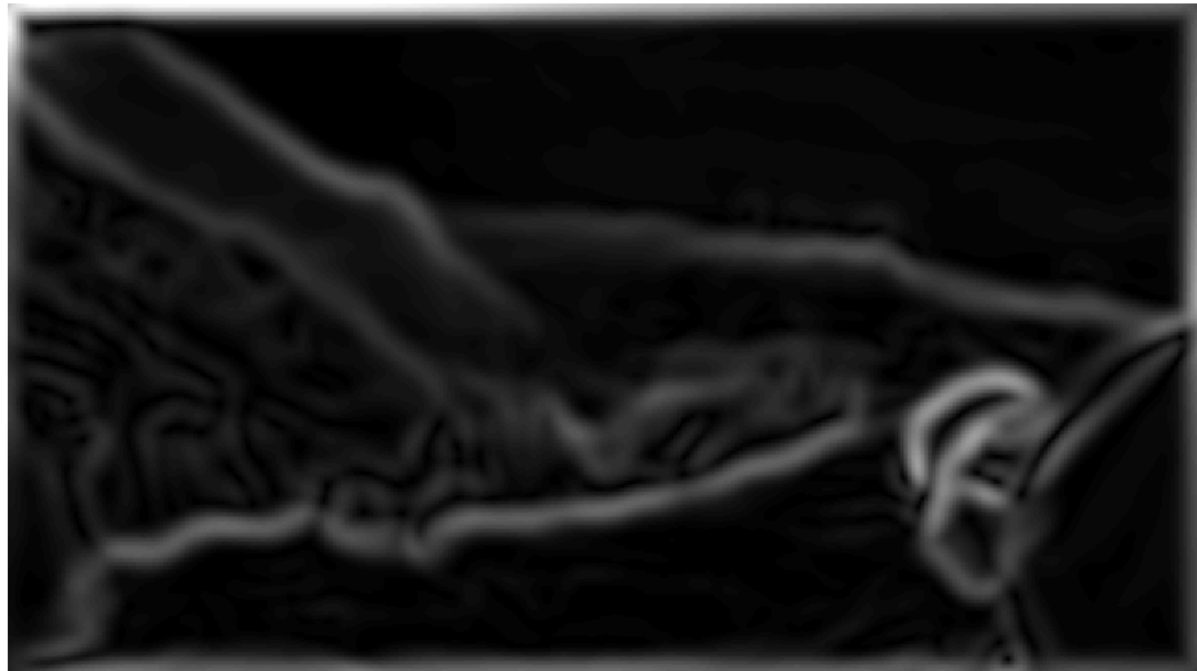
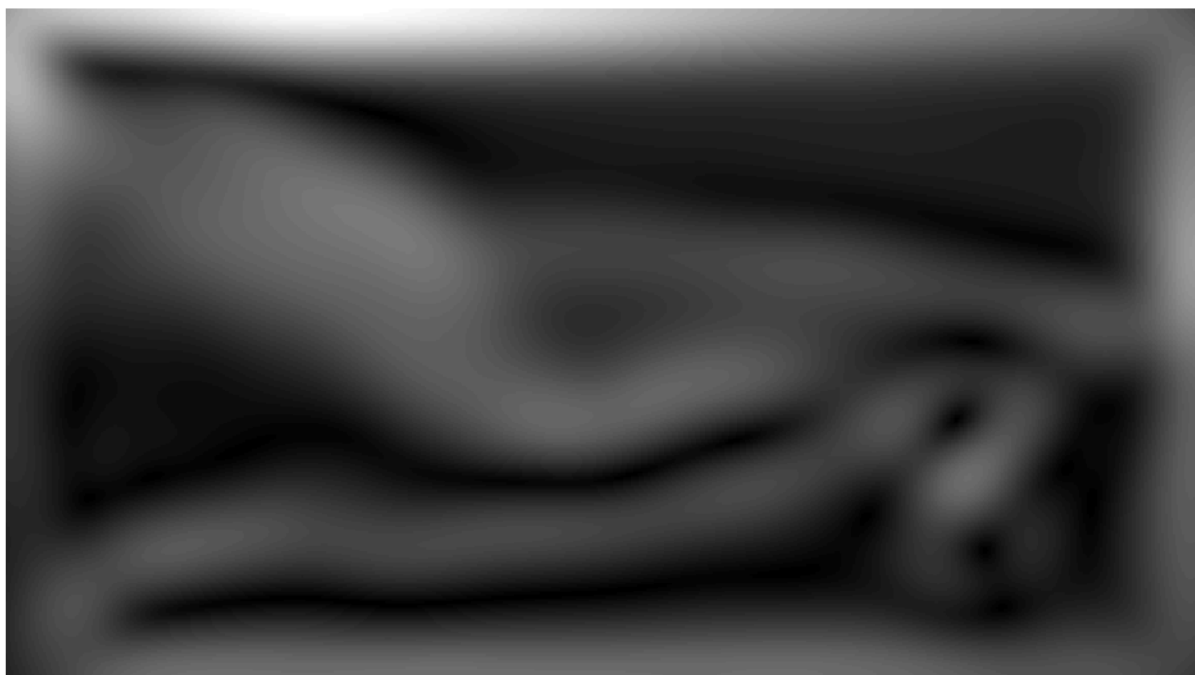


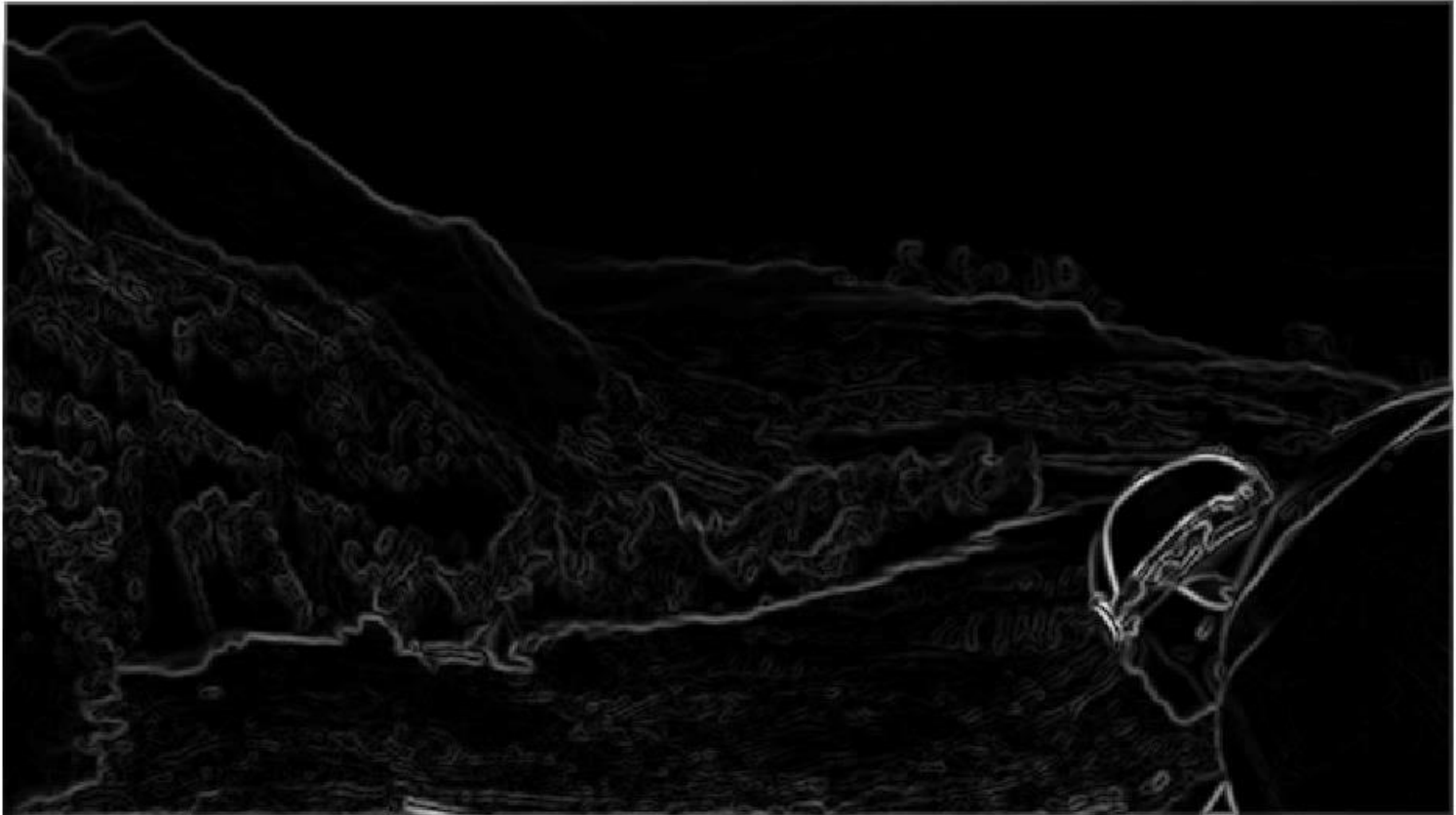


Image Scale





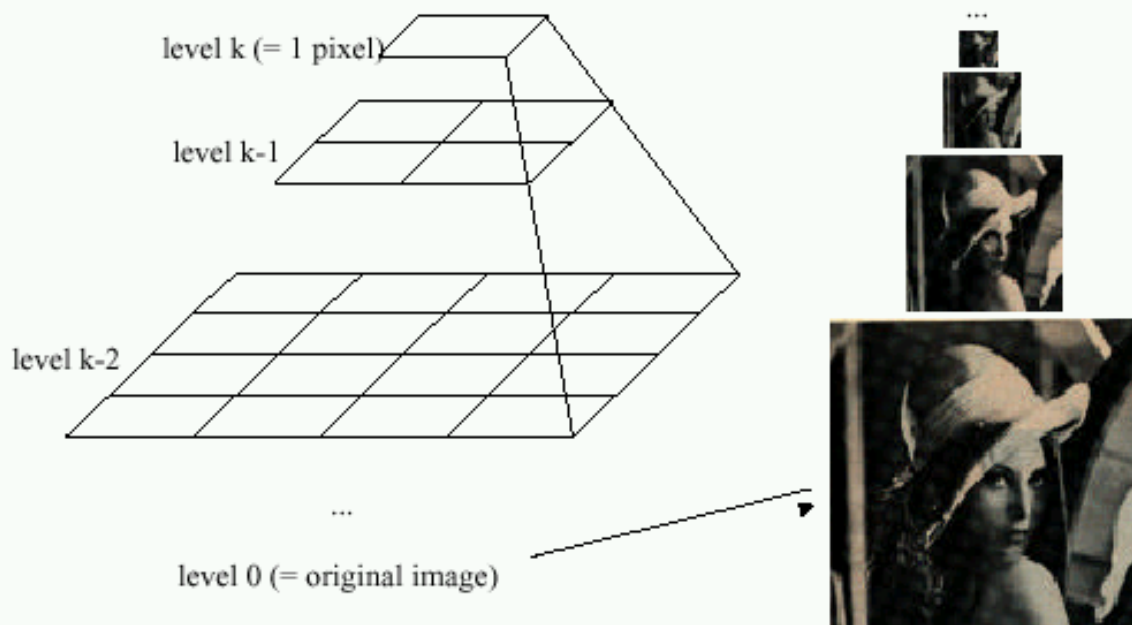




Different scale of image encodes different edge response.

Image Pyramids

Idea: Represent $N \times N$ image as a “pyramid” of $1 \times 1, 2 \times 2, 4 \times 4, \dots, 2^k \times 2^k$ images (assuming $N = 2^k$)



Known as a Gaussian Pyramid [Burt and Adelson, 1983]

- In computer graphics, a *mip map* [Williams, 1983]
- A precursor to *wavelet transform*



512

256

128

64

32

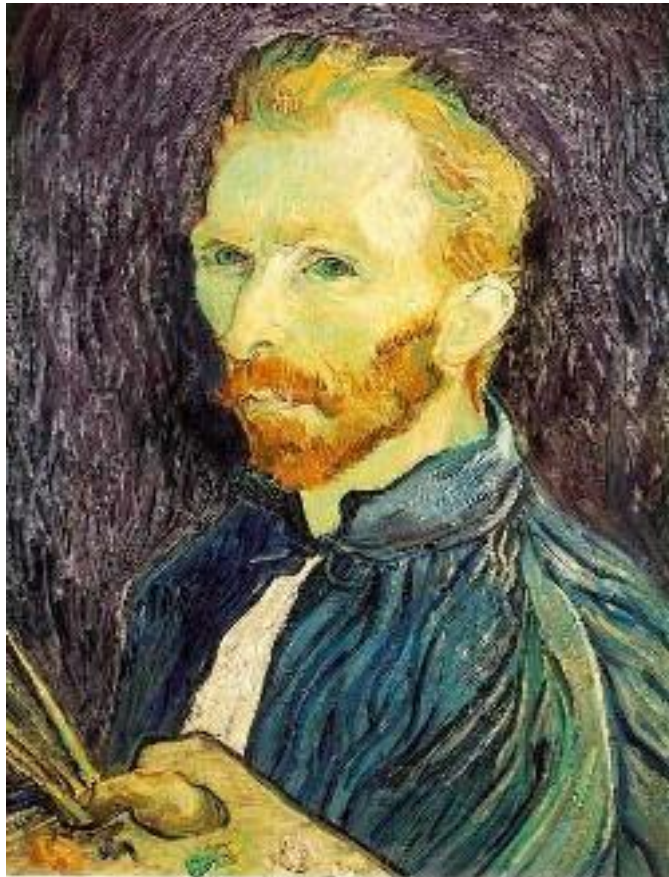
16

8



Figure from David Forsyth

Image sub-sampling



1/4



1/8

Throw away every other row and column to create a $1/2$ size image
- called *image sub-sampling*

Image sub-sampling



1/2



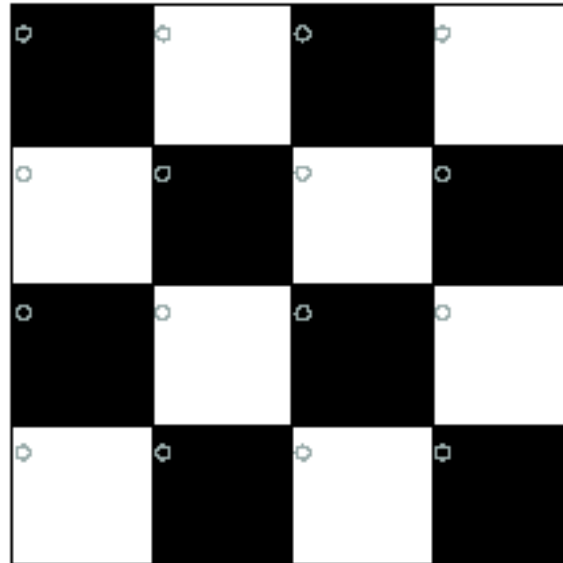
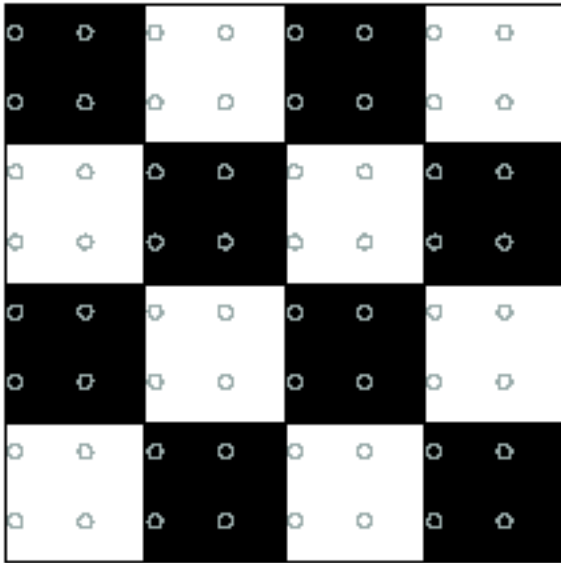
1/4 (2x zoom)



1/8 (4x zoom)

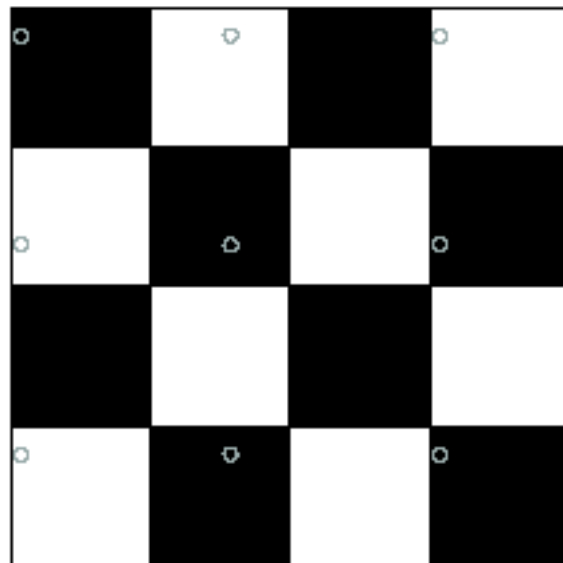
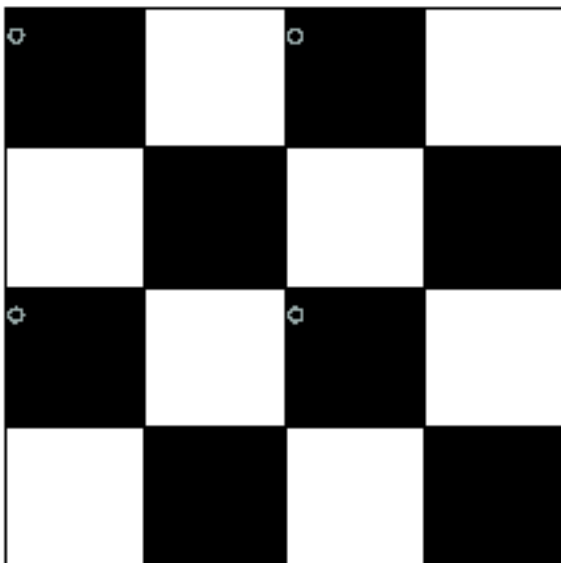
Why does this look so bad?

Sampling



Good sampling:

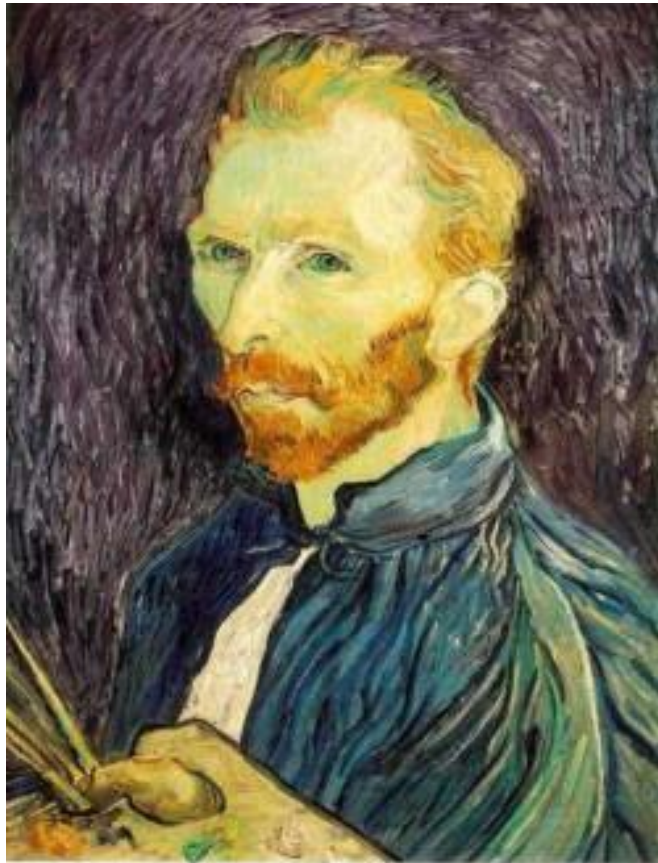
- Sample often or,
- Sample wisely



Bad sampling:

- see aliasing in action!

Gaussian pre-filtering



Gaussian 1/2



G 1/4



G 1/8

Solution: filter the image, *then* subsample

- Filter size should double for each $\frac{1}{2}$ size reduction. Why?

Subsampling with Gaussian pre-filtering



Gaussian 1/2



G 1/4



G 1/8

Solution: filter the image, *then* subsample

- Filter size should double for each $\frac{1}{2}$ size reduction. Why?
- How can we speed this up?

Comparison



1/2



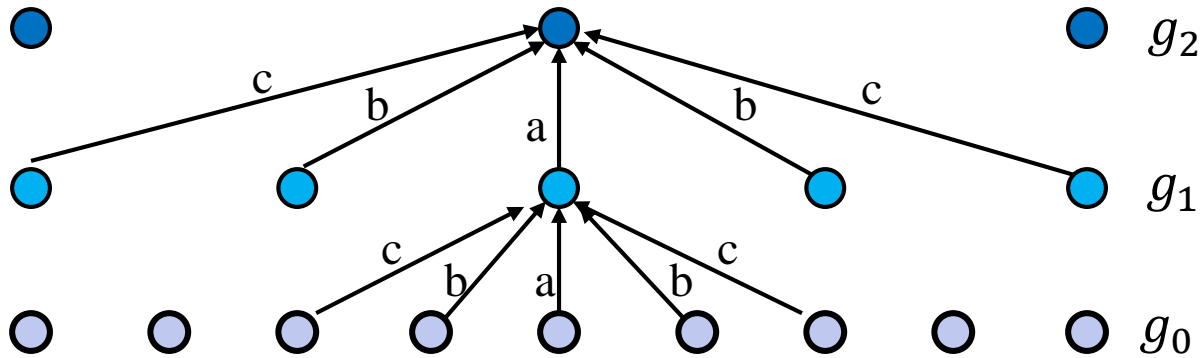
1/4 (2x zoom)



1/8 (4x zoom)

Image Reduce

[Burt & Adelson, 1983]

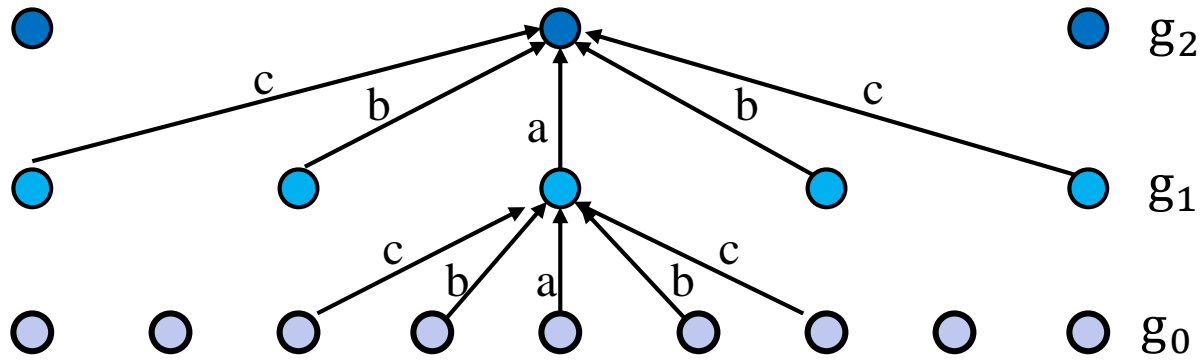


$g_0 = \text{Image}$

$g_1 = \text{REDUCE}[g_{1-1}]$

Image Reduce

[Burt & Adelson, 1983]



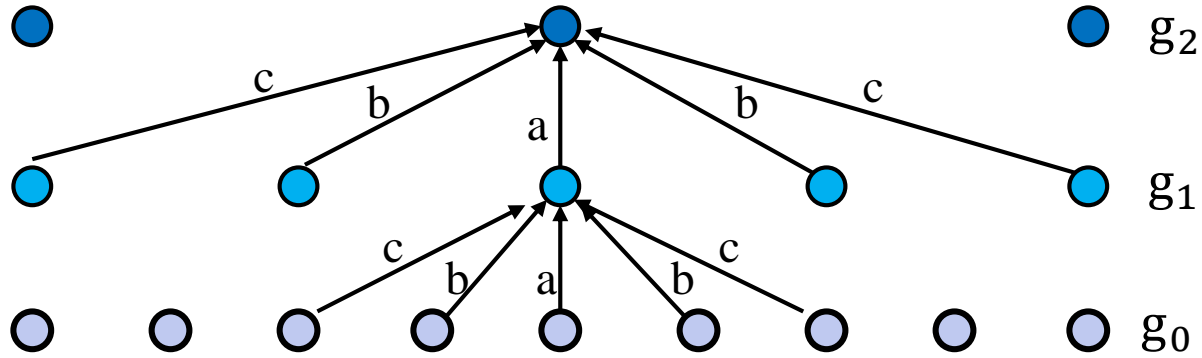
$g_0 = \text{Image}$

$g_l = \text{REDUCE}[g_{l-1}]$

$$g_l(i, j) = \sum_{m=-2}^2 \sum_{n=-2}^2 w(m, n) g_{l-1}(2i + m, 2j + n)$$

$$w(m, n) = \hat{w}(m)\hat{w}(n) \quad \sum_m \hat{w}(m) = 1 \quad \hat{w}(m) = \hat{w}(-m)$$

Image Reduce



$g_0 = \text{IMAGE}$

$g_l = \text{REDUCE}[g_{l-1}]$

$$g_l(i, j) = \sum_{m=-2}^2 \sum_{n=-2}^2 w(m, n) g_{l-1}(2i + m, 2j + n)$$

$$g_l = [g_{l-1} \otimes w] \downarrow 2$$

Choice in weighting function

$$\hat{w}(0) = a$$

$$\hat{w}(1) = \hat{w}(-1) = 1/4$$

$$\hat{w}(1) = \hat{w}(-1) = 1/4 - a/2$$

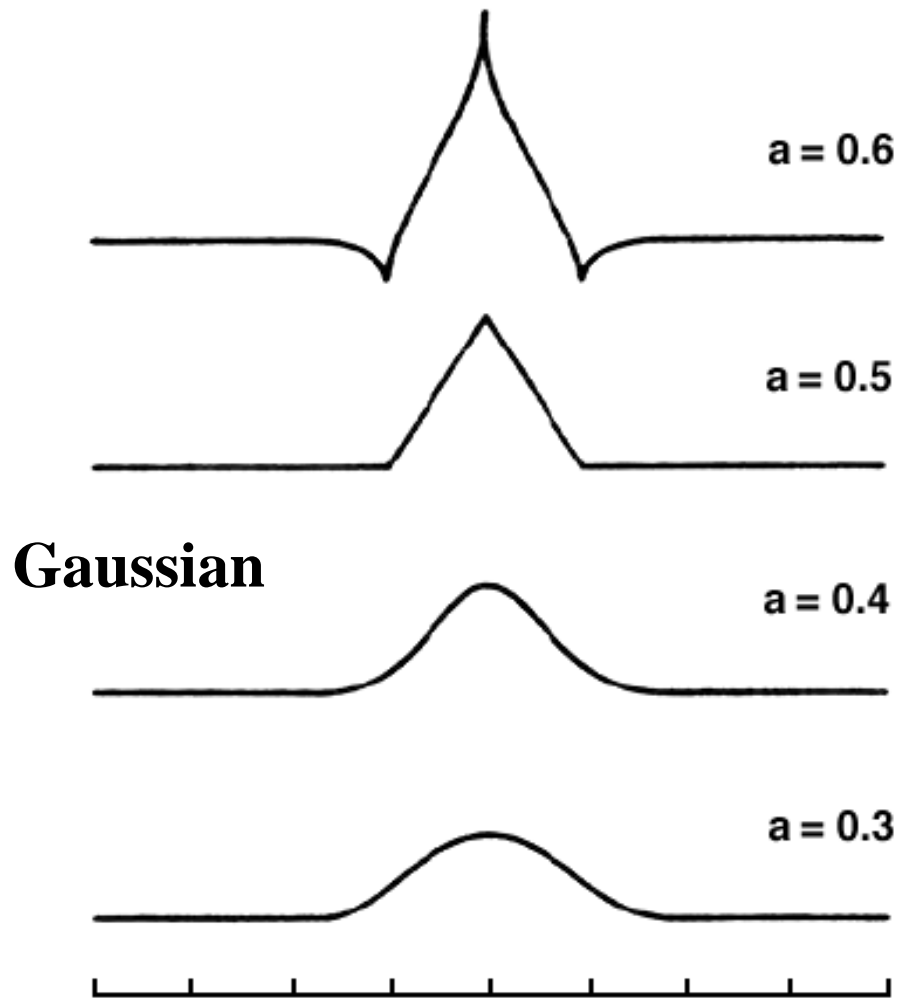
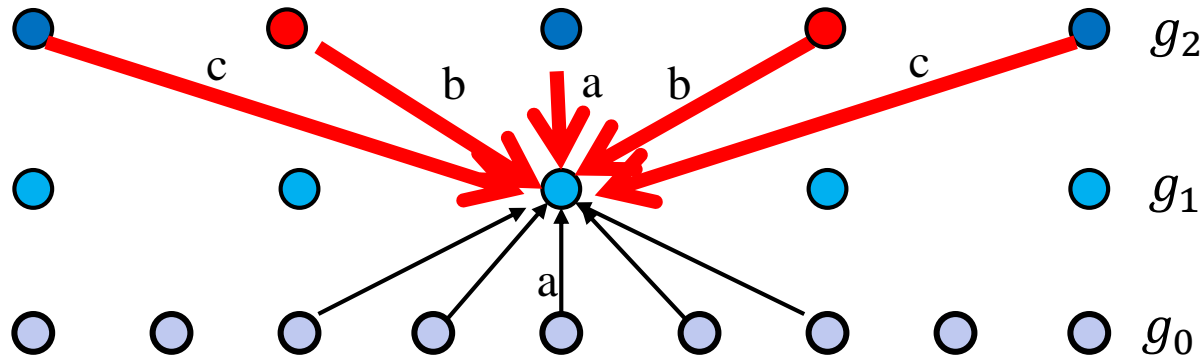


Image Expansion

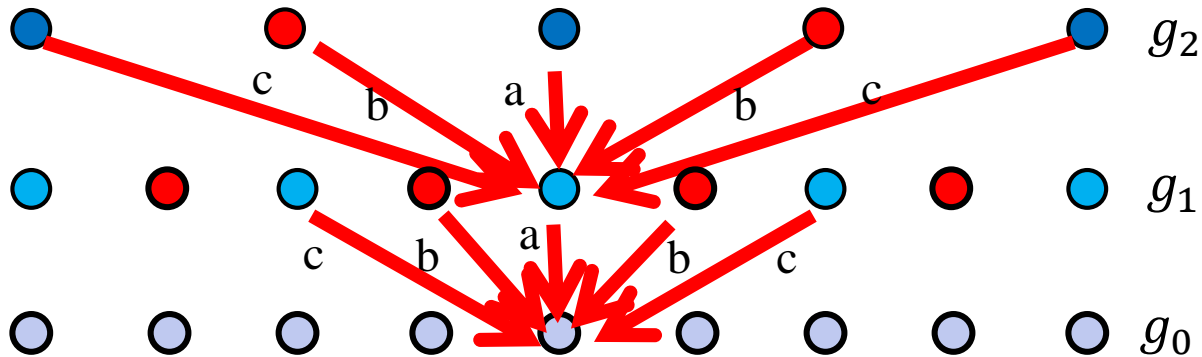


$$g_{l-1} = \text{EXPAND}[g_l]$$

$$g_l(i, j) = 4 \sum_{m=-2}^2 \sum_{n=-2}^2 w(m, n) \cdot g_{l-1} \left(\frac{i-m}{2}, \frac{j-n}{2} \right)$$

$(i-m)/2$ and $(j-n)/2$ are integers

Image Expansion

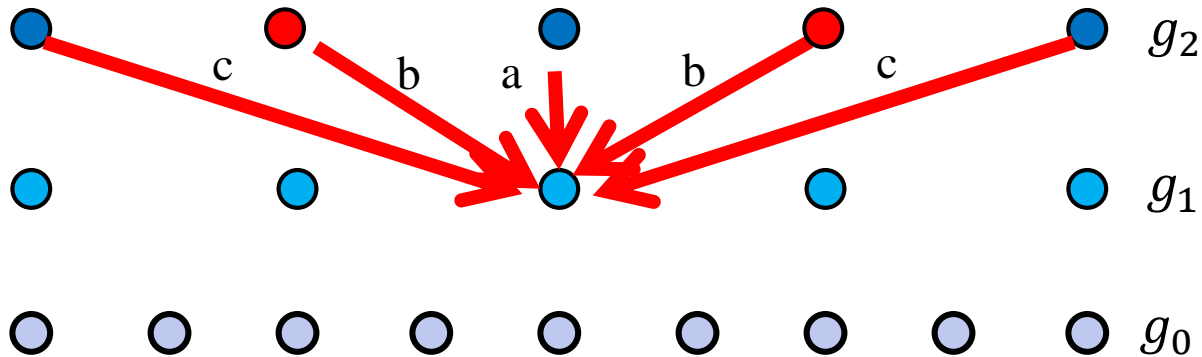


$$g_{l-1} = \text{EXPAND}[g_l]$$

$$g_l(i, j) = 4 \sum_{m=-2}^2 \sum_{n=-2}^2 w(m, n) \cdot g_{l-1} \left(\frac{i-m}{2}, \frac{j-n}{2} \right)$$

$(i-m)/2$ and $(j-n)/2$ are integers

Image Expansion

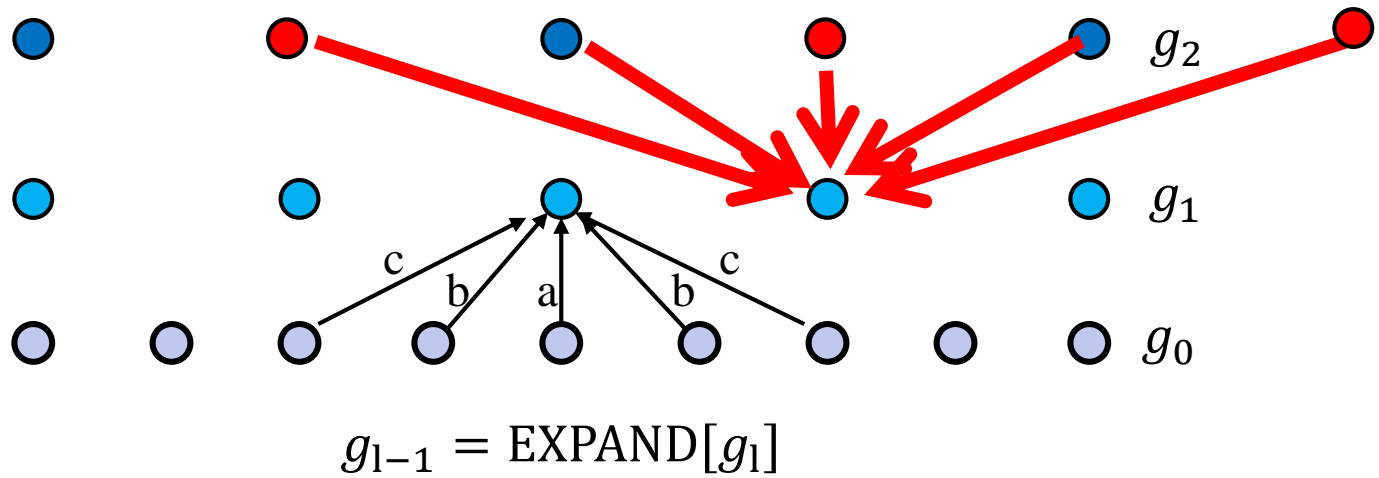


$$g_{l-1} = \text{EXPAND}[g_l]$$

$$g_l(i, j) = 4 \sum_{m=-2}^2 \sum_{n=-2}^2 w(m, n) \cdot g_{l-1} \left(\frac{i-m}{2}, \frac{j-n}{2} \right)$$

$(i-m)/2$ and $(j-n)/2$ are integers

Image Expansion

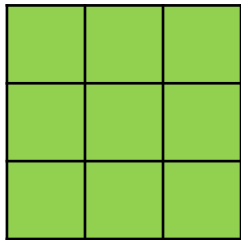


$$g_l(i, j) = 4 \sum_{m=-2}^2 \sum_{n=-2}^2 w(m, n) \cdot g_{l-1} \left(\frac{i-m}{2}, \frac{j-n}{2} \right)$$

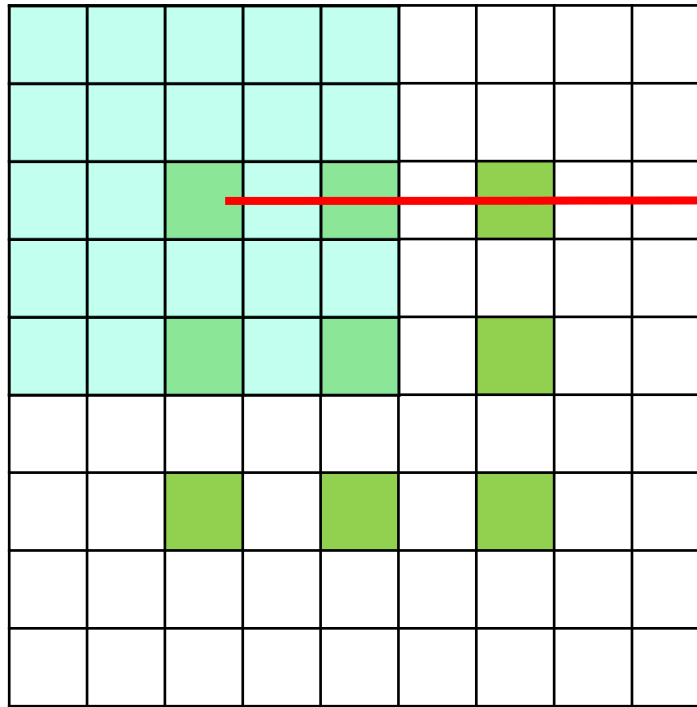
$(i-m)/2$ and $(j-n)/2$ are integers

2D Image Expansion (part1)

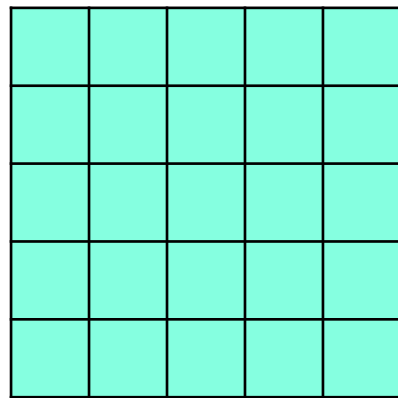
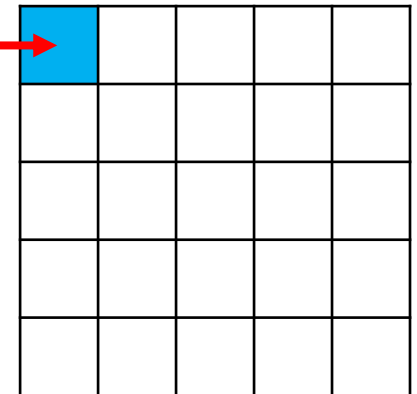
g_1



g_1 padded with 0s



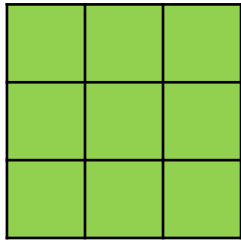
g_0



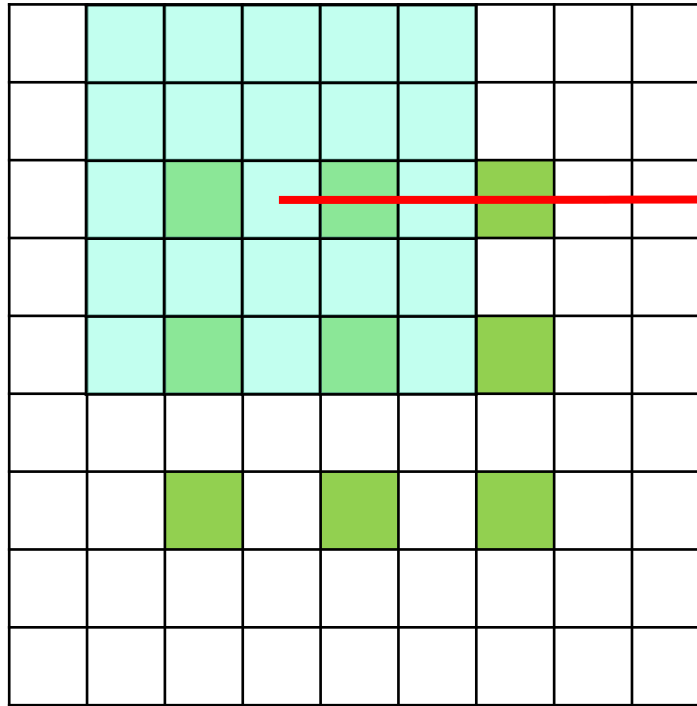
2D Gaussian kernel

2D Image Expansion (part2)

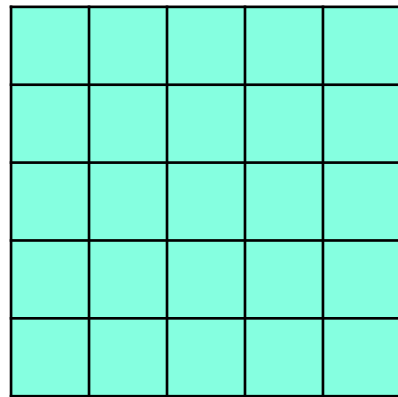
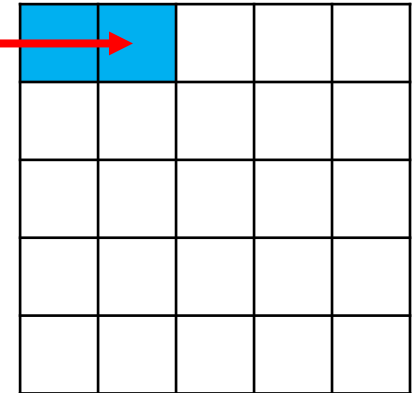
g_1



g_1 padded with 0s



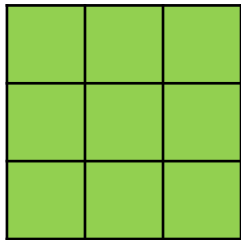
g_0



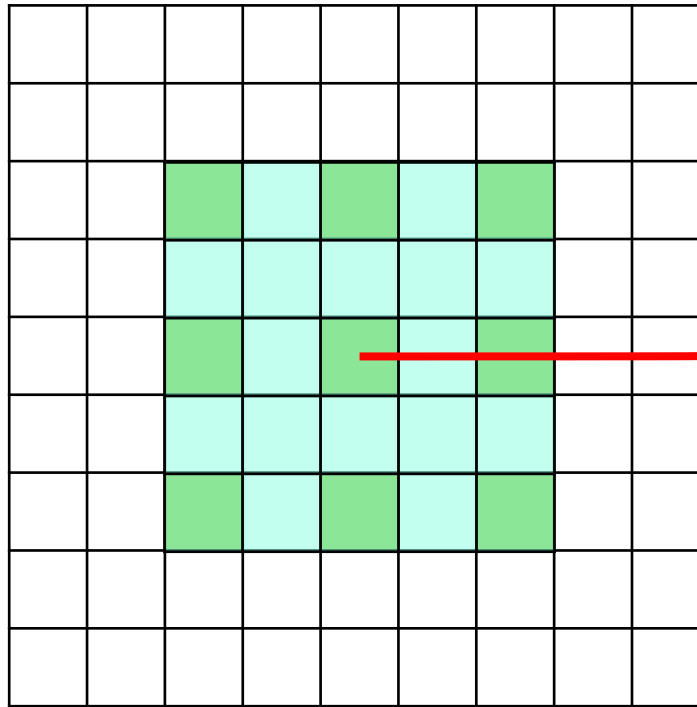
2D Gaussian kernel

2D Image Expansion (part3)

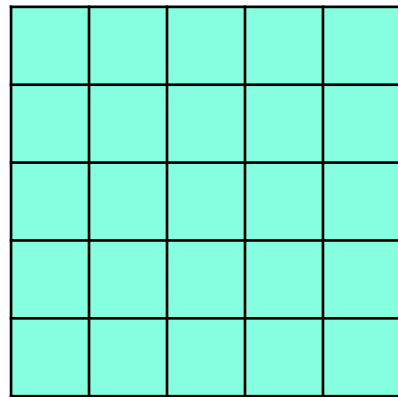
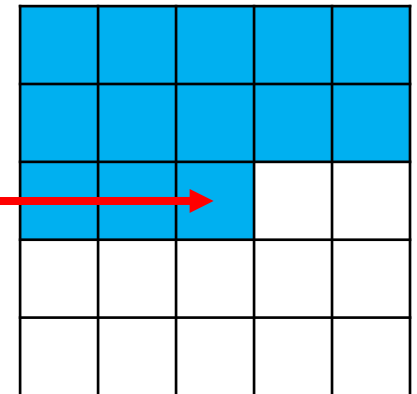
g_1



g_1 padded with 0s



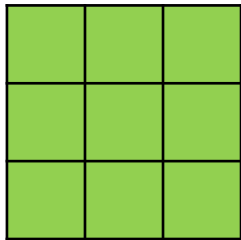
g_0



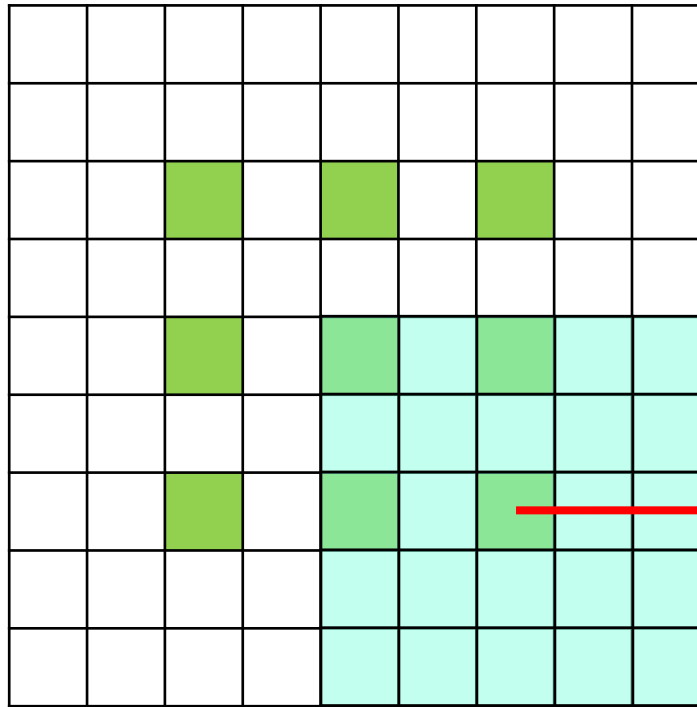
2D Gaussian kernel

2D Image Expansion (part4)

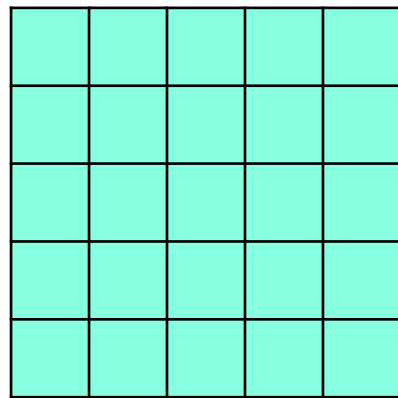
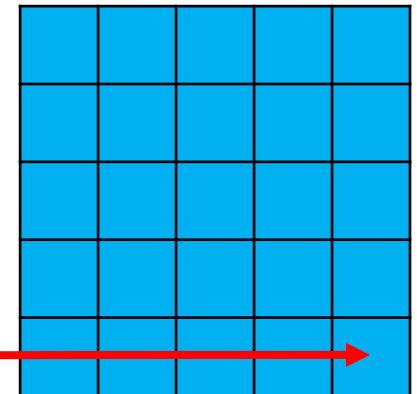
g_1



g_1 padded with 0s



g_0



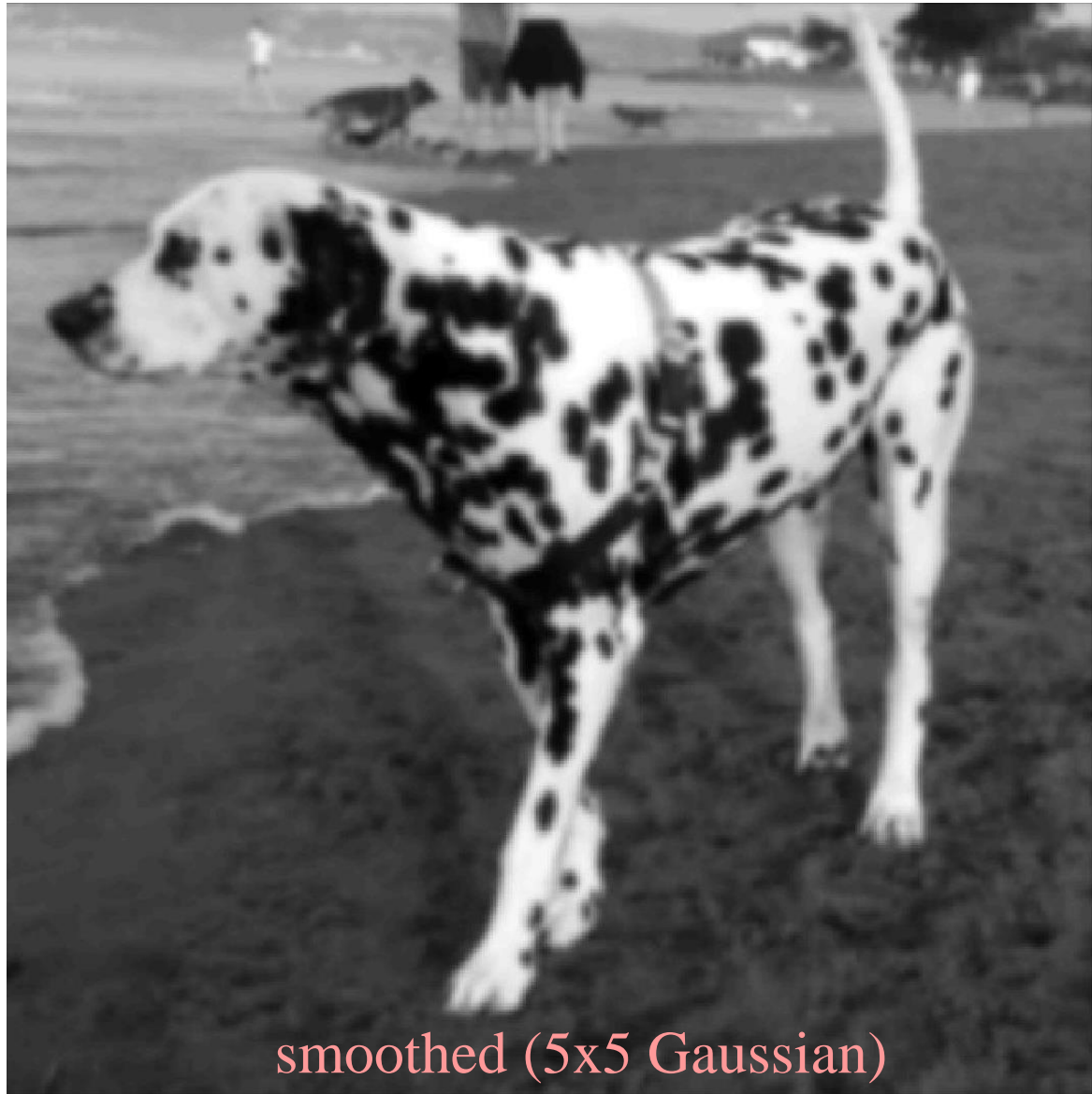
2D Gaussian kernel

What does blurring take away?



original

What does blurring take away?



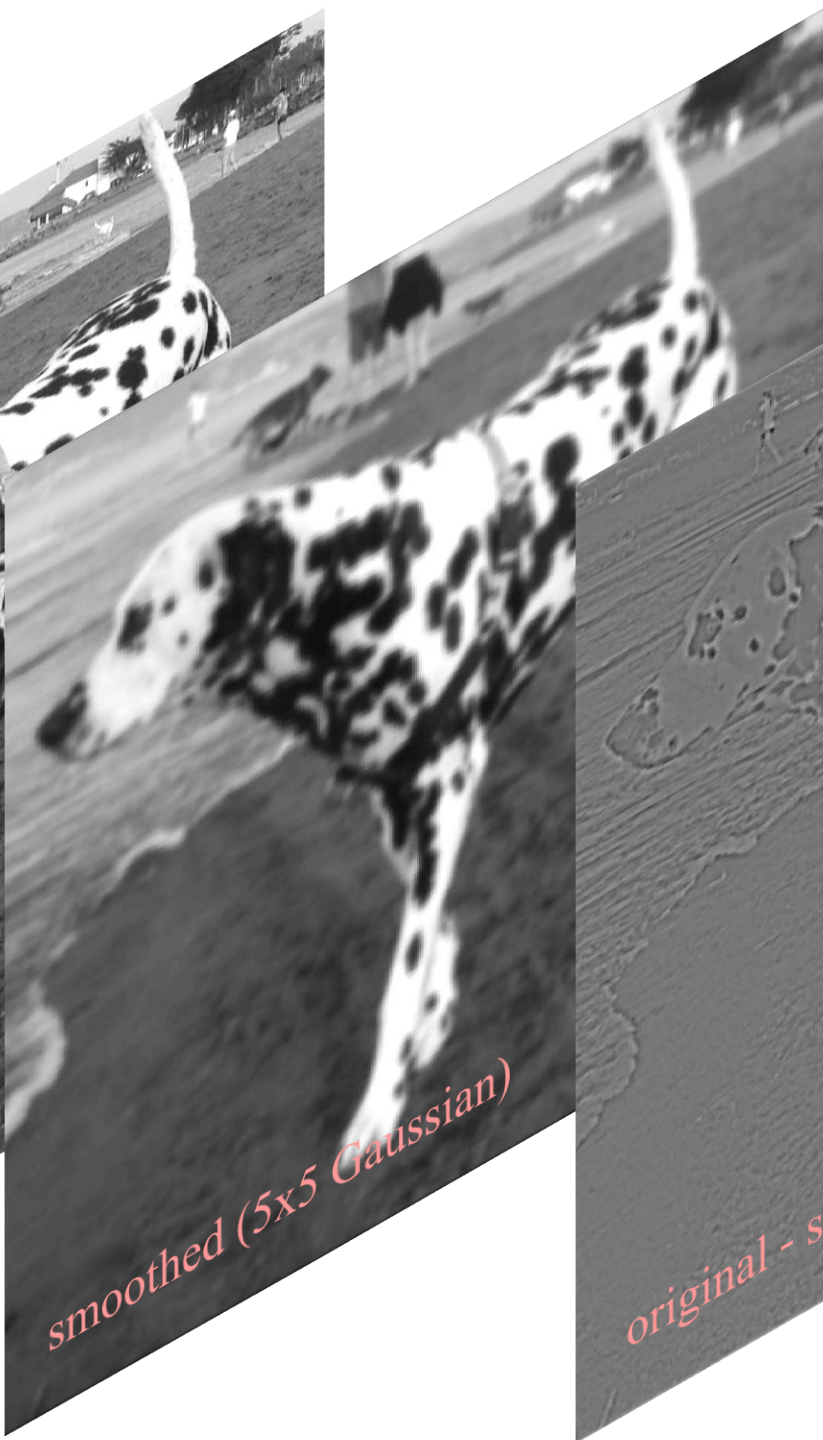
Difference as result of smoothing



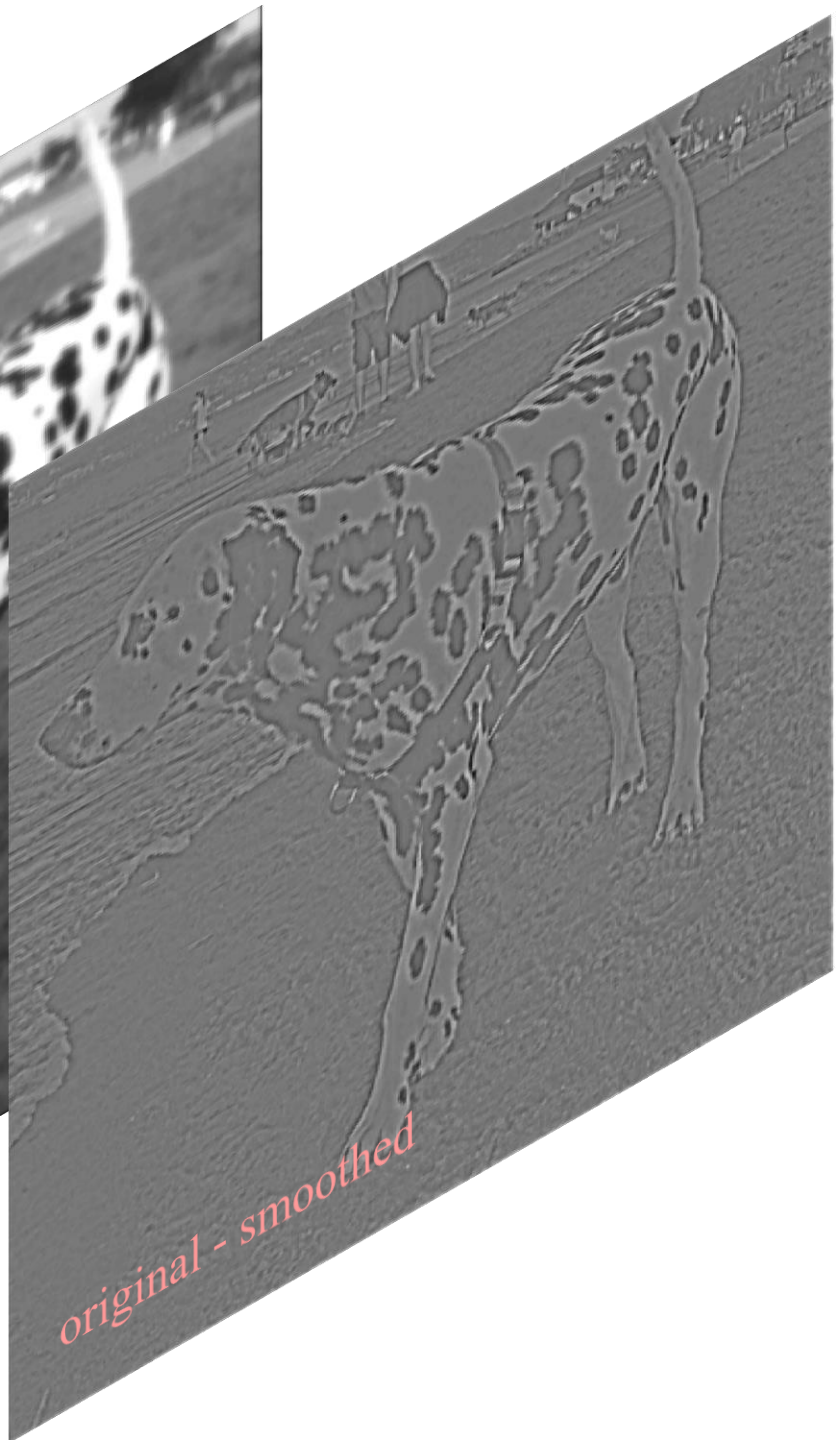
original - smoothed



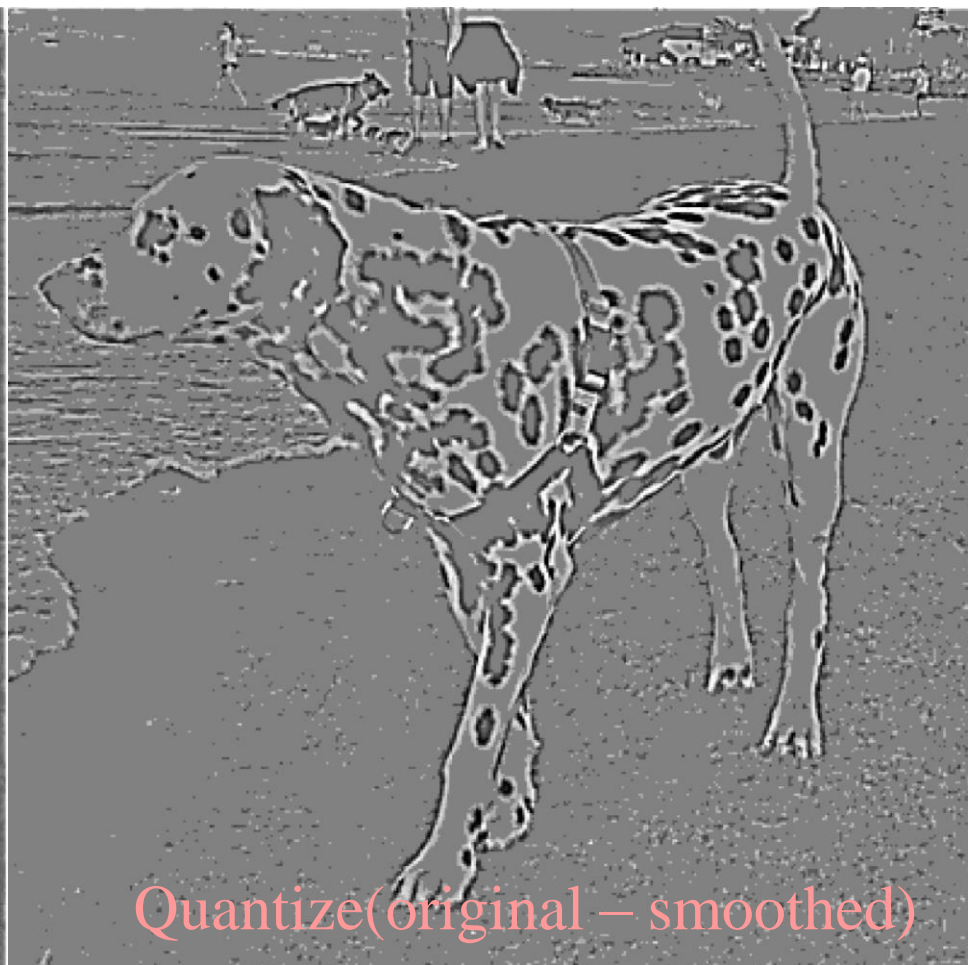
original



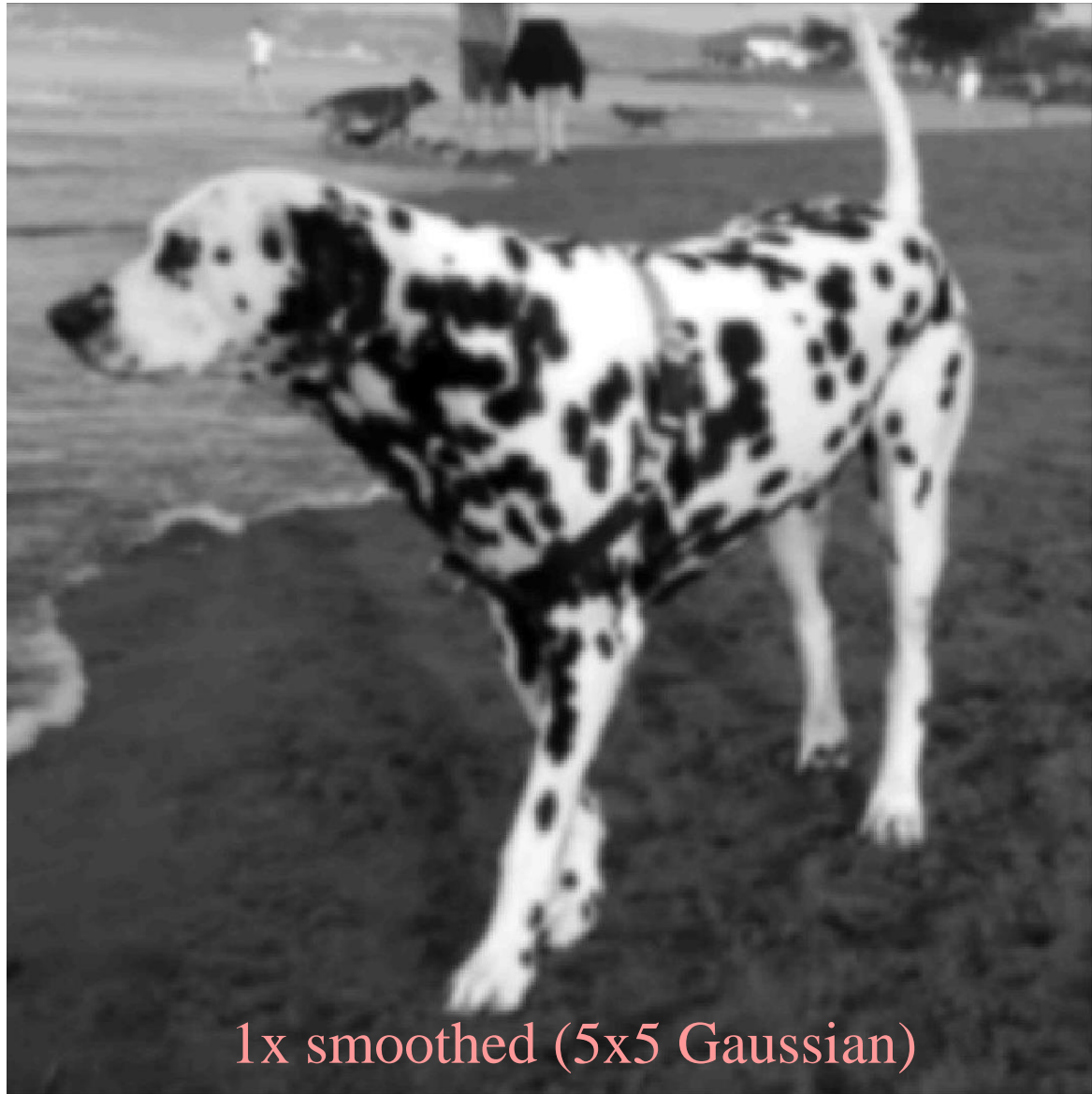
smoothed (5x5 Gaussian)



original - smoothed

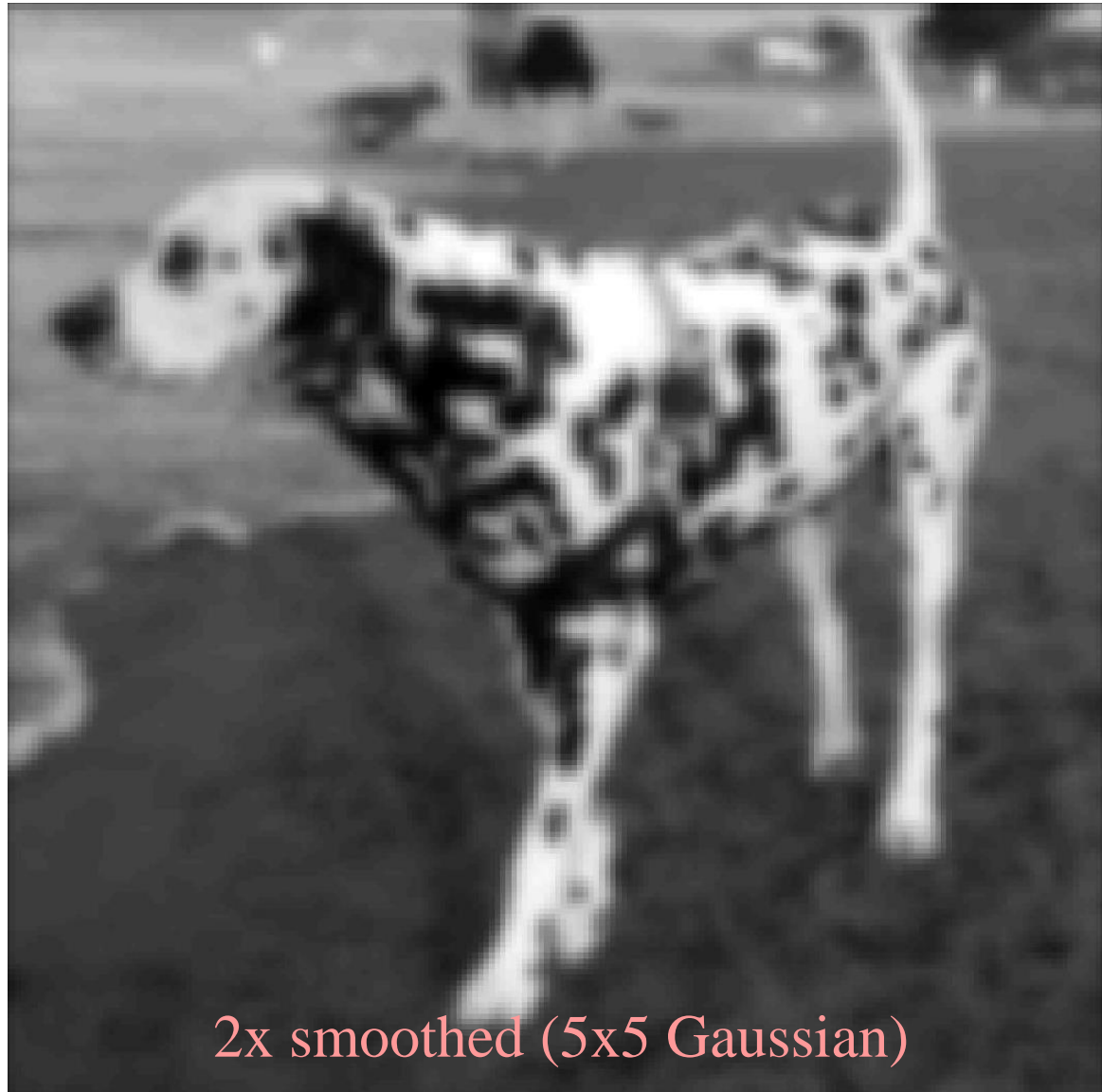


What does blurring take away?



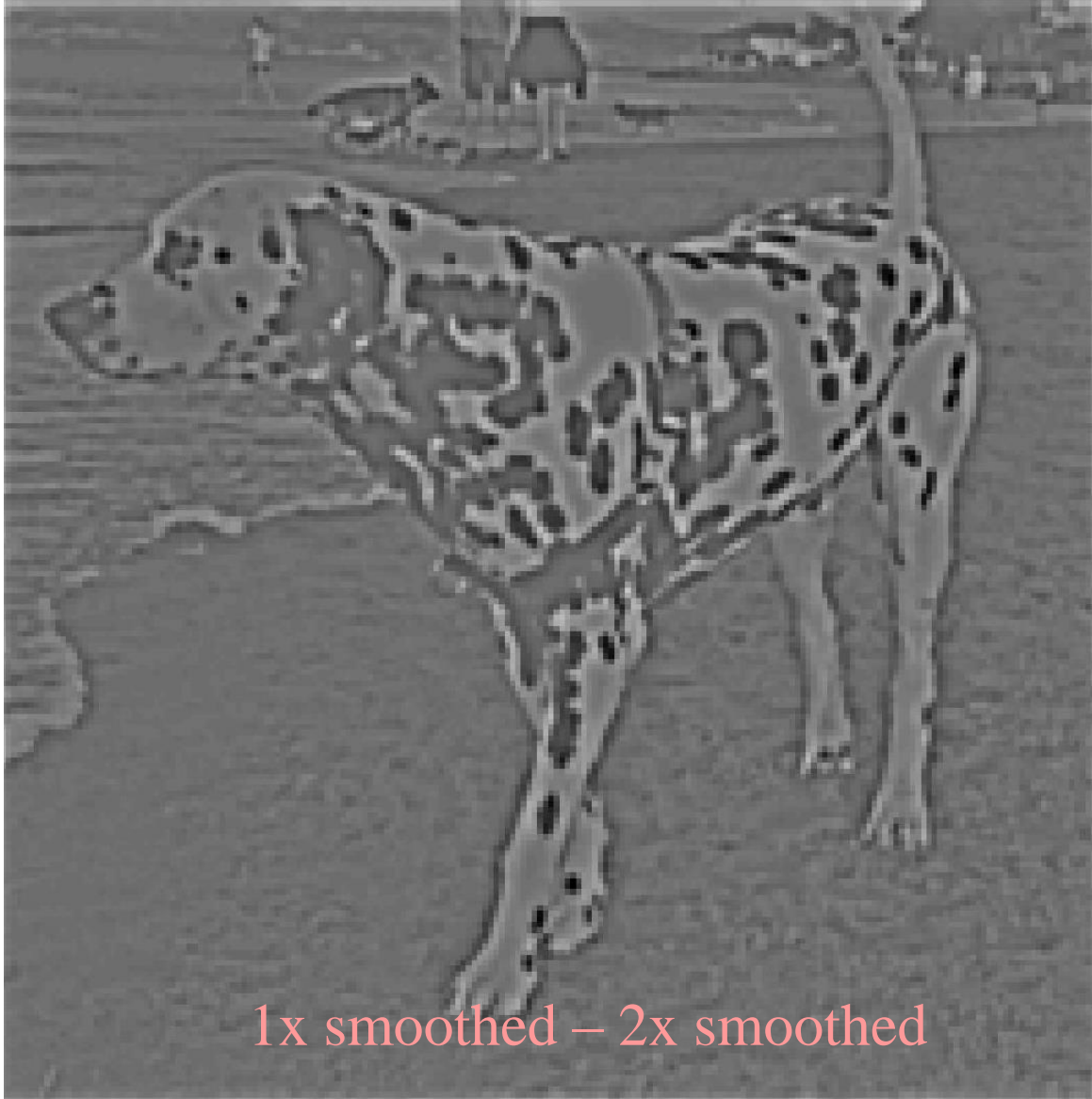
1x smoothed (5x5 Gaussian)

What does blurring take away?



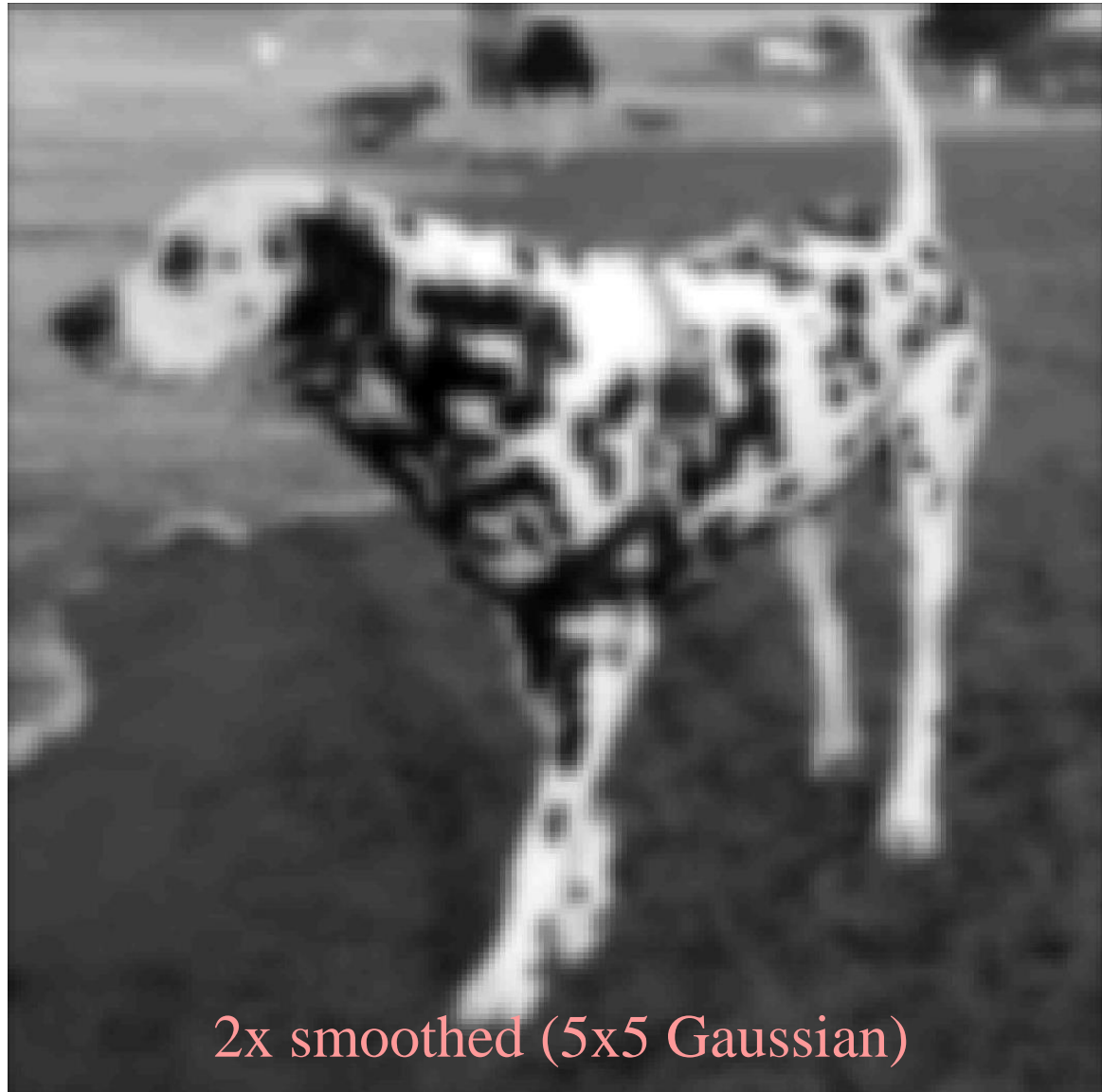
2x smoothed (5x5 Gaussian)

Difference of Gaussian



1x smoothed - 2x smoothed

What does blurring take away?

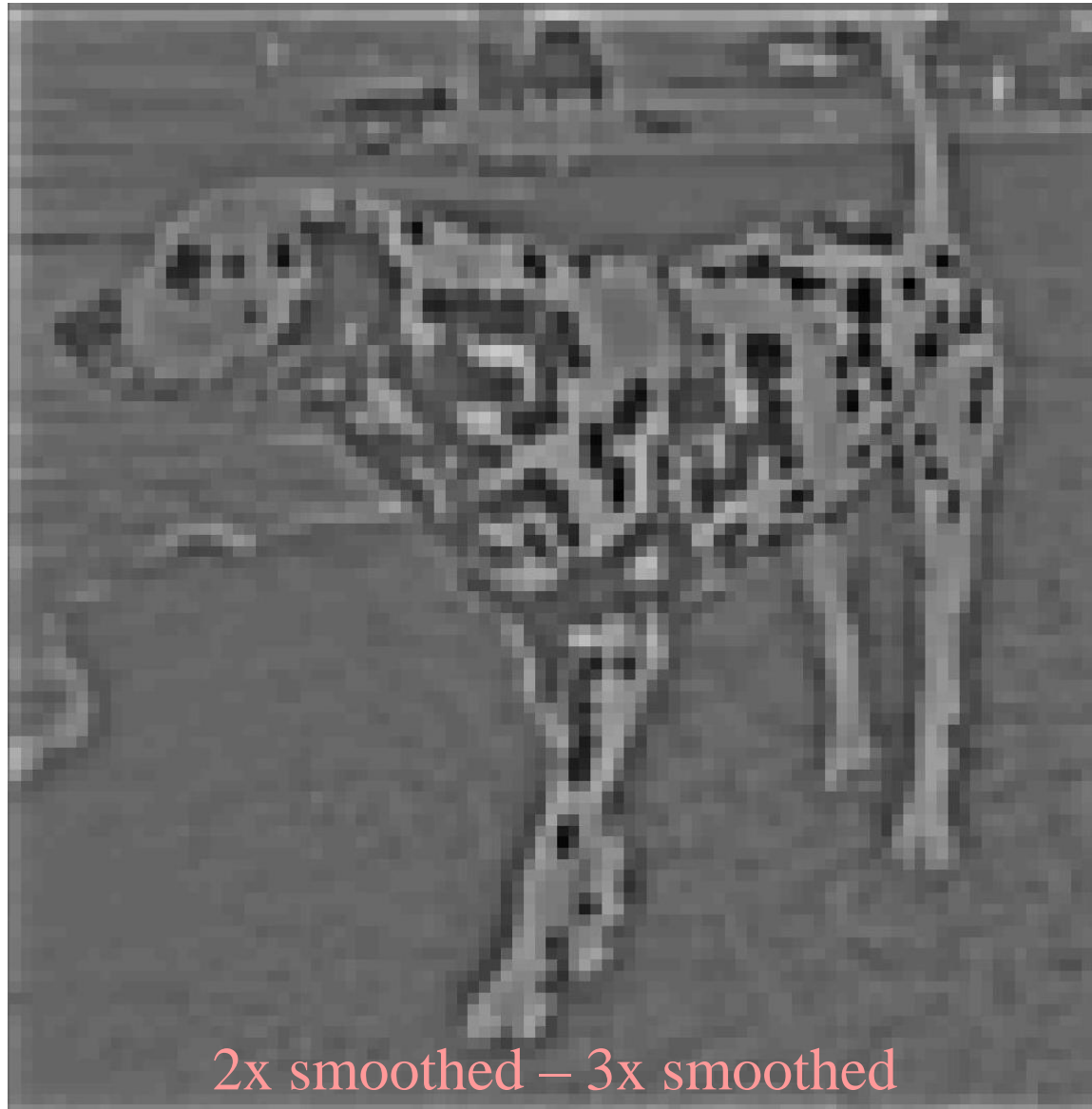


2x smoothed (5x5 Gaussian)



3x smoothed (5x5 Gaussian)

Difference of Gaussian

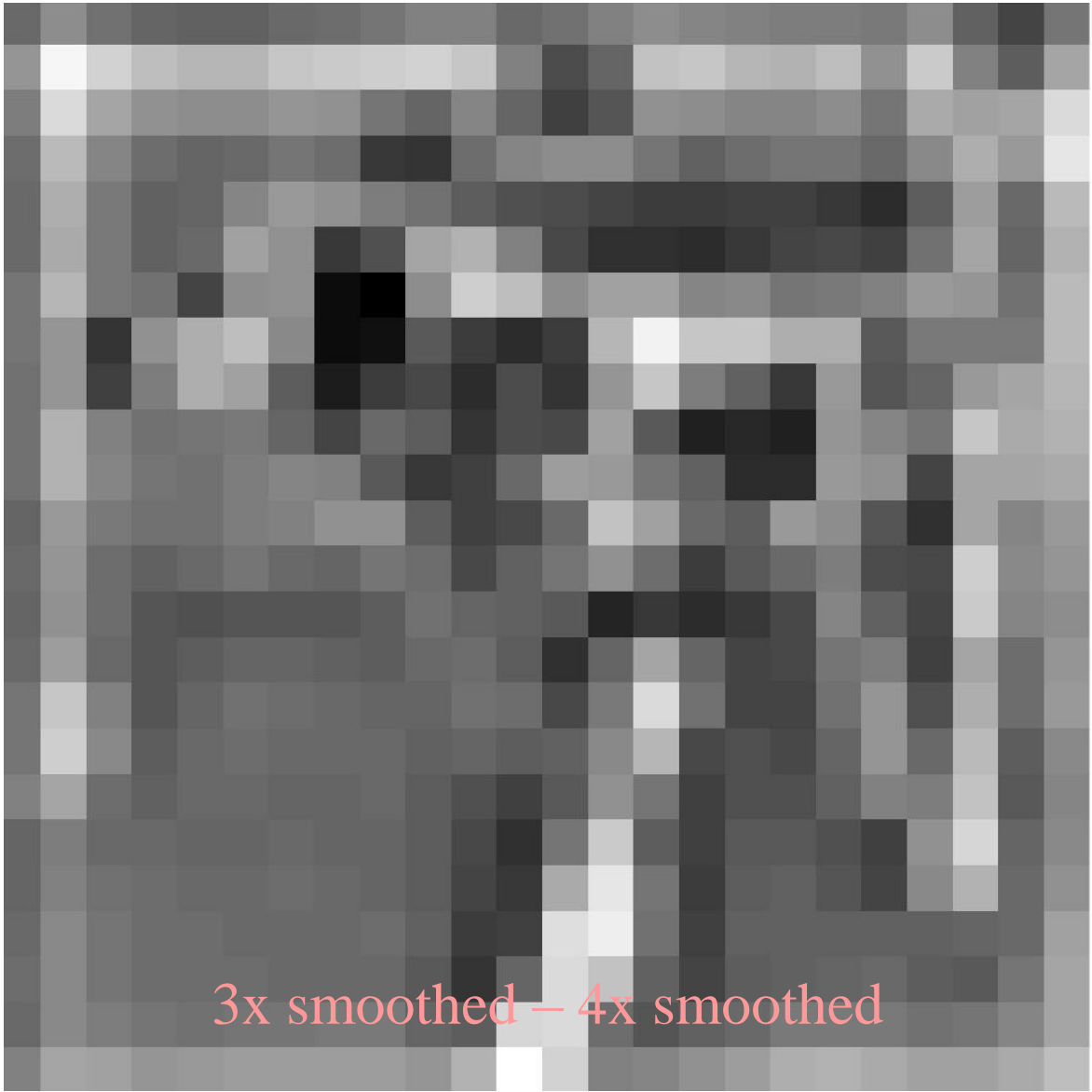




3x smoothed (5x5 Gaussian)



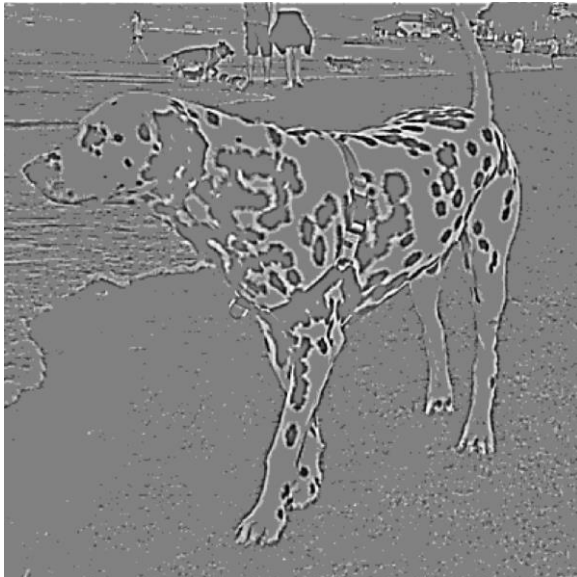
4x smoothed (5x5 Gaussian)





+ ↓

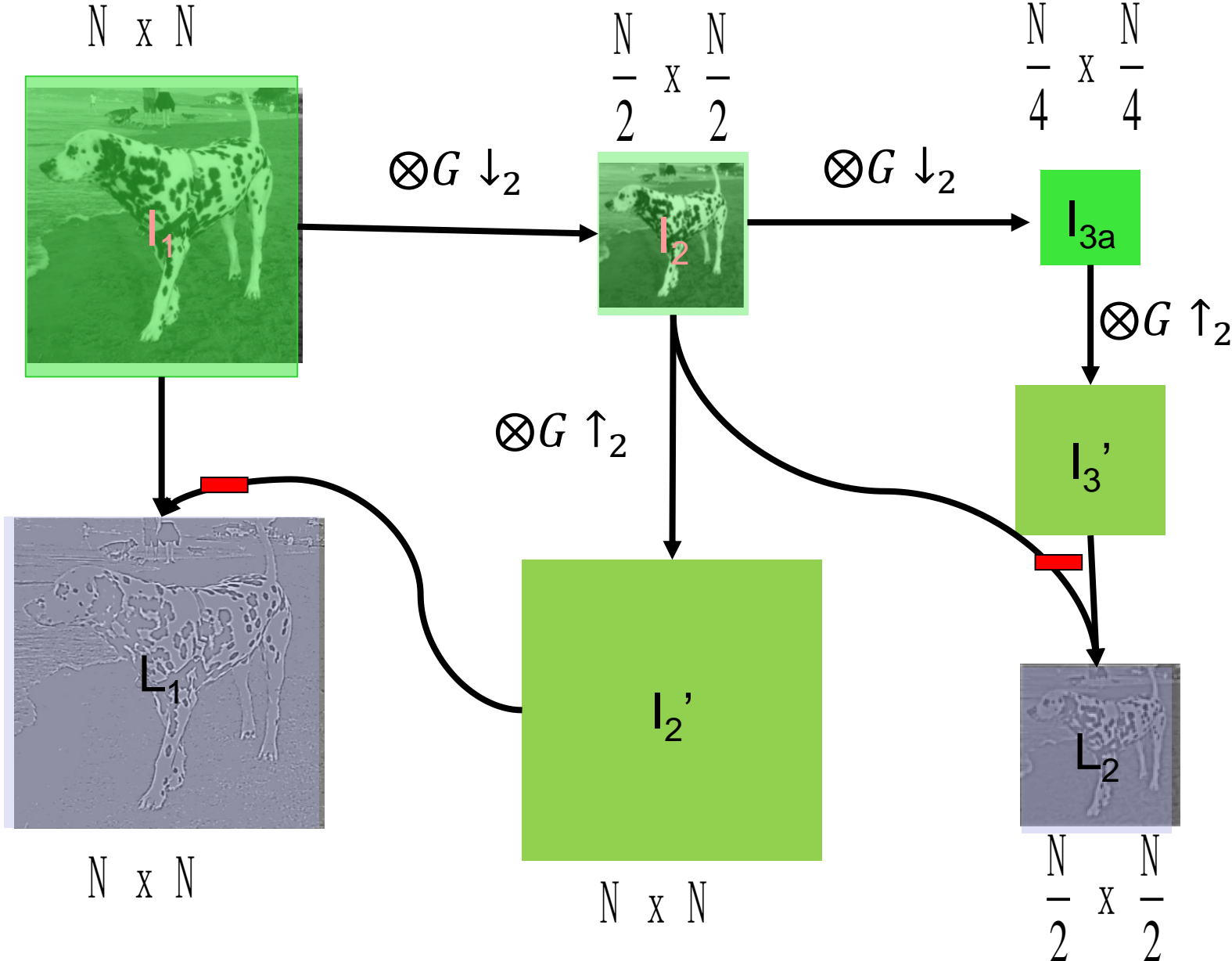
-

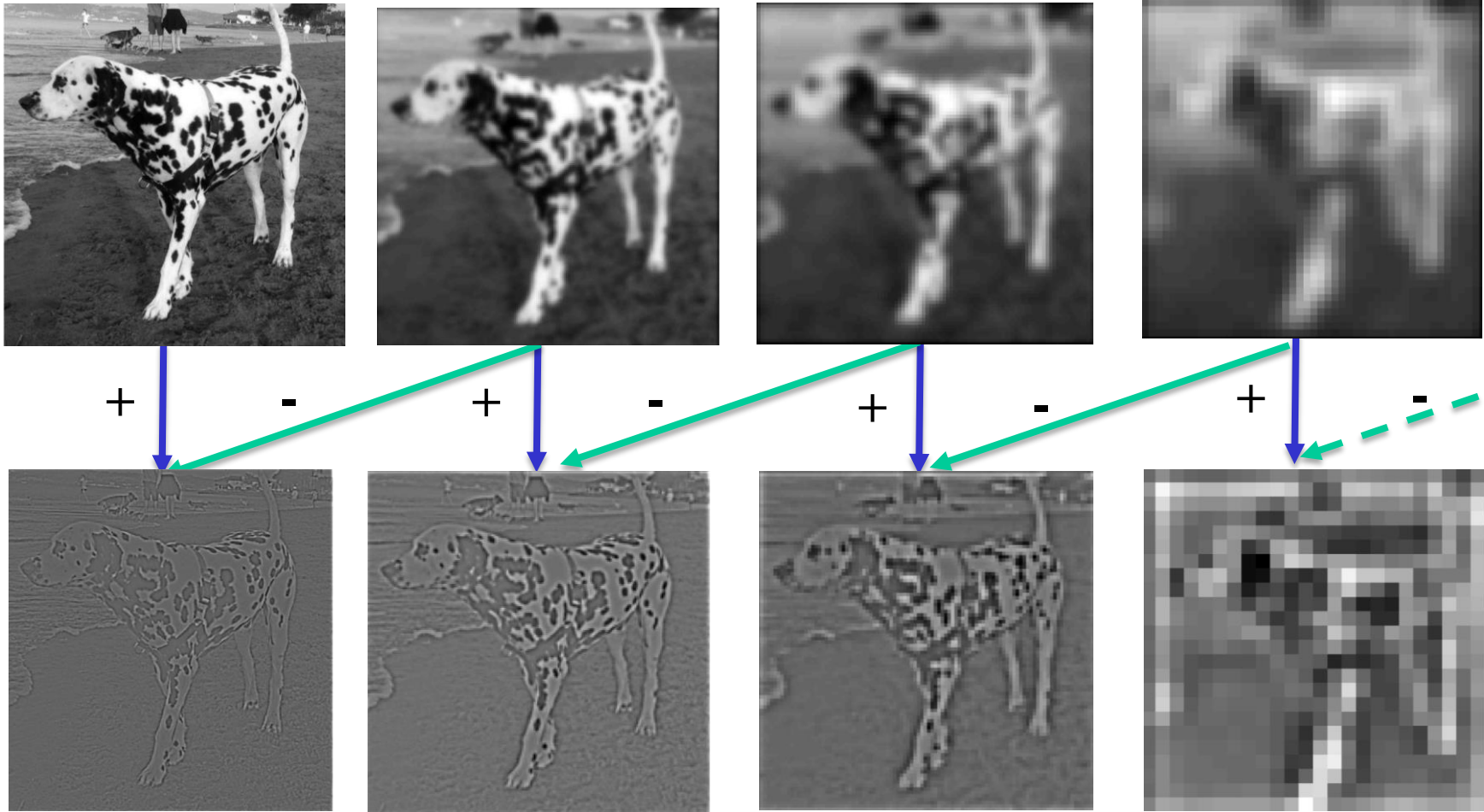


Laplacian Image

$$L_1 = g_l - \text{EXPAND}[g_{l+1}]$$

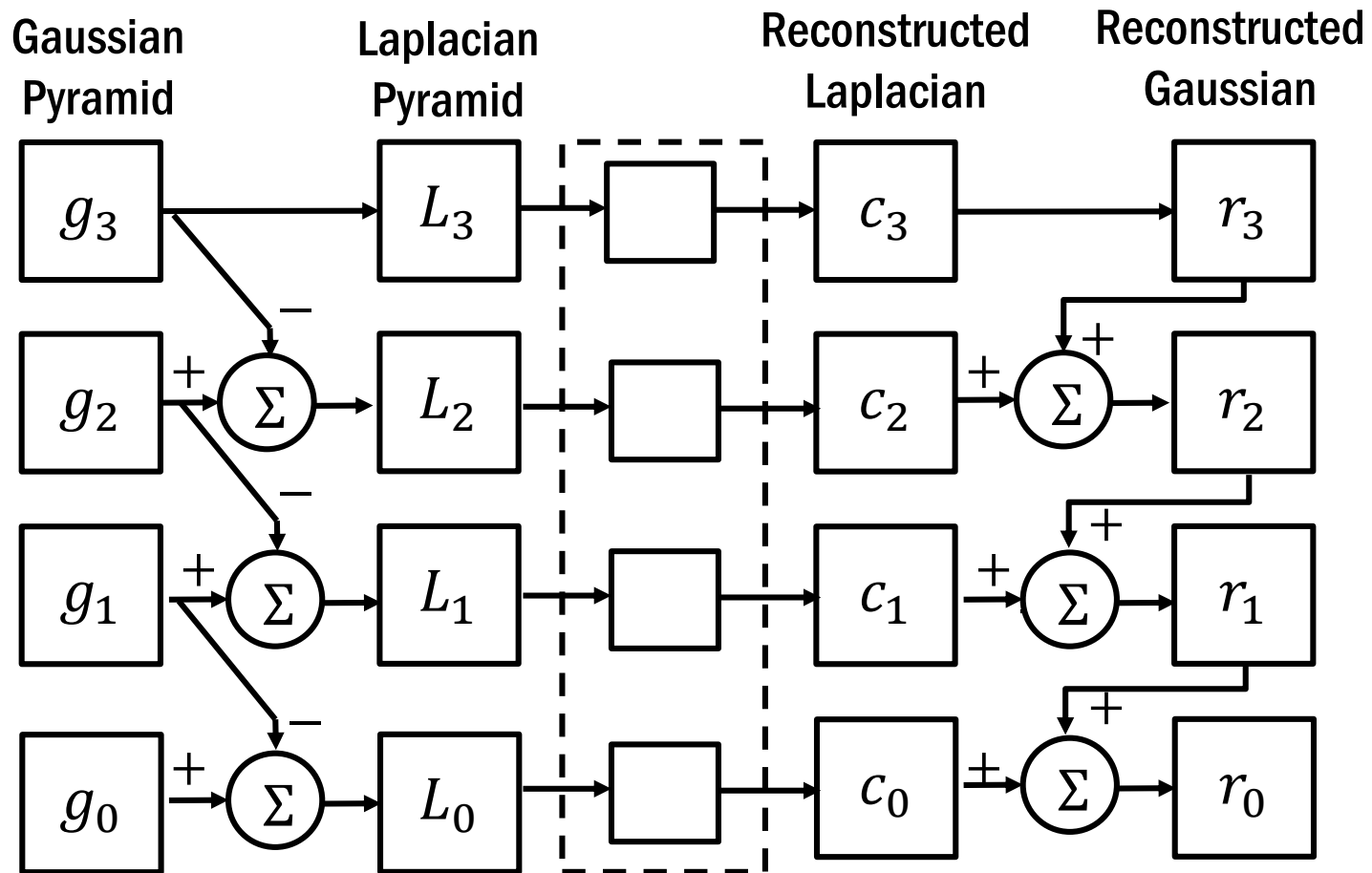
Extraction of Laplacian





Gaussian pyramid is smooth=> can be subsampled

Laplacian pyramid has narrow band of frequency=> compressed



$$g_N = L_N$$

$$g_l = L_l + \text{EXPAND}[g_{l+1}]$$

Pyramid Blending



laplacian
level
4



laplacian
level
2



laplacian
level
0



top pyramid



bottom pyramid

laplacian
level
4



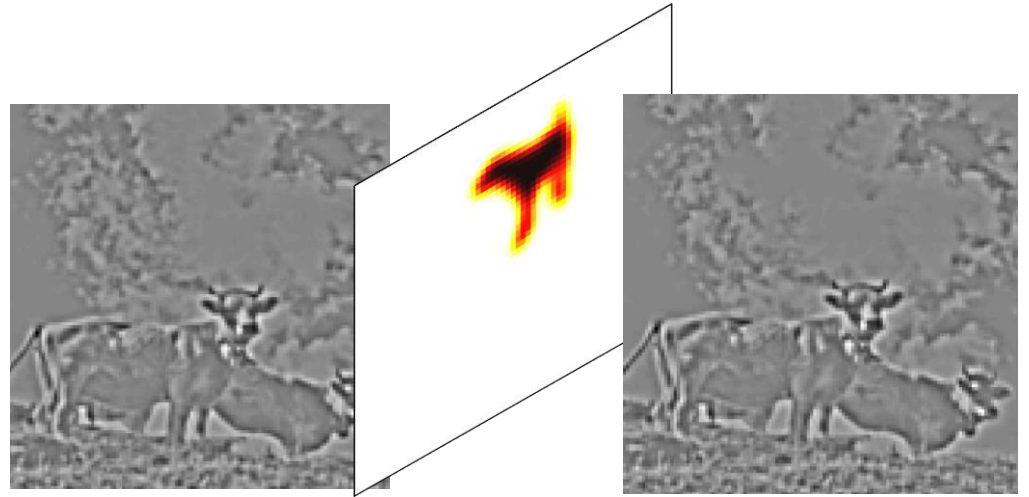
laplacian
level
2



laplacian
level
0



top pyramid



bottom pyramid

laplacian
level
4



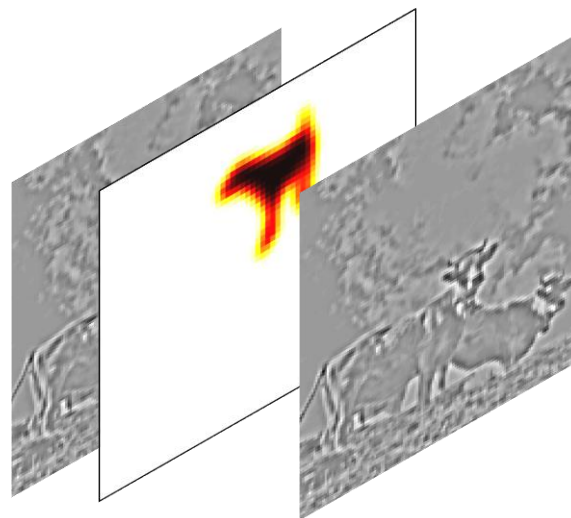
laplacian
level
2



laplacian
level
0



top pyramid



bottom pyramid

laplacian
level
4



laplacian
level
2



laplacian
level
0



top pyramid

bottom pyramid

blended pyramid

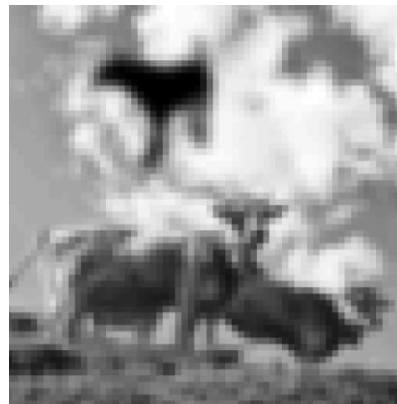
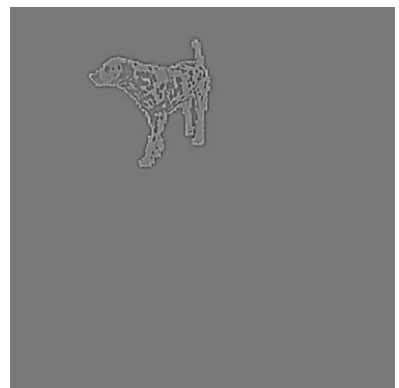
laplacian
level
4



laplacian
level
2



laplacian
level
0

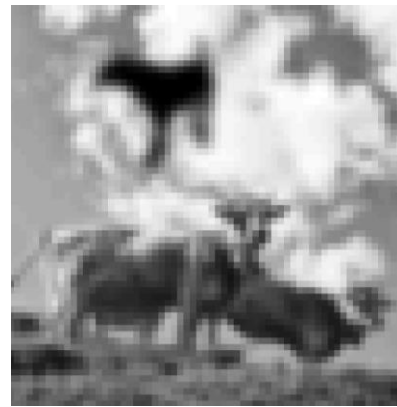
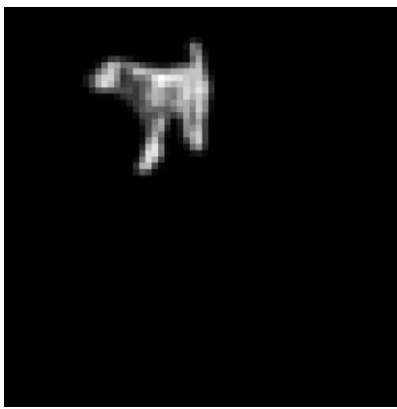


top pyramid

bottom pyramid

blended pyramid

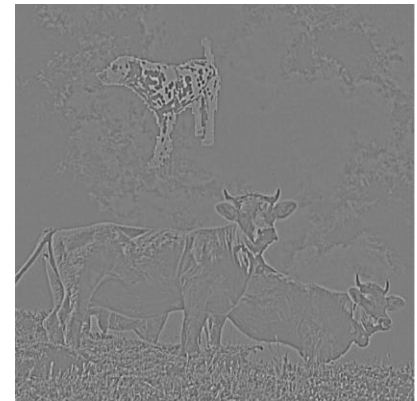
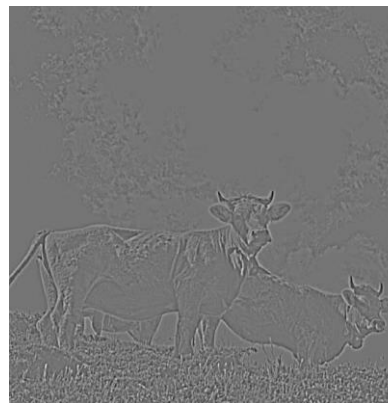
laplacian
level
4



laplacian
level
2



laplacian
level
0



top pyramid

bottom pyramid

blended pyramid

Laplacian Pyramid: Blending

General Approach:

1. Build Laplacian pyramids LA and LB from images A and B
2. Build a Gaussian pyramid $MASK$ from selected region R
3. Form a combined pyramid LS from LA and LB using nodes of GR as

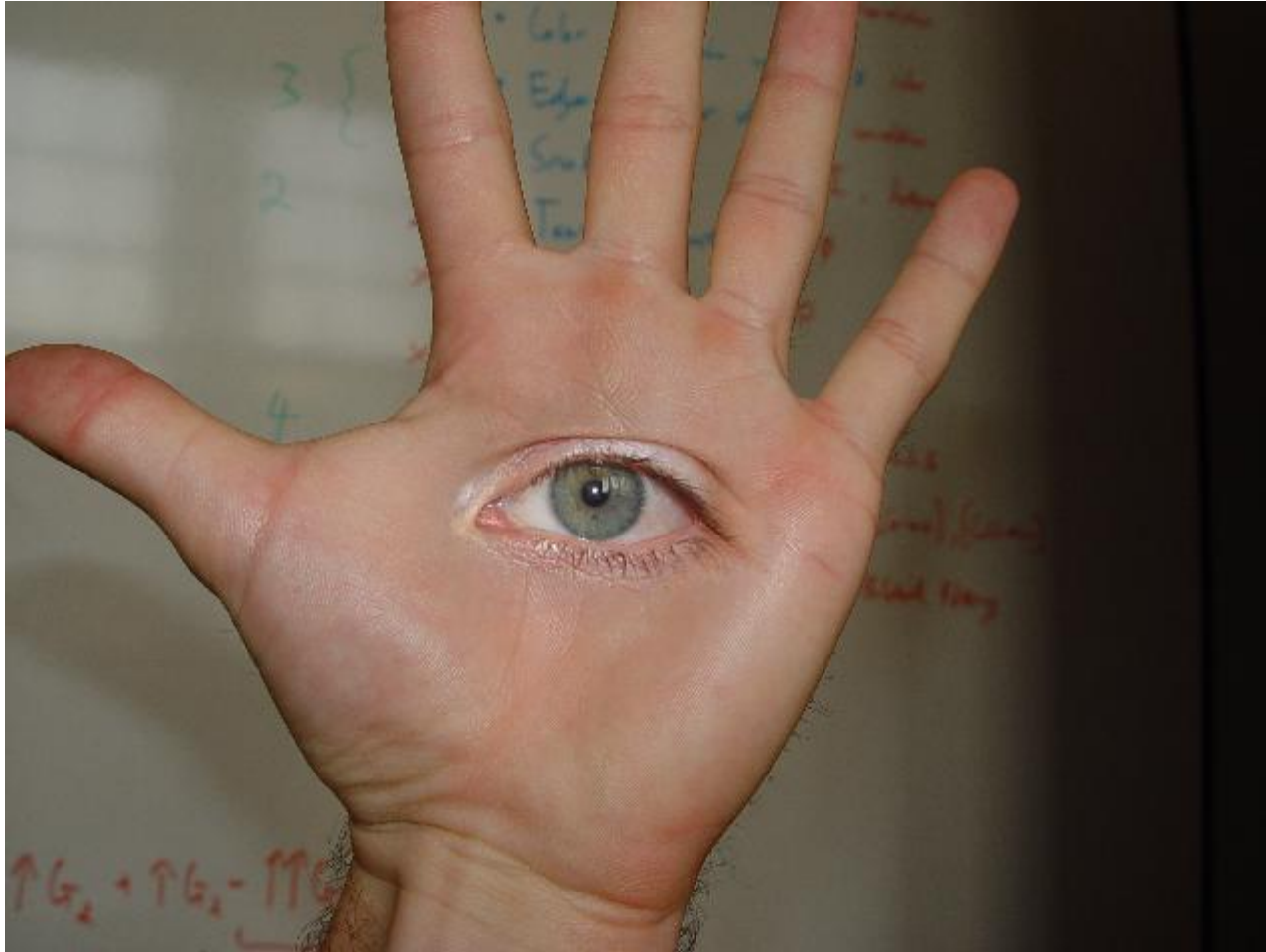
weights:

$$LS(i, j) = MASK(i, j) * LA(i, j) + (1 - MASK(i, j)) * LB(i, j)$$

4. Collapse the LS pyramid to get the final blended image



Horror Photo



© prof. dmartin