

Lecture 10: Pyramids and Scale Space



Recall

- Cascaded Gaussians
 - Repeated convolution by a smaller Gaussian to simulate effects of a larger one.
- $G^*(G*f) = (G*G)*f$ [associativity]

$$G_{\sigma_1} * G_{\sigma_2} = G_{\sigma} \quad \sigma^2 = \sigma_1^2 + \sigma_2^2$$

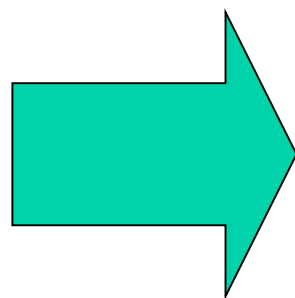
Example: Cascaded Convolutions

$$[1 \ 1] * [1 \ 1] \rightarrow [1 \ 2 \ 1]$$

$$[1 \ 1] * [1 \ 2 \ 1] \rightarrow [1 \ 3 \ 3 \ 1]$$

$$[1 \ 1] * [1 \ 3 \ 3 \ 1] \rightarrow [1 \ 4 \ 6 \ 4 \ 1]$$

..and so on...



$$\begin{array}{ccccccc} & & 1 & & 1 & & \\ & & & 1 & 2 & 1 & \\ & & & & 1 & 3 & 3 & 1 \\ & & & & & 1 & 4 & 6 & 4 & 1 \\ & & & & & & 1 & 5 & 10 & 10 & 5 & 1 \\ & & & & & & & \text{and so on...} \end{array}$$

Pascal's
Triangle

Aside: Binomial Approximation

1 1
1 2 1
1 3 3 1
1 4 6 4 1
1 5 10 10 5 1
and so on...

Pascal's
Triangle

$$a_{nr} \equiv \frac{n!}{r!(n-r)!} \equiv \binom{n}{r}$$

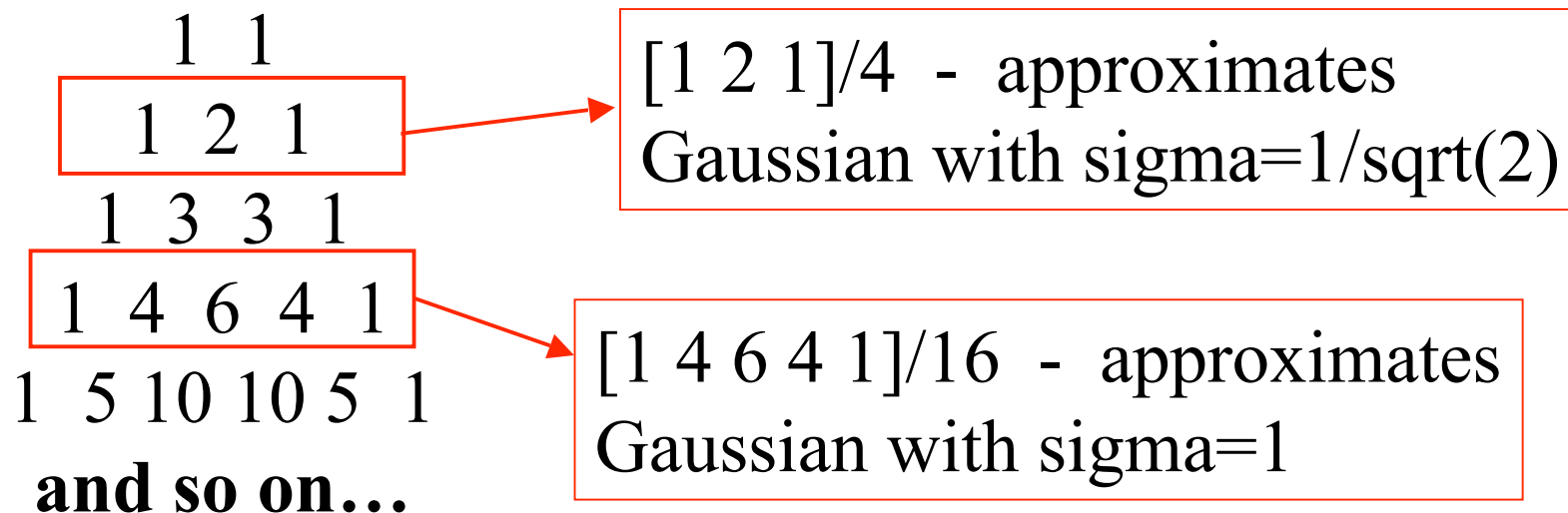
n = number of elements in the 1D filter minus 1

r = position of element in the filter kernel (0, 1, 2...)

Binomial
Coefficients

Aside: Binomial Approximation

Look at odd-length rows of Pascal's triangle:



An easy way to generate integer-coefficient Gaussian approximations.

From Homework 2

Row 1	1 1	$\sigma = 1/2$
Row 2	1 2 1	$\sigma = 1/\sqrt{2}$
Row 3	1 3 3 1	$\sigma = \underline{\hspace{1cm}}$
Row 4	1 4 6 4 1	$\sigma = \underline{\hspace{1cm}}$
Row 5	$\underline{\hspace{1cm}} \underline{\hspace{1cm}} \underline{\hspace{1cm}} \underline{\hspace{1cm}} \underline{\hspace{1cm}}$	$\sigma = \sqrt{5}/2$
Row 6	$\underline{\hspace{1cm}} \underline{\hspace{1cm}} \underline{\hspace{1cm}} \underline{\hspace{1cm}} \underline{\hspace{1cm}} \underline{\hspace{1cm}}$	$\sigma = \sqrt{3}/2$

$$G_{\sigma_1} * G_{\sigma_2} = G_{\sigma} \quad \sigma^2 = \sigma_1^2 + \sigma_2^2$$

More about Cascaded Convolutions

(for the mathematically inclined)

Fun facts:

The distribution of the sum of two random variables $X + Y$ is the convolution of their two distributions

Given N i.i.d. random variables, $X_1 \dots X_N$, the distribution of their sum approaches a Gaussian distribution (aka the central limit theorem)

Therefore:

The repeated convolution of a (nonnegative) filter with itself takes on a Gaussian shape.

recall Gaussian Smoothing at Different Scales



original



sigma = 1

Gaussian Smoothing at Different Scales



original



$\sigma = 3$

Gaussian Smoothing at Different Scales



original



$\sigma = 10$

Idea for Today:

Form a Multi-Resolution Representation



original



$\sigma = 1$



$\sigma = 3$



$\sigma = 10$

Pyramid Representations

Because a large amount of smoothing limits the frequency of features in the image, we do not need to keep all the pixels around!

Strategy: progressively reduce the number of pixels as we smooth more and more.

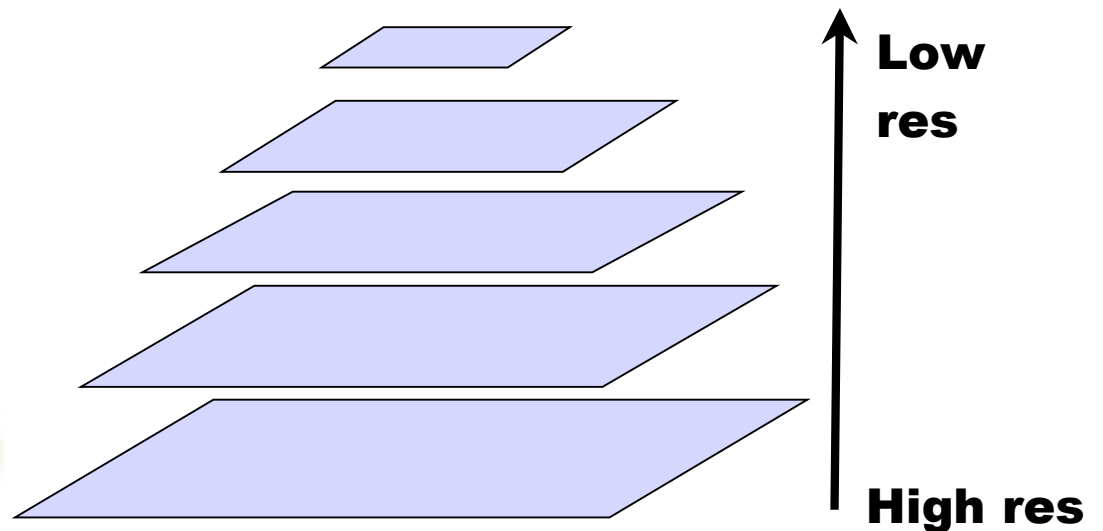
Leads to a “pyramid” representation if we subsample at each level.

Gaussian Pyramid

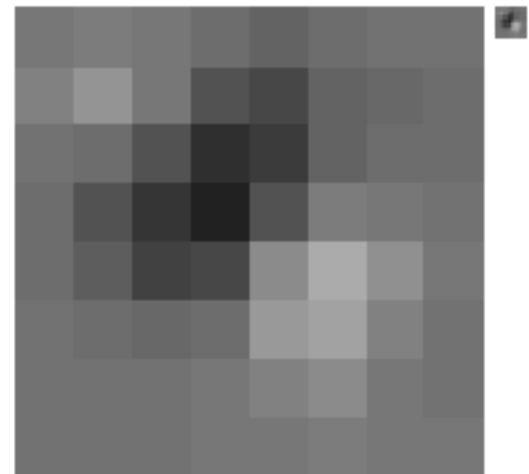
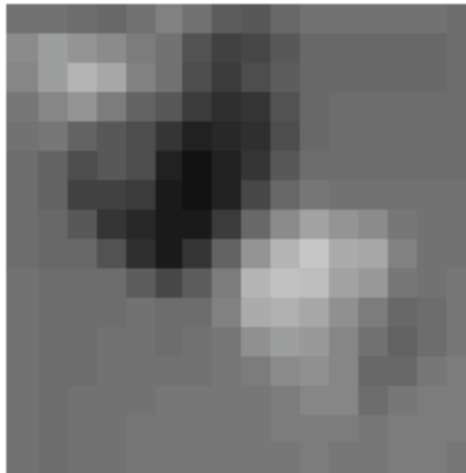
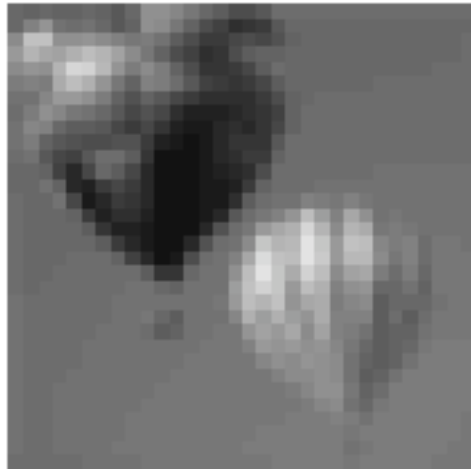
- Synthesis: Smooth image with a Gaussian and downsample. Repeat.
- Gaussian is used because it is self-reproducing (enables incremental smoothing).
- Top levels come “for free”. Processing cost typically dominated by two lowest levels (highest resolution).

Gaussian Pyramid

High resolution  Low resolution



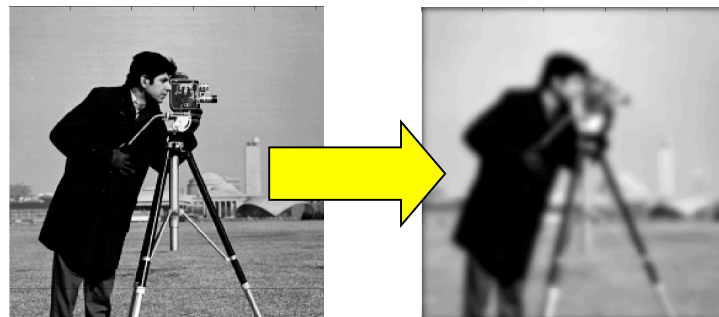
Emphasis: Smaller Images have Lower Resolution



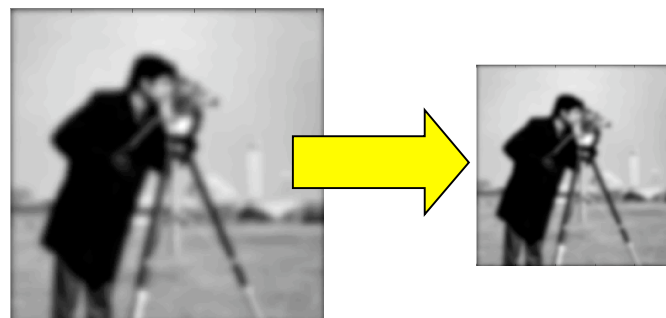
Generating a Gaussian Pyramid

Basic Functions:

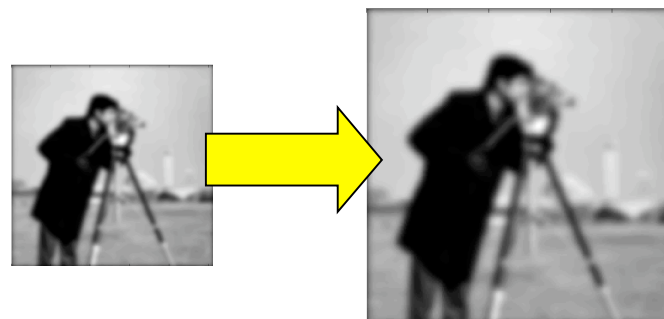
Blur (convolve with Gaussian to smooth image)



DownSample (reduce image size by half)



Upsample (double image size)



Generating a Gaussian Pyramid

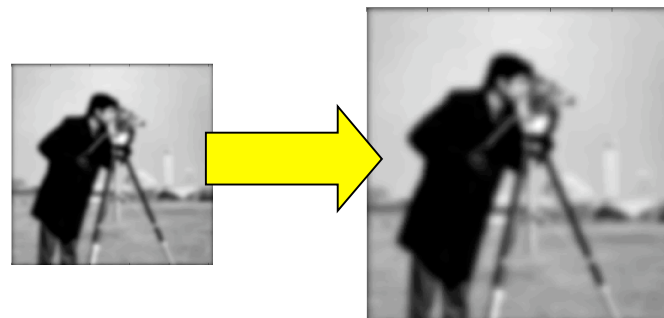
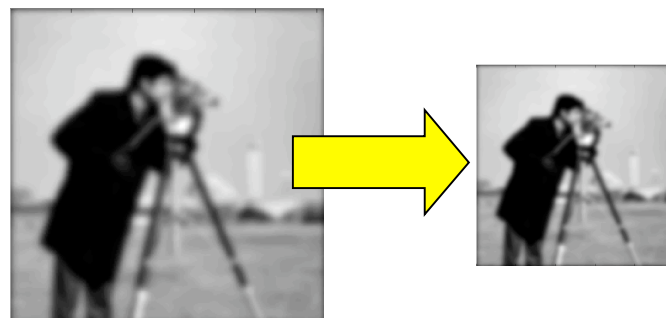
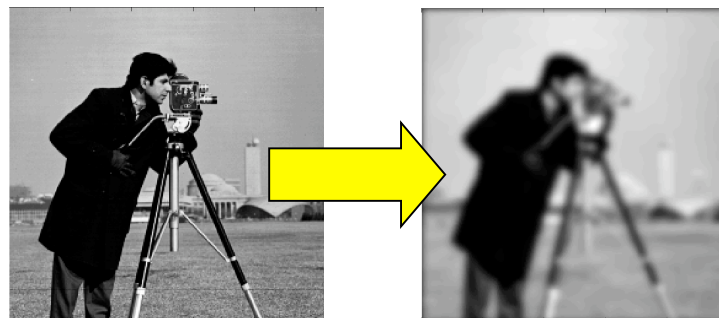
Basic Functions:

Blur (convolve with Gaussian
to smooth image)

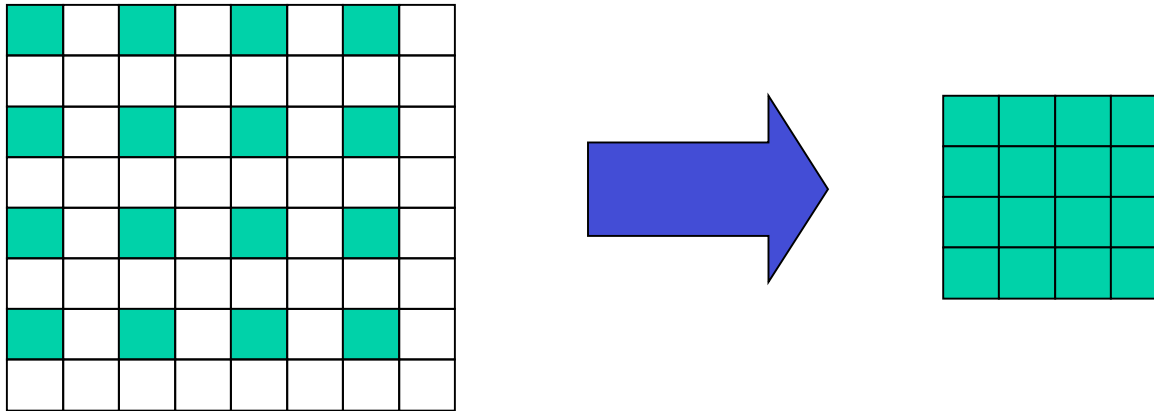
**We've talked about
blur already**

DownSample (reduce image
size by half)

Upsample (double image size)



Downsample



By the way: Subsampling is a bad idea unless you have previously blurred/smoothed the image! (because it leads to aliasing)

To Elaborate: Thumbnails



original image
262x195



131x97



65x48



32x24

downsampled (left)
vs. smoothed then
downsampled (right)

To Elaborate: Thumbnails



**original image
262x195**



**downsampled (left)
vs. smoothed then
downsampled (right)
131x97**

To Elaborate: Thumbnails



**original image
262x195**



**downsampled (left)
vs. smoothed then
downsampled (right)**

65x48

To Elaborate: Thumbnails



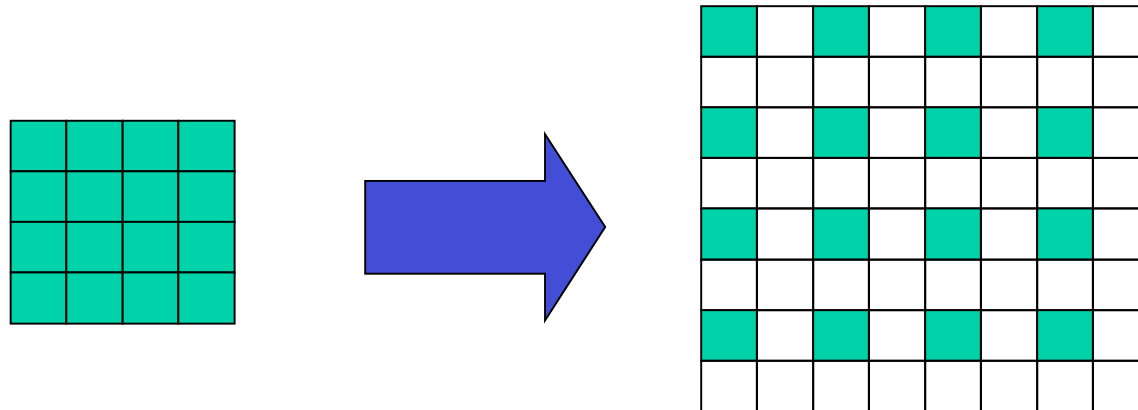
**original image
262x195**



**downsampled (left)
vs. smoothed then
downsampled (right)**

32x24

Upsample



How to fill in the empty values?

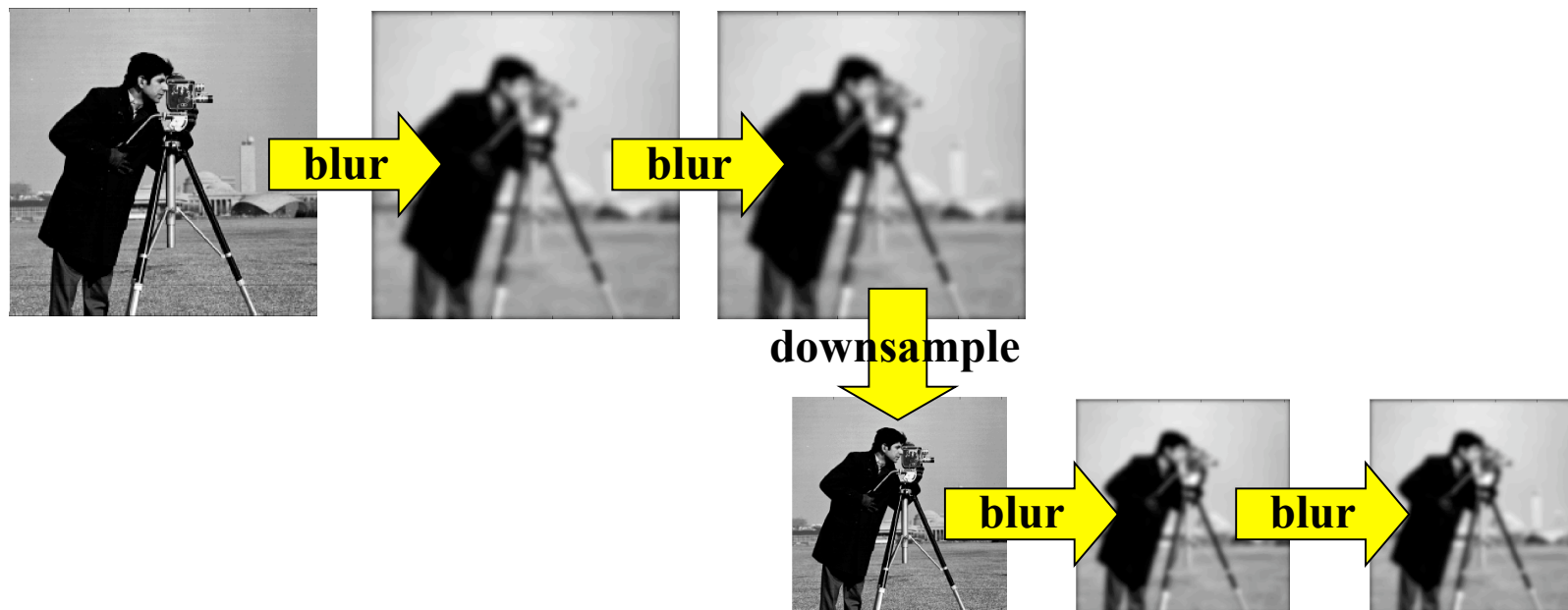
Interpolation:

- initially set empty pixels to zero
- convolve upsampled image with Gaussian filter!
e.g. 5x5 kernel with $\sigma = 1$.
- **Must also multiply by 4. Explain why.**

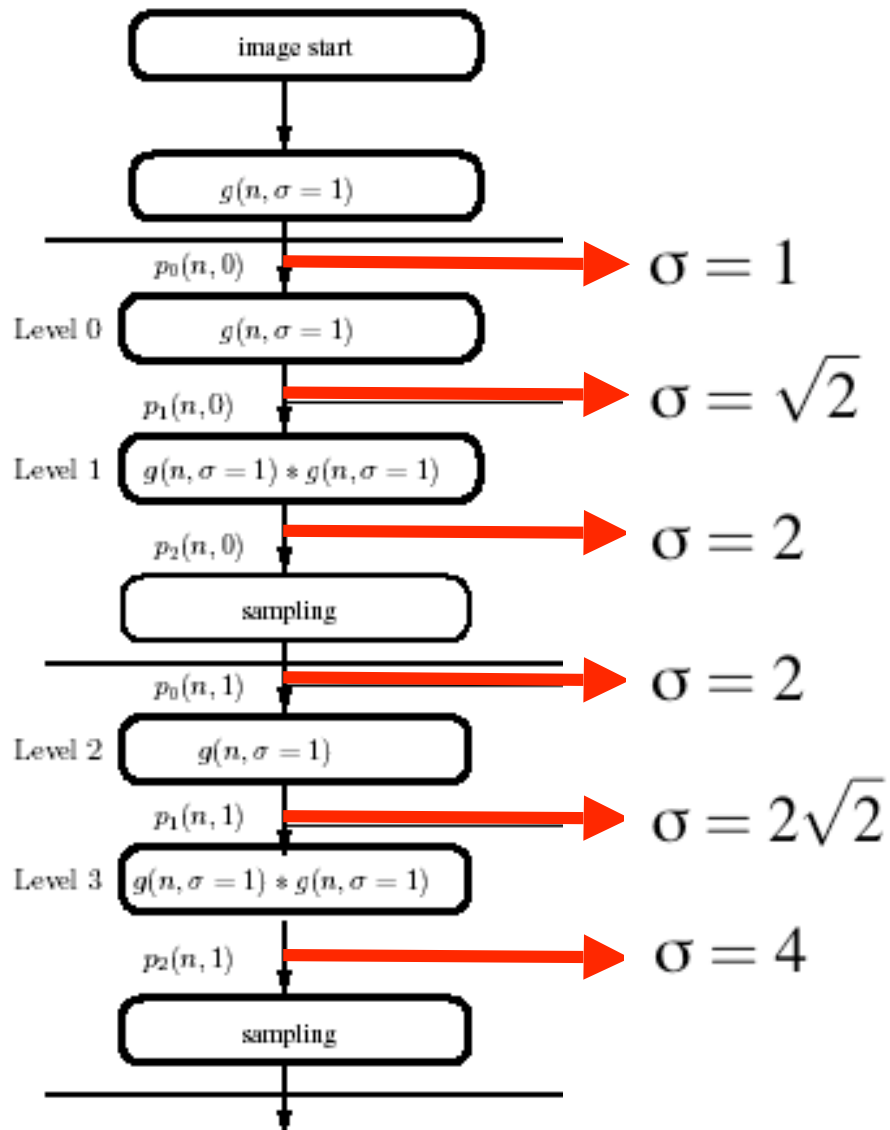
Specific Example

From Crowley et.al., “Fast Computation of Characteristic Scale using a Half-Octave Pyramid.” *Proc International Workshop on Cognitive Vision (CogVis)*, Zurich, Switzerland, 2002.

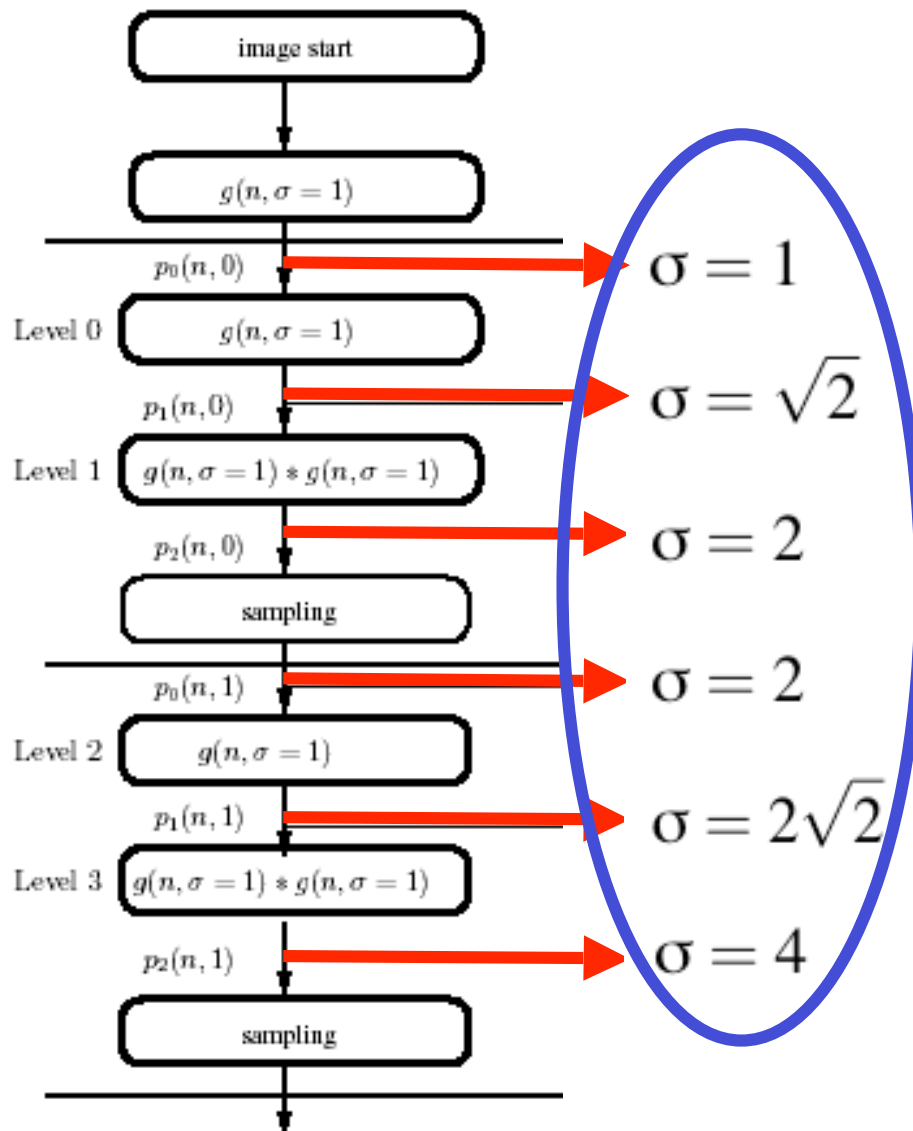
General idea: cascaded filtering using $[1 \ 4 \ 6 \ 4 \ 1]$ kernel to generate a pyramid with two images per octave (power of 2 change in resolution). When we reach a full octave, downsample the image.



Effective Sigma at Each Level



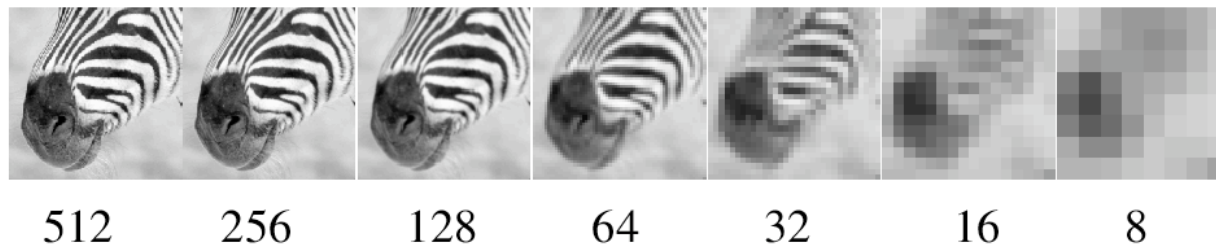
Effective Sigma at Each Level



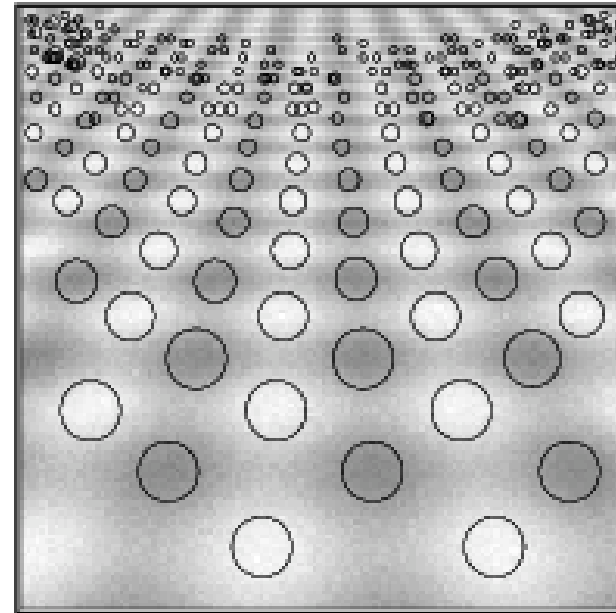
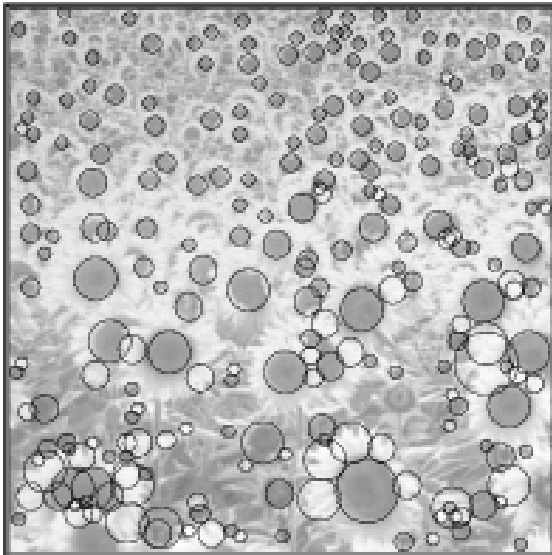
**CAN YOU
EXPLAIN HOW
THESE VALUES
ARISE?**

Concept: Scale Space

Basic idea: different scales are appropriate for describing different objects in the image, and we may not know the correct scale/size ahead of time.



Example: Detecting “Blobs” at Different Scales.



**But first, we have to talk
about detecting blobs
at one scale...**

