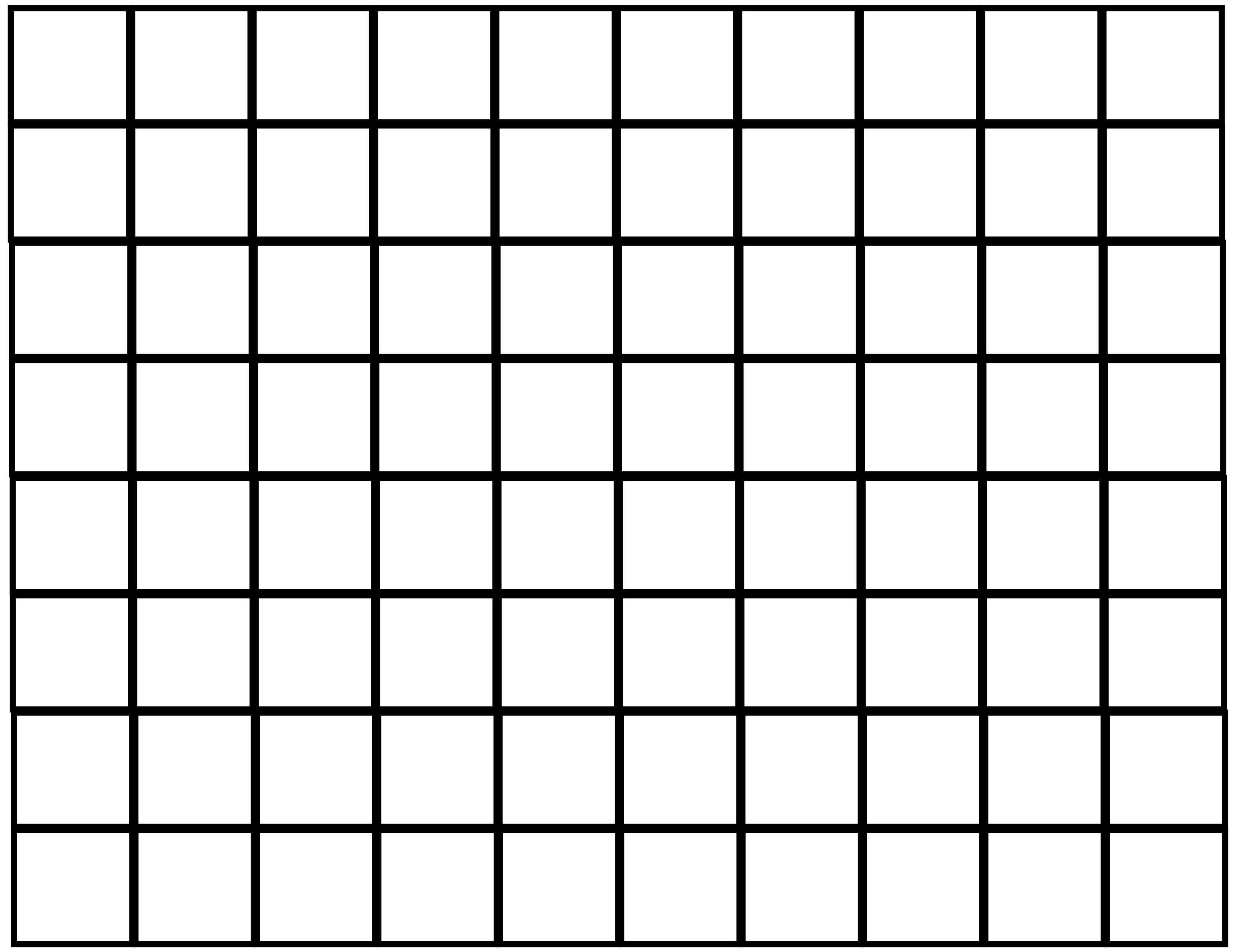
Sometimes **undersampling** is unavoidable, and there is a trade-off between “things missing” and “artifacts.”

— **Medical imaging**: usually try to maximize information content, tolerate some artifacts

— **Computer graphics**: usually try to minimize artifacts, tolerate some information missing

Example

Sensor Resolution: 10 x 8



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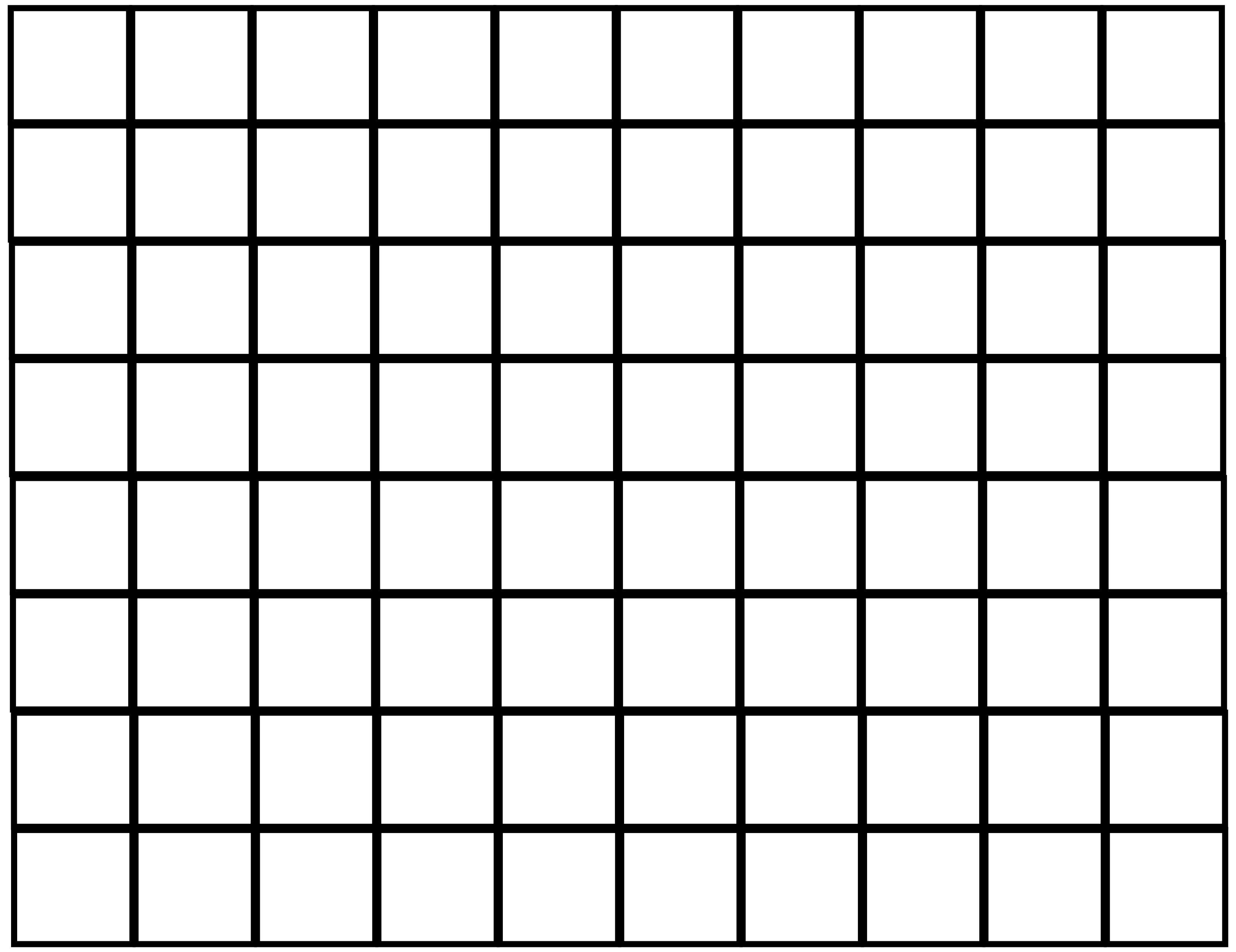

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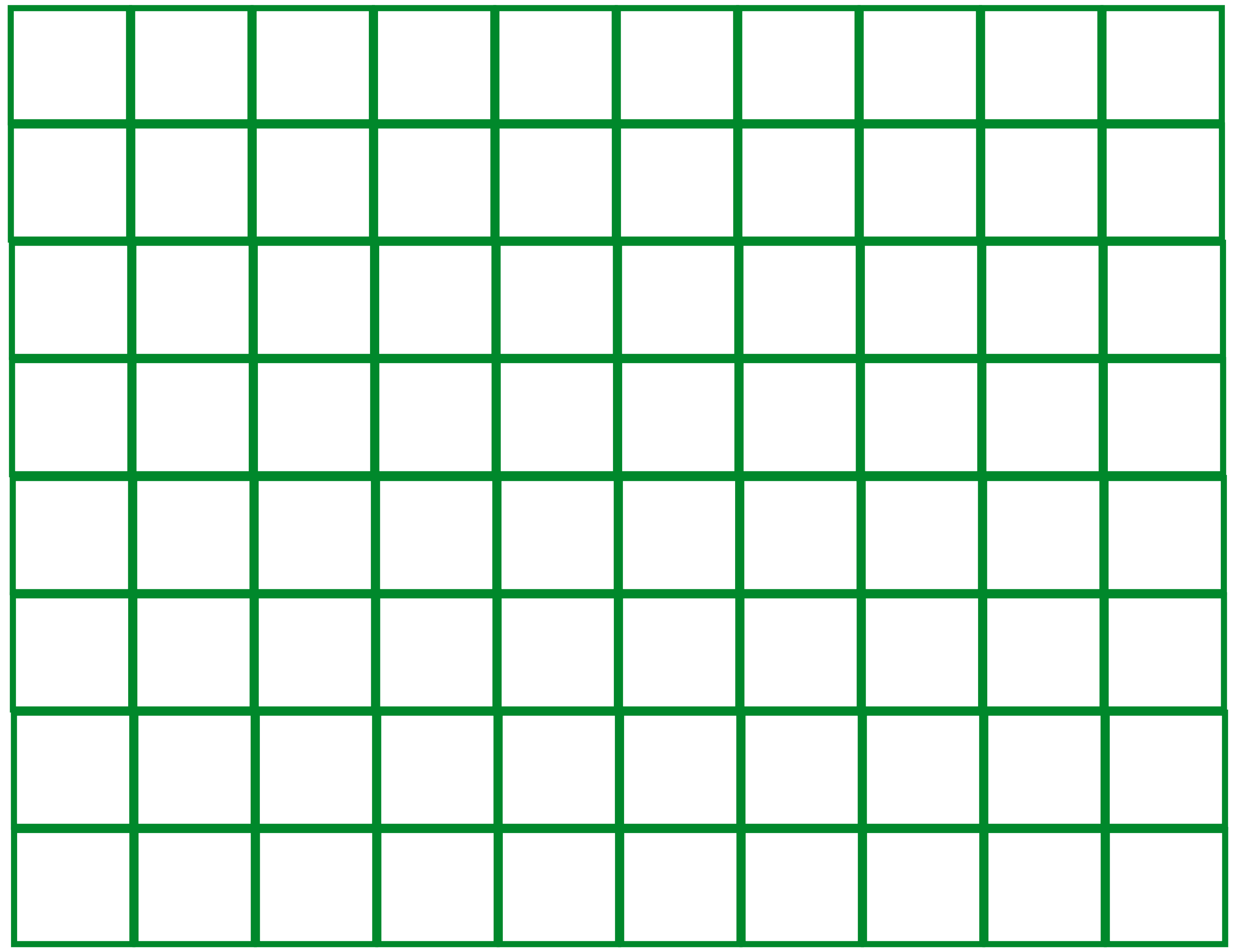


Image Resolution: 10 x 8

Sensor Resolution: 10 x 8

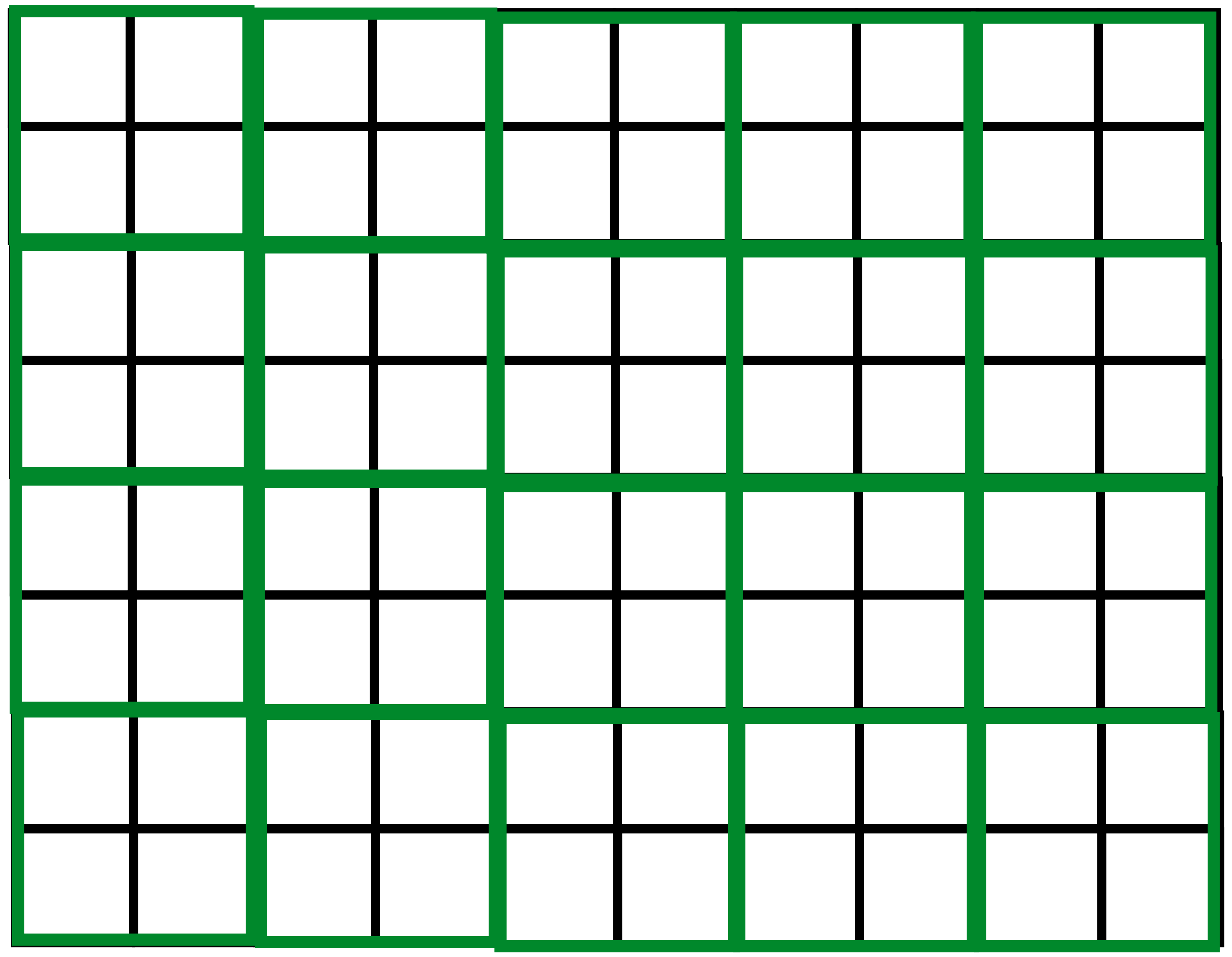
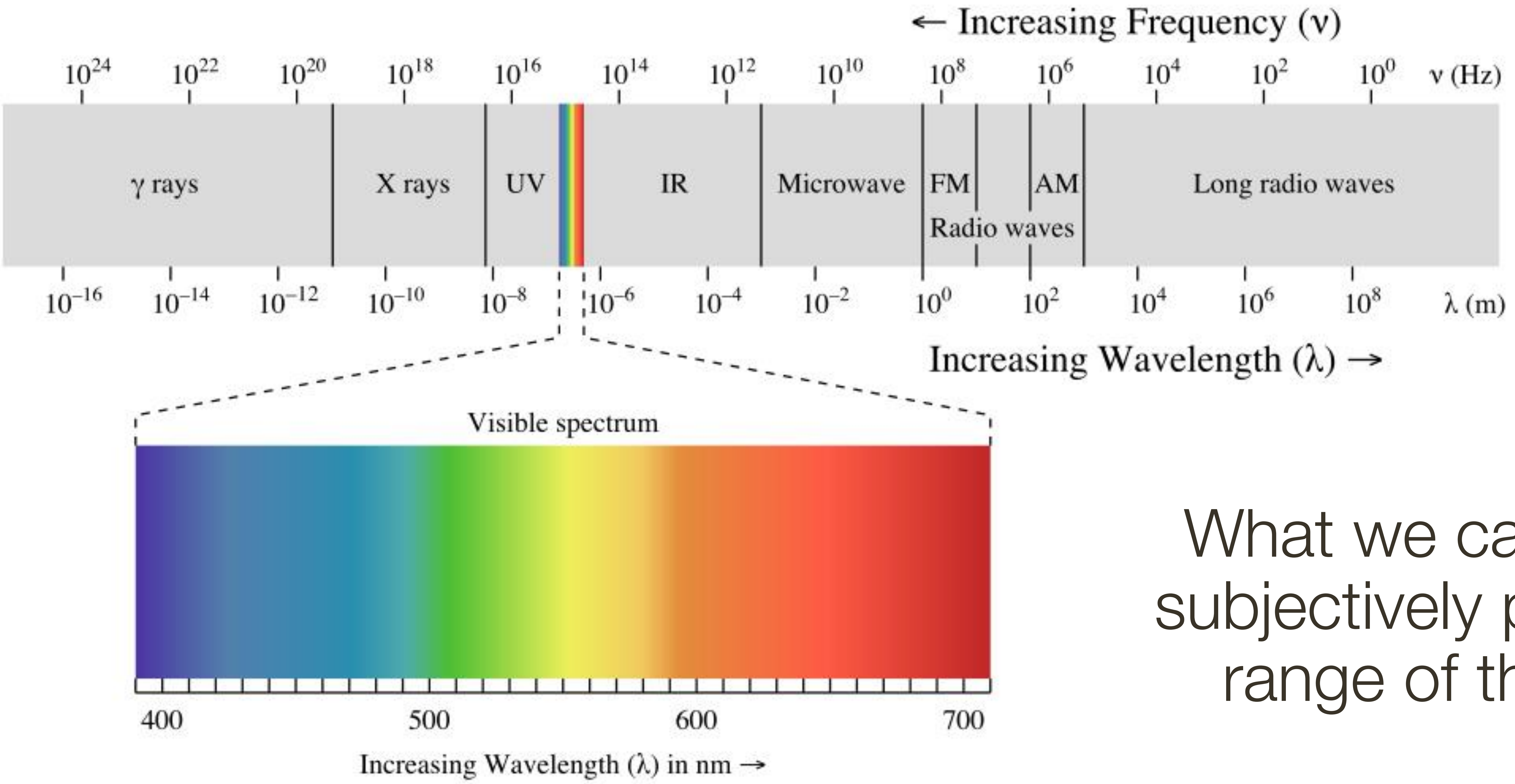


Image Resolution: 5 x 4

Color is an Artifact of Human Perception

"Color" is **not** an objective physical property of light (electromagnetic radiation).

Instead, light is characterized by its wavelength.

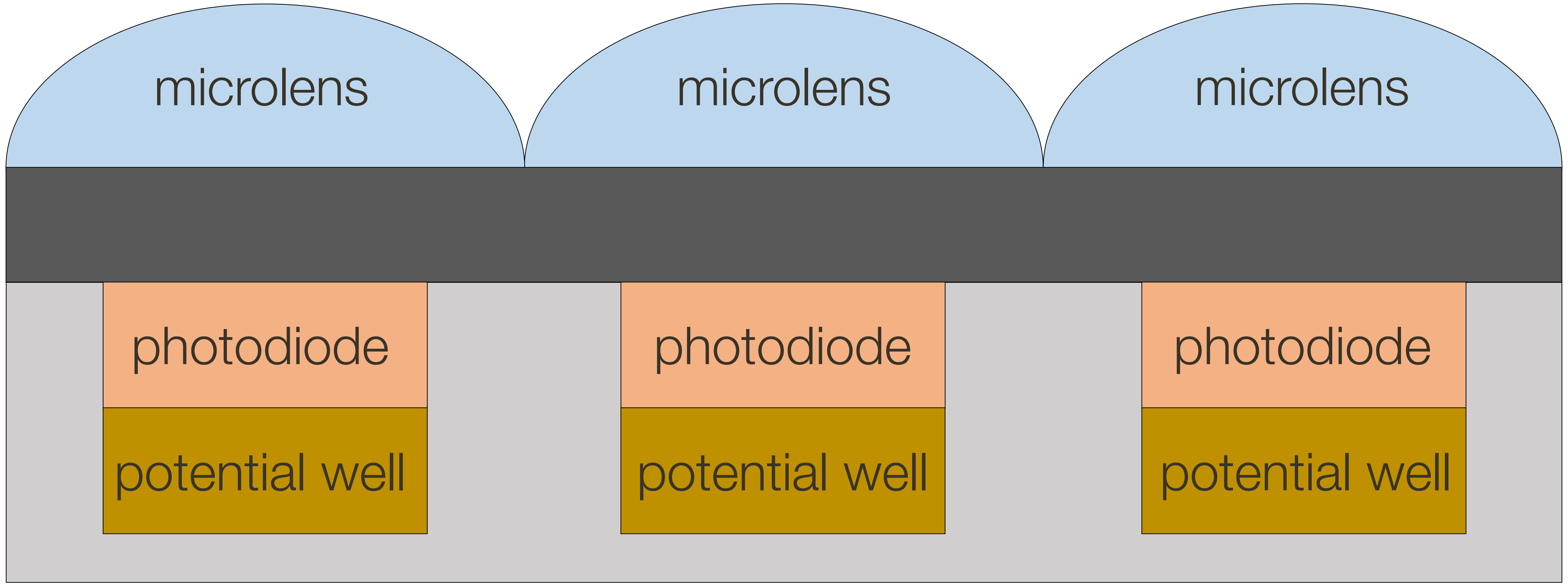


electromagnetic spectrum

What we call "color" is how we subjectively perceive a very small range of these wavelengths.

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Color Filter Arrays (CFA)

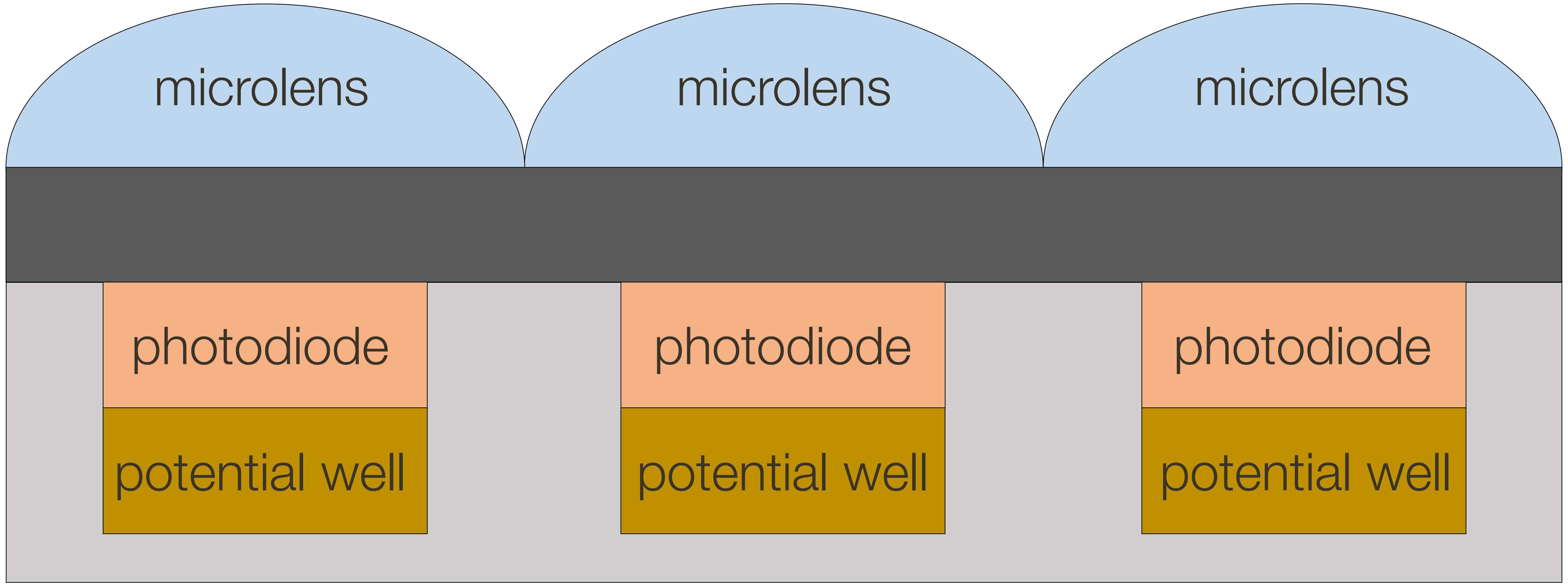


Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Color Filter Arrays (CFA)

In addition to a camera lens,

each pixel has a microns



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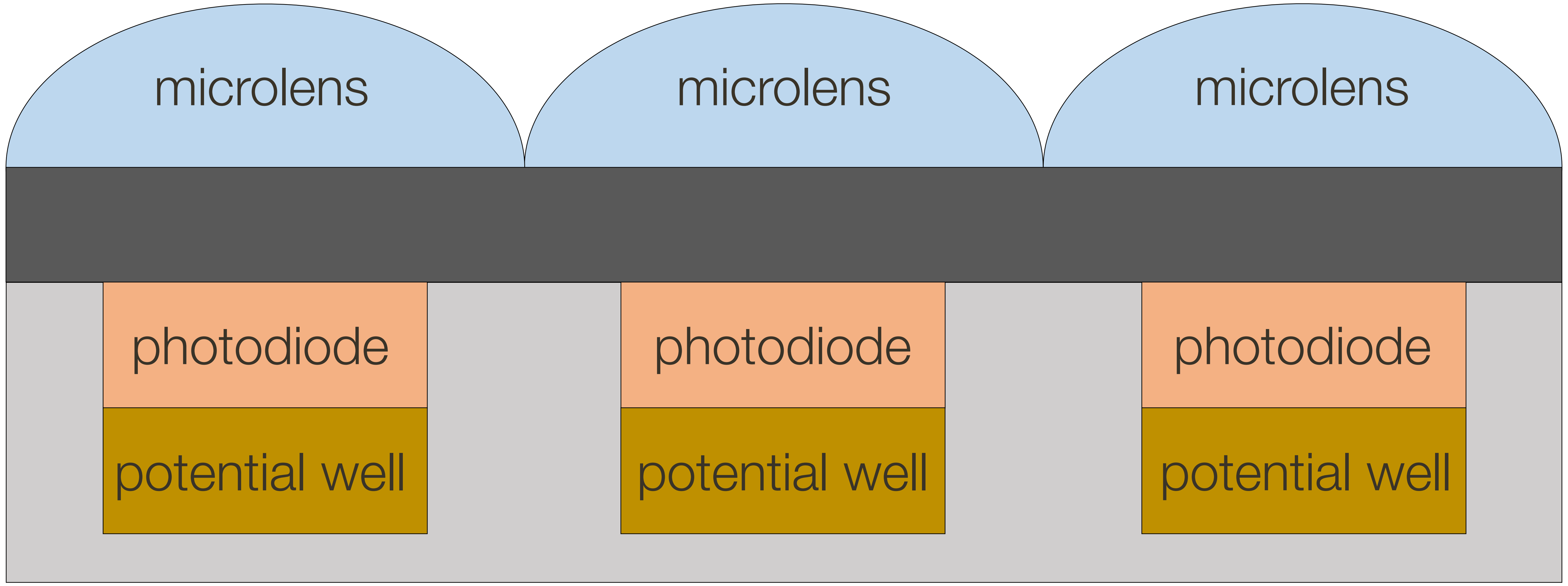

Photodiode: converts photons to electrons

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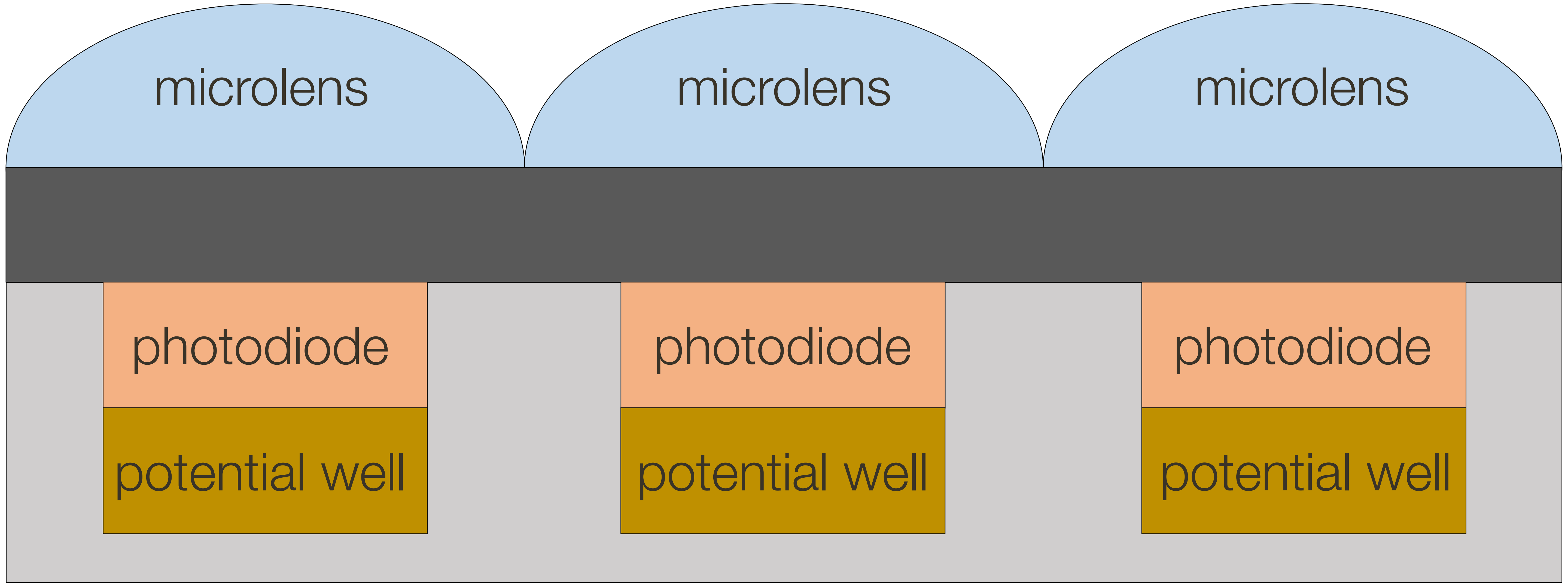

Photodiode: converts photons to electrons

Electrons stored in the **potential well**, until they are read off

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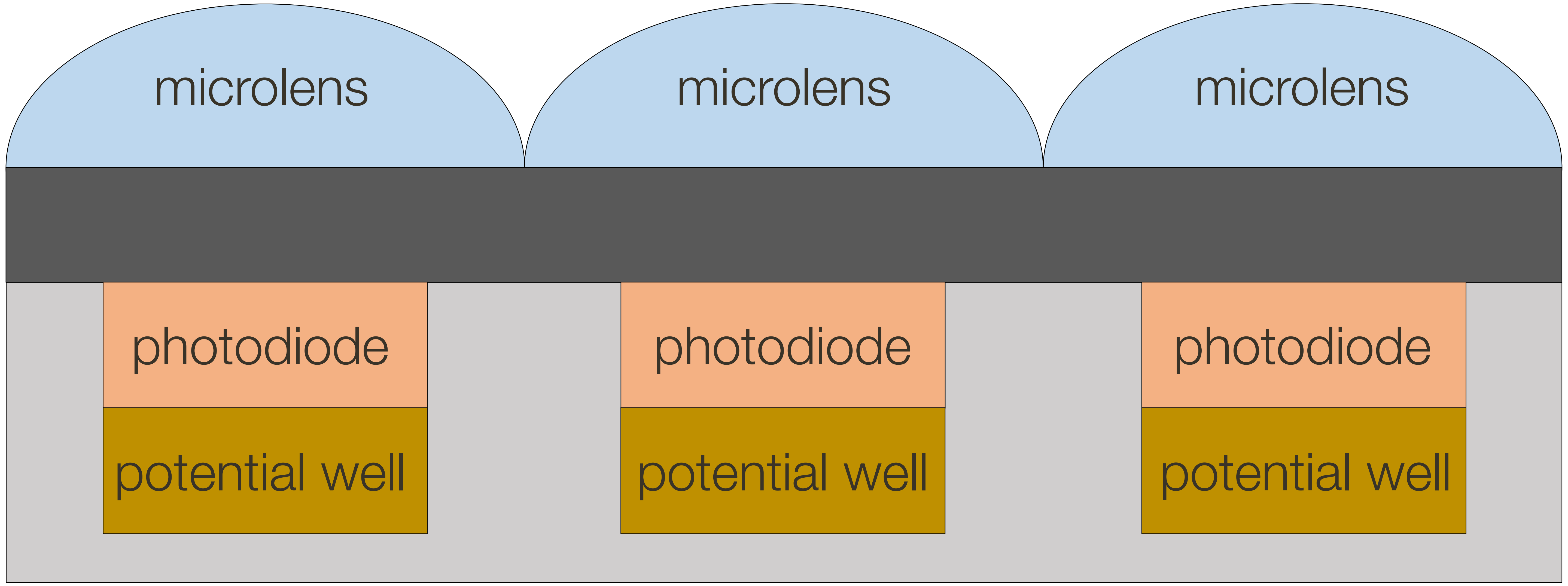

Photodiode: converts photons to electrons

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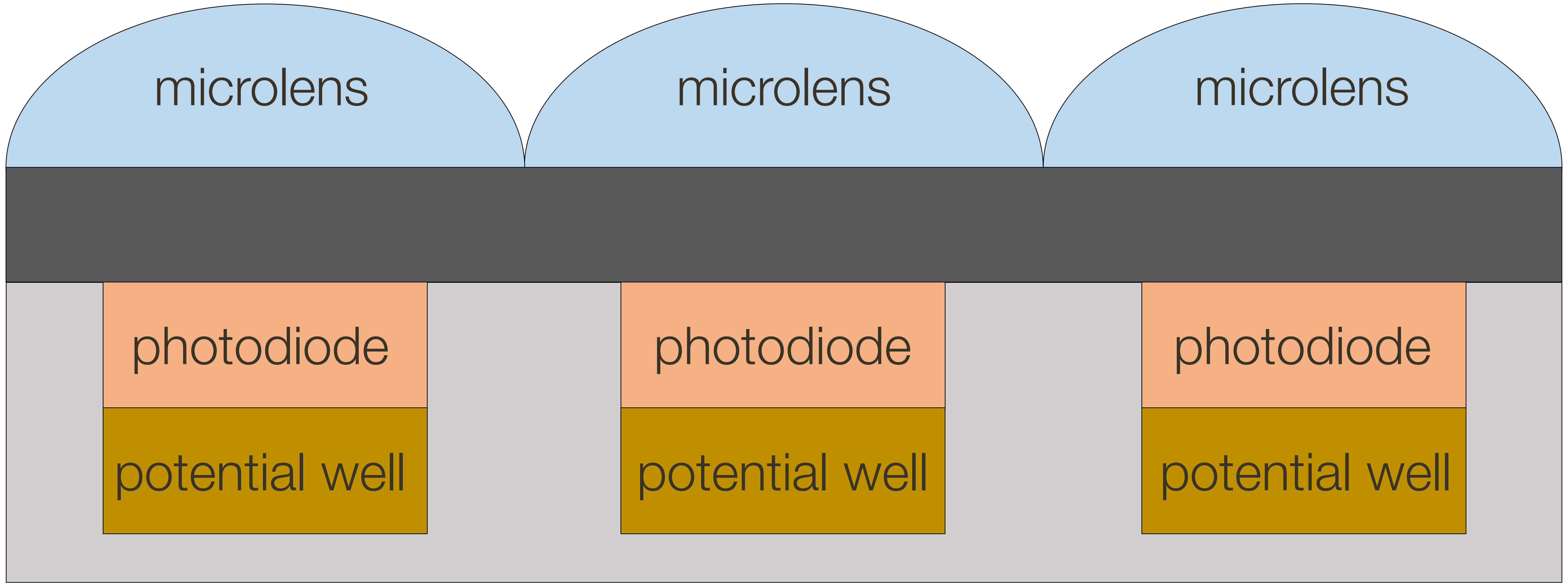
Quantum efficiency: fraction of photons being "detected" through this process (human eye QE: 20%, film cameras QE: 10%, CCD QE: 80%)

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Color Filter Arrays (CFA)

Issue: Color Filter Array (SFA) by itself has no way of distinguishing wavelengths of light, just ability to record the amount of light incident on an element



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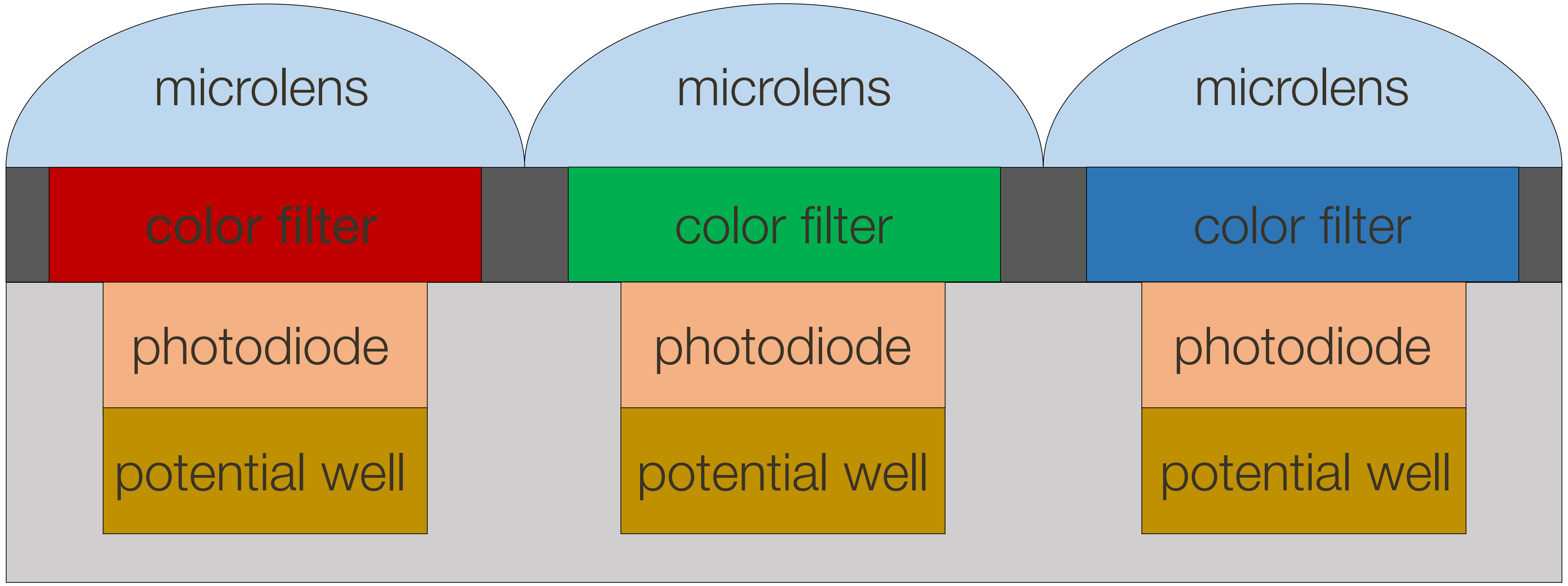

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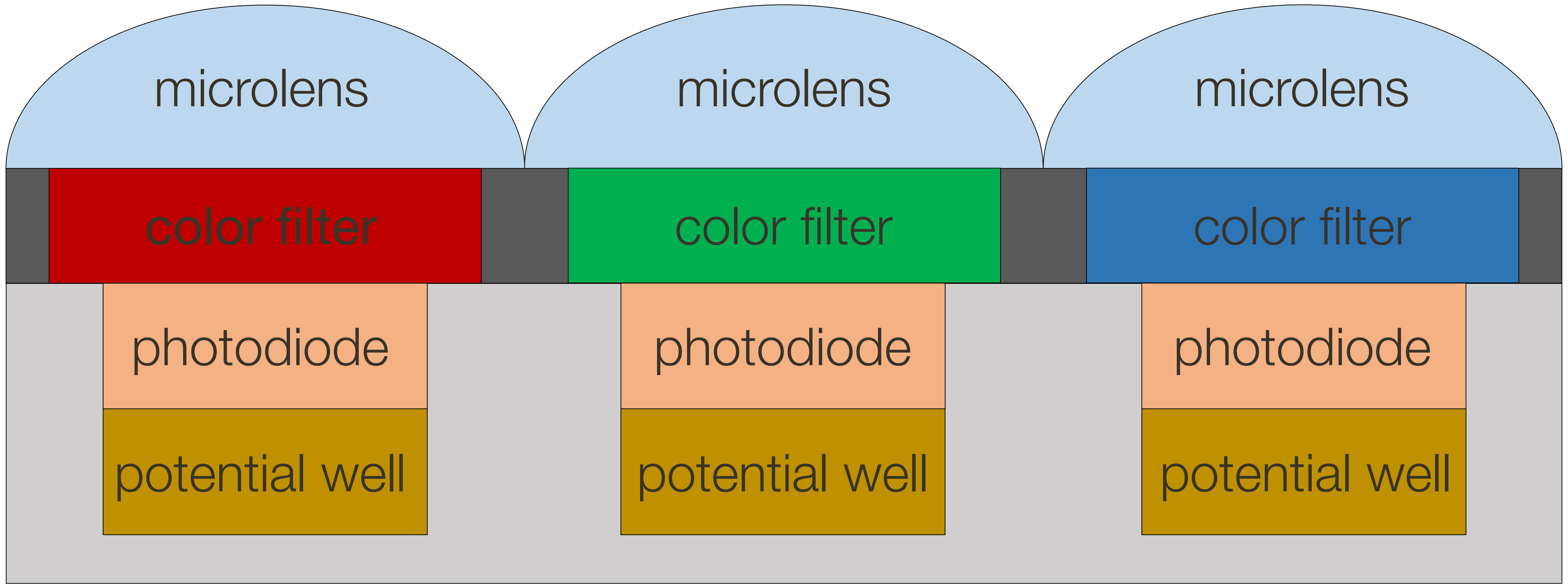
Color Filter Arrays (CFA)

Implication: Only certain wavelengths of light are recorded at a given pixel



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Color Filters

Two **design choices**:

— What spectral sensitivity functions $f(\lambda)$ to use for each color filter?

— How to spatially arrange ("**mosaic**") different color filters?

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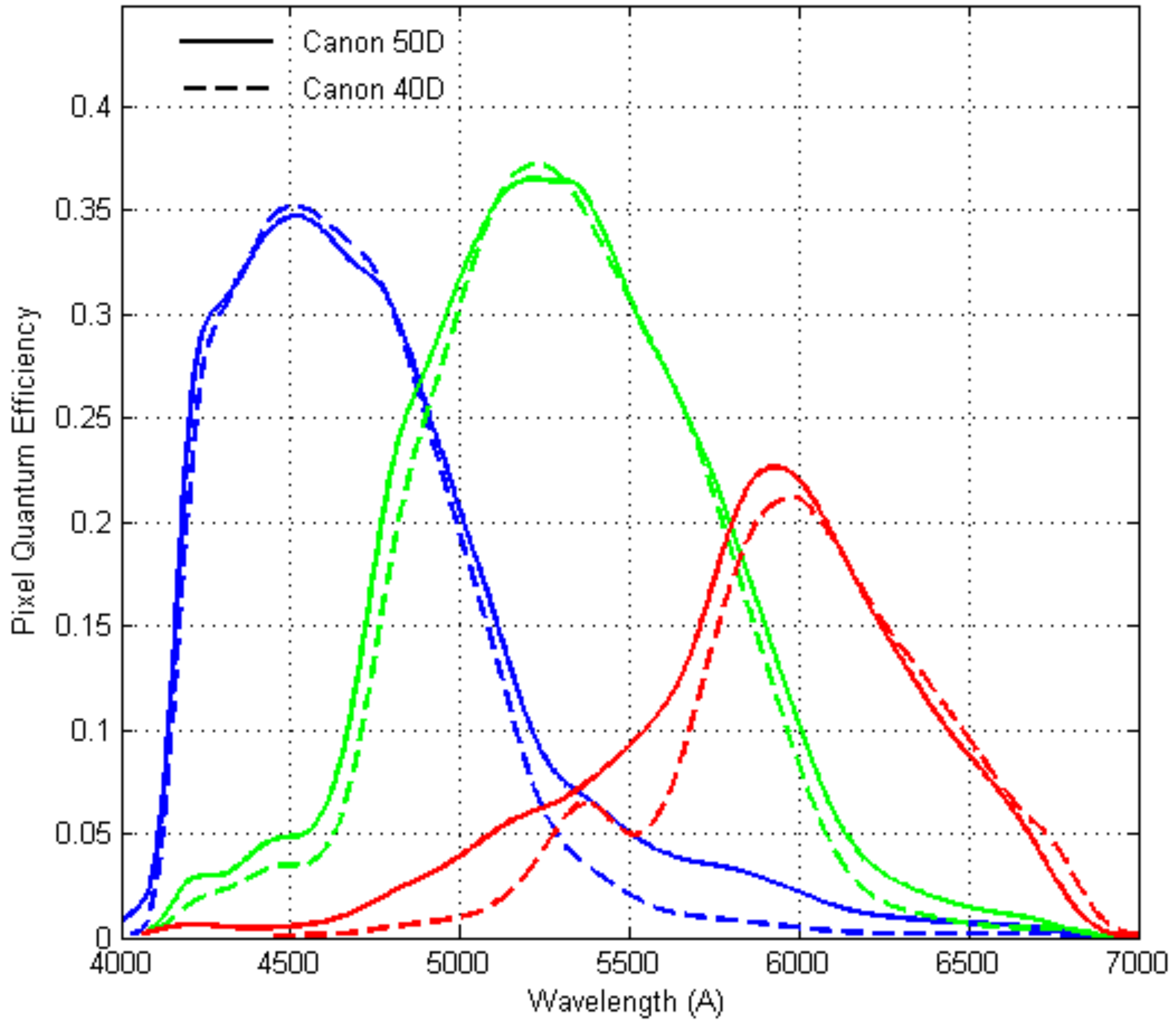
Canon 50D



$f(\lambda)$

Generally do not match human sensitivity

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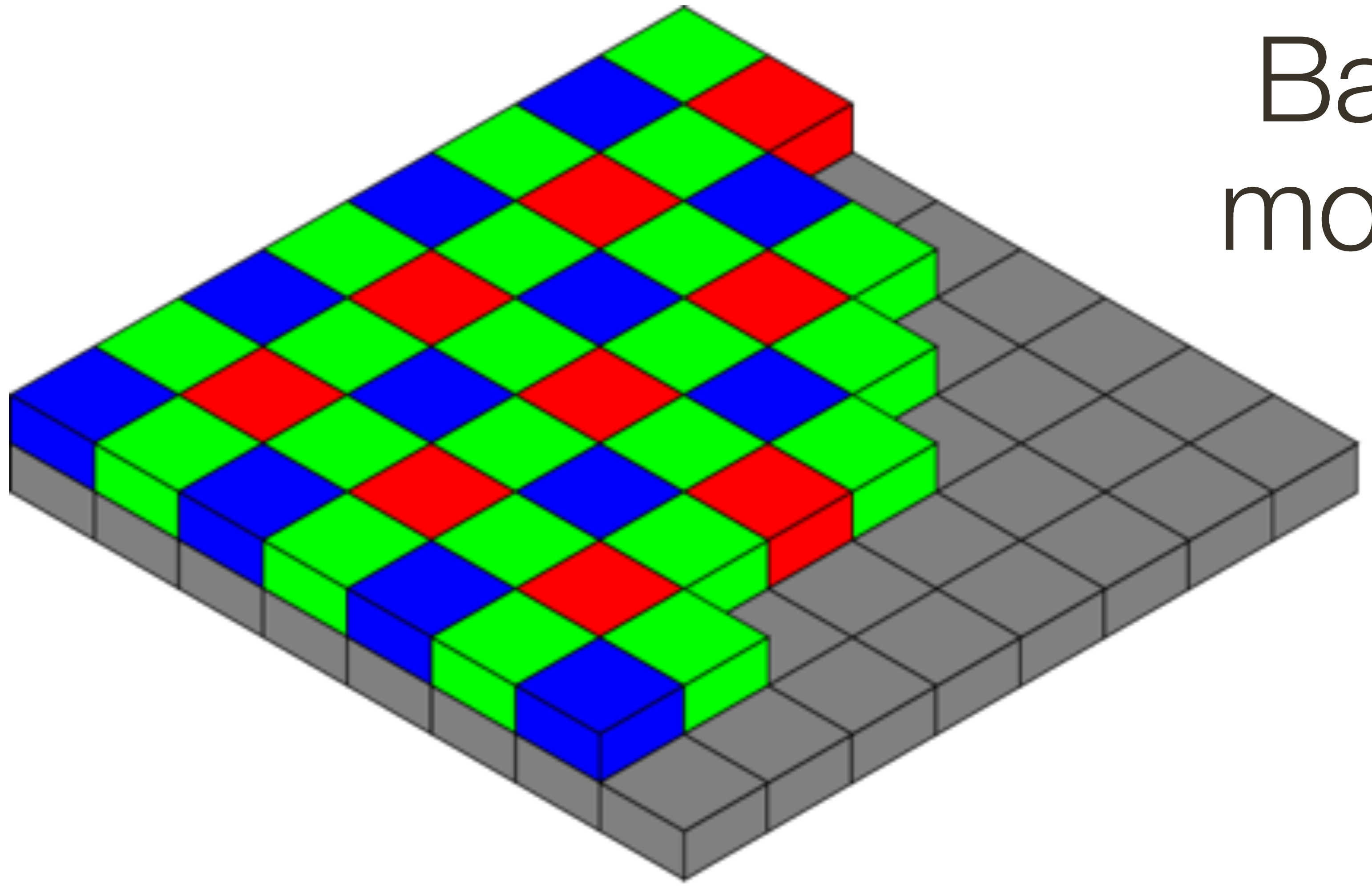
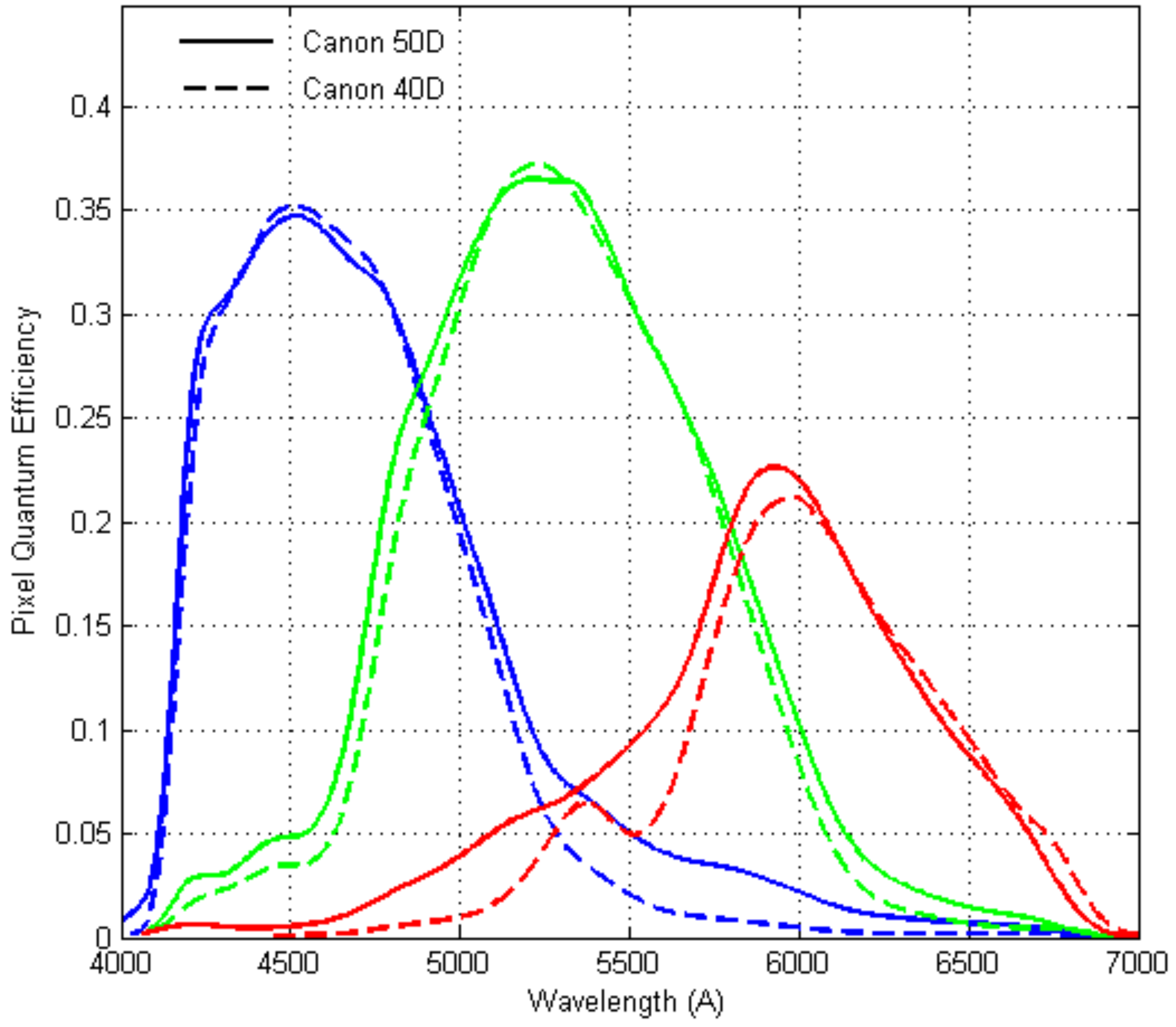


Bayer mosaic

Generally do not match human sensitivity

Canon 50D



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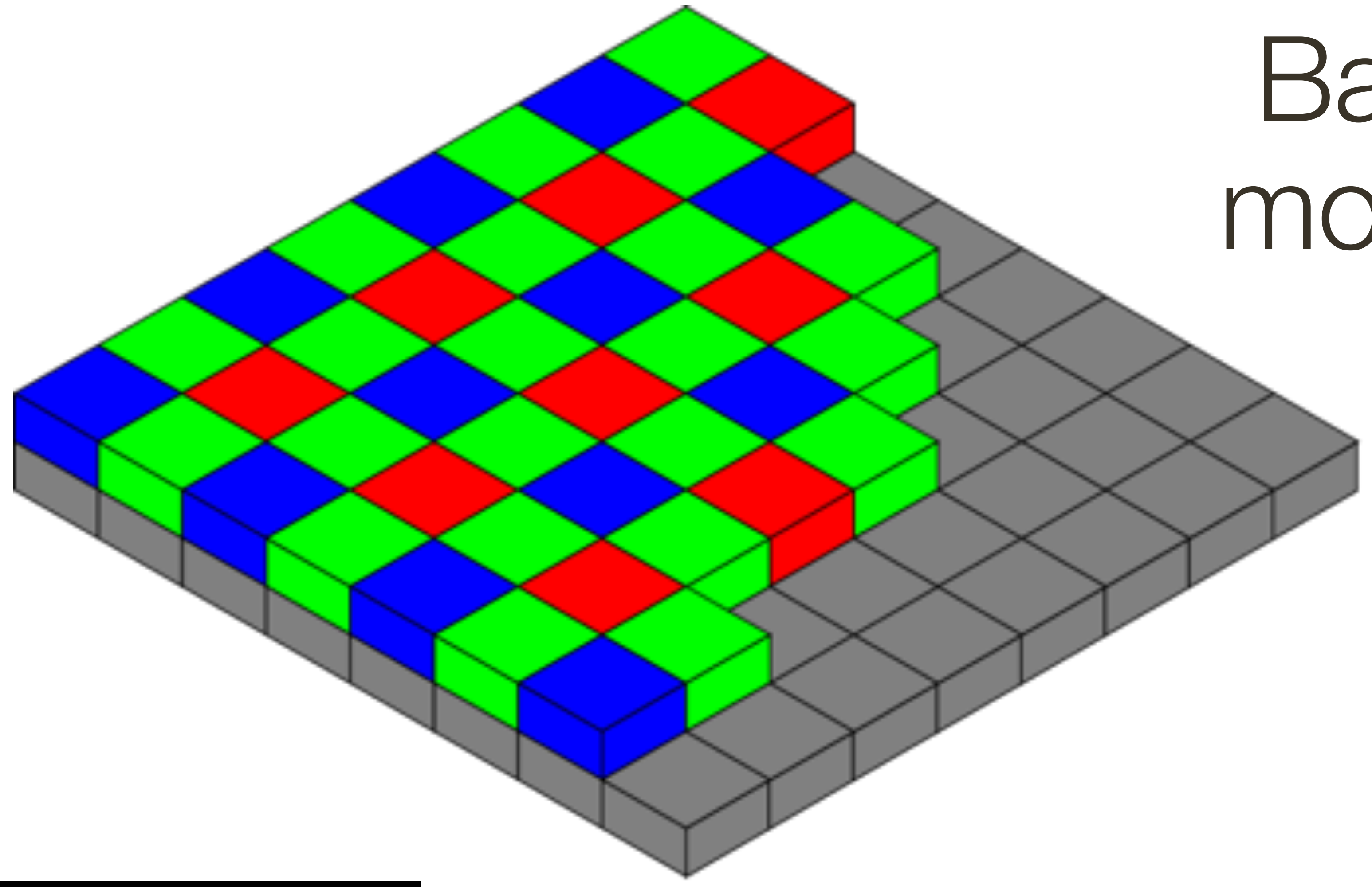
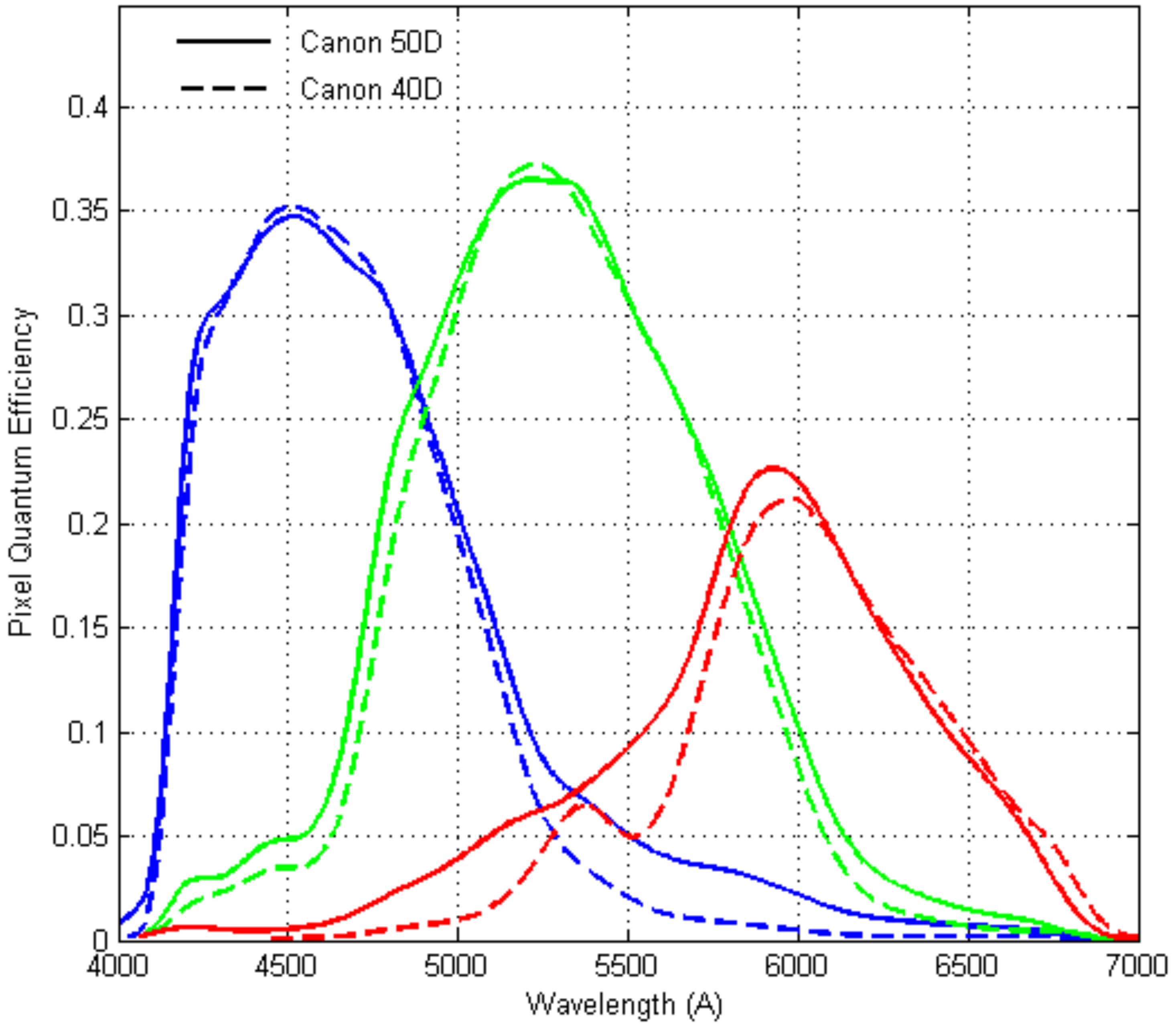


Bayer mosaic

Why more green pixels?

Generally do not match human sensitivity

Canon 50D



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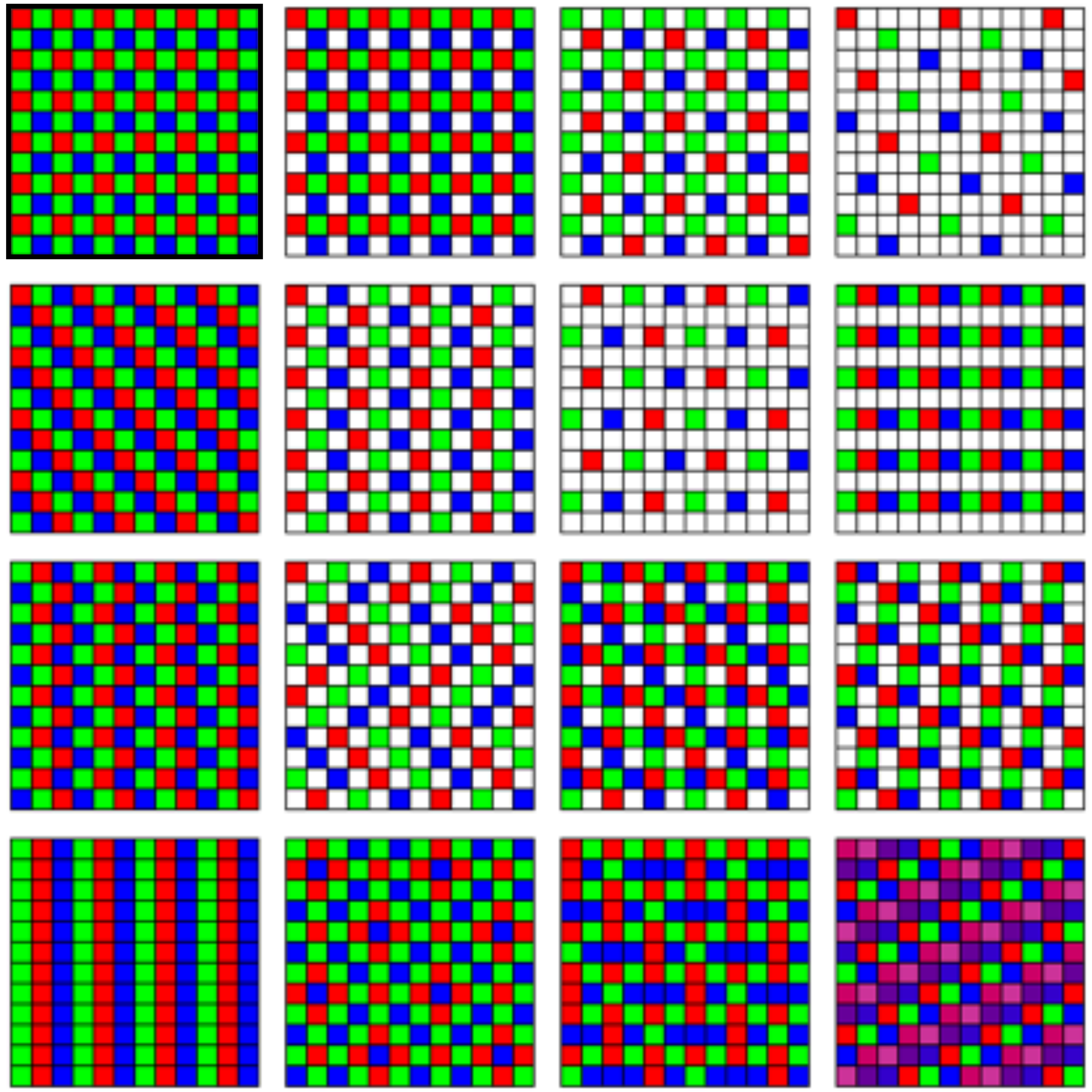
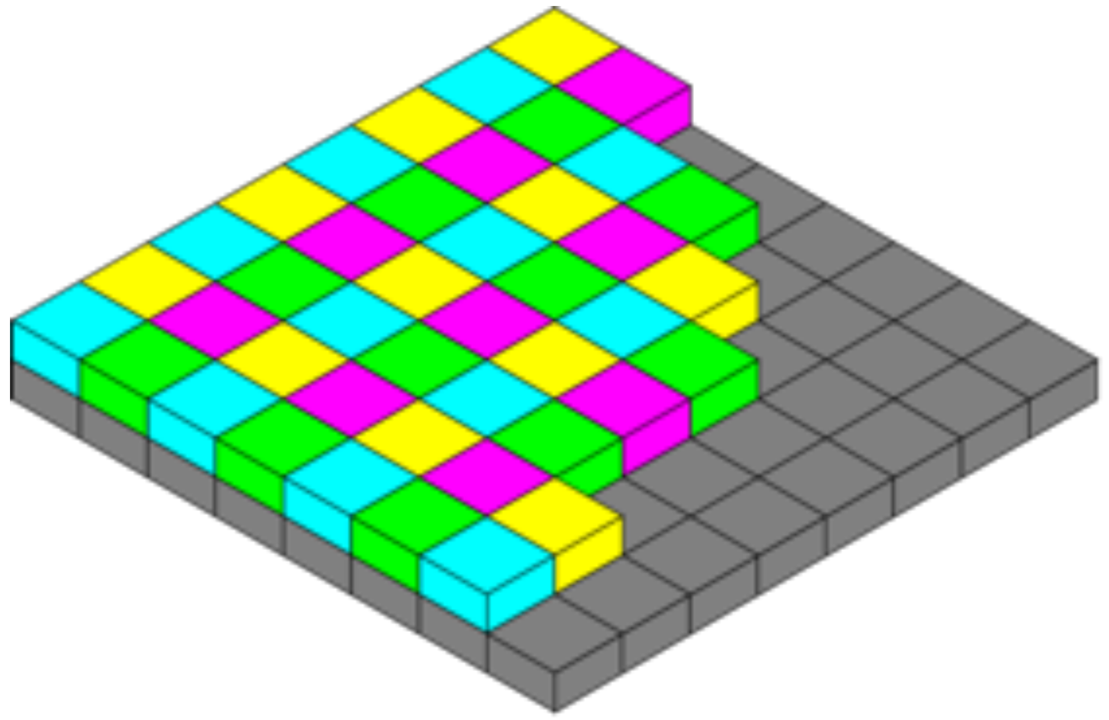
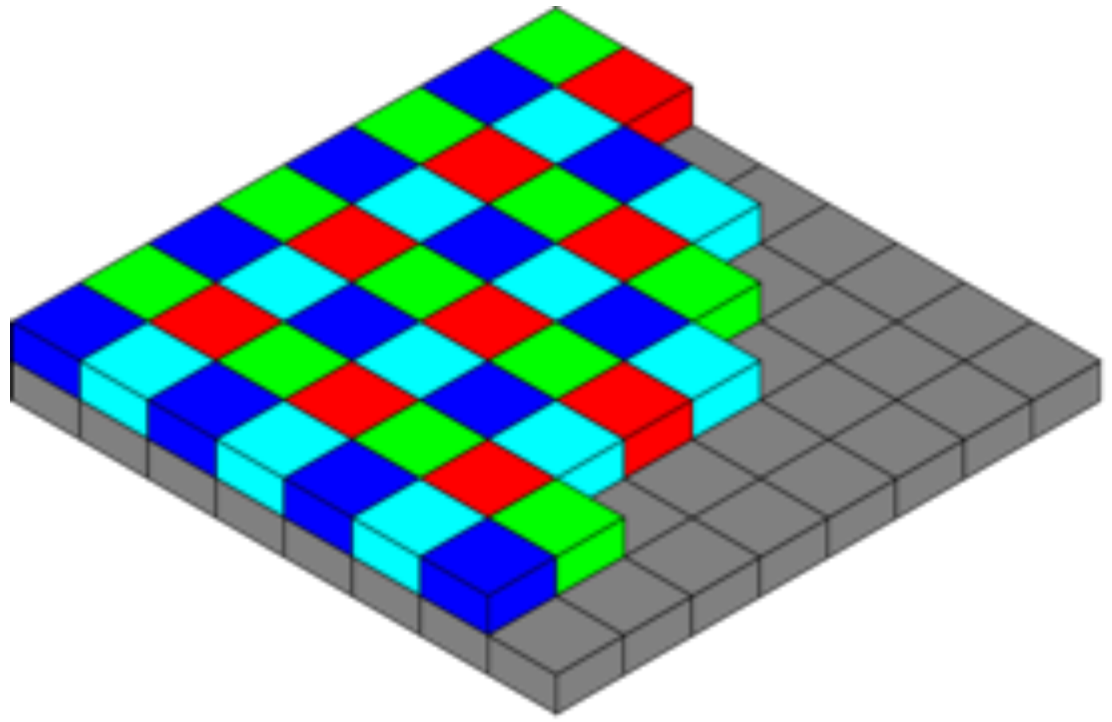
Different Color Filter Arrays (CFAs)

Finding the “**best**” CFA mosaic is an active research area.





CYGM
Canon IXUS, Powershot



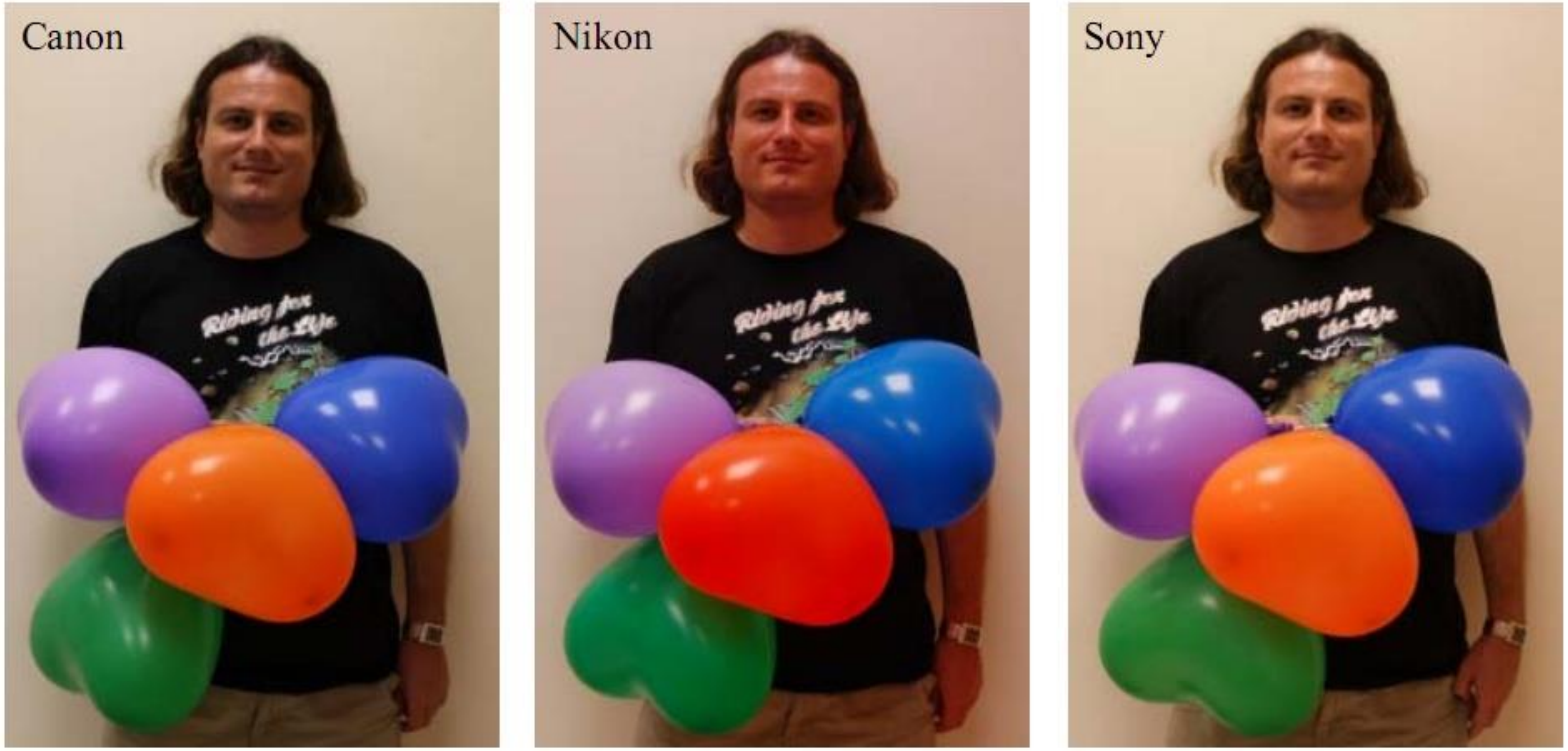
RGBE
Sony Cyber-shot

How would you go about designing your own CFA? What criteria would you consider?

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Many **Different Spectral Sensitivity** Functions

Each camera has its more or less unique, and most of the time secret, SSF

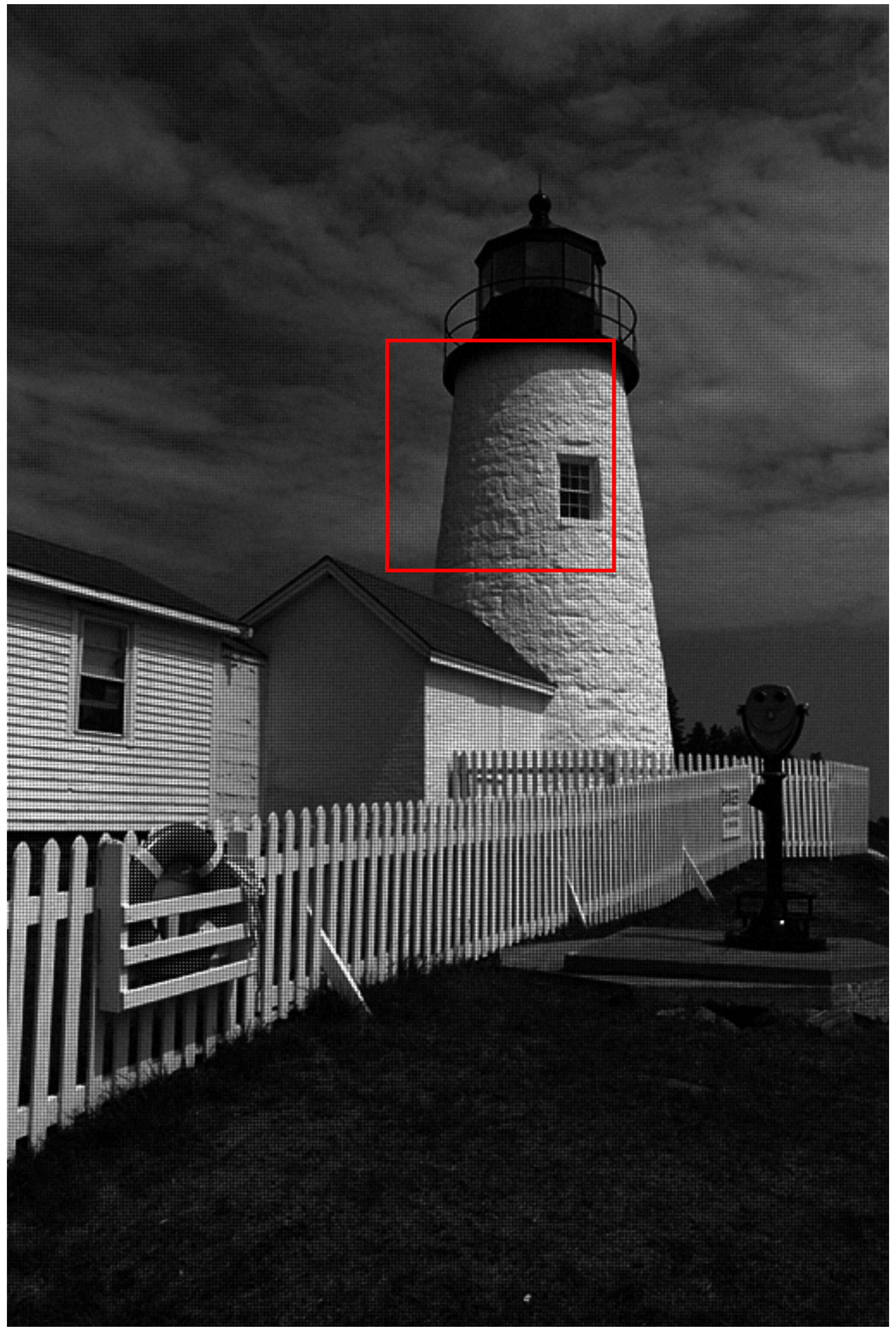


Same scene captured using 3 different cameras with identical settings

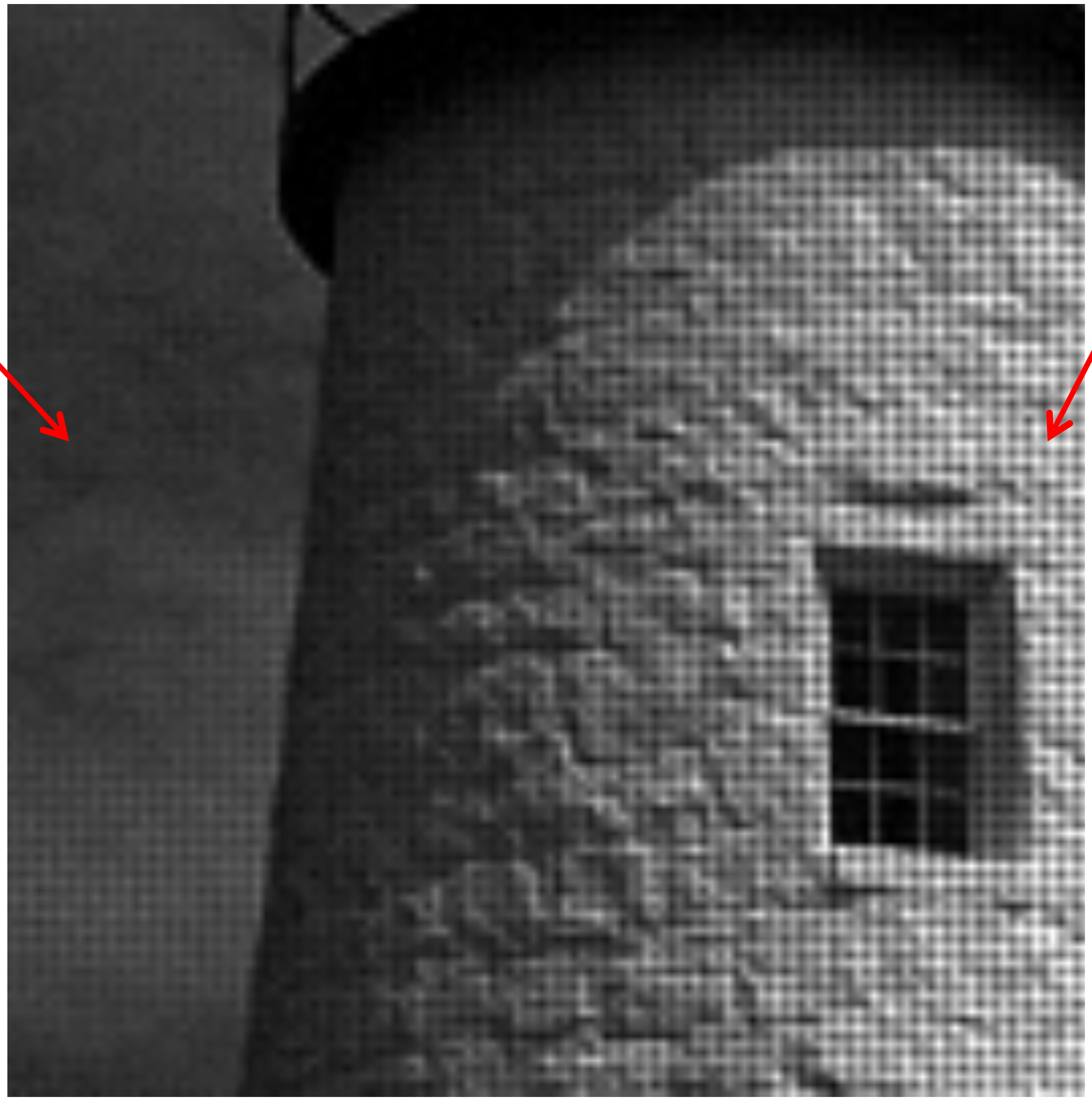
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

RAW Bayer Image

After all of this, what does an image look like?



lots of noise



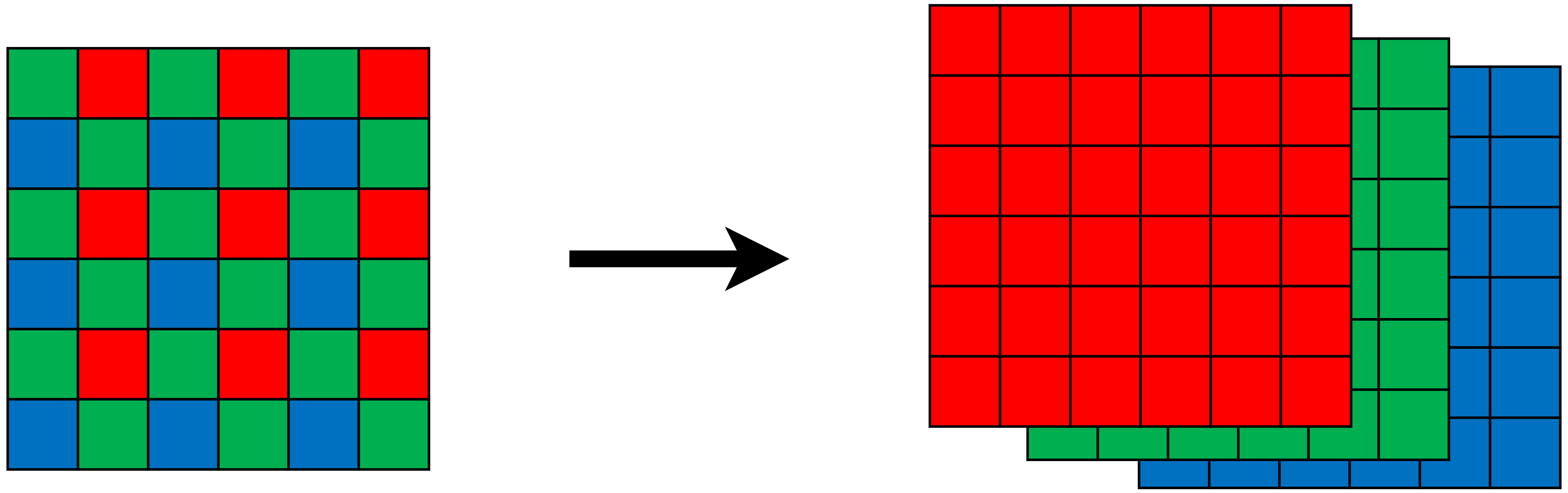
mosaicking artifacts

- Kind of disappointing
- We call this the RAW image

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

CFA **Demosicing**

Produce full RGB image from mosaiced sensor output

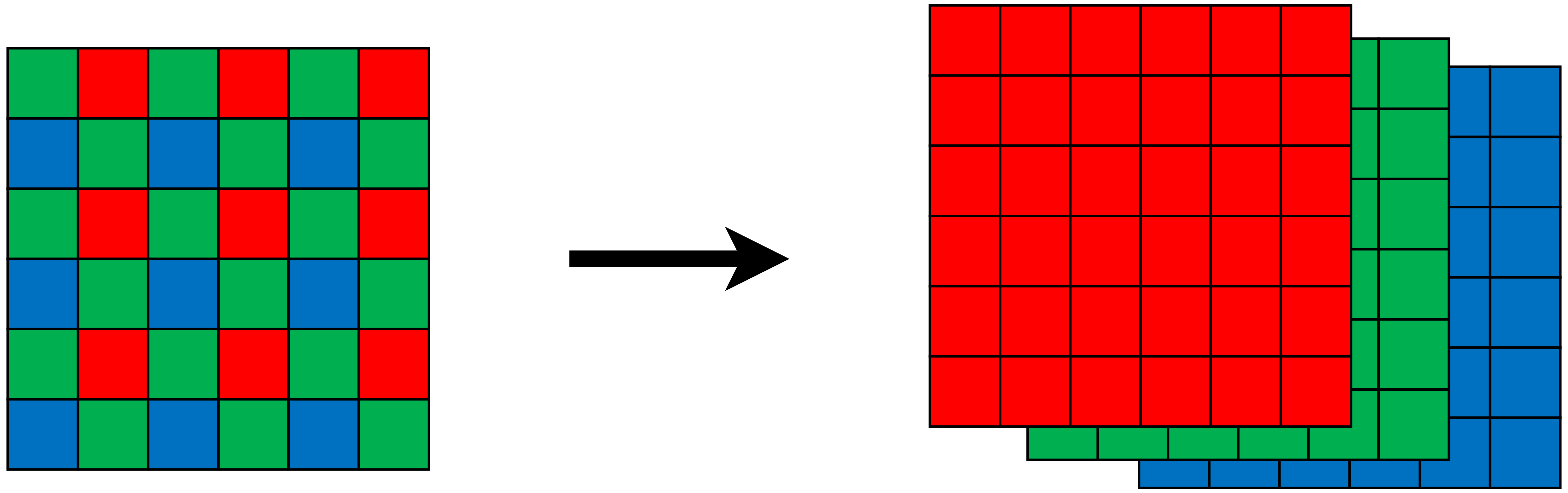


Any ideas on how to do this?

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

CFA **Demosicing**

Produce full RGB image from mosaiced sensor output



Interpolate from neighbors:

— Bilinear interpolation (needs 4 neighbors)

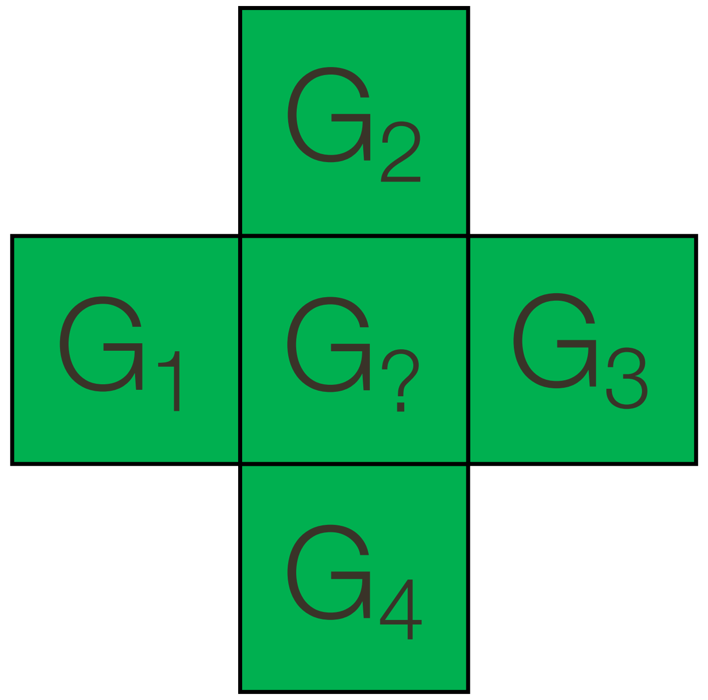
— Bicubic interpolation (needs more neighbors, may overblur)

— Edge-aware interpolation (e.g., Bilateral)

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

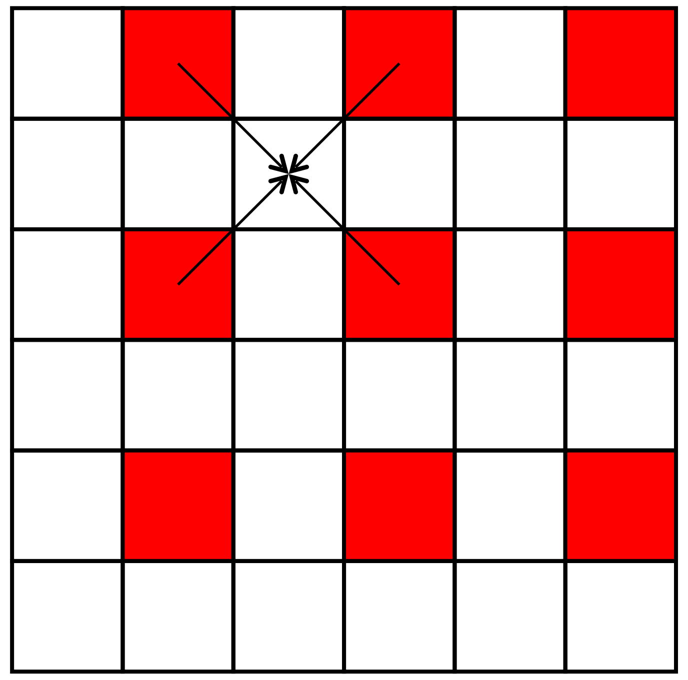
Demosaicing by Bilinear Interpolation

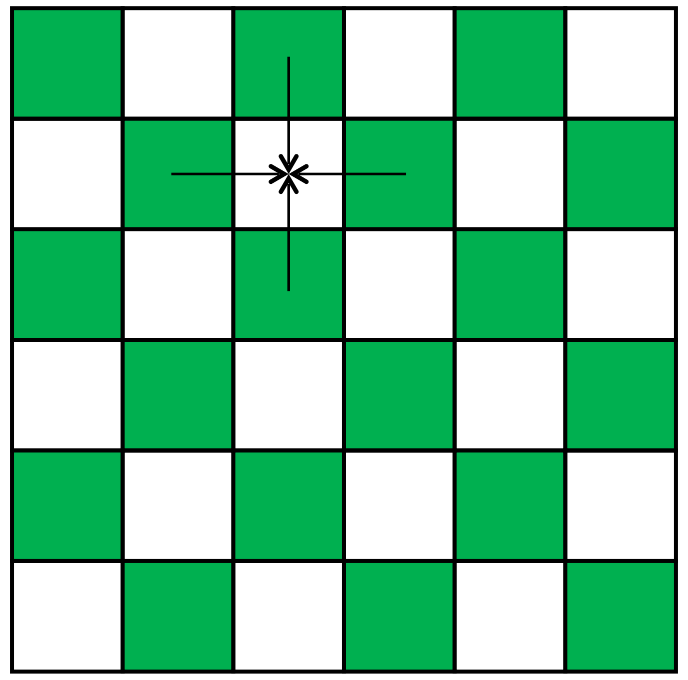
Bilinear interpolation: Simply average your 4 neighbors.

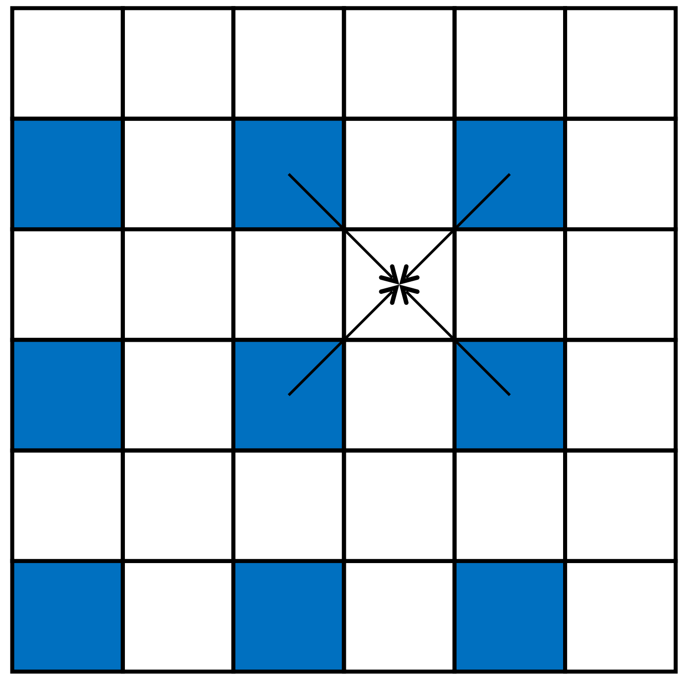


$$G_? = \frac{G_1 + G_2 + G_3 + G_4}{4}$$

Neighborhood changes for different channels:



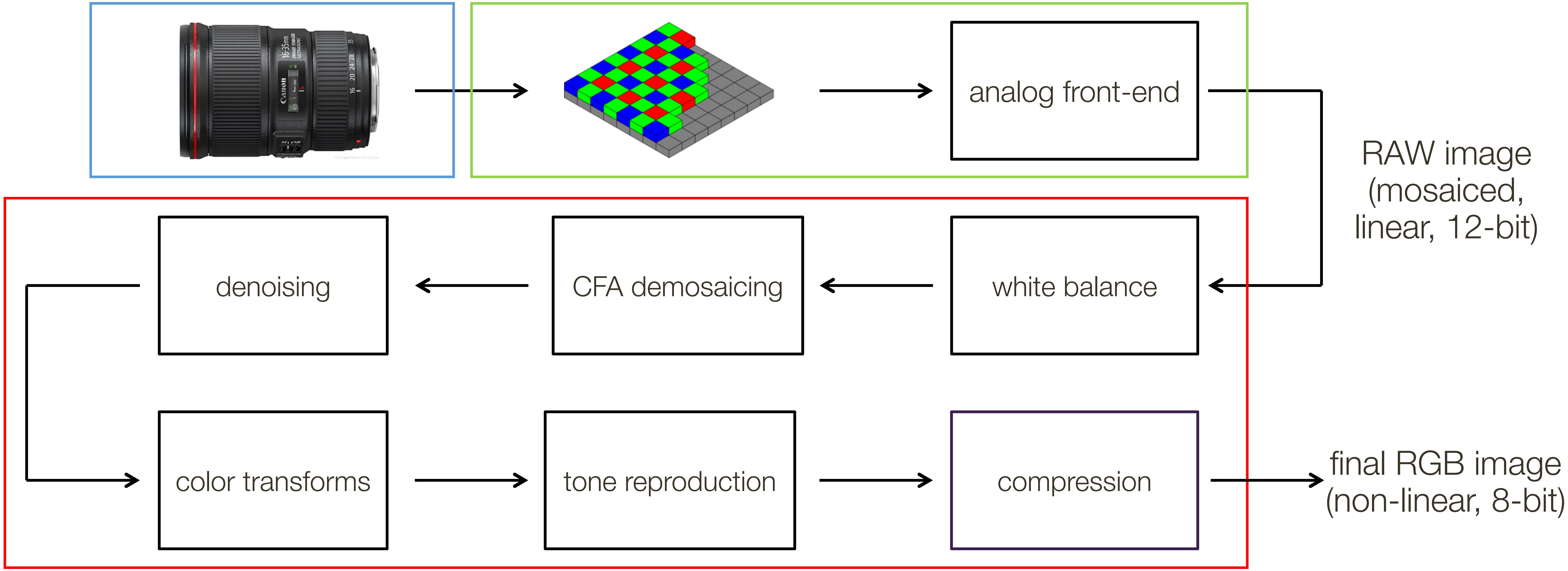




Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

(in camera) **Image** Processing Pipeline

The sequence of image processing operations applied by the camera's image signal processor (ISP) to convert a RAW image into a "conventional" image.



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

(in camera) **White** balance

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

(in camera) **White** balance

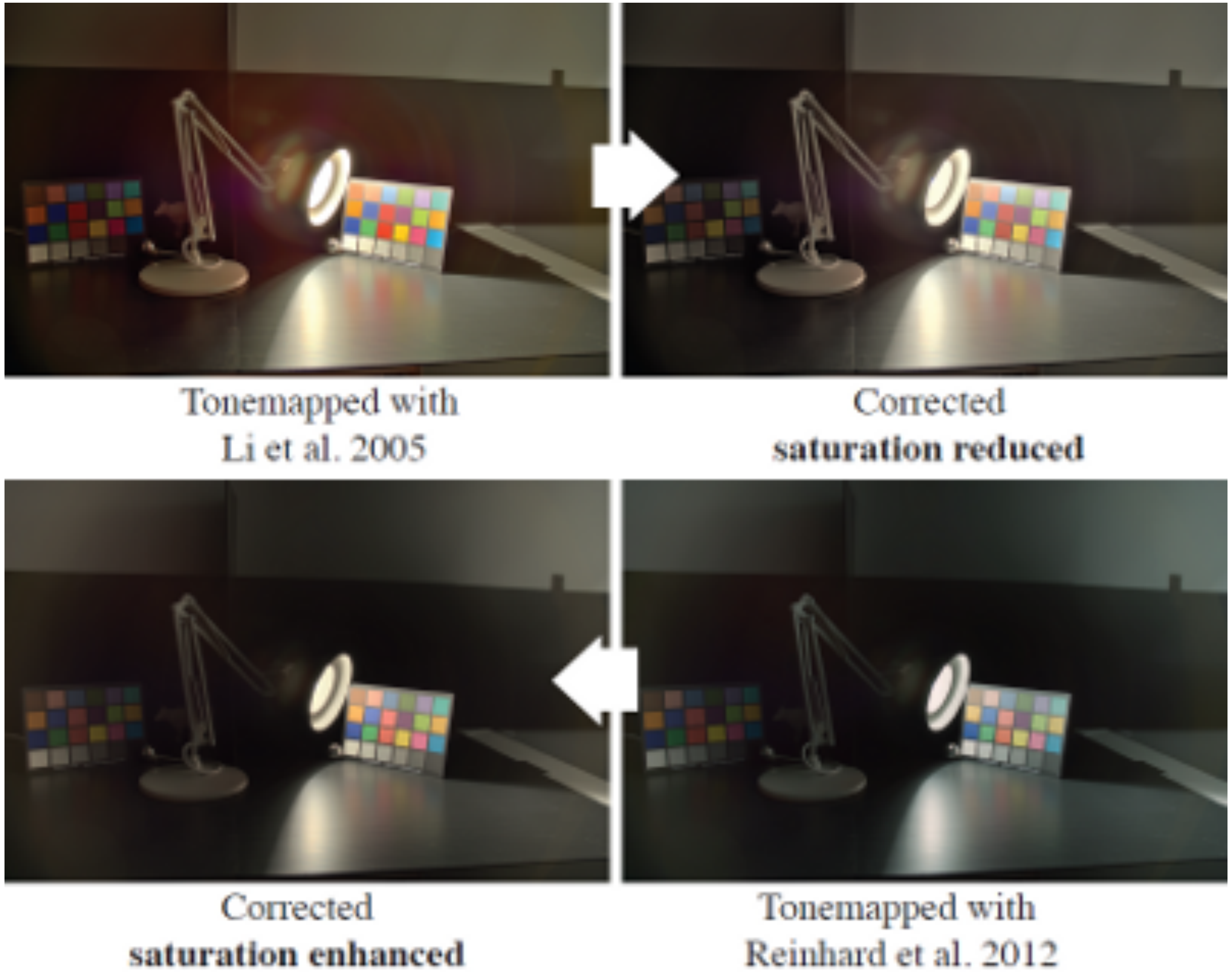
R: 200
G: 255
B: 190

→

R-correction: + 55
G-correction: + 0
B-correction: + 65

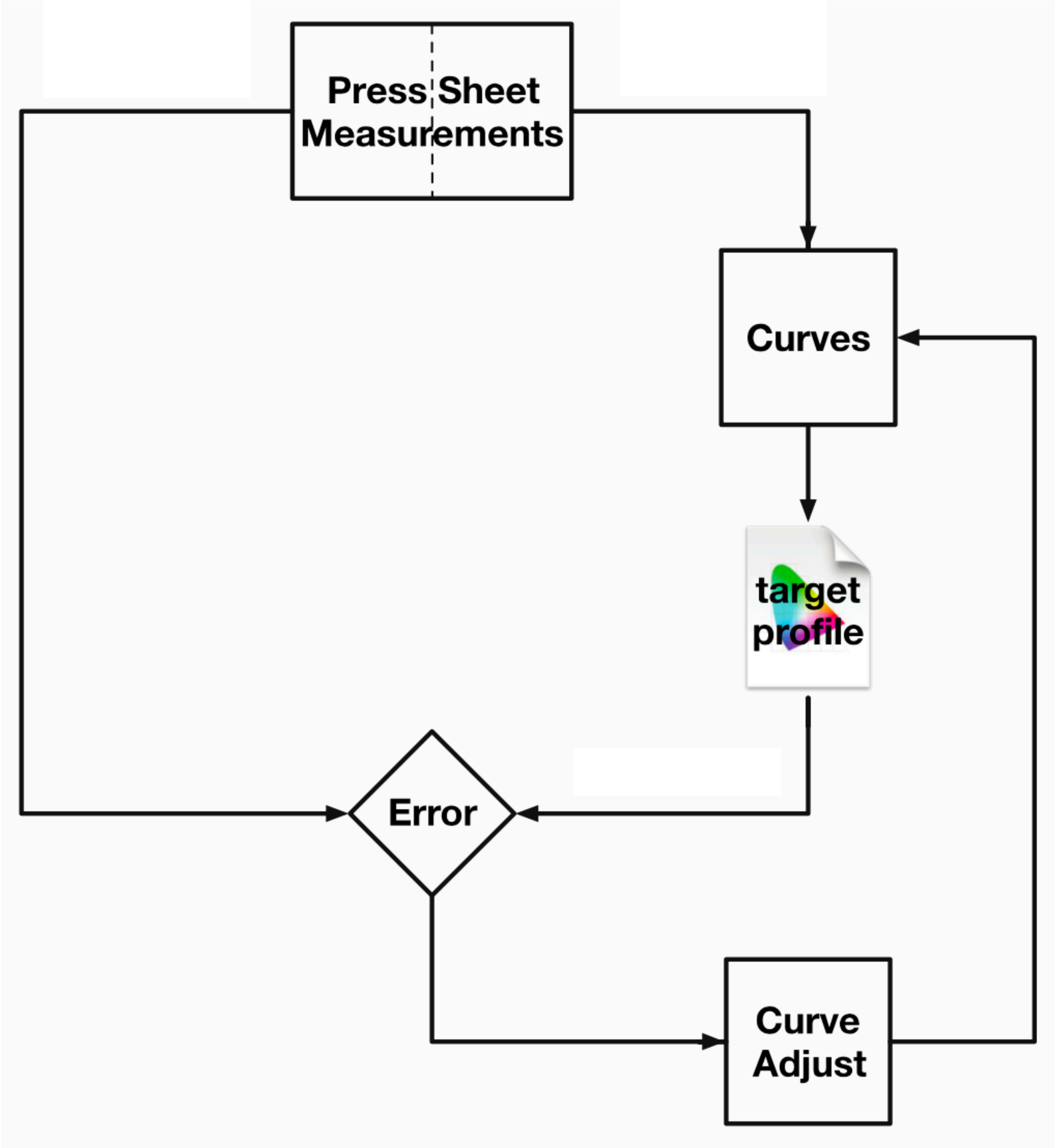
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

(in camera) **Tone** reproduction



Tonemapped with Li et al. 2005 → Corrected **saturation reduced**

Corrected **saturation enhanced** ← Tonemapped with Reinhard et al. 2012



Summary

"Color" is **not** an objective physical property of light (electromagnetic radiation). Instead, light is characterized by its wavelength.

Color Filter Arrays (CFAs) allow capturing of mosaiced color information; the layout of the mosaic is called **Bayer** pattern.

Demosaicing is the process of taking the RAW image and interpolating missing color pixels per channel