Lecture 4:

# Frankencamera +
# Finishing up the Camera Pipeline

Visual Computing Systems
Stanford CS348K, Spring 2022

# Local tone adjustment

Pixel values

Weights


**Improve picture's aesthetics by locally adjusting contrast, boosting dark regions, decreasing bright regions**

**(no physical basis)**

Combined image
(unique weights per pixel)

Image credit: Mertens 2007

# Challenge of merging images

Four exposures (weights not shown)

Merged result (based on weight masks)
Notice heavy "banding" since absolute intensity of different exposures is different

Merged result
(after blurring weight mask)
Notice "halos" near edges

# Gaussian pyramid

$G_0$ = image

$G_1$ = down($G_0$)

$G_2$ = down($G_1$)

**Each image in pyramid contains increasingly low-pass filtered signal**

down() = downsample operation

# Gaussian pyramid

$G_0$

# Gaussian pyramid

$G_1$

# Gaussian pyramid

$G_2$

# Gaussian pyramid

$G_3$

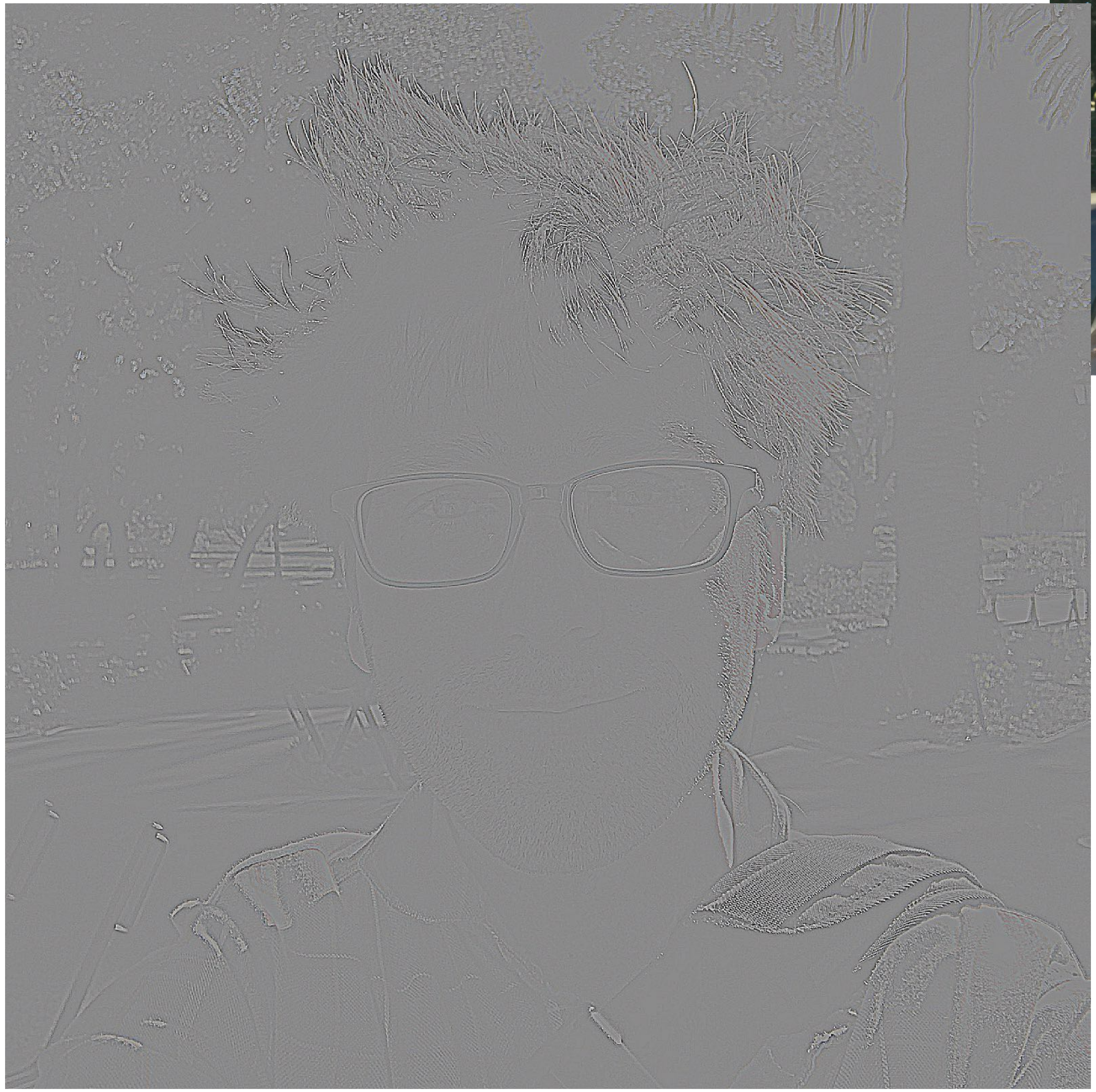
# Gaussian pyramid

$G_4$

# Gaussian pyramid

$G_5$

# Laplacian pyramid



$L_0 = G_0 - up(G_1)$

$G_0$

$G_1 = down(G_0)$

Each (increasingly numbered) level in Laplacian pyramid represents a band of (increasingly lower) frequency information in the image

[Burt and Adelson 83]

# Laplacian pyramid

$L_0 = G_0 - up(G_1)$

$L_1 = G_1 - up(G_2)$

# Laplacian pyramid

$L_0 = G_0 - up(G_1)$

$L_1 = G_1 - up(G_2)$

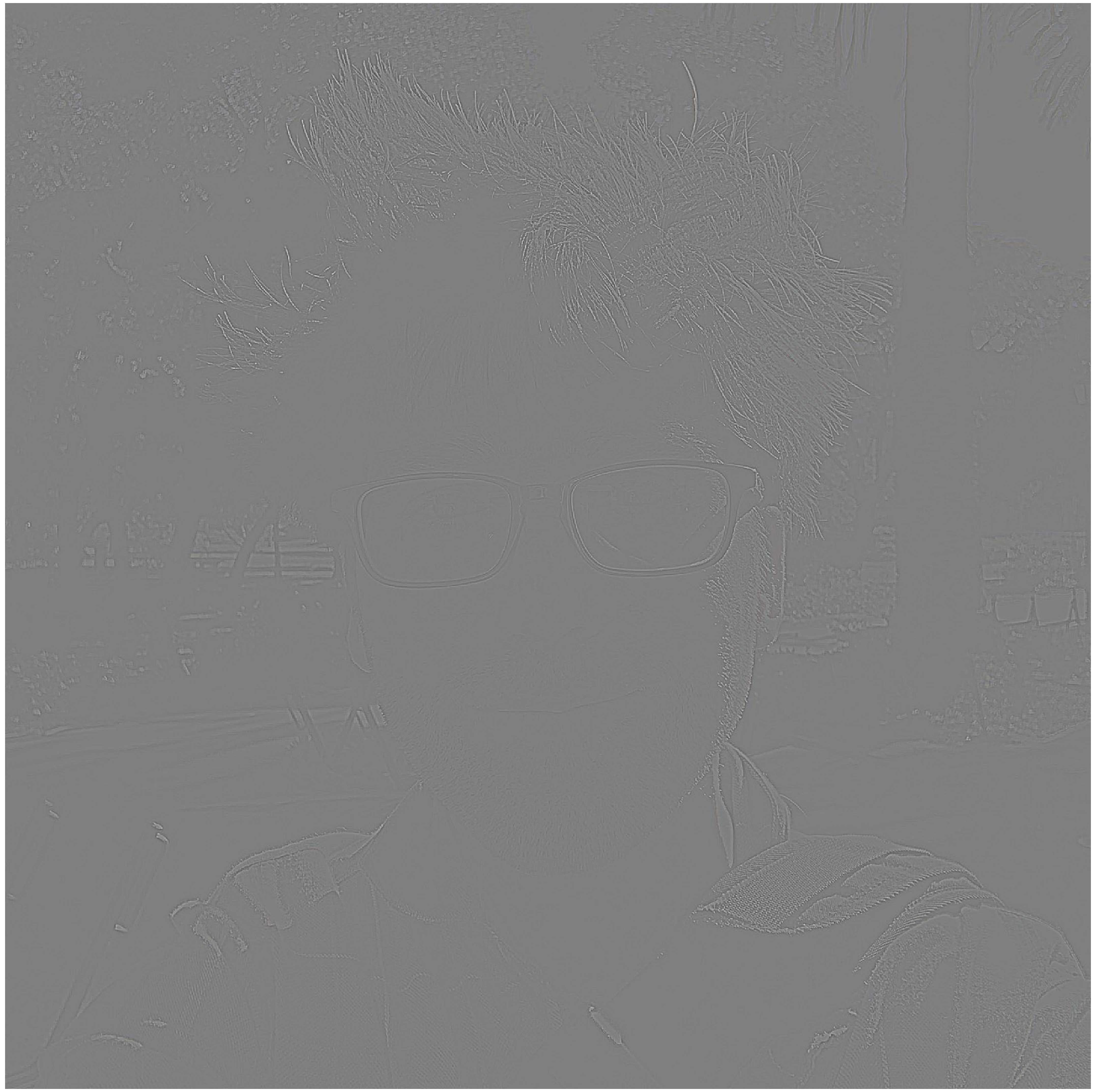
$L_2 = G_2 - up(G_3)$

$L_3 = G_3 - up(G_4)$

$L_4 = G_4$

**Question: how do you reconstruct original image from its Laplacian pyramid?**

# Laplacian pyramid



$L_0 = G_0 - up(G_1)$

# Laplacian pyramid

$L_1 = G_1 - up(G_2)$

# Laplacian pyramid

$L_2 = G_2 - up(G_3)$

# Laplacian pyramid

$L_3 = G_3$ - up($G_4$)

# Laplacian pyramid

$L_4 = G_4 - up(G_5)$

# Laplacian pyramid

**$L_5 = G_5$**

# Summary

- Gaussian and Laplacian pyramids are image representations where each pixel maintains information about frequency content in a region of the image

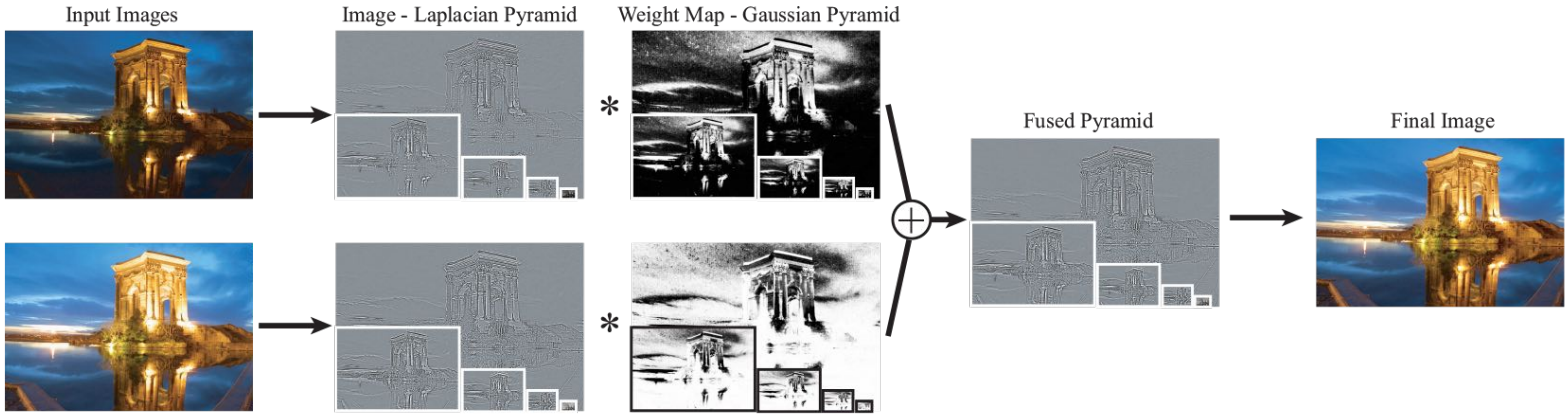
- $G_i(x,y)$ — frequencies up to limit given by *i*

- $L_i(x,y)$ — frequencies added to $G_{i+1}$ to get $G_i$

- Notice: to boost the band of frequencies in image around pixel (x,y), increase coefficient $L_i(x,y)$ in Laplacian pyramid

# Use of Laplacian pyramid in tone mapping

- Compute weights for all Laplacian pyramid levels
- Merge pyramids (image features) not image pixels
- Then “flatten” merged pyramid to get final image



# Challenges of merging images

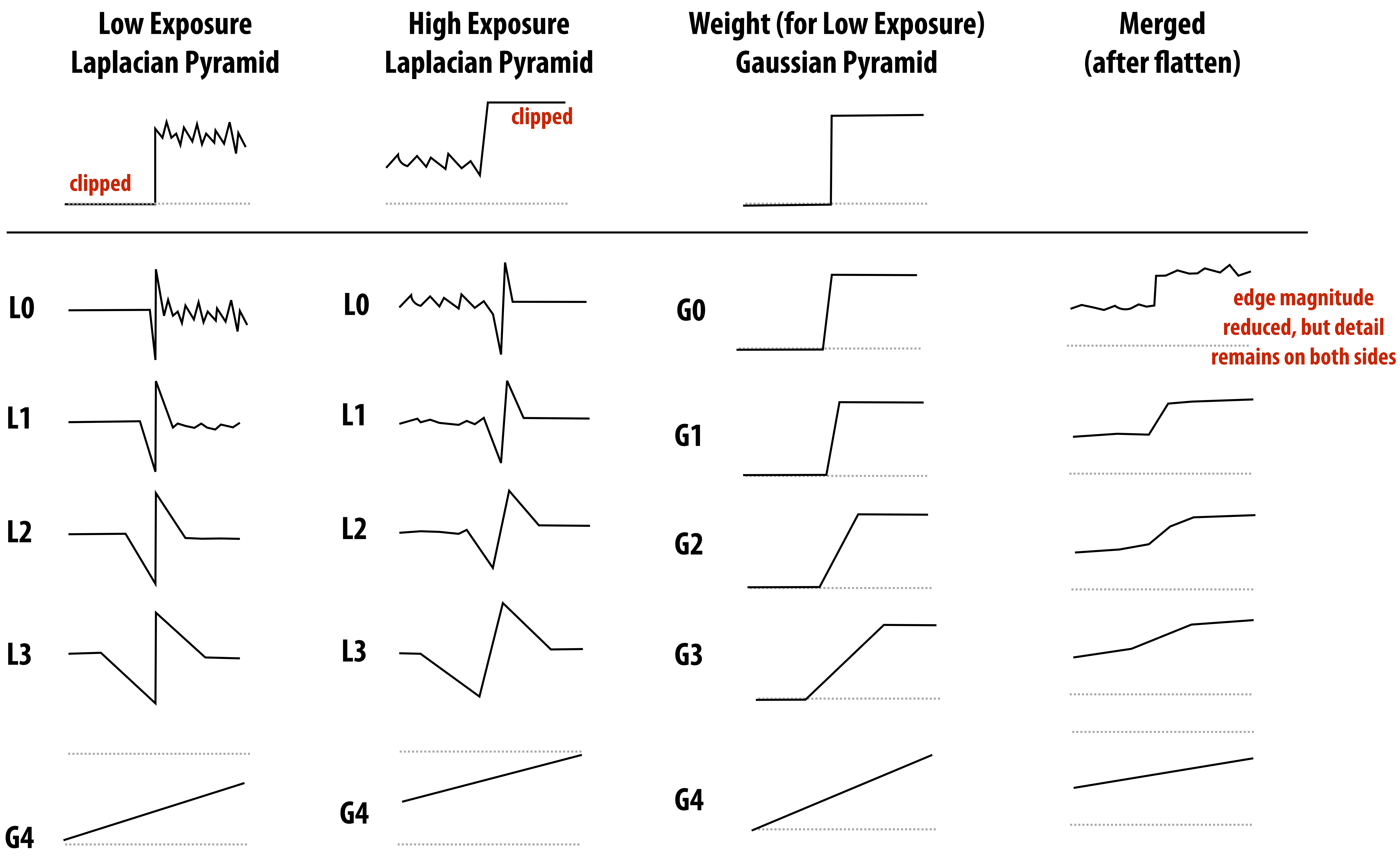
**Four exposures (weights not shown)**

**Merged result**
**(after blurring weight mask)**
**Notice "halos" near edges**

**Merged result**
**(based on multi-resolution pyramid merge)**

## Why does merging Laplacian pyramids work better than merging image pixels?

# Consider low and high exposures of an edge



# Frankencamera
# (Discussion)

# Choosing the "right" representation for the job

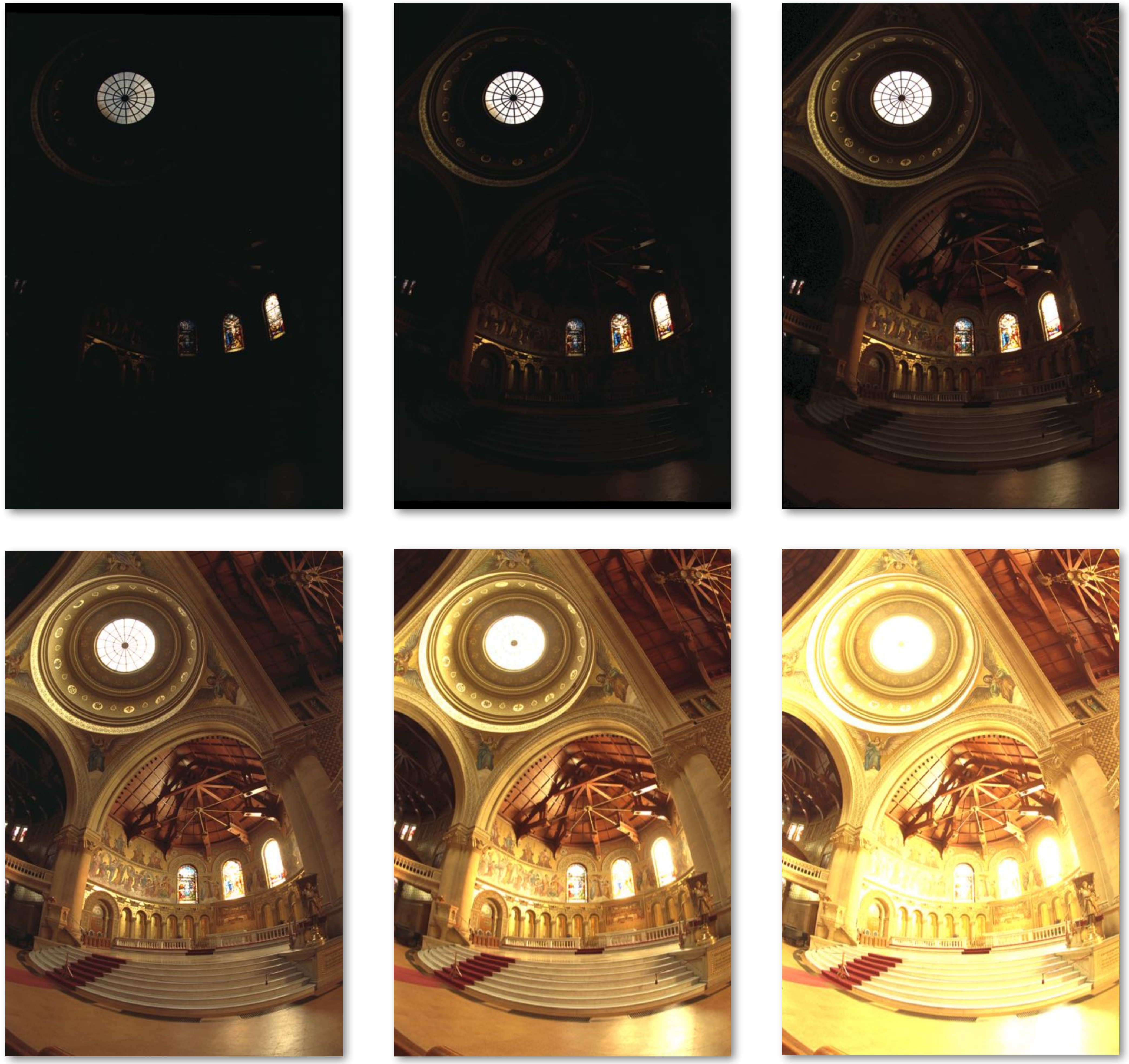
- **Good representations are productive to use:**
  - They embody the natural way of thinking about a problem

- **Good representations enable the system to provide the application developer useful services:**
  - Validating/providing certain guarantees (correctness, resource bounds, conversation of quantities, type checking)
  - Performance optimizations (parallelization, vectorization, use of specialized hardware)
  - Implementations of common, difficult-to-implement functionality (texture mapping and rasterization in 3D graphics, auto-differentiation in ML frameworks)

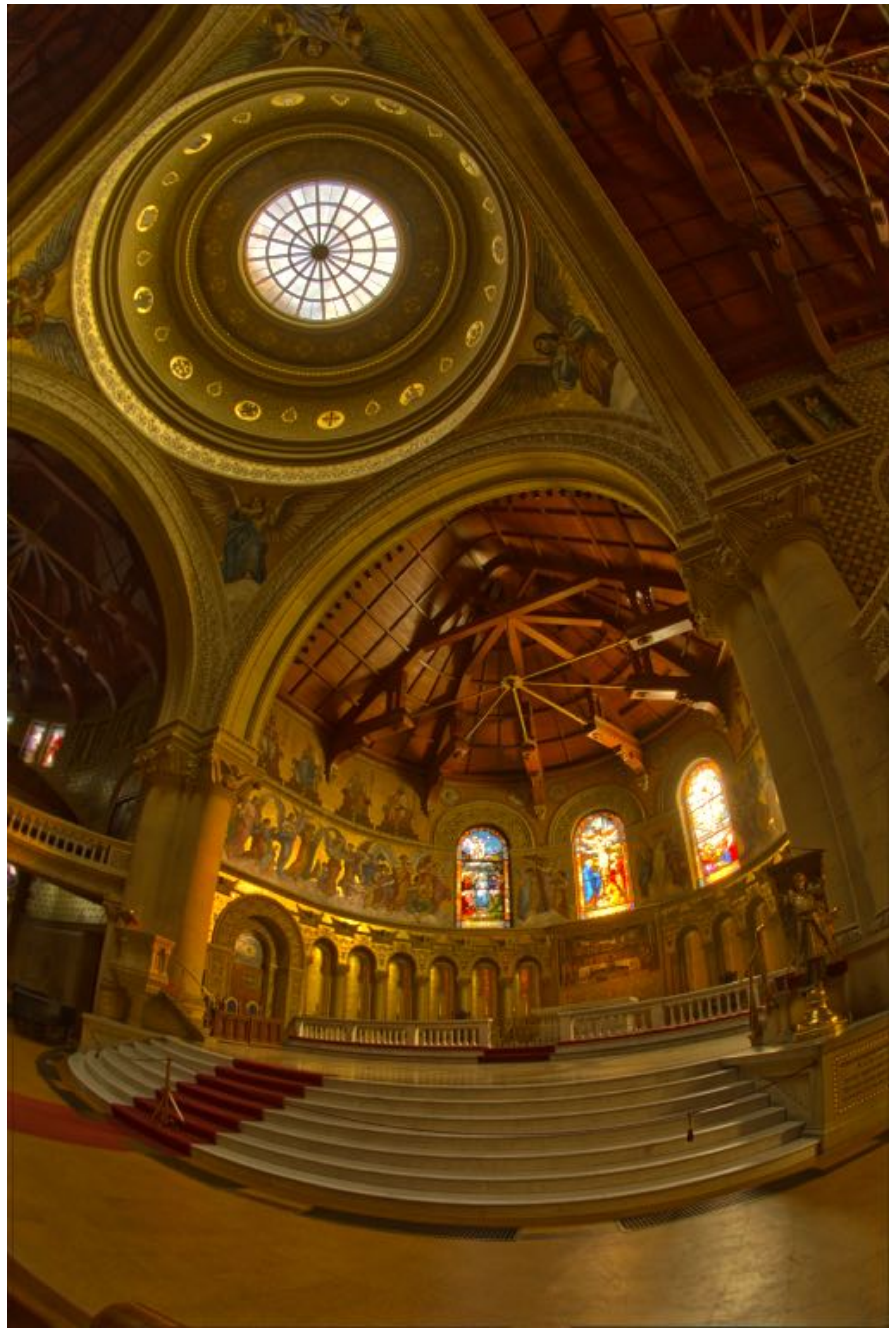
# Frankencamera: some 2010 context

- Cameras: becoming increasingly cheap and ubiquitous
- Significant processing capability available on cameras
- Many techniques for combining multiple photos to overcome deficiencies of traditional camera systems

# Multi-shot photography example: high dynamic range (HDR) images



Source photographs: each photograph has different exposure



Tone mapped HDR image

# More multi-shot photography examples

"Lucky" imaging

Take several photos in rapid succession: likely to find one without camera shake

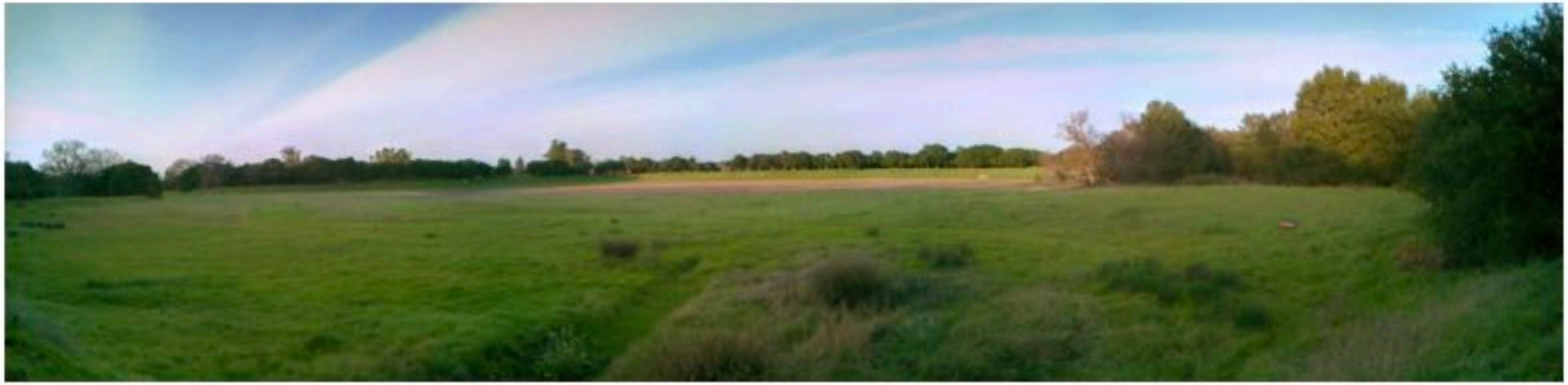
no-flash flash result

**Flash-no-flash photography [Eisemann and Durand]**
**(use flash image for sharp, colored image, infer room lighting from no-flash image)**

# More multi-shot photography examples

**Panorama capture**

individual images



extended dynamic range panorama

# Frankencamera: some 2010 context

- Cameras are cheap and ubiquitous
- Significant processing capability available on cameras
- Many emerging techniques for combining multiple photos to overcome deficiencies in traditional camera systems

- Problem: the ability to implement multi-shot techniques on cameras was limited by camera system programming abstractions
  - Programmable interface to camera was very basic
  - Influenced by physical button interface to a point-and-shoot camera:
    - `take_photograph(parameters, output_jpg_buffer)`
  - Result: on most implementations, latency between two photos was high, mitigating utility of multi-shot techniques (large scene movement, camera shake, between shots)

# Frankencamera goals

[Adams et al. 2010]

1. Create open, handheld computational camera platform for researchers

2. Define system architecture for computational photography applications
   - Motivated by impact of OpenGL on graphics application and graphics hardware development (portable apps despite highly optimized GPU implementations)
   - Motivated by proliferation of smart-phone apps

F2 Reference Implementation

Note: Apple was not involved in Frankencamera's industrial design. ;-)

Nokia N900 Smartphone Implementation

# F-cam scope

- F-cam provides a set of abstractions that allow for manipulating configurable camera components
  - Timeline-based specification of actions
  - Feed-forward system: no feedback loops

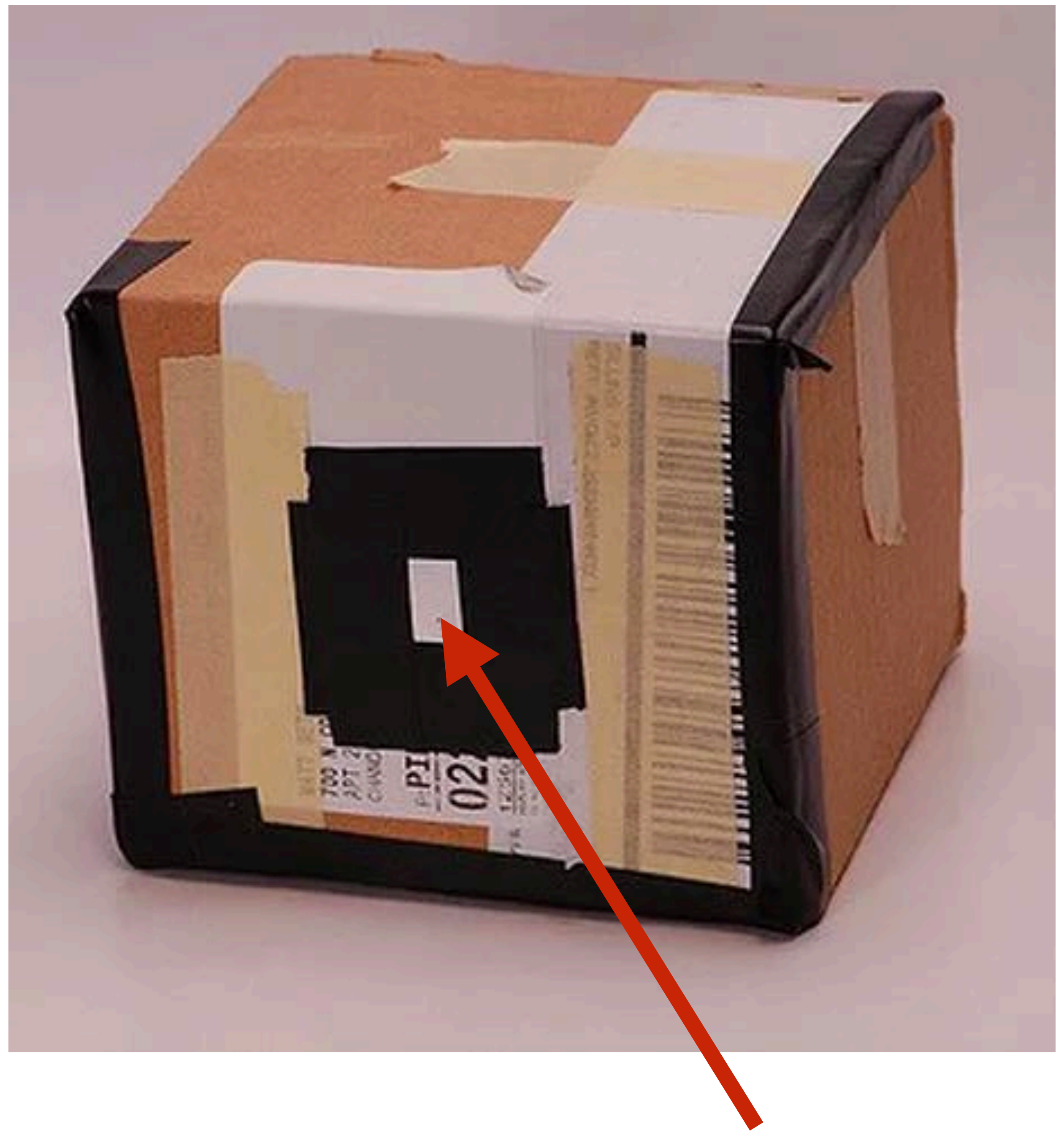
- F-cam architecture performs image processing, but...
  - This functionality as presented by the architecture is <u>not programmable</u>
  - Hence, F-cam does not provide an image processing language (it's like fixed-function OpenGL)
  - Other than work performed by the image processing stage, F-cam applications perform their own image processing (e.g., on smartphone/camera's CPU or GPU resources)

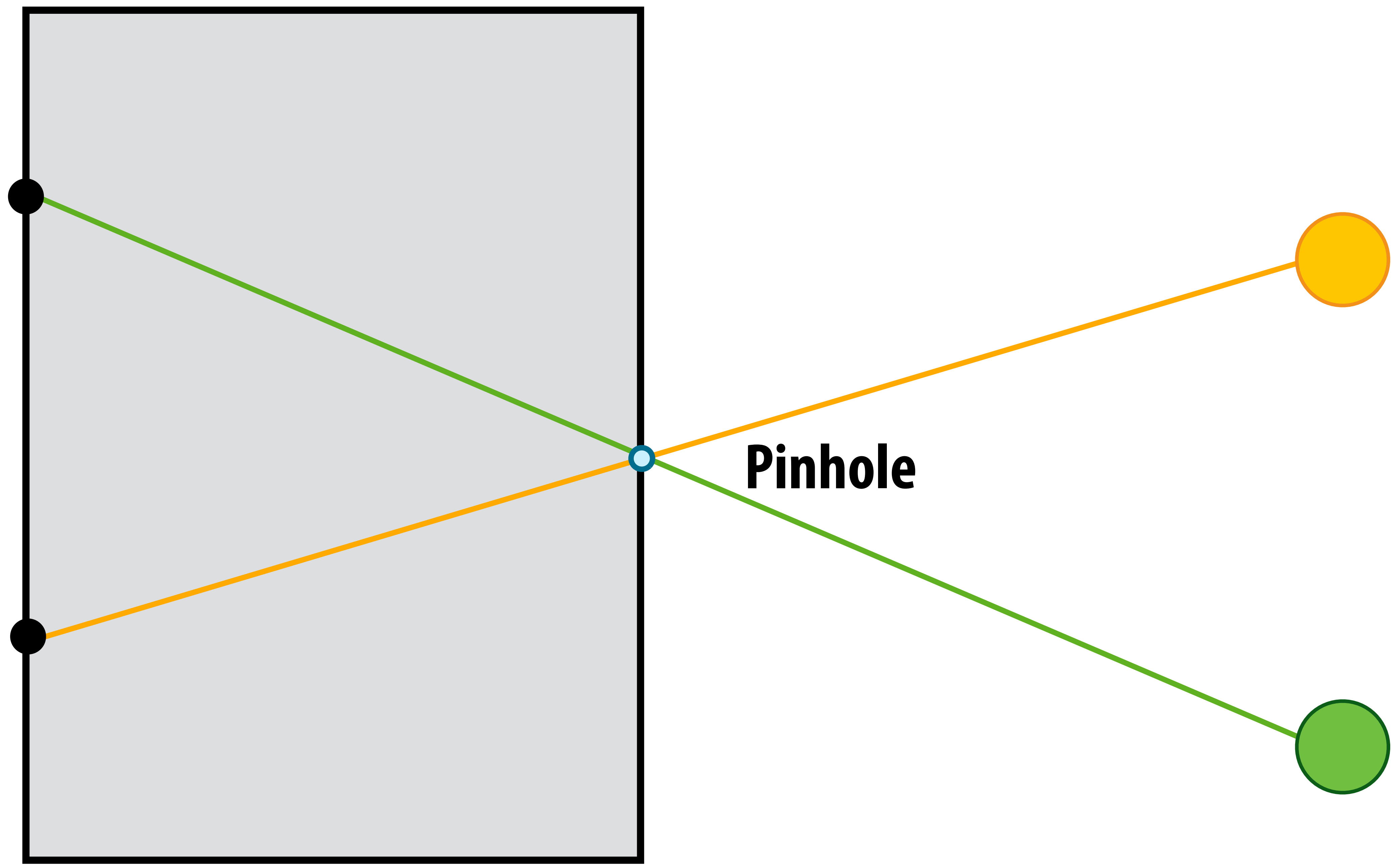
# Android Camera2 API

- Take a look at the documentation of the Android Camera2 API, and you'll see influence of F-Cam.

# Auto Focus

# Pinhole camera (no lens)



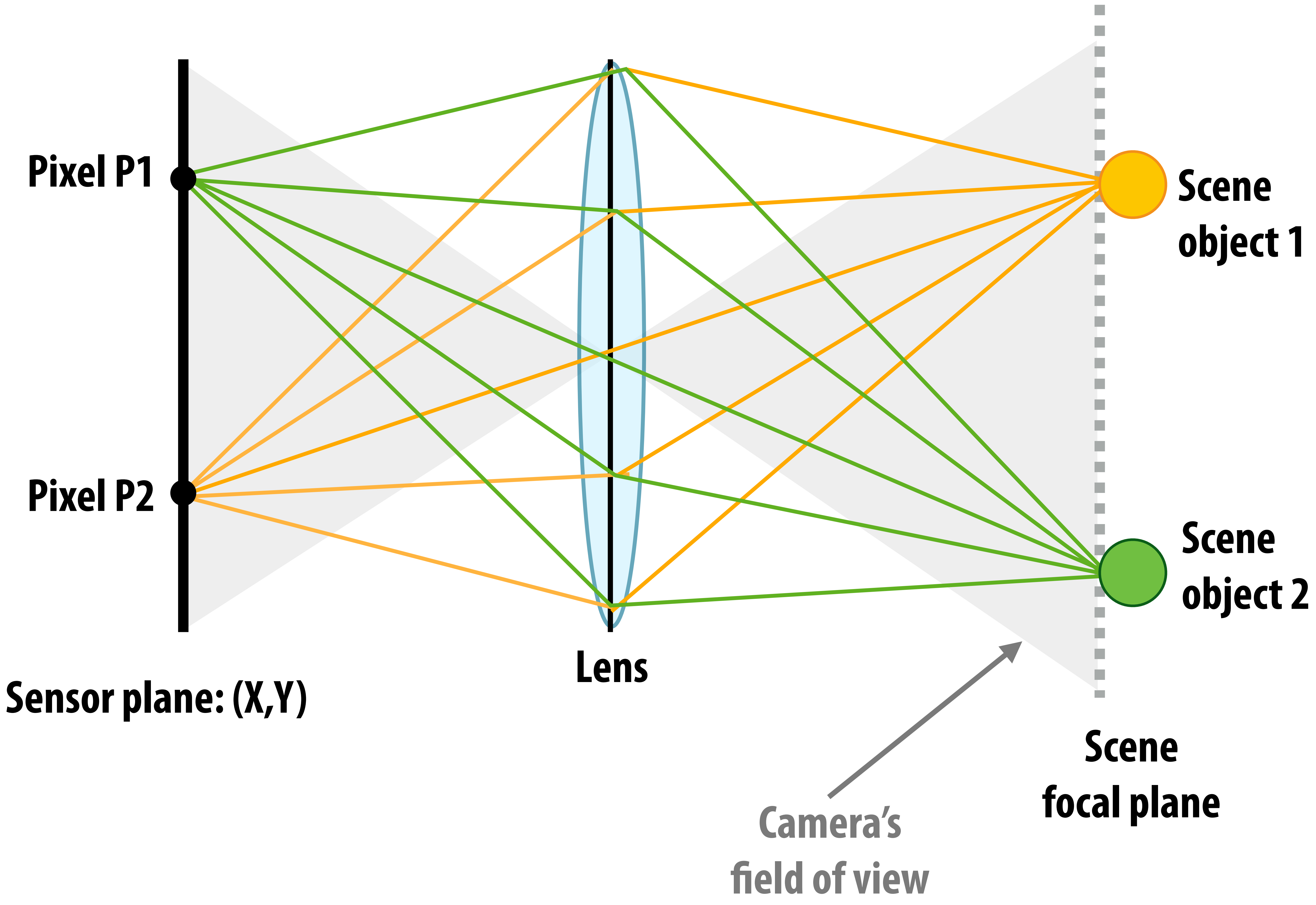



# What does a lens do?

A lens refracts light.

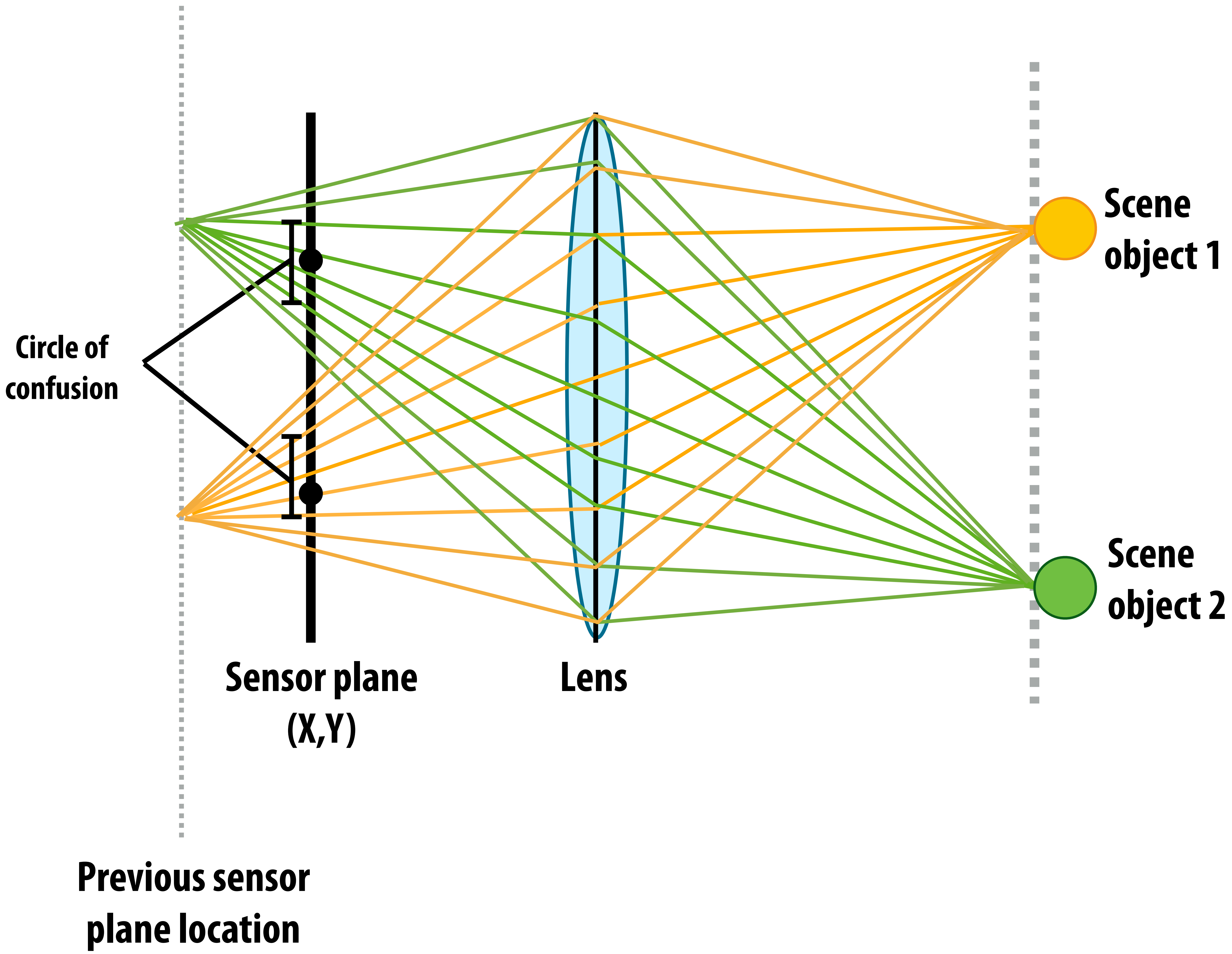
Camera with lens: every pixel accumulates all rays of light that pass through lens aperture and refract toward that pixel

In-focus camera: all rays of light from a point in the scene arrive at a point on sensor plane



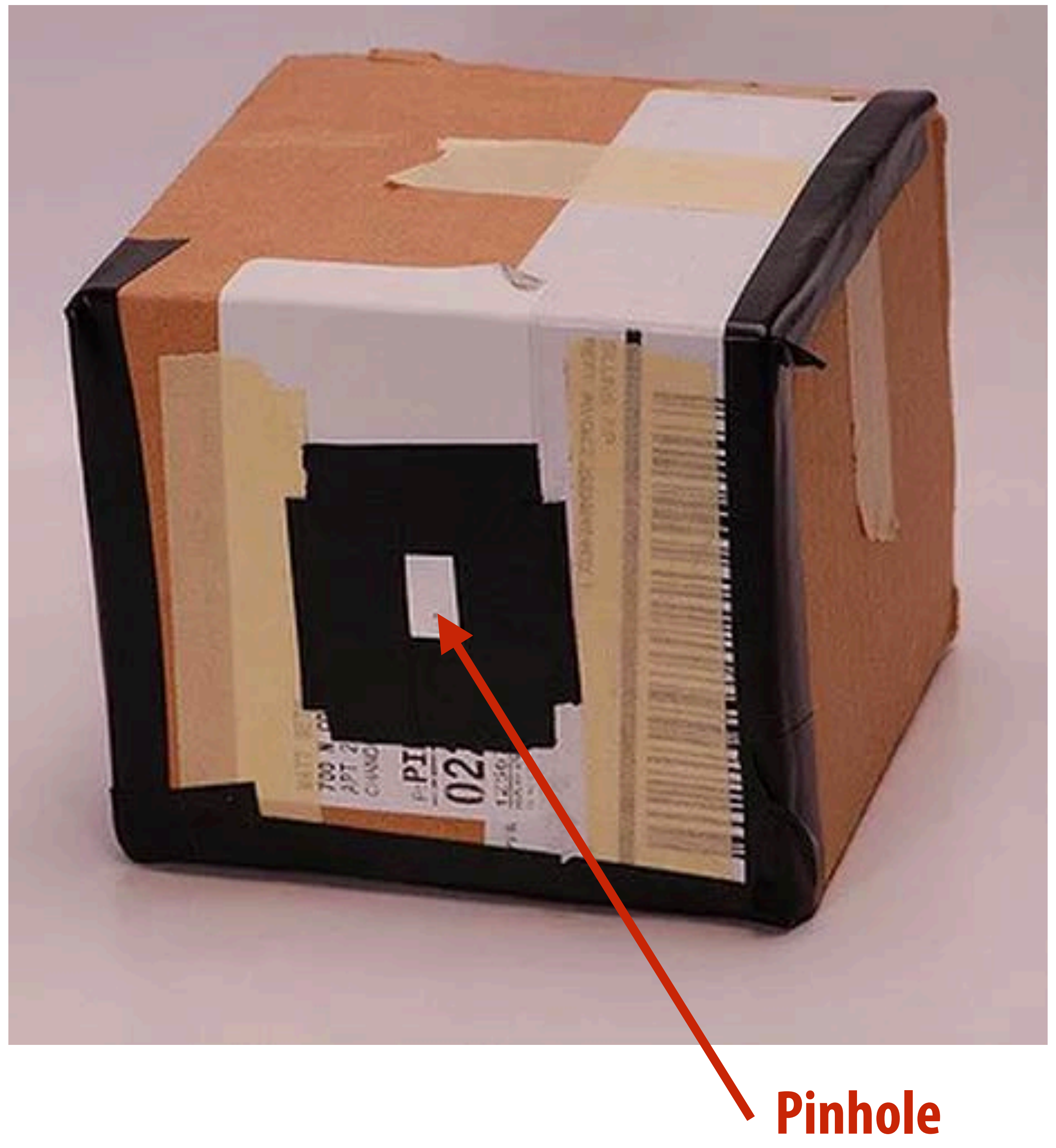
# Out of focus camera

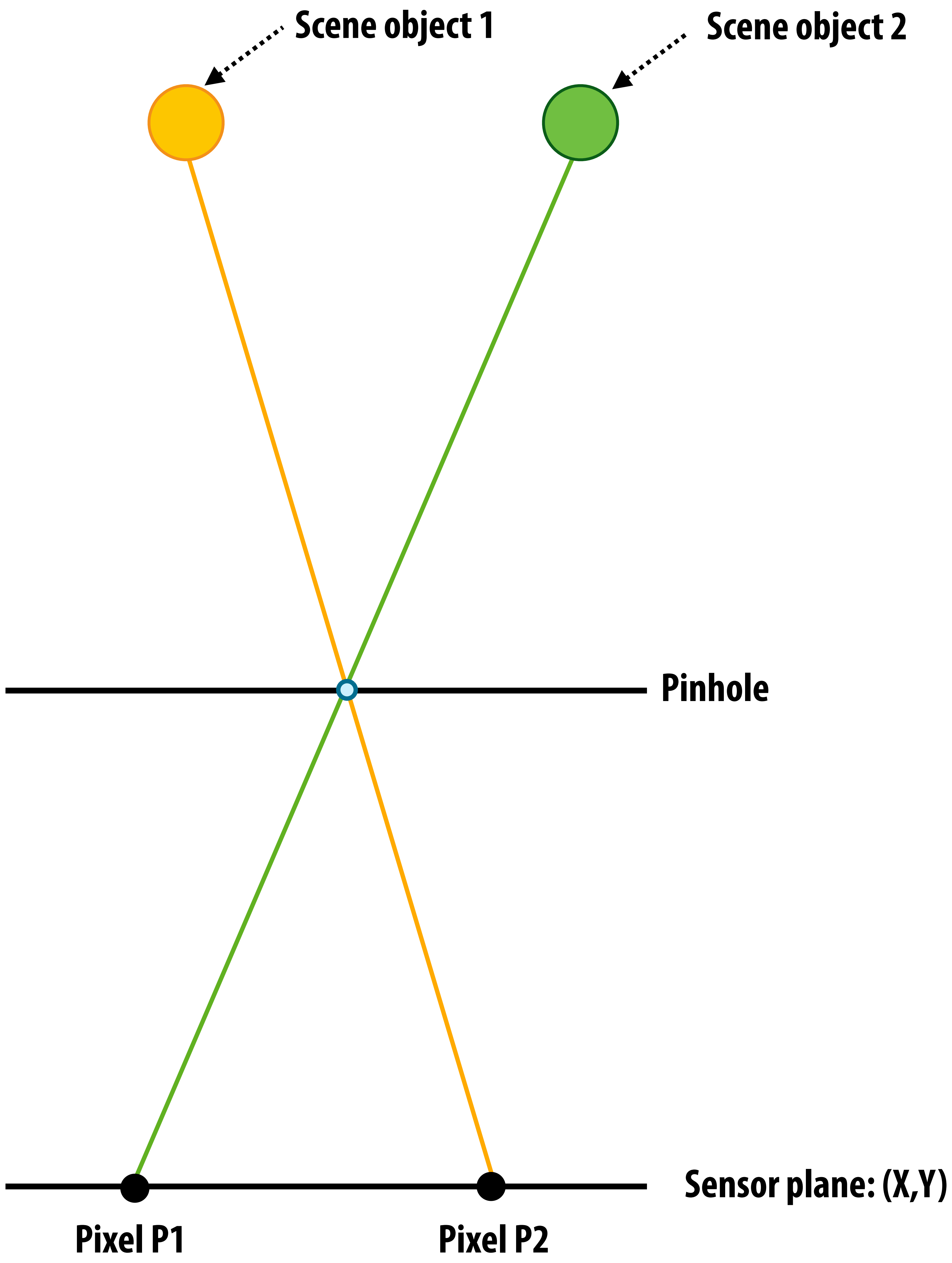
**Out of focus camera: rays of light from one point in scene do not converge to the same point on the sensor**



# What does a lens do?

Recall: pinhole camera you may have made in science class
(every pixel measures ray of light passing through pinhole and arriving at pixel)



# Bokeh

# Sharp foreground, defocused background

Common technique to emphasize subject in a photo

# Cell phone camera lens(es) (small aperture)

# Portrait mode in modern smartphones

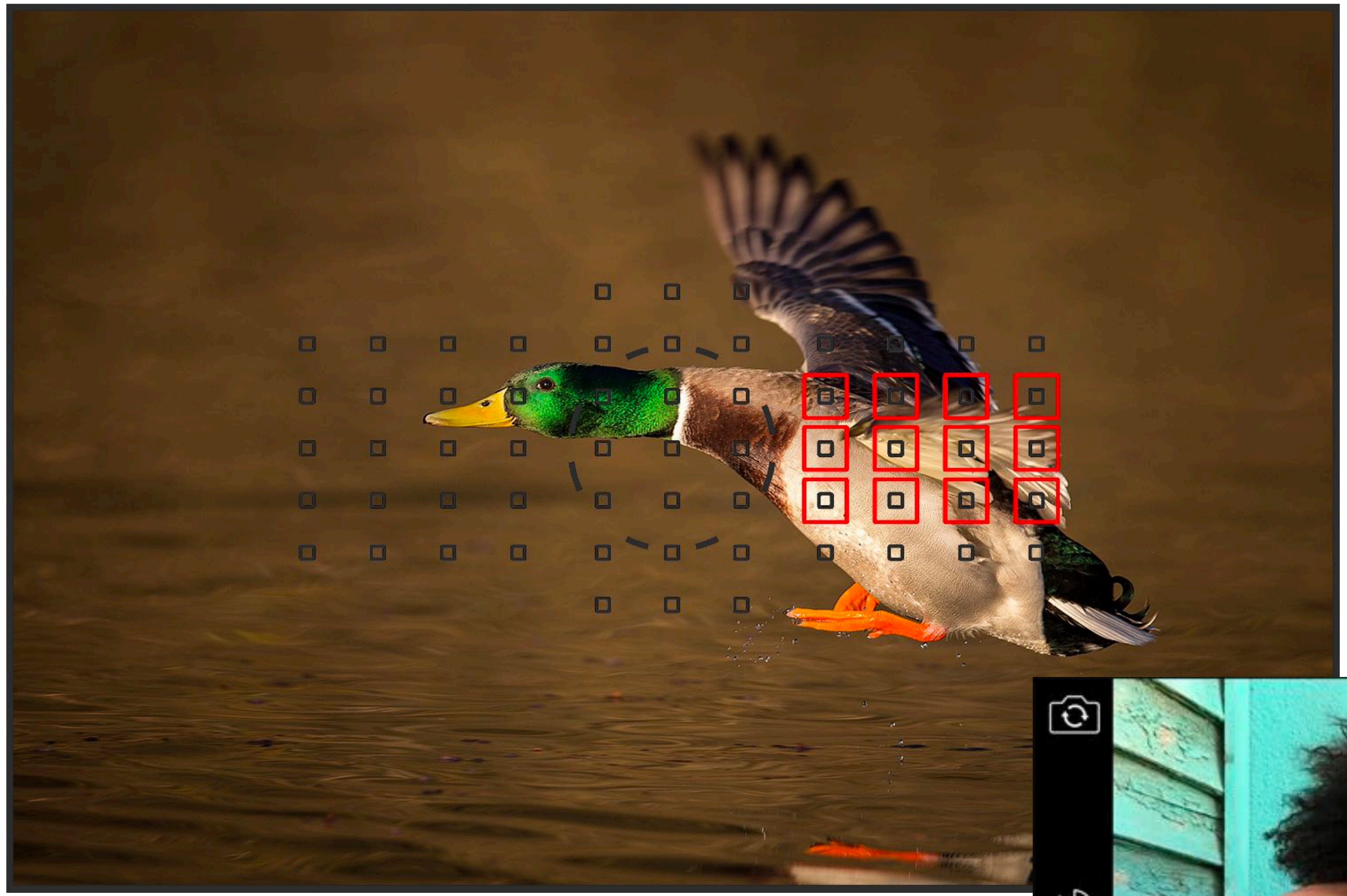
- **Smart phone cameras have small apertures**
  - Good: thin. lightweight lenses, often fast focus
  - Bad: cannot physically create aesthetically please photographs with nice bokeh, blurred background
- **Answer: simulate behavior of large aperture lens (hallucinate image formed by large aperture lens)**


(a) Input image with detected face | (c) Mask + disparity from DP | (d) Our output synthetic shallow depth-of-field image

**Input image /w detected face** | **Scene Depth Estimate** | **Generated image (note blurred background. Blur increases with depth)**

Image credit: [Wadha 2018]

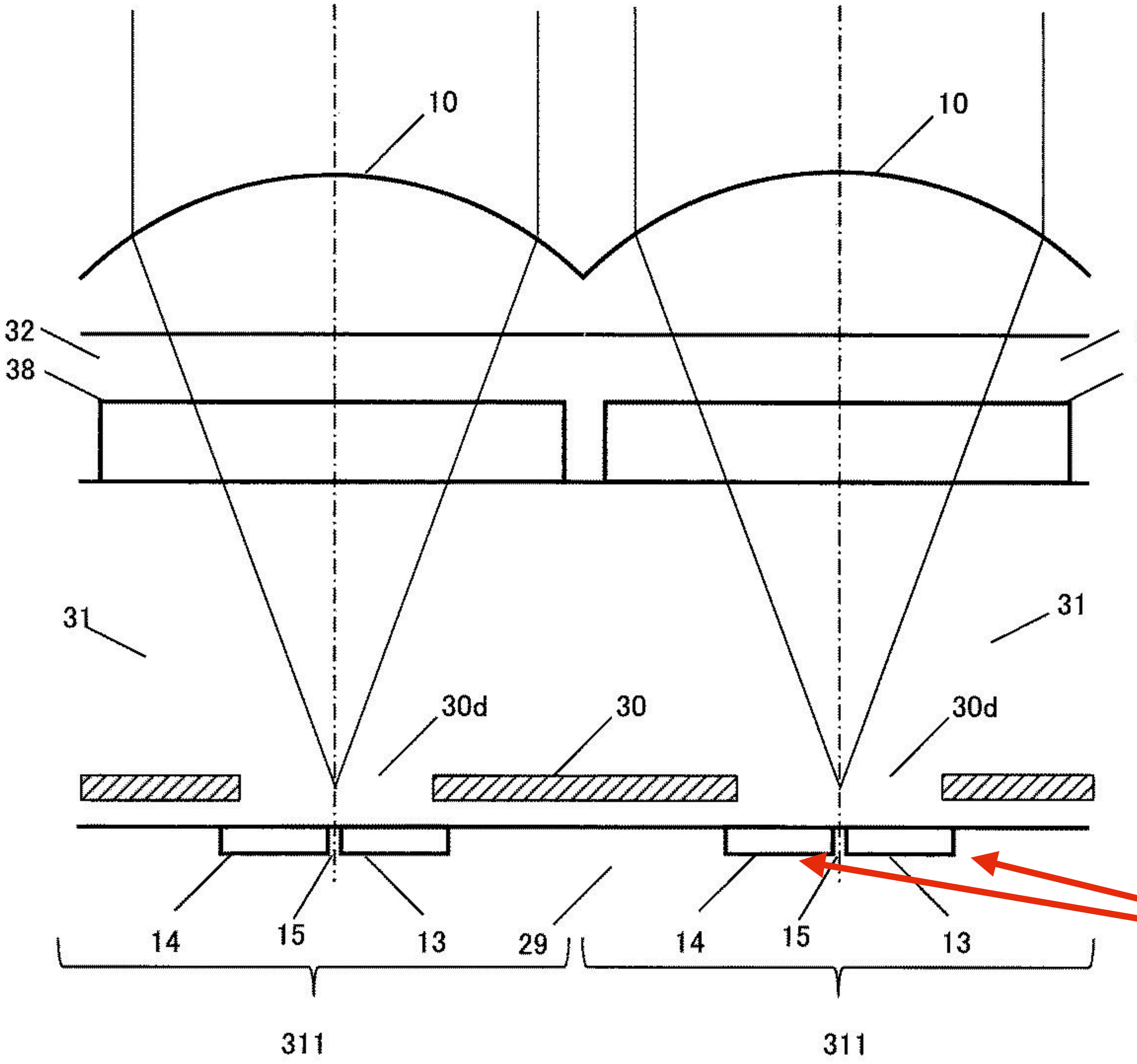
# What part of image should be in focus?




**Heuristics:**
**Focus on closest scene region**
**Put center of image in focus**
**Detect faces and focus on closest/largest face**

**Image credit: DPReview:**
**https://www.dpreview.com/articles/9174241280/configuring-your-5d-mark-iii-af-for-fast-action**

# Split pixel sensor




When both pixels have the same response, camera is in focus, why?

Now two pixels under each microlens (not one)

Image credit: Nikon

# Additional sensing devices and modalities


# Additional sensing modalities

**Fuse information from all modalities to obtain best estimate of depth**

**iPhone Xr depth estimate with lights ON in room**

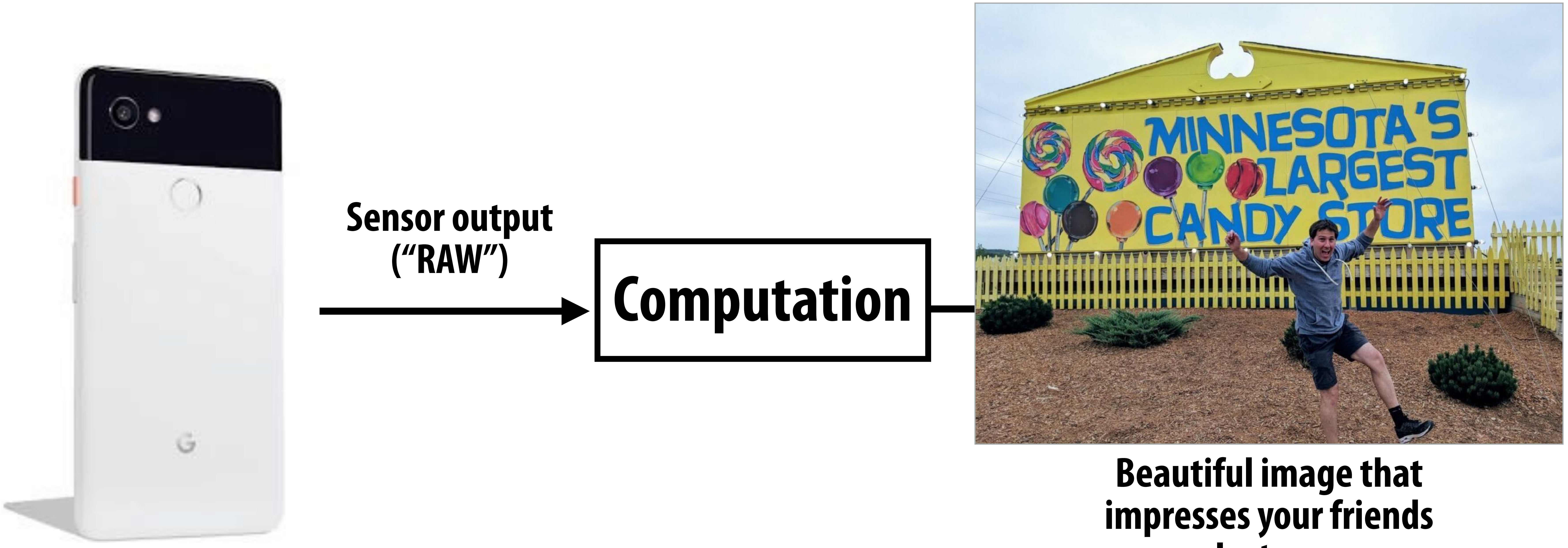
**iPhone Xr depth estimate with lights OFF in room (No help from RGB)**

**Image credit: https://blog.halide.cam/iphone-xr-a-deep-dive-into-depth-47d36ae69a81**

# Summary

# Summary

- Computation now a fundamental part of producing a pleasing photograph
- Used to compensate for physical constraints (demosaic, denoise, lens corrections)
- Used to analyze image to guess system parameters (focus, exposure), or scene contents (white balance, portrait mode)
- Used to make non-physically plausible images that have aesthetic merit




Beautiful image that impresses your friends on Instagram

# Image processing workload characteristics

- "Pointwise" operations
  - output_pixel = f(input_pixel)
- "Stencil" computations (e.g., convolution, demosaic, etc.)
  - Output pixel (x,y) depends on fixed-size local region of input around (x,y)
- Lookup tables
  - e.g., contrast s-curve
- Multi-resolution operations (upsampling/downsampling)
- Fast-fourier transform
  - We didn't talk about Fourier domain techniques in class (but Hasinoff 16 reading has many examples)
- Long pipelines of these operations

**Upcoming classes: efficiently mapping these workloads to modern processors**

# Abstractions for authoring image processing pipelines

# Reminder: choosing the "right" representation for the job

- This was the theme of our Frankencamera discussion

- Good representations are productive to use:
  - They embody the natural way of thinking about a problem

- Good representations enable the system to provide the application developer useful services:
  - Validating/providing certain guarantees (correctness, resource bounds, conversation of quantities, type checking)
  - Performance optimizations (parallelization, vectorization, use of specialized hardware)
  - Implementations of common, difficult-to-implement functionality (texture mapping and rasterization in 3D graphics, auto-differentiation in ML frameworks)

# Goals

- Expressive: facilitate intuitive expression of a broad class of image processing applications
  - e.g., all the components of a modern camera RAW pipeline

- High performance: want to generate code that efficiently utilizes the multi-core and SIMD processing resources of modern CPUs and GPUs, and is memory bandwidth efficient

# What does this code do?

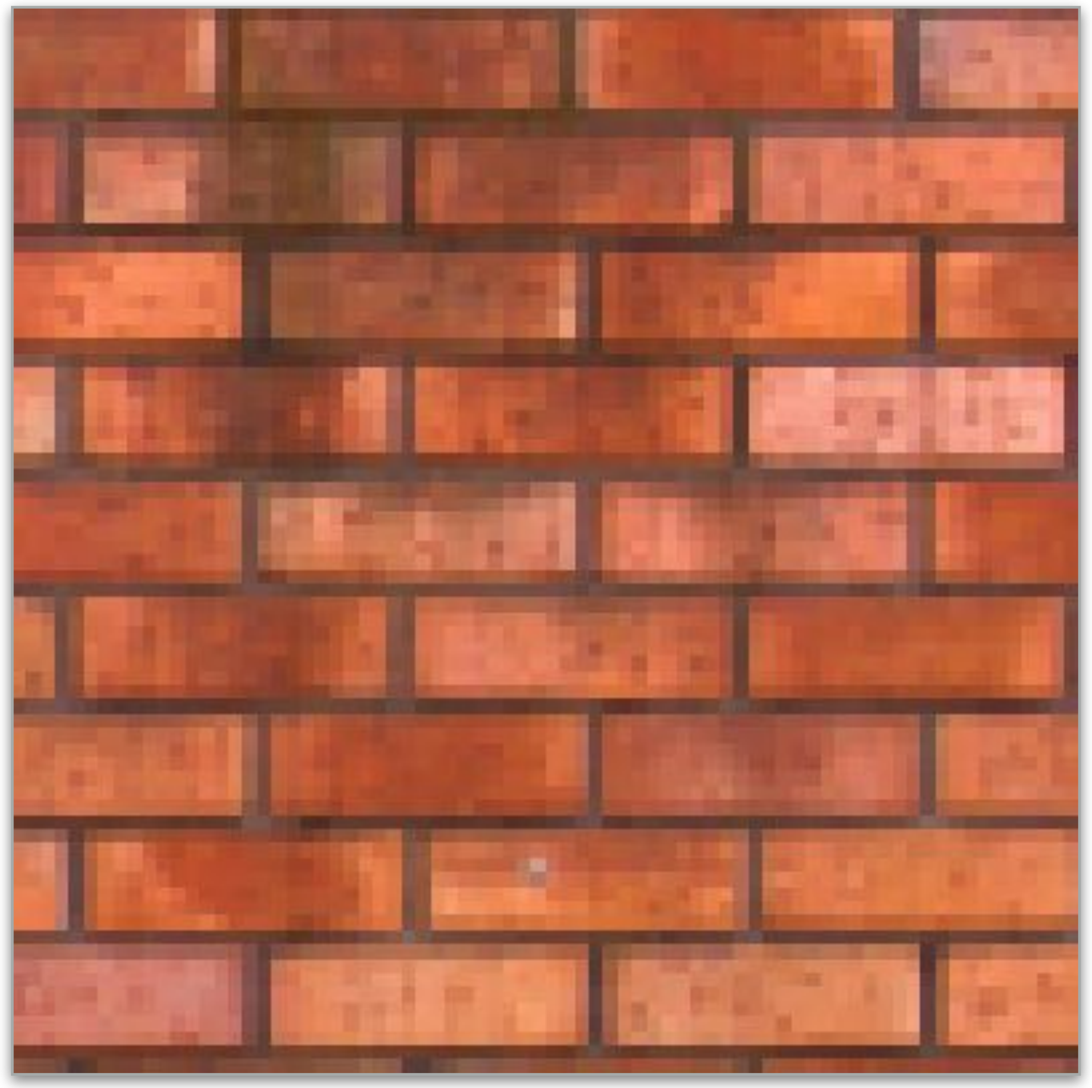
```
void   mystery (const Image &in, Image & output ) {
 __m128i one_third = _mm_set1_epi16(21846);
 #pragma omp parallel for
 for (int yTile = 0; yTile < in.height(); yTile += 32) {
  __m128i a, b, c, sum, avg;
  __m128i tmp[(256/8)*(32+2)];
  for (int xTile = 0; xTile < in.width(); xTile += 256) {
   __m128i *tmpPtr = tmp;
   for (int y = -1; y < 32+1; y++) {
    const uint16_t *inPtr = &(in(xTile, yTile+y));
    for (int x = 0; x < 256; x += 8) {
     a = _mm_loadu_si128((__m128i*)(inPtr-1));
     b = _mm_loadu_si128((__m128i*)(inPtr+1));
     c = _mm_load_si128((__m128i*)(inPtr));
     sum = _mm_add_epi16(_mm_add_epi16(a, b), c);
     avg = _mm_mulhi_epi16(sum, one_third);
     _mm_store_si128(tmpPtr++, avg);
     inPtr += 8;
   }}
   tmpPtr = tmp;
   for (int y = 0; y < 32; y++) {
    __m128i *outPtr = (__m128i *)(&( output (xTile, yTile+y)));
    for (int x = 0; x < 256; x += 8) {
     a = _mm_load_si128(tmpPtr+(2*256)/8);
     b = _mm_load_si128(tmpPtr+256/8);
     c = _mm_load_si128(tmpPtr++);
     sum = _mm_add_epi16(_mm_add_epi16(a, b), c);
     avg = _mm_mulhi_epi16(sum, one_third);
     _mm_store_si128(outPtr++, avg);
}}}}}
```

I'll tell you next class.

# Consider a single task: sharpen an image

## Example: sharpen an image

$$F = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$



Input

Output

# Four different representations of sharpen

1

```
Image input;
Image output = sharpen(input);
```

2

$$F = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

```
Image input;
Image output = convolve(input, F);
```

3

```
Image input;
Image output;
output[i][j]
    = F[0][0] * input[i-1][j-1] +
      F[0][1] * input[i-1][j]   +
      F[0][2] * input[i-1][j+1] +
      F[1][0] * input[i][j-1]   +
      F[1][1] * input[i][j]     +
      ...
```

4

```
float input[(WIDTH+2) * (HEIGHT+2)];
float output[WIDTH * HEIGHT];

float weights[] = {0., -1., 0.,
                   -1., 5, -1.,
                   0., -1., 0.};

for (int j=0; j<HEIGHT; j++) {
  for (int i=0; i<WIDTH; i++) {
    float tmp = 0.f;
    for (int jj=0; jj<3; jj++)
      for (int ii=0; ii<3; ii++)
        tmp += input[(j+jj)*(WIDTH+2) + (i+ii)]
                  * weights[jj*3 + ii];
    output[j*WIDTH + i] = tmp;
  }
}
```

# Image processing tasks from previous lectures

**Sobel Edge Detection**

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * I$$

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} * I$$

$$G = \sqrt{{G_x}^2 + {G_y}^2}$$

**3x3 Gaussian blur**

$$F = \begin{bmatrix} .075 & .124 & .075 \\ .124 & .204 & .124 \\ .075 & .124 & .075 \end{bmatrix}$$

**2x2 downsample (via averaging)**

```
output[x][y] = (input[2x][2y]   + input[2x+1][2y] +
                input[2x][2y+1] + input[2x+1][2y+1]) / 4.f;
```

**Gamma Correction**

```
output[x][y] = pow(input[x][y], 0.5f);
```

**LUT-based correction**

```
output[x][y] = lookup_table[input[x][y]];
```

**Local Pixel Clamp**

```
float f(image input) {
   float min_value = min( min(input[x-1][y], input[x+1][y]),
                          min(input[x][y-1], input[x][y+1]) );
   float max_value = max( max(input[x-1][y], input[x+1][y]),
                          max(input[x][y-1], input[x][y+1]) );
output[x][y] = clamp(min_value, max_value, input[x][y]);
output[x][y] = f(input);
```

**Histogram**

```
bin[input[x][y]]++;
```