

# Computer Vision

## Scale spaces

Silvia Pinte

# Scale spaces: Reading material

- **Article:**

- Lindeberg, Tony. "Scale-space." (2009): 2495-2504.
- <https://www.diva-portal.org/smash/get/diva2:441147/FULLTEXT01.pdf>

- UvA tutorial on scale-space:

<https://staff.fnwi.uva.nl/r.vandenboomgaard/IPCV20172018/LectureNotes/IP/ScaleSpace/index.html>

- Prof. Kristen Grauman slides: [https://www.cs.utexas.edu/~grauman/courses/378/slides/lecture13\\_full.pdf](https://www.cs.utexas.edu/~grauman/courses/378/slides/lecture13_full.pdf)

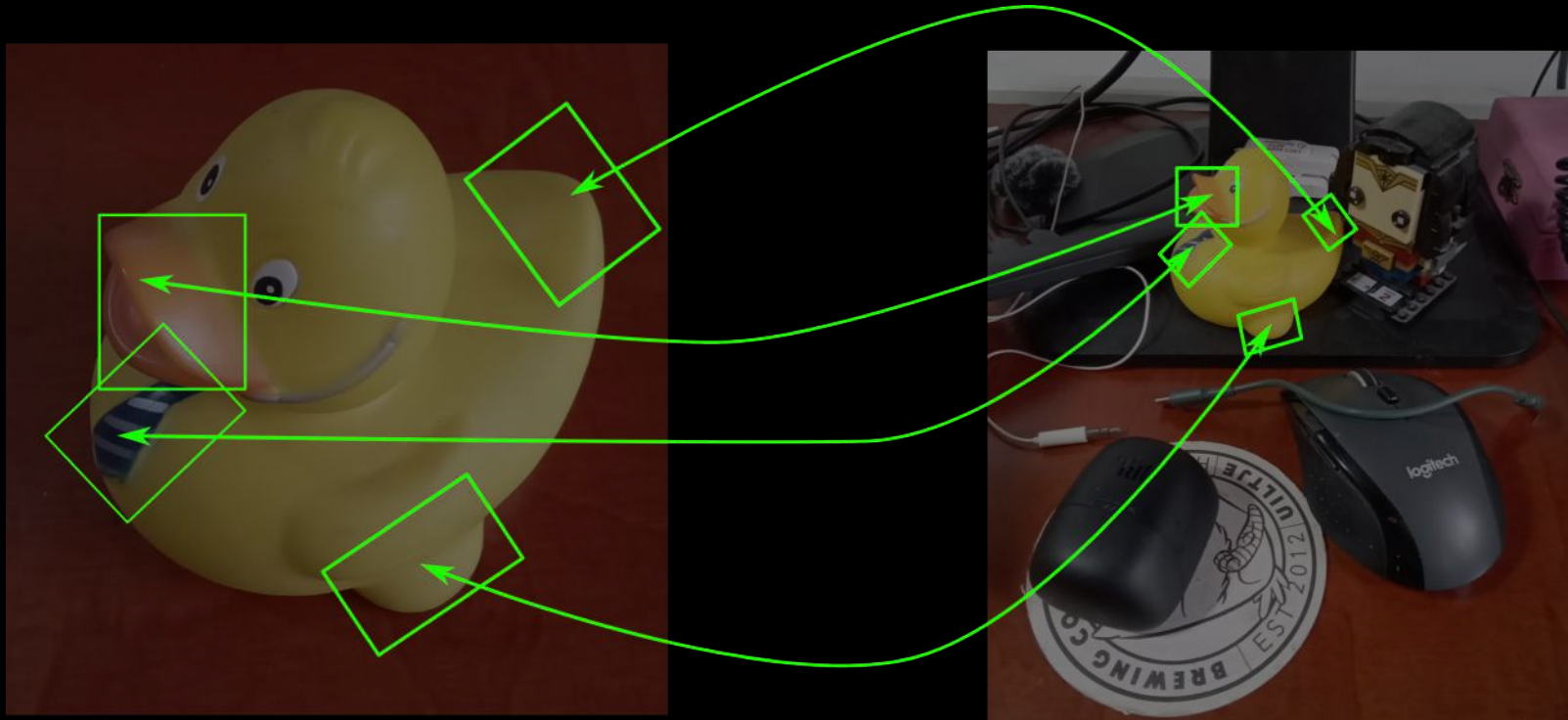
# Find objects across images

- How would you describe an object in an image? e.g. which features can you use?



# Find objects across images

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- Will this work? Why yes/no?

# Scale

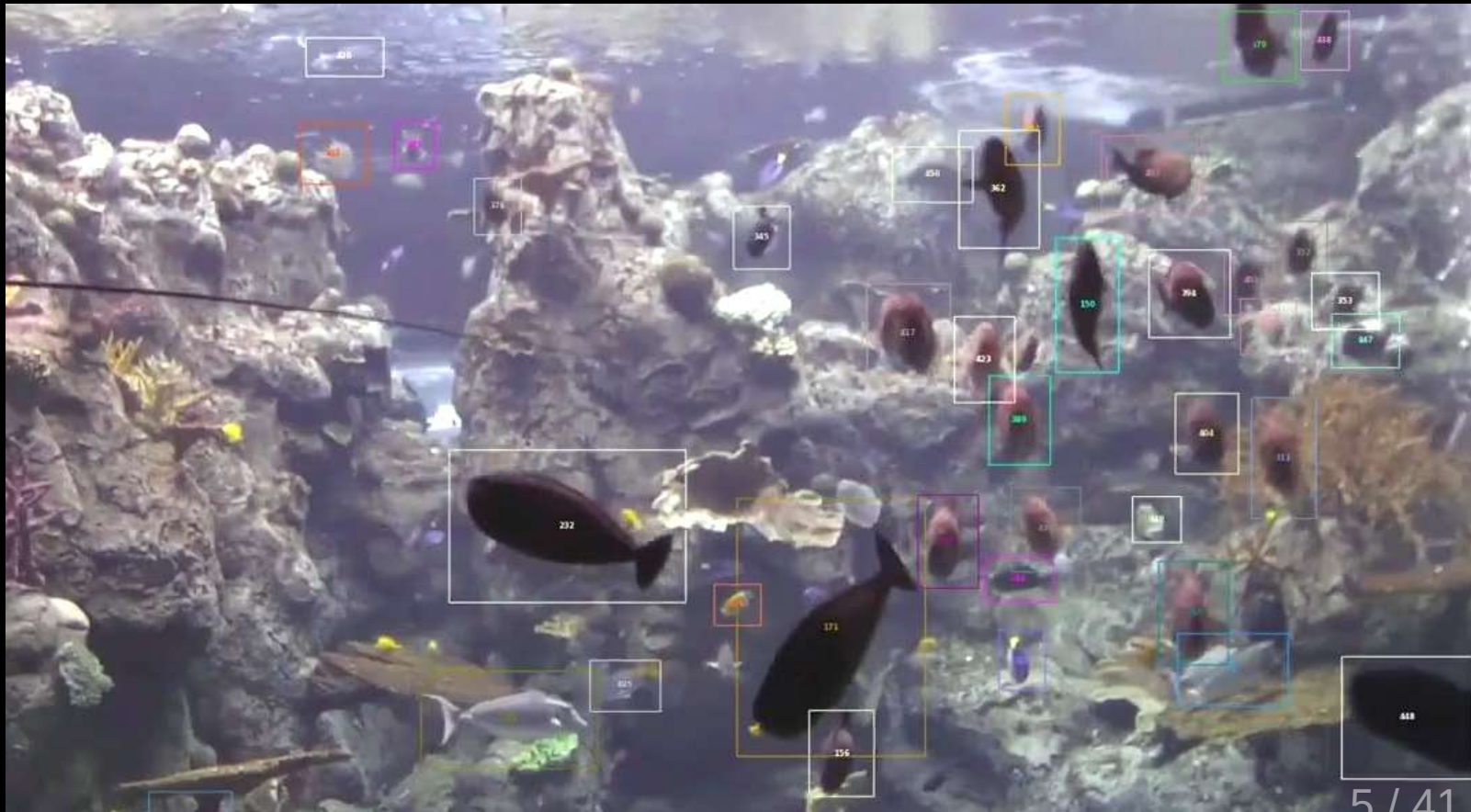
What do I mean by "scale"?

Where do we deal with multiple scales?

# Scale

What do I mean by "scale"?

Where do we deal with multiple scales?

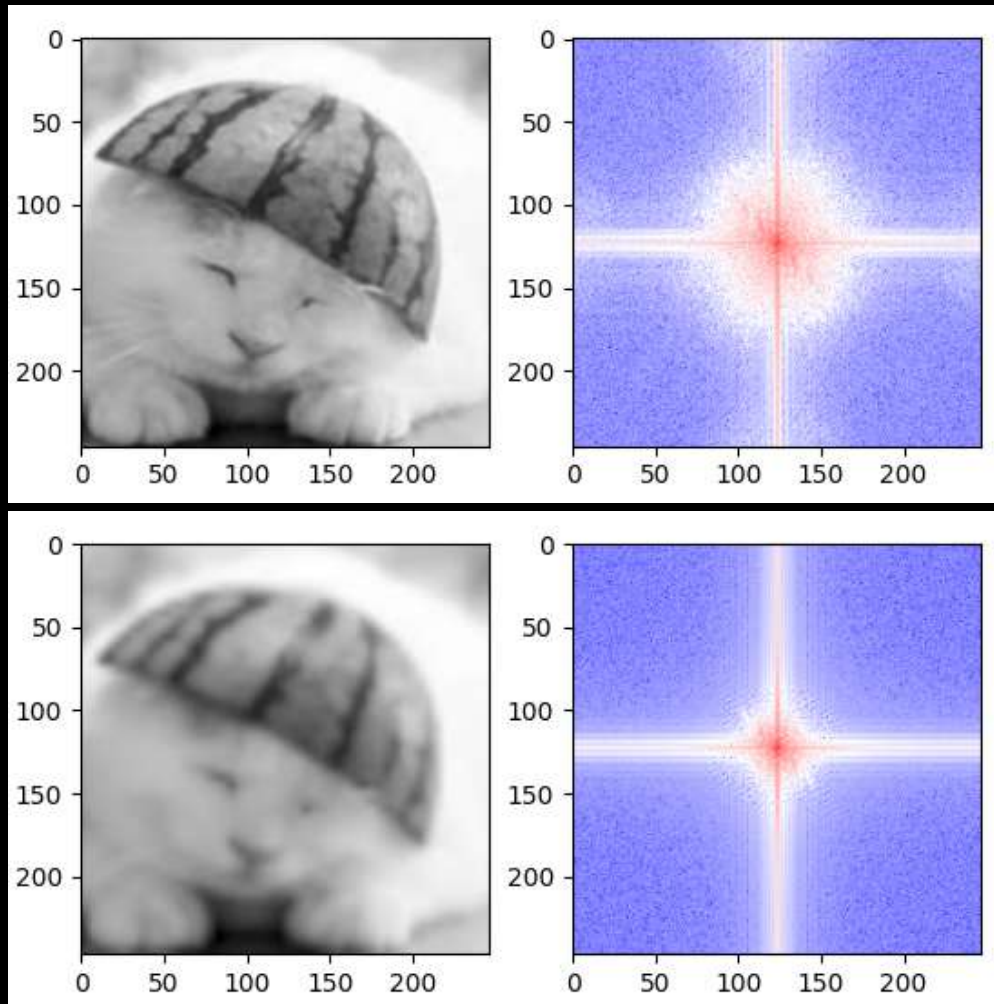


# High / low scale

What information do we have at high scale and not at low scale?

# High / low scale

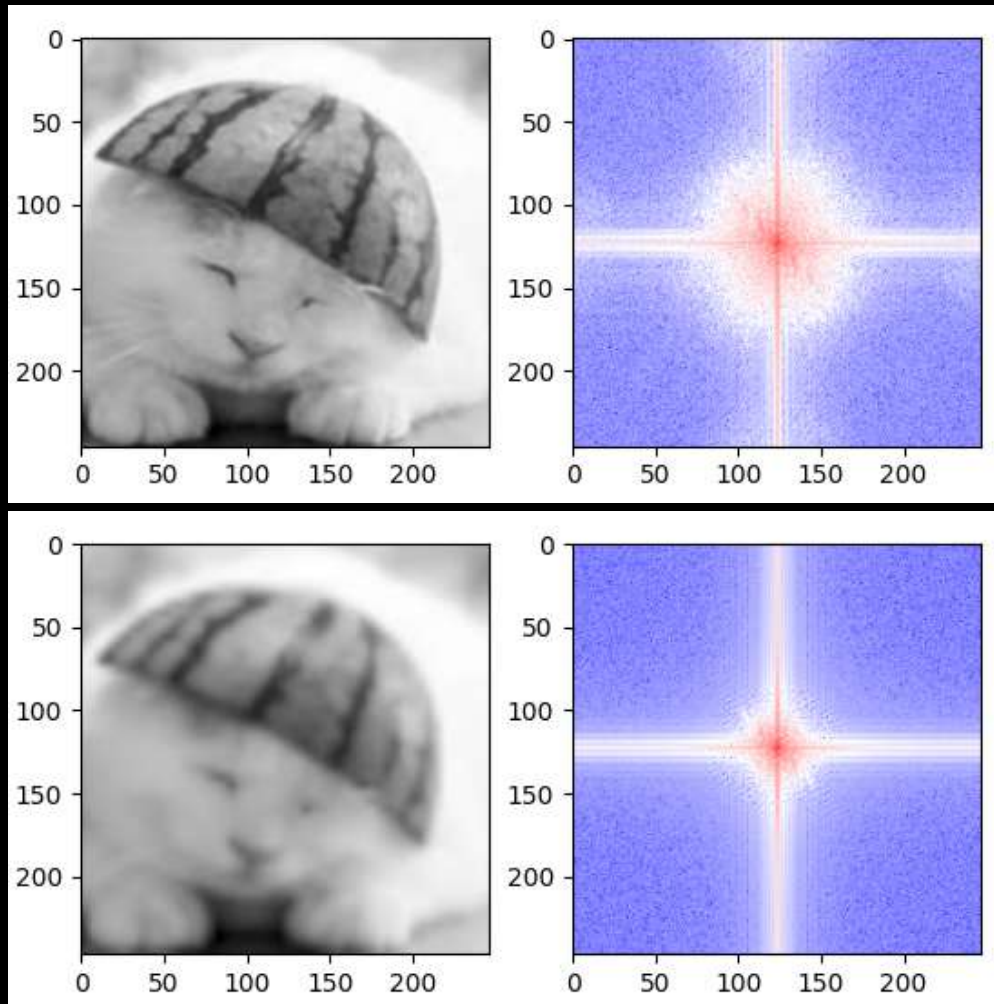
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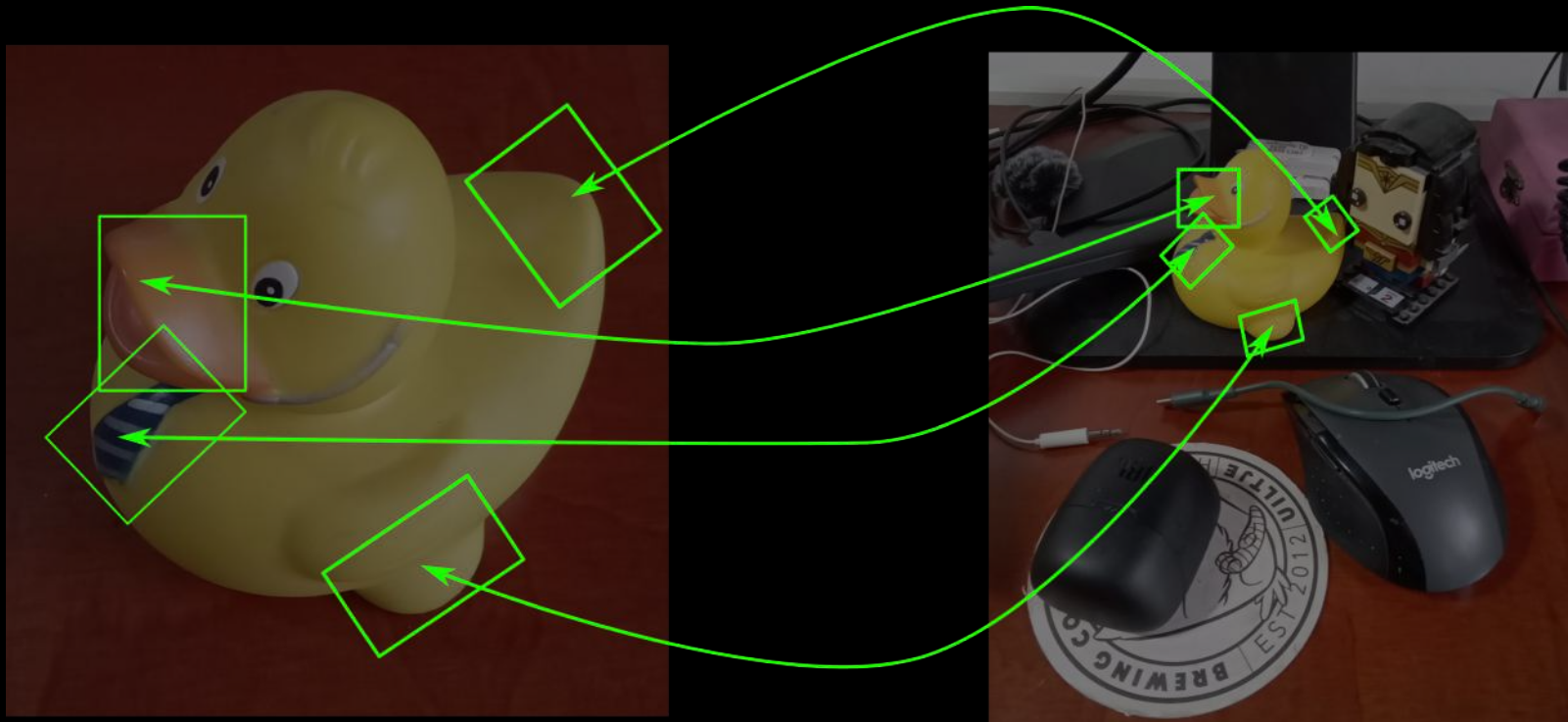
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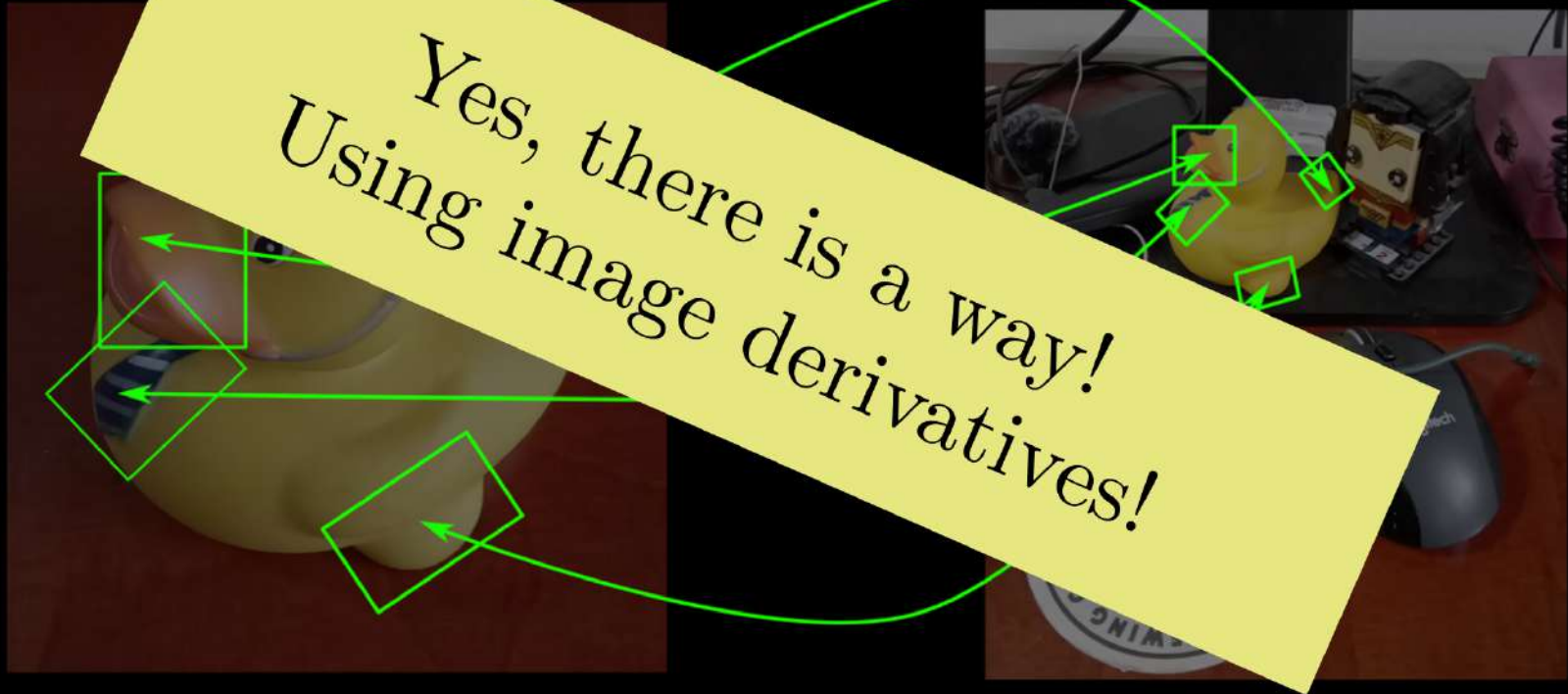
A "magic" way to find the correct scale at which to analyze each part of an image



Find blobs = keypoints / interest points.

# Scale

A "magic" way to find the correct scale at which to analyze each part of an image.



Find blobs = keypoints / interest points.

## Recap: Edge detection

- What causes an edge in an image?



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- What causes an edge in an image?



Edges are changes or discontinuities in brightness or color.

## Recap: Edge detection

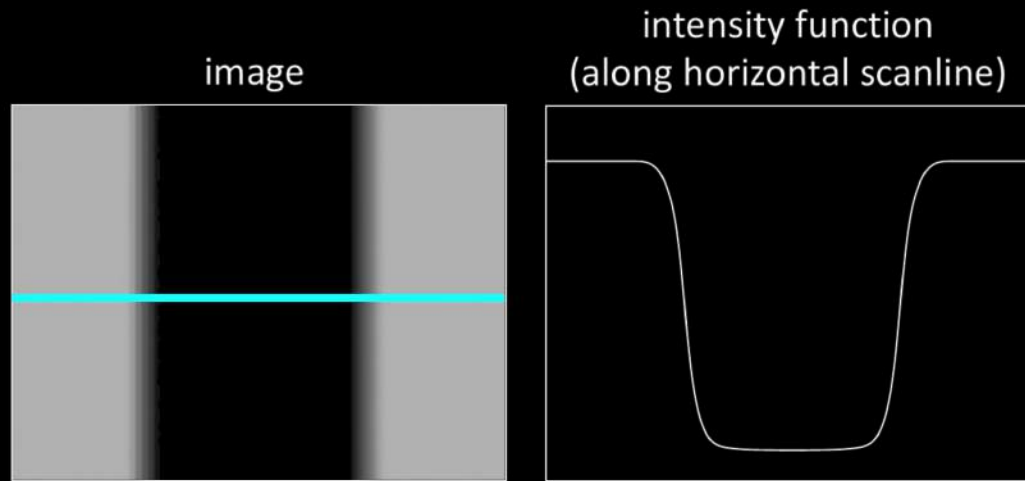
- What causes an edge in an image?



Edges are changes or discontinuities in brightness or color.

- What mathematical operator detects rapid **changes** in a signal?

# Recap: Edge detection

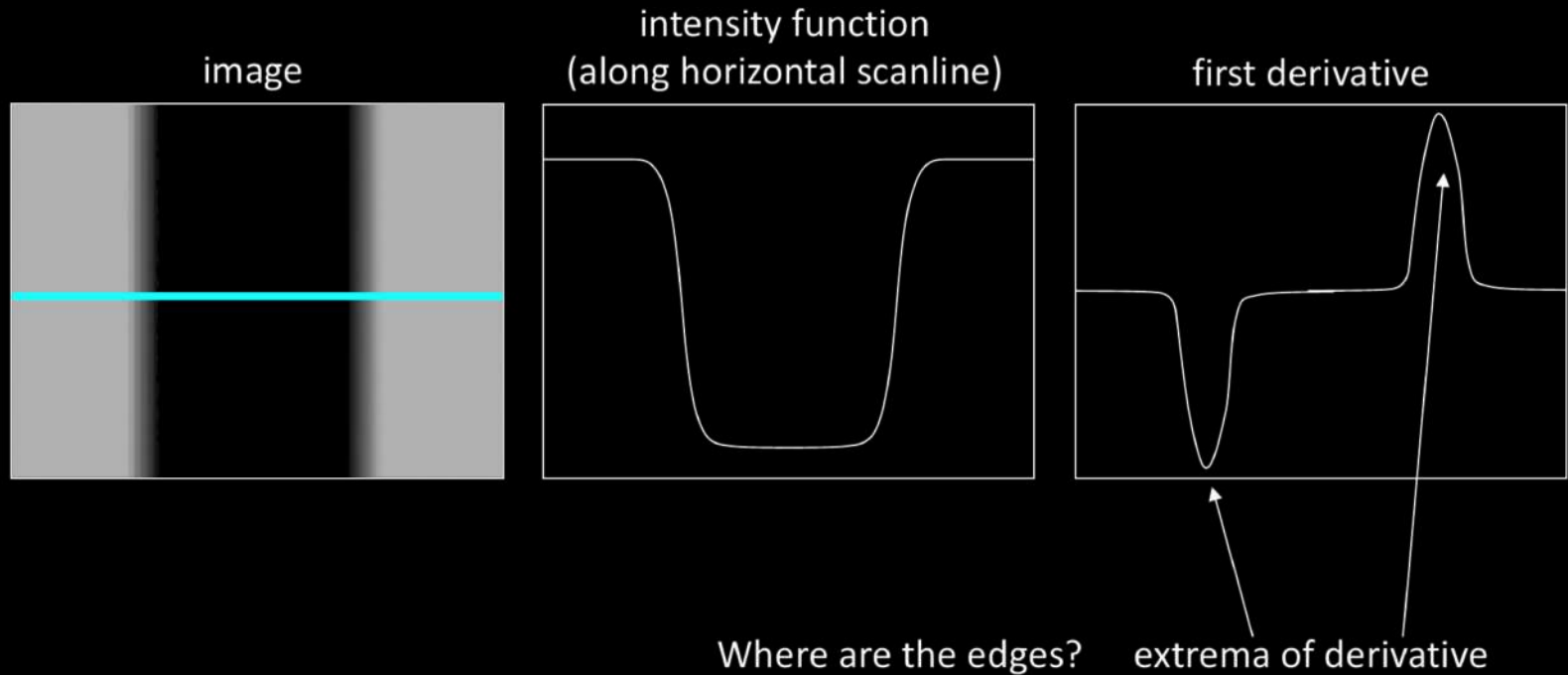


Where are the edges?

From Fei-Fei Li



# Recap: Edge detection

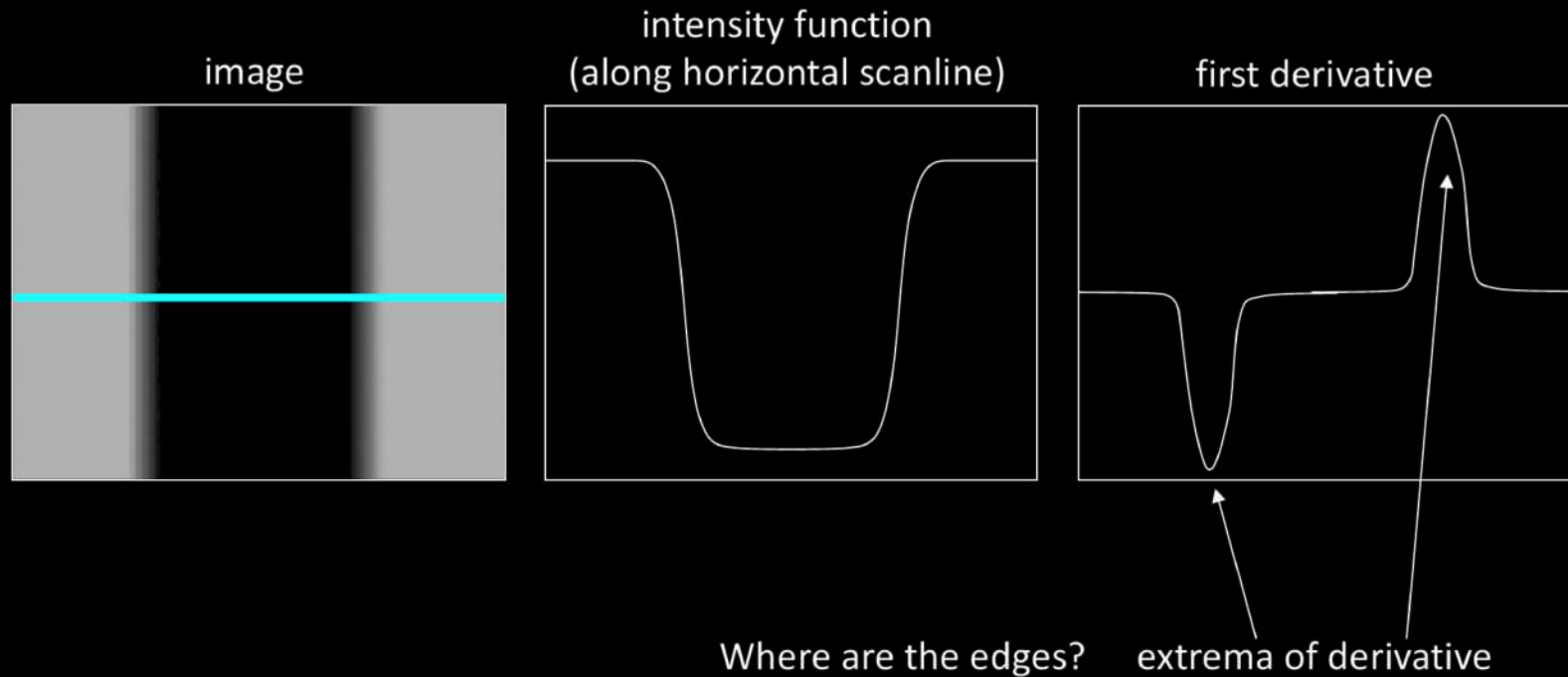


From Fei-Fei Li

- What is a good approximation of a derivative?



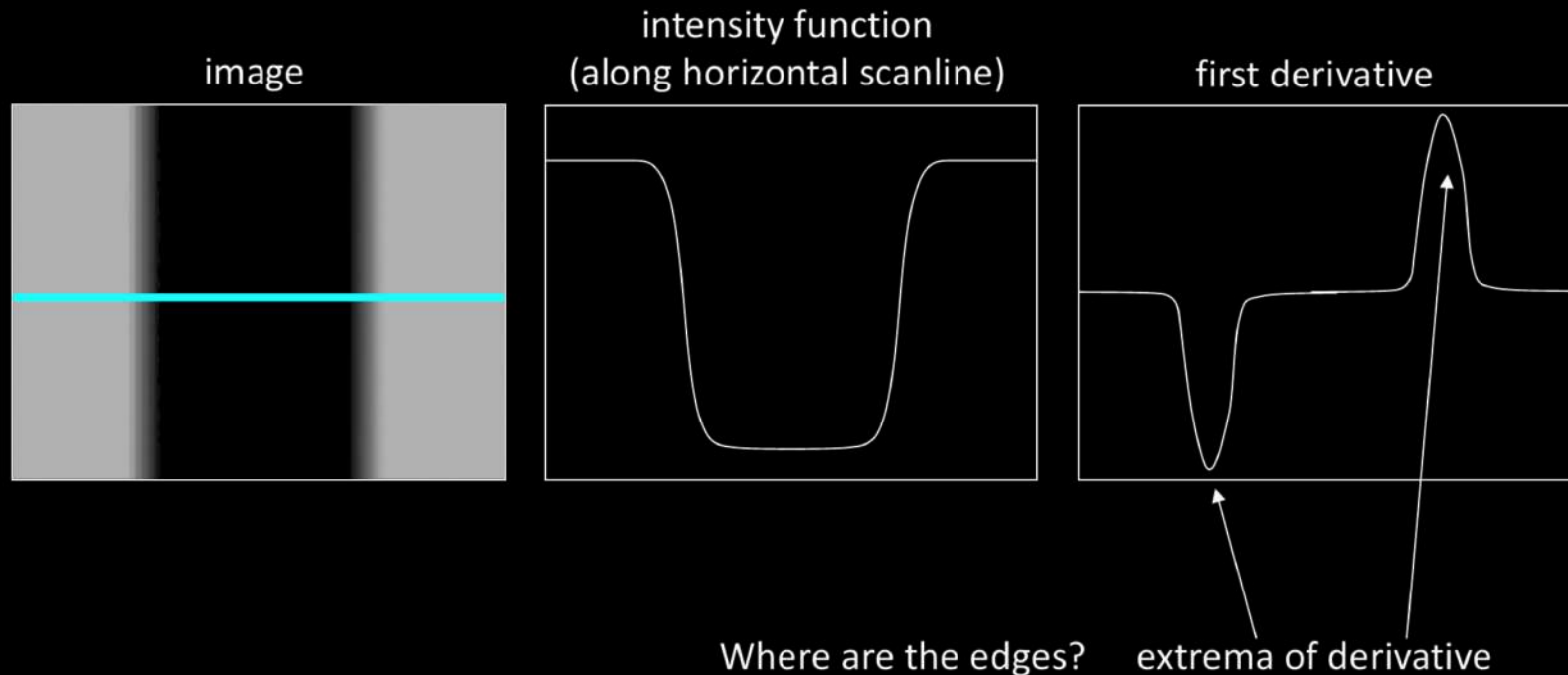
# Recap: Edge detection



From Fei-Fei Li

- What is a good approximation of a derivative?
- Finite differences:  $\frac{\partial f(x)}{\partial x} \approx \frac{f(x+\epsilon) - f(x)}{\epsilon}$

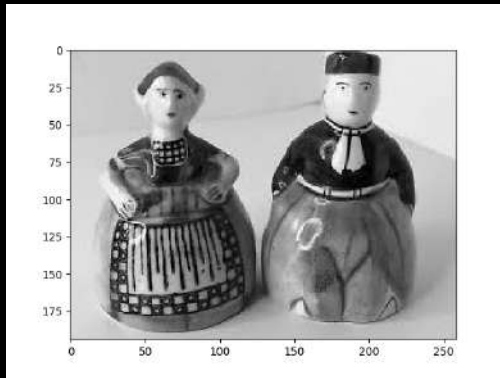
# Recap: Edge detection



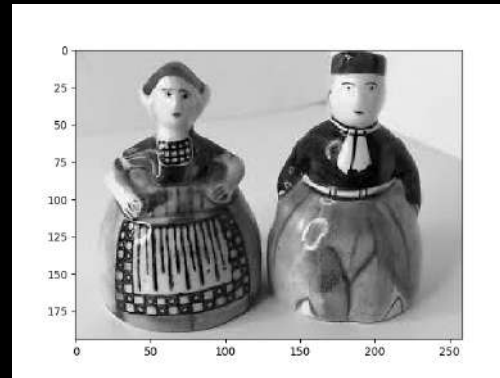
From Fei-Fei Li

- What is a good approximation of a derivative?
- Finite differences:  $\frac{\partial f(x)}{\partial x} \approx \frac{f(x+\epsilon) - f(x)}{\epsilon}$
- How can I implement finite differences efficiently?

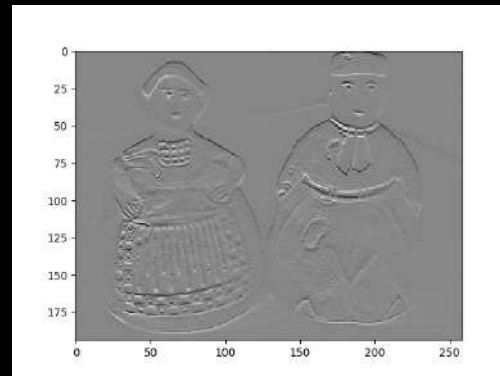
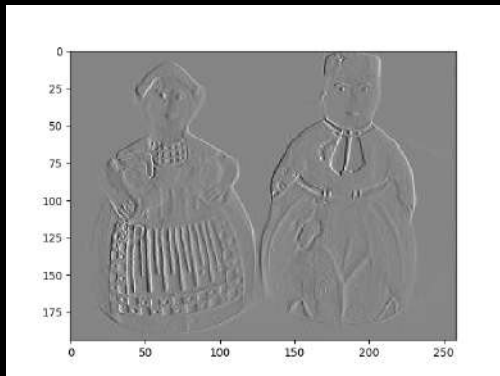
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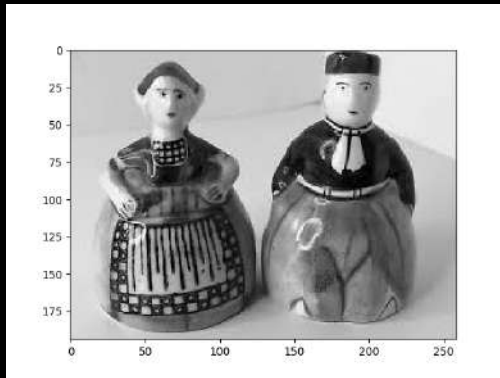
?



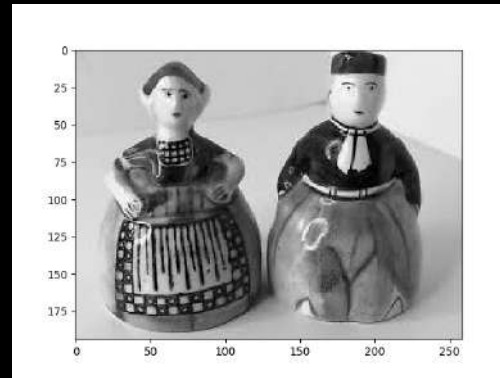
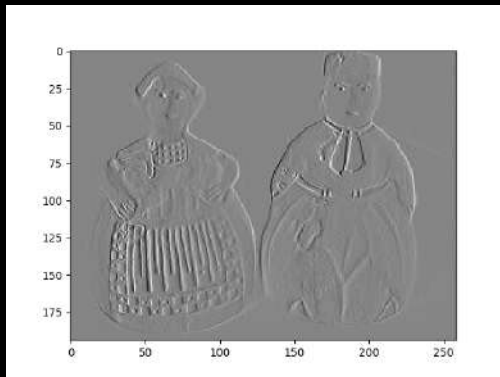
?



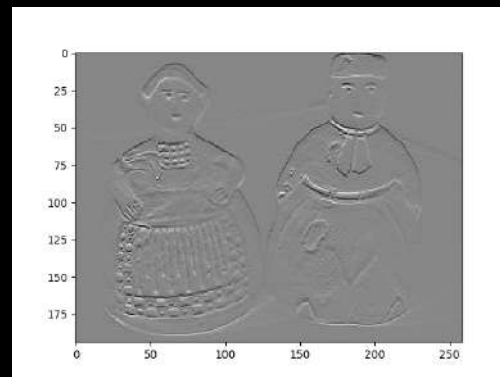
# Recap: Edge detection



$$\begin{bmatrix} 1 & -1 \end{bmatrix}$$

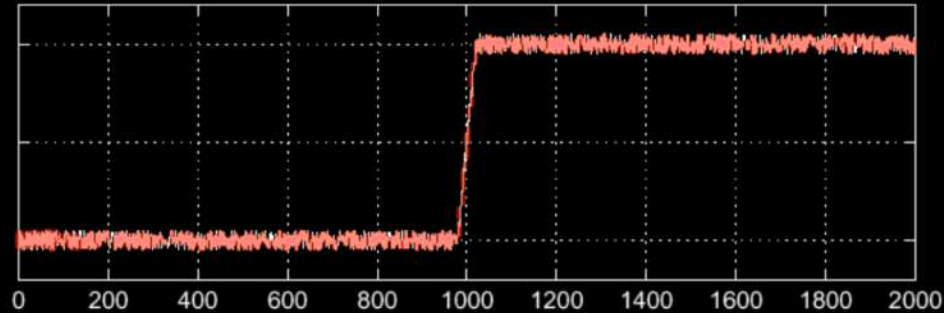


$$\begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

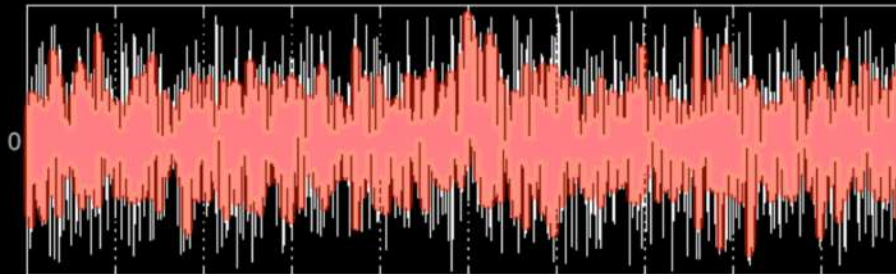


# Recap: Noisy edge detection

$$f(x)$$



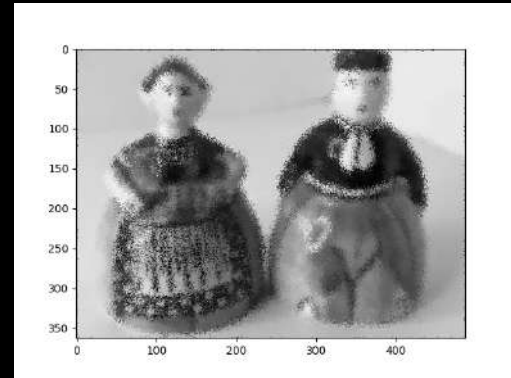
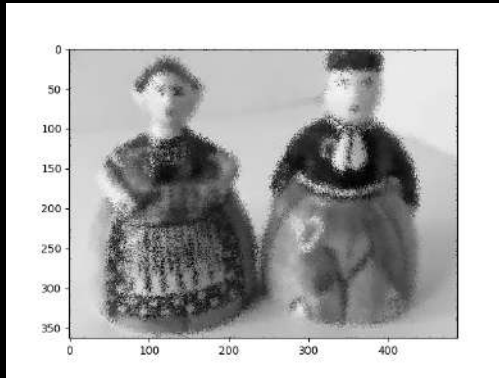
$$\frac{\partial f(x)}{\partial x}$$



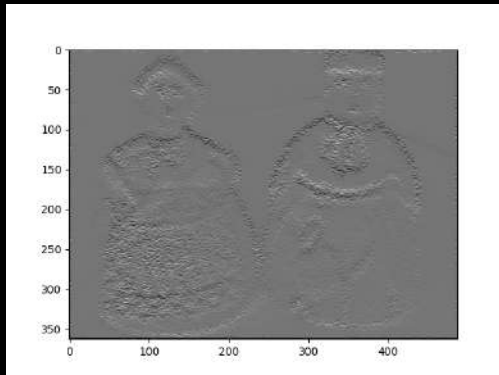
From Fei-Fei Li

- Why does this happen?

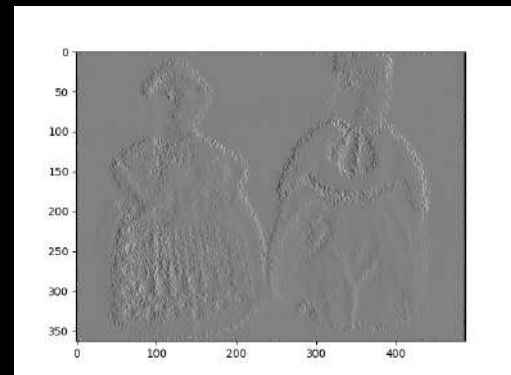
# Recap: Noisy edge detection



$$\begin{bmatrix} 1 & -1 \end{bmatrix}$$



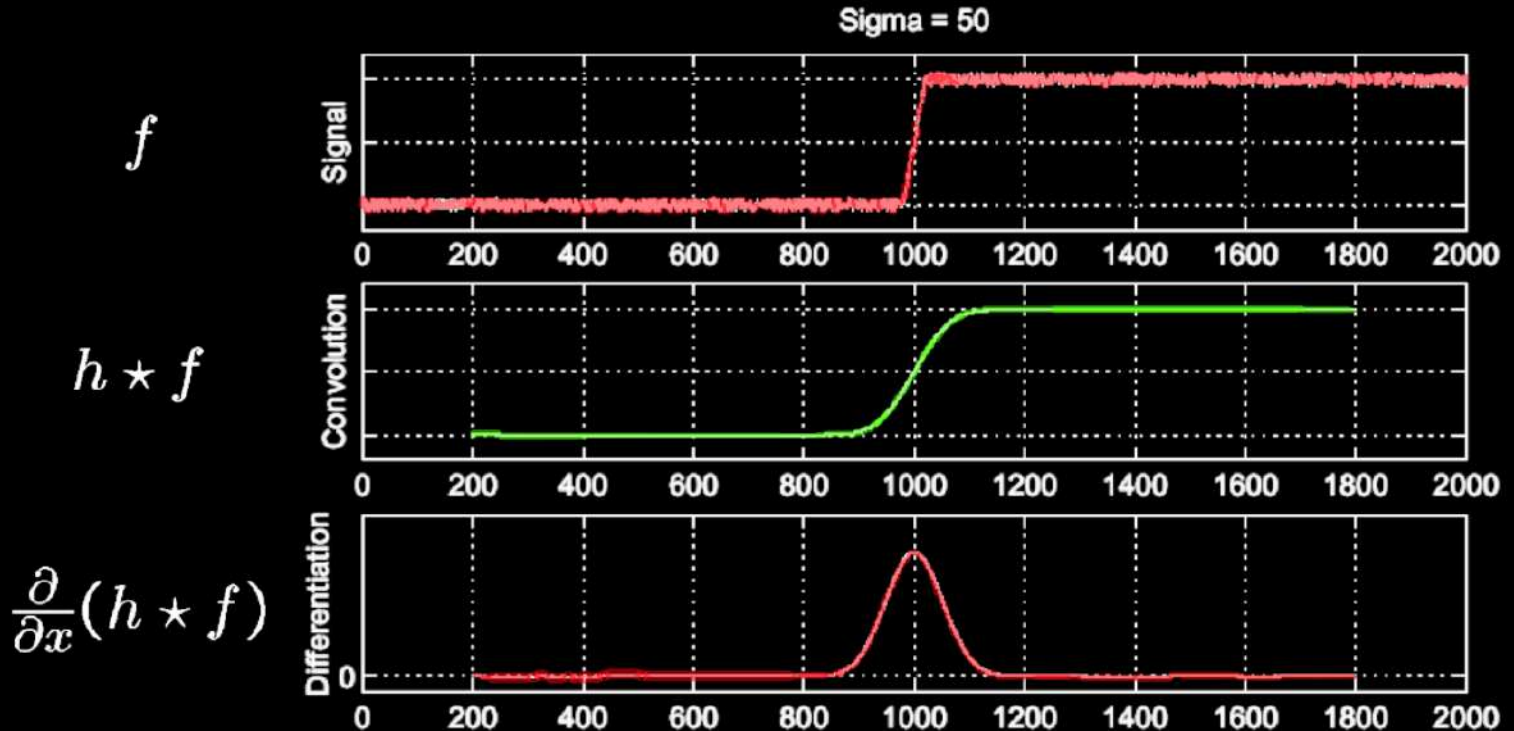
$$\begin{bmatrix} 1 \\ -1 \end{bmatrix}$$



How can we fix this?

# Recap: Noisy edge detection

First smooth then take the image derivative



From Fei-Fei Li

- Where  $h(x)$  is a Gaussian smoothing kernel

# Derivative of convolution theorem

$$\frac{\partial \left( h(x) \star f(x) \right)}{\partial x} = \frac{\partial h(x)}{\partial x} \star f(x)$$

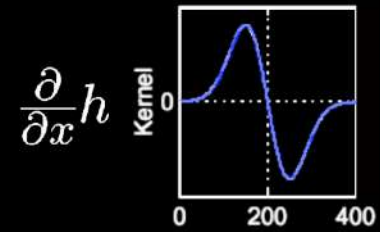
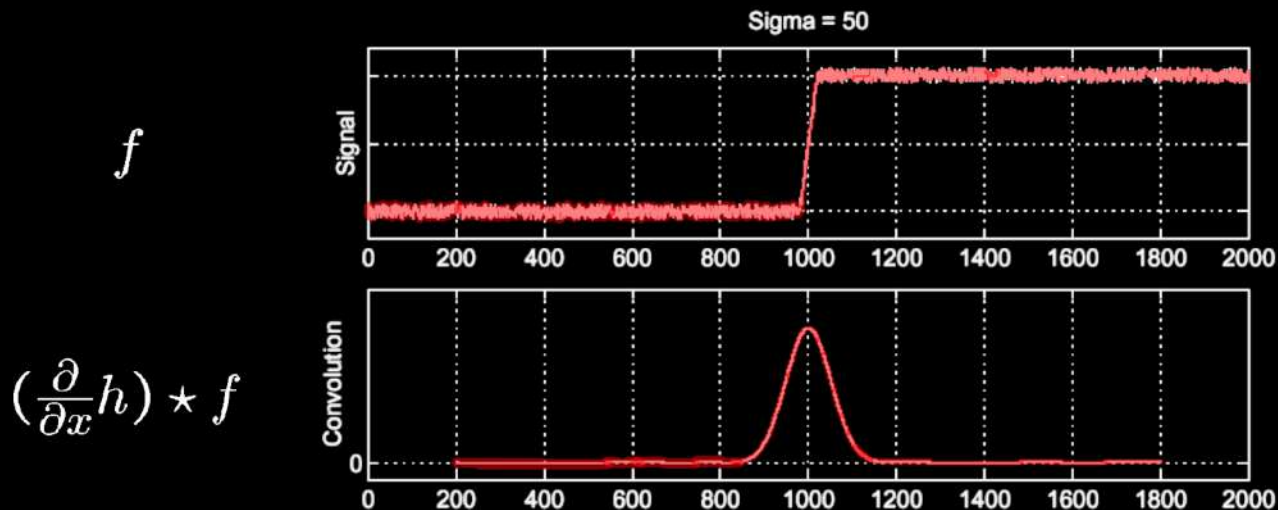
- What does this say?



# Derivative of convolution theorem

$$\frac{\partial \left( h(x) \star f(x) \right)}{\partial x} = \frac{\partial h(x)}{\partial x} \star f(x)$$

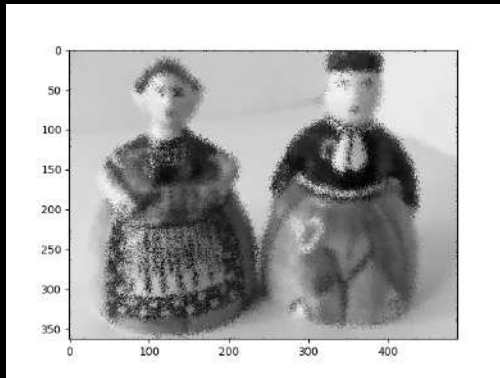
- What does this say?  
Derivative of convolution = convolution with derivative



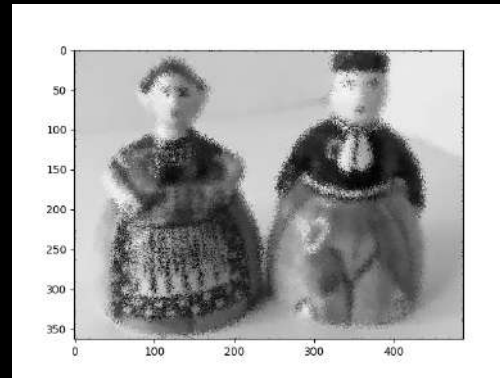
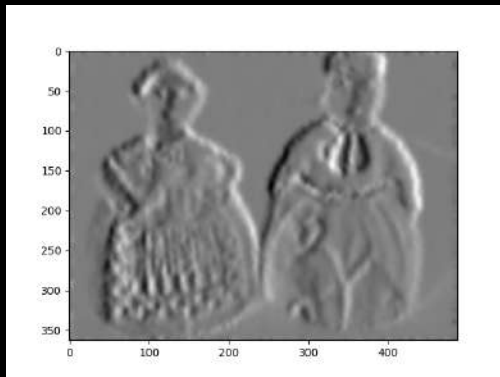
From Fei-Fei Li

- Why is this useful?

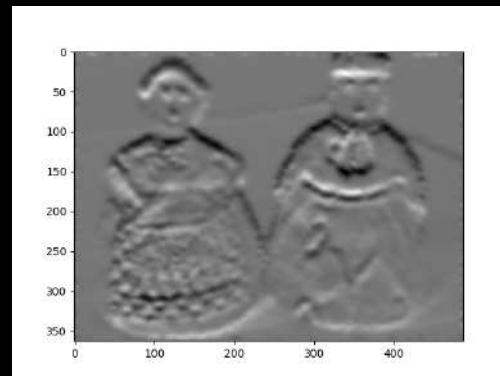
# Noisy edge detection



$$\frac{\partial h(x, y)}{\partial x}$$



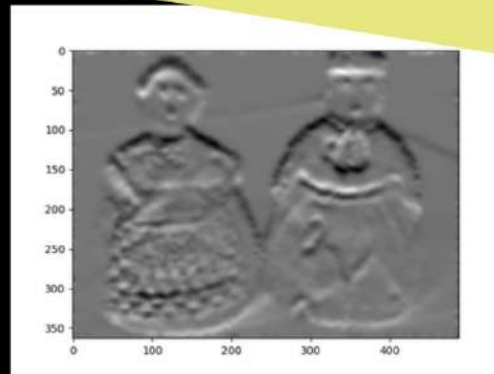
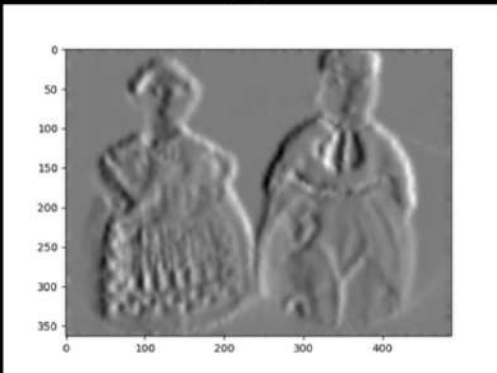
$$\frac{\partial h(x, y)}{\partial y}$$



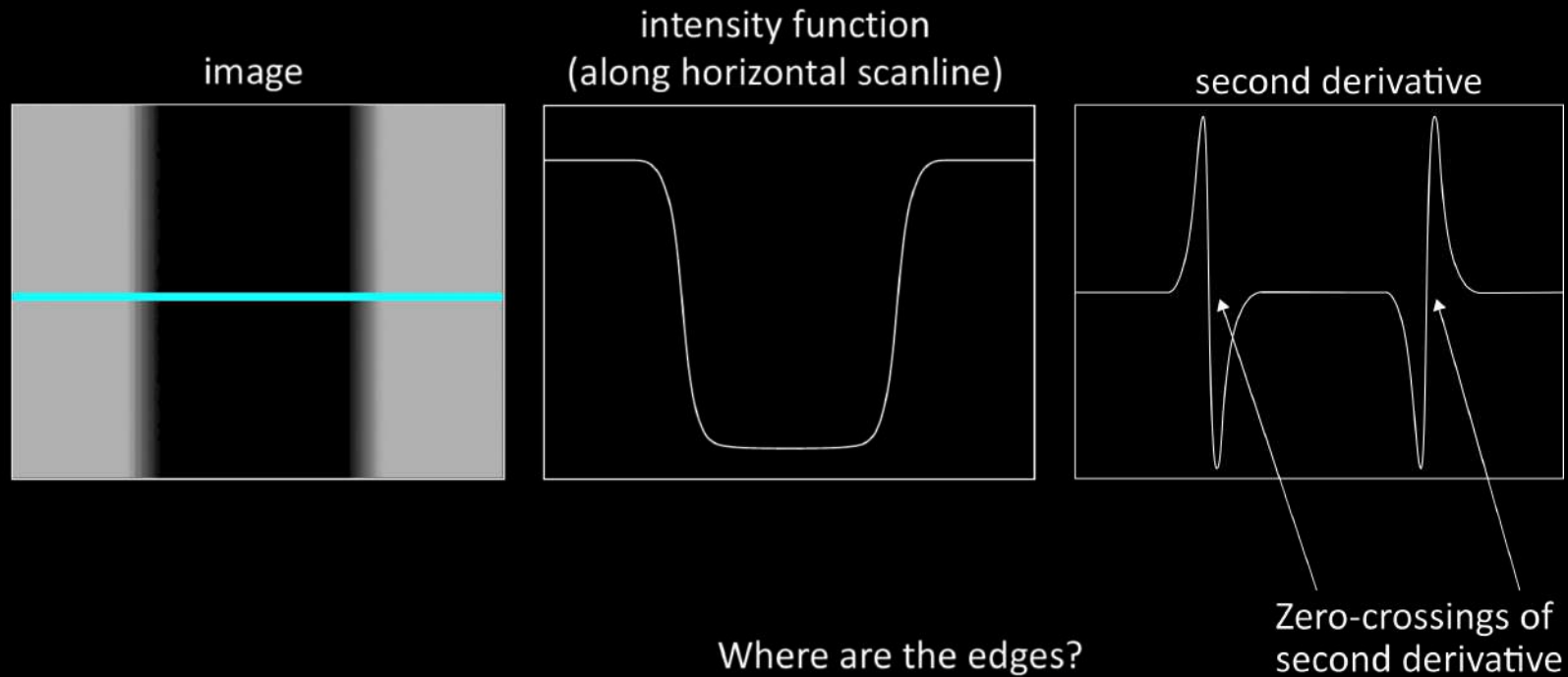
# Noisy edge detection



Gradient:  $\nabla h(x, y) = \left[ \frac{\partial h(x, y)}{\partial x}, \frac{\partial h(x, y)}{\partial y} \right]$

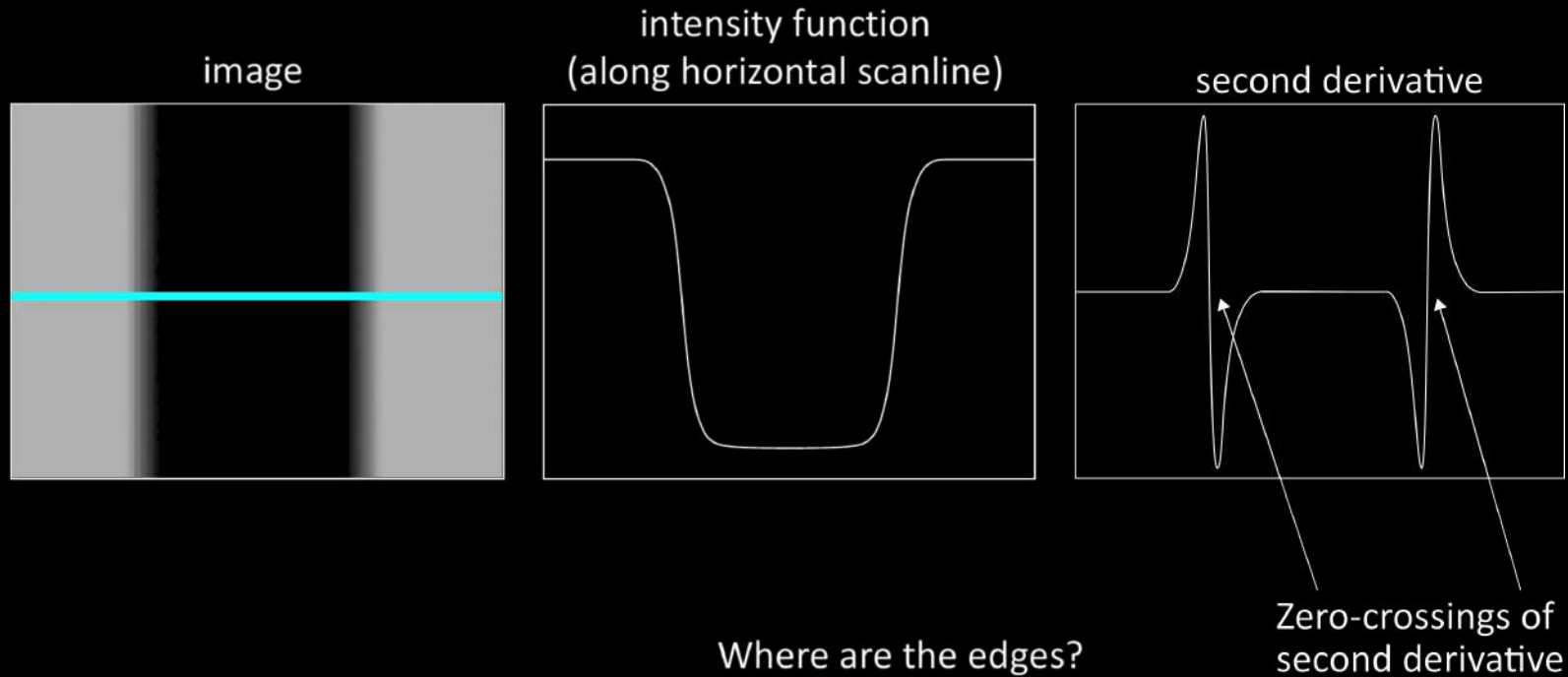


# Edge detection



From Fei-Fei Li

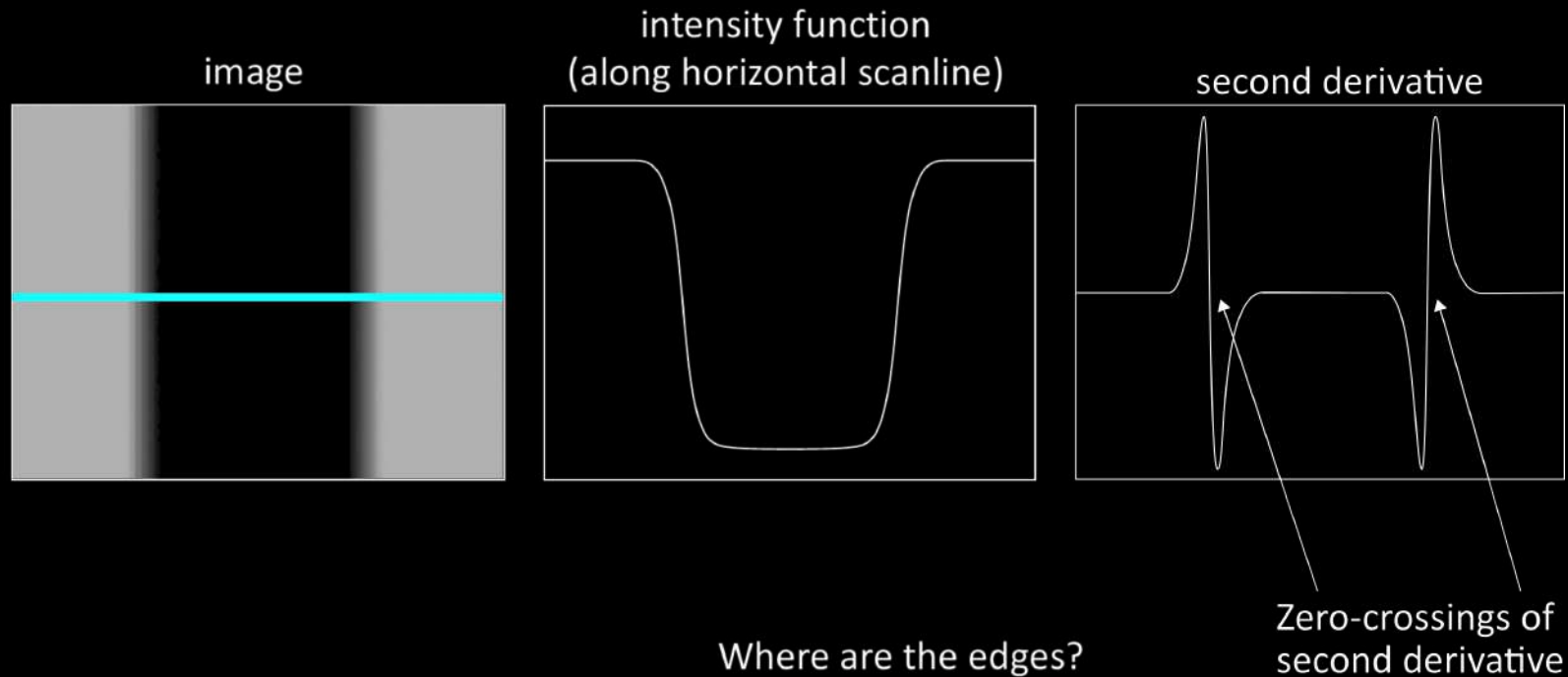
# Edge detection



From Fei-Fei Li

- How can I take a second order image derivative?

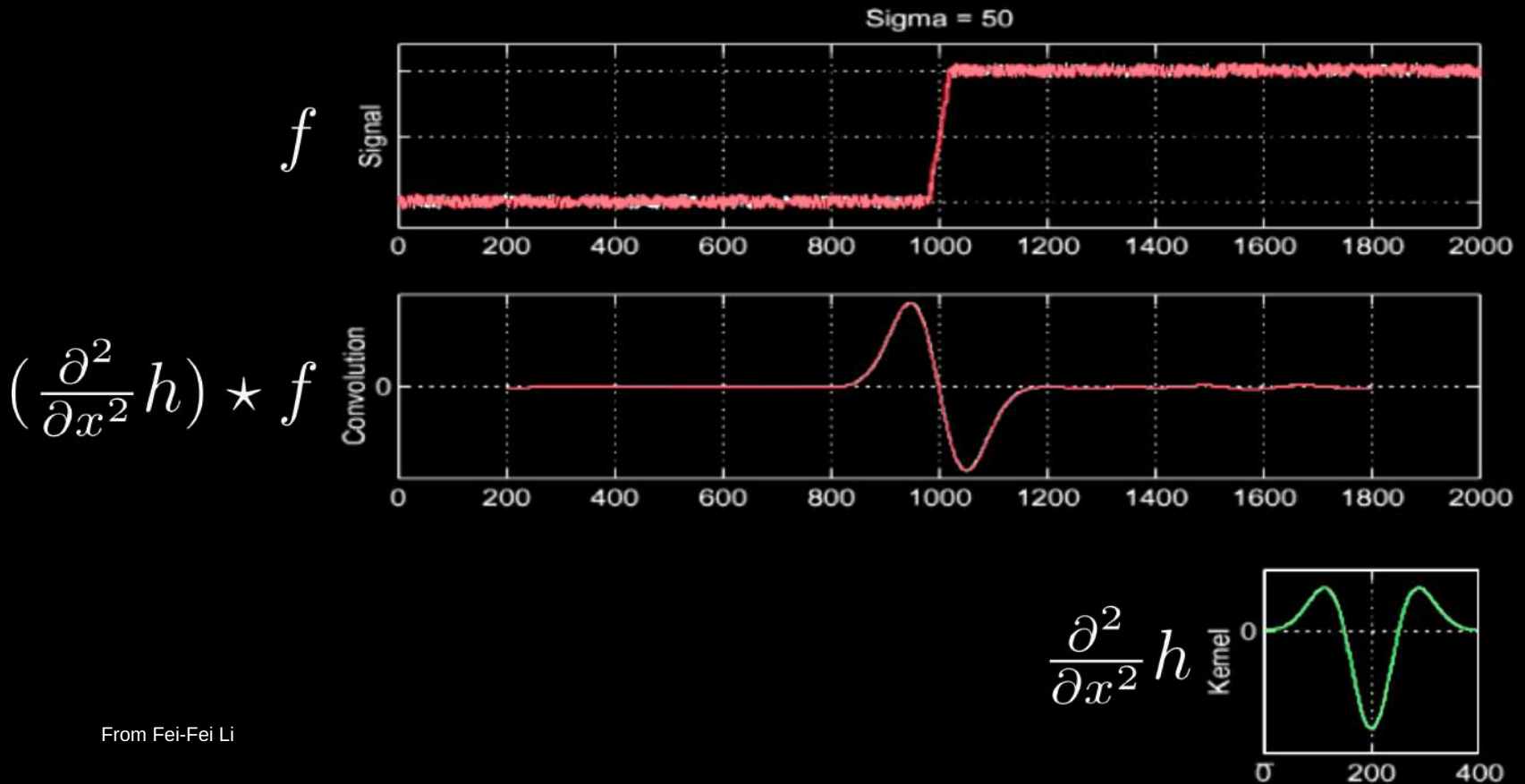
# Edge detection



From Fei-Fei Li

- How can I take a second order image derivative?
- Convolve with  $[1, -2, 1]$ . Is there a problem with this?

# Second order derivative

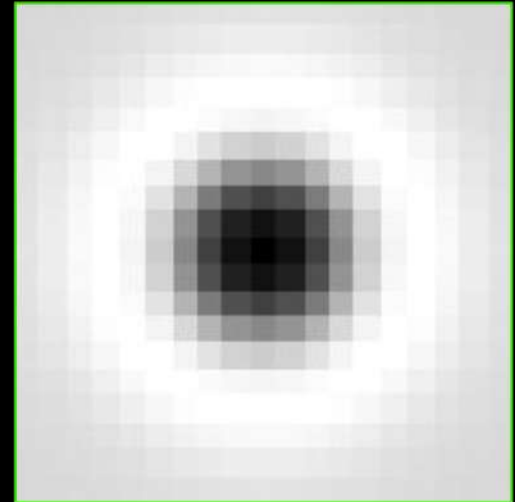
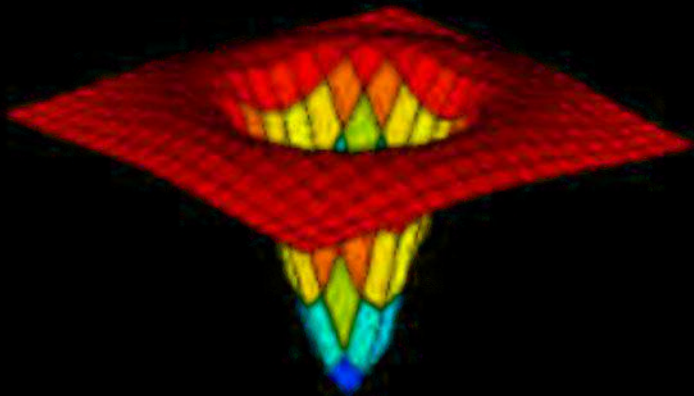


From Fei-Fei Li

- Convolve with the 2nd order Gaussian derivative.

# Laplacian of Gaussian

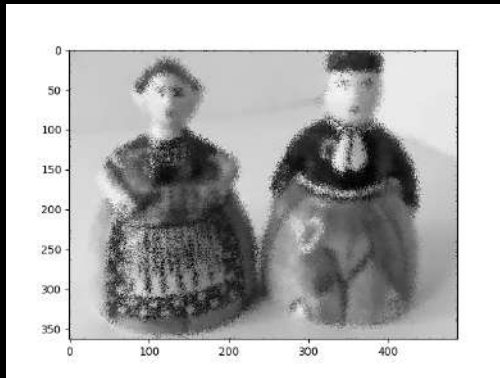
- $LoG(x, y) = \frac{\partial^2 h(x, y)}{\partial^2 x} + \frac{\partial^2 h(x, y)}{\partial^2 y}$



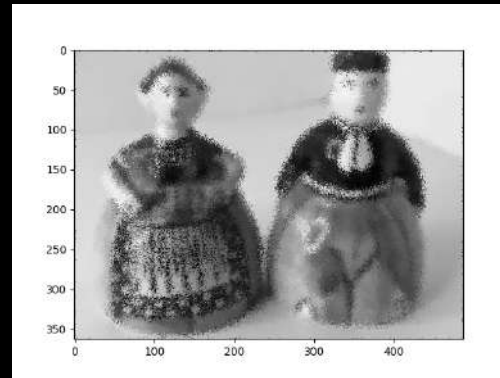
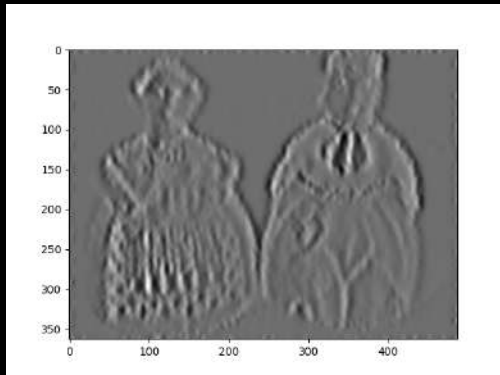
- What controls the scale of the Laplacian of Gaussian?



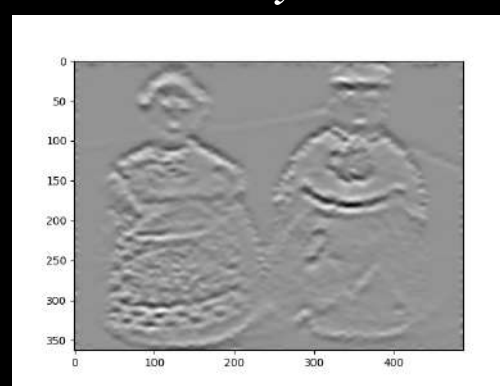
# Noisy edge detection



$$\frac{\partial^2 h(x, y)}{\partial^2 x}$$



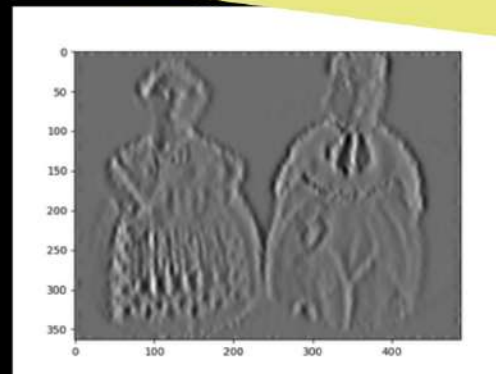
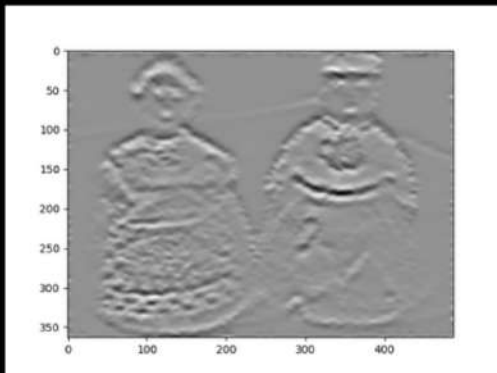
$$\frac{\partial^2 h(x, y)}{\partial^2 y}$$



## Noisy edge detection

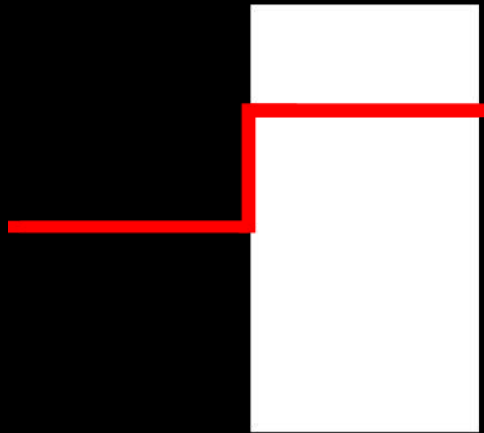


Laplacian: 
$$\frac{\partial^2 h(x,y)}{\partial^2 x} + \frac{\partial^2 h(x,y)}{\partial^2 y}$$

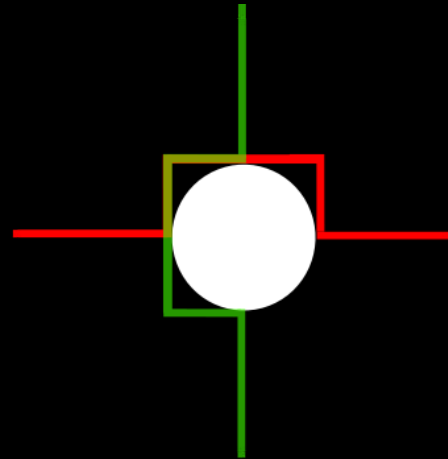


# Blob detection

- An edge is a ripple in the image.



Edge



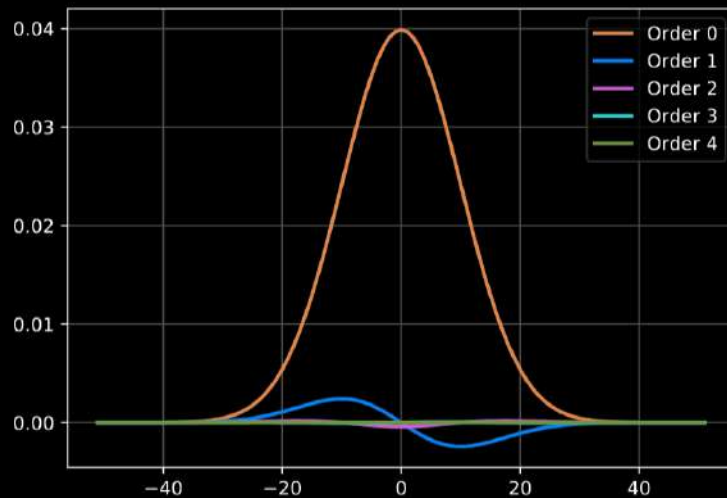
Blob

- We can find blobs at the intersection of ripples.
- So we can use the Laplacian of Gaussian to find blobs.

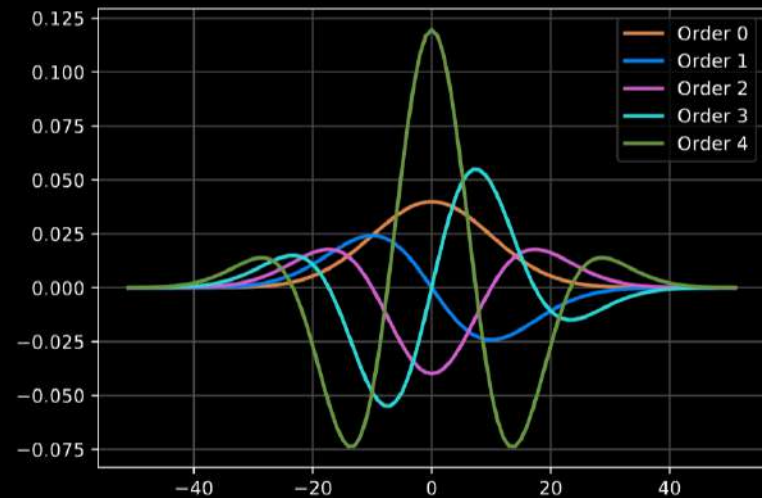
# Laplacian normalization

The "scale" of the Laplacian is  $\sigma$ .

- **Problem:** the response of a derivative of Gaussian decreases as  $\sigma$  increases
- **Solution:** multiple the  $m^{th}$  derivative by  $\sigma^m$ .



(a) Unnormalized



(b) Normalized

- How should we normalize the Laplacian of Gaussian?

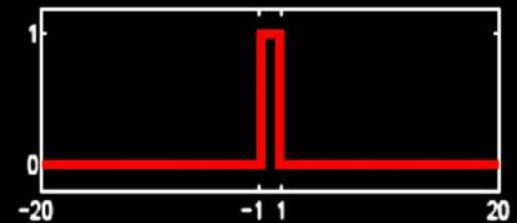
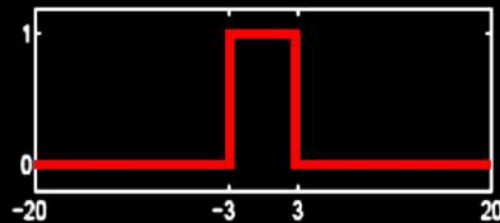
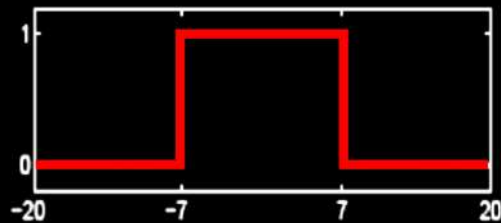
# Scale selection

So the normalized Laplacian is:  $\sigma^2 \left( \frac{\partial^2}{\partial x^2} h(x, y) + \frac{\partial^2}{\partial y^2} h(x, y) \right)$

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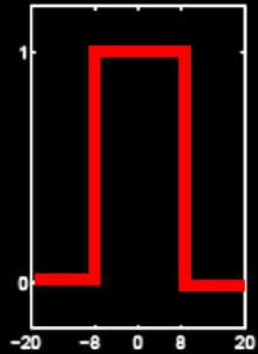
- The magnitude of the Laplacian response will achieve a maximum/minimum at the center of the blob, provided the scale of the Laplacian is “matched” to the scale of the blob.



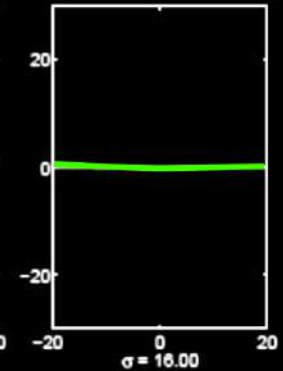
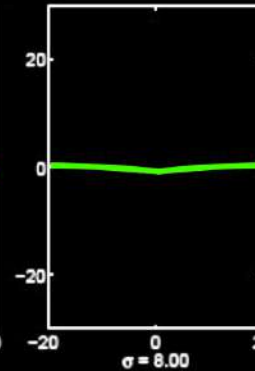
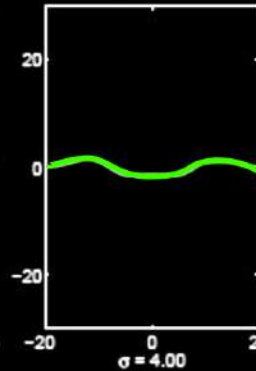
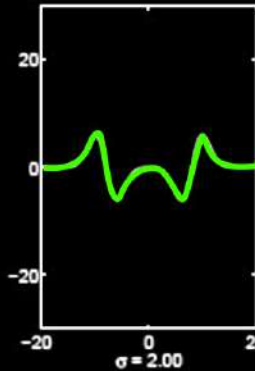
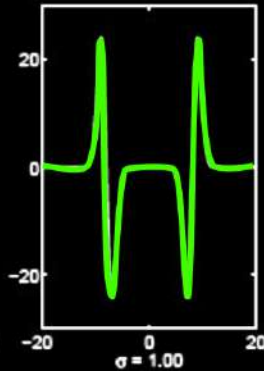
What does this say?

# Normalized Laplacian of Gaussian

Original signal

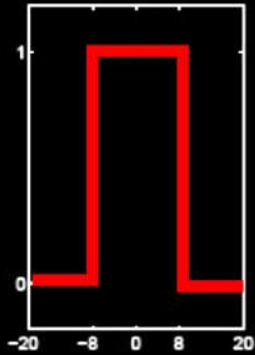


Unnormalized Laplacian response

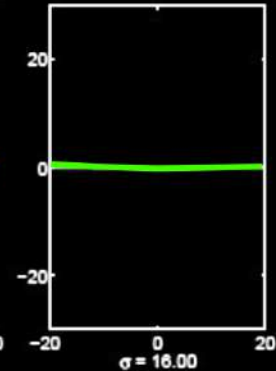
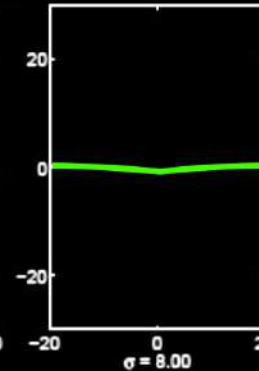
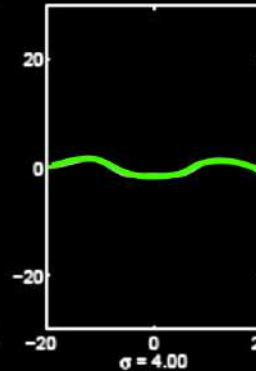
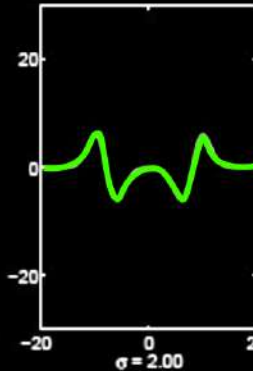
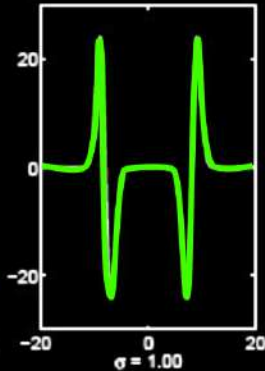


# Normalized Laplacian of Gaussian

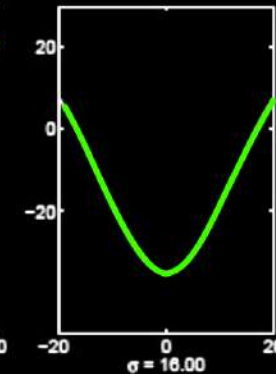
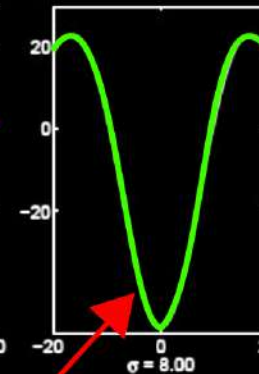
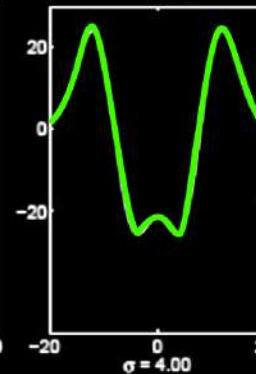
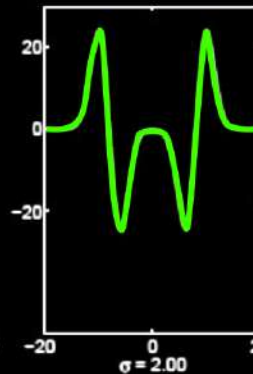
Original signal



Unnormalized Laplacian response



Scale-normalized Laplacian response



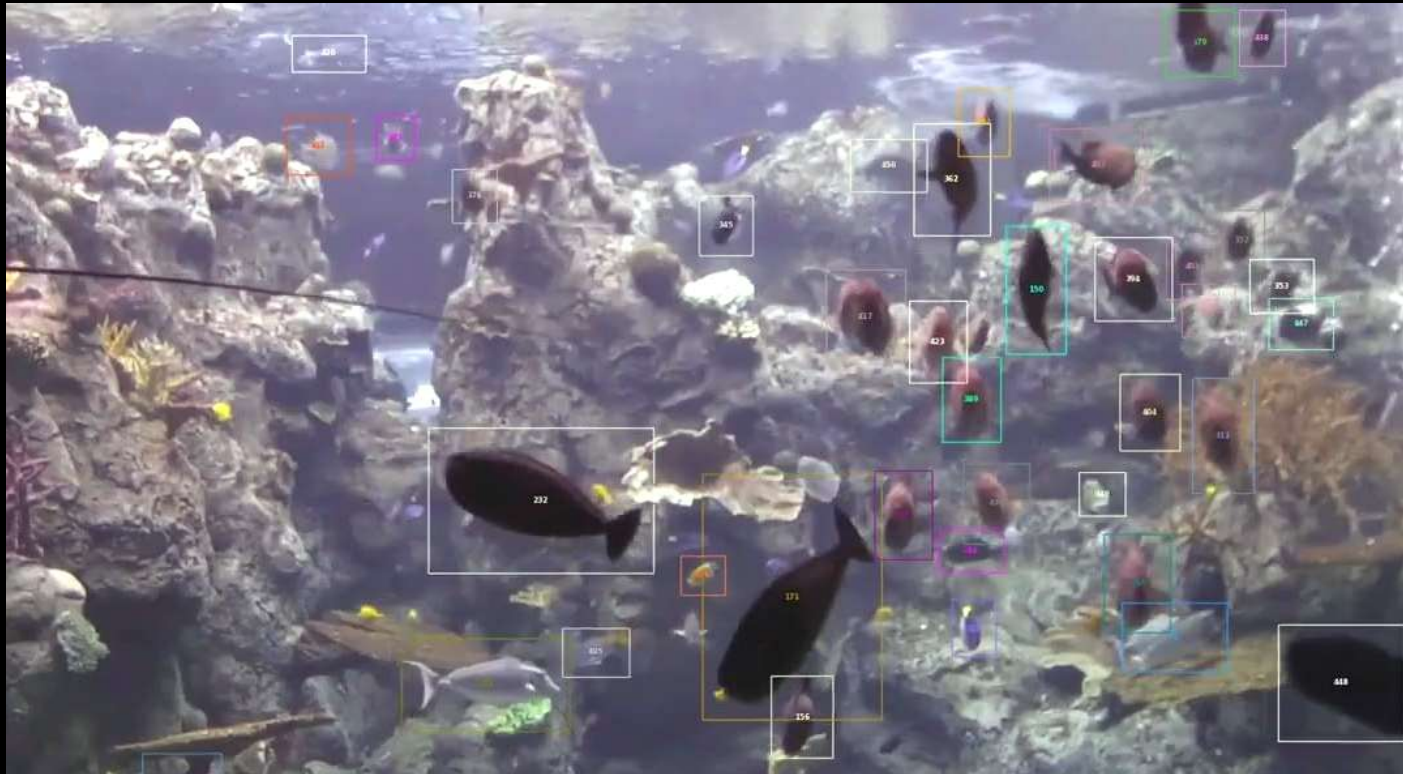
maximum



# Questions?

# Scale

A "magic" way to find the correct scale at which to analyze each part of an image



# Scale selection

- Each circle is centered at a Laplacian extremum and has a radius proportional to the Laplacian scale,  $\sigma$ .



Which scale  $\sigma$  to use?



# Scale selection

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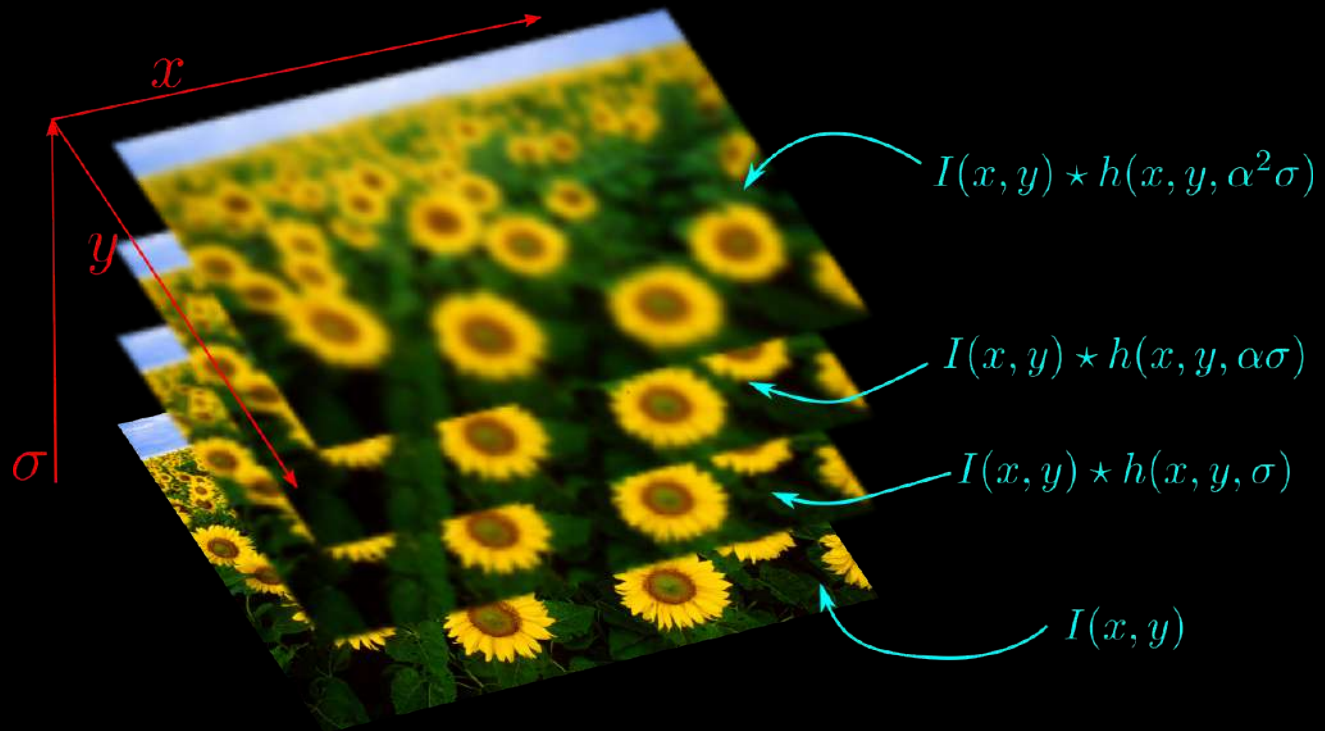
Which scale  $\sigma$  to use? Use a range of values.

# Scale selection

- We can use a range of  $\sigma$  values in the Laplacian.
- Alternatively what can we do? (hint: "derivative of convolution" theorem).

# Scale selection

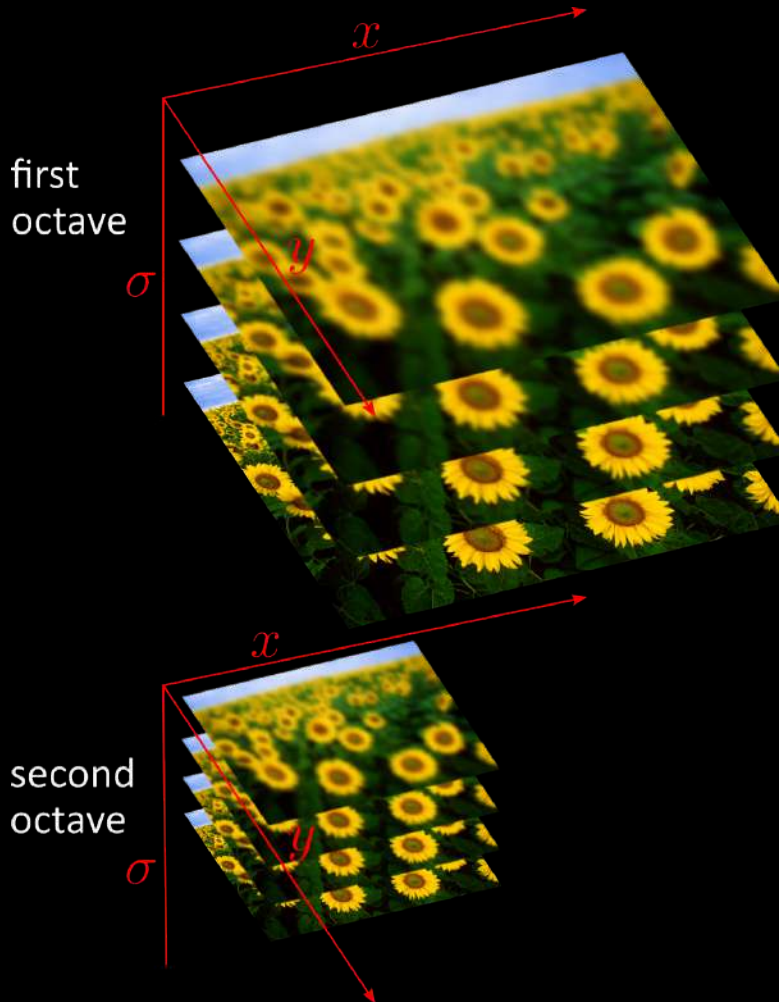
- We can use a range of  $\sigma$  values in the Laplacian.
- Alternatively what can we do? (hint: "derivative of convolution" theorem).



We can blur the image with increasing values of  $\sigma$  and then compute the Laplacian responses.



# Scale spaces



## Build a scale-space:

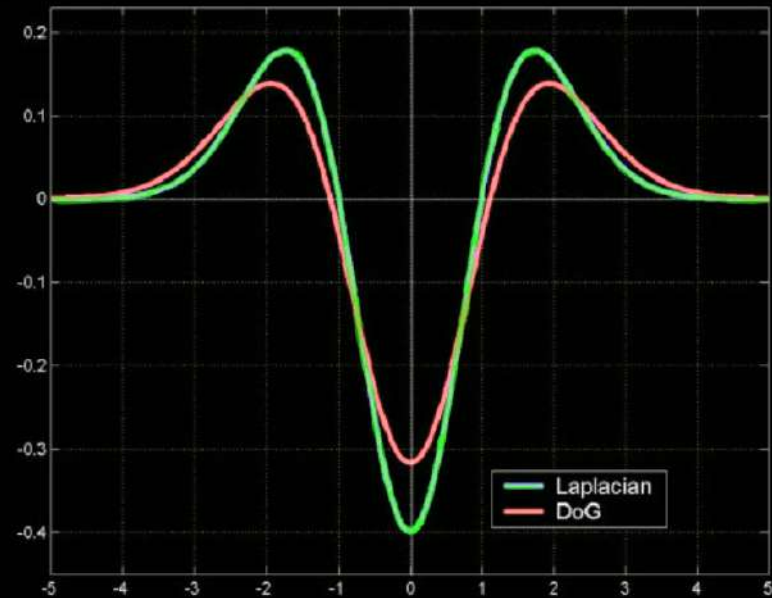
- 1) **Octave:** Take the original image and progressively blur it  $N$  times with increasing  $\sigma$  such that:  $\sigma_k = \alpha^k \sigma_0$
- 2) Resize the image to its half and repeat the process.



# Fast Laplacian responses

Compute Laplacian responses at every layer in the "scale space".

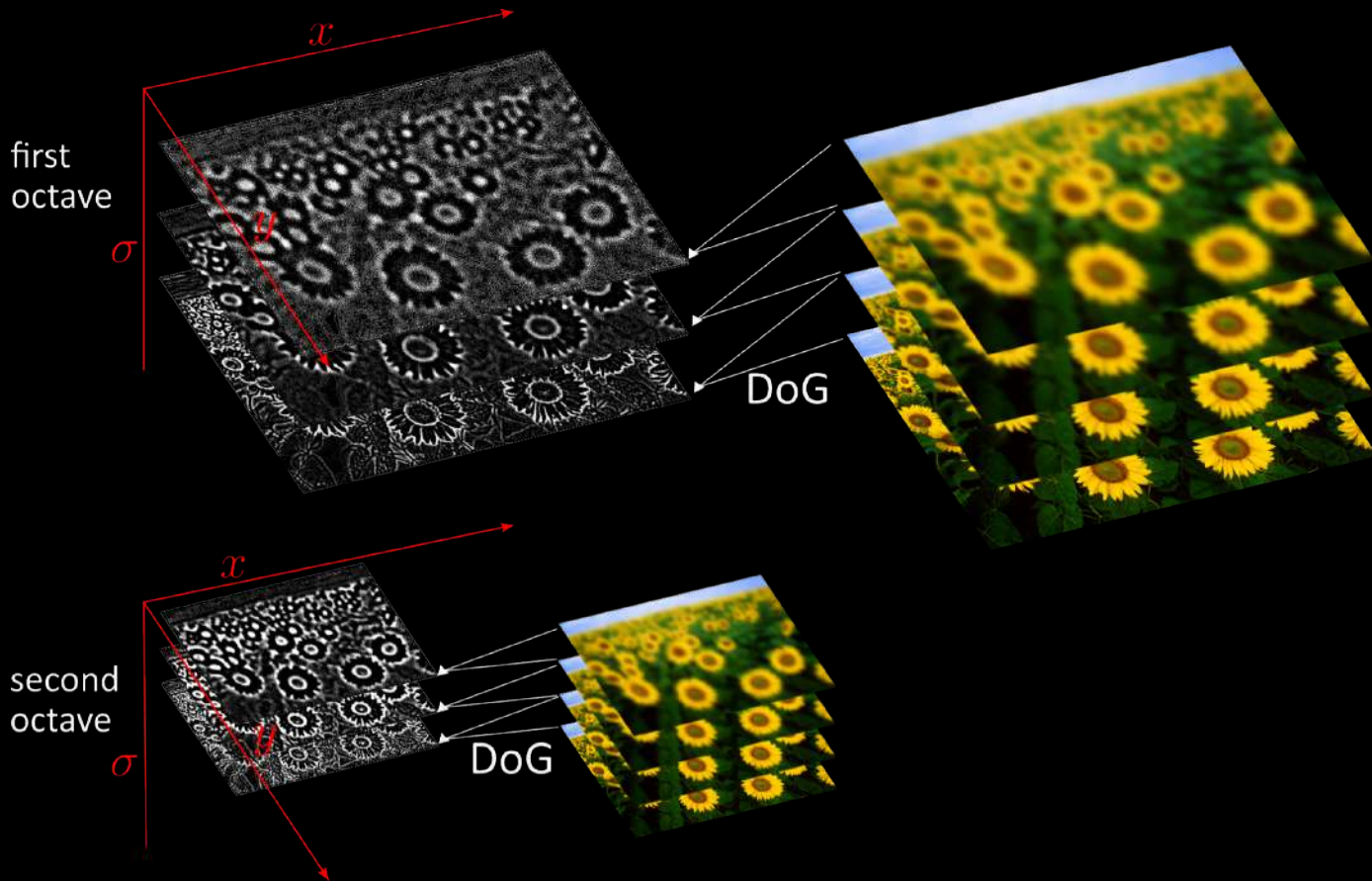
- Laplacian of Gaussian  $\approx$  Difference of Gaussians



$$LoG = \sigma^2 \left( \frac{\partial^2}{\partial x^2} h(x, y) + \frac{\partial^2}{\partial y^2} h(x, y) \right)$$

$$DoG = h(x, y, k\sigma) - h(x, y, \sigma)$$

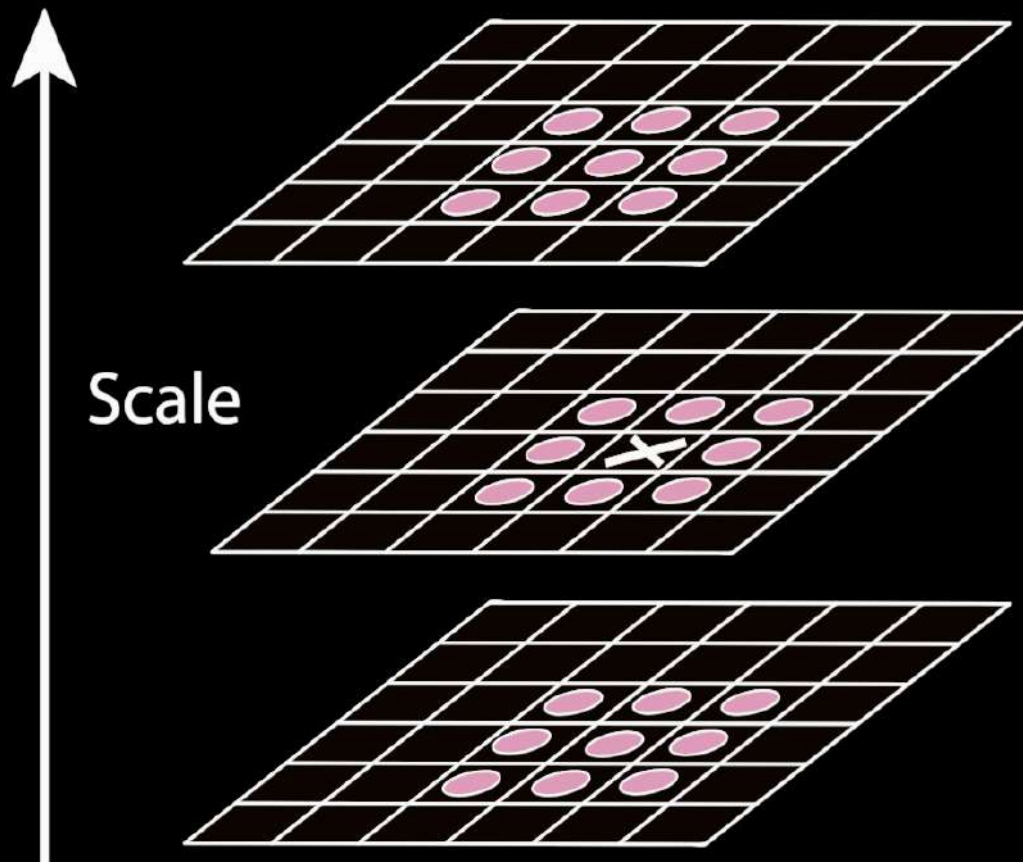
# Fast Laplacian responses



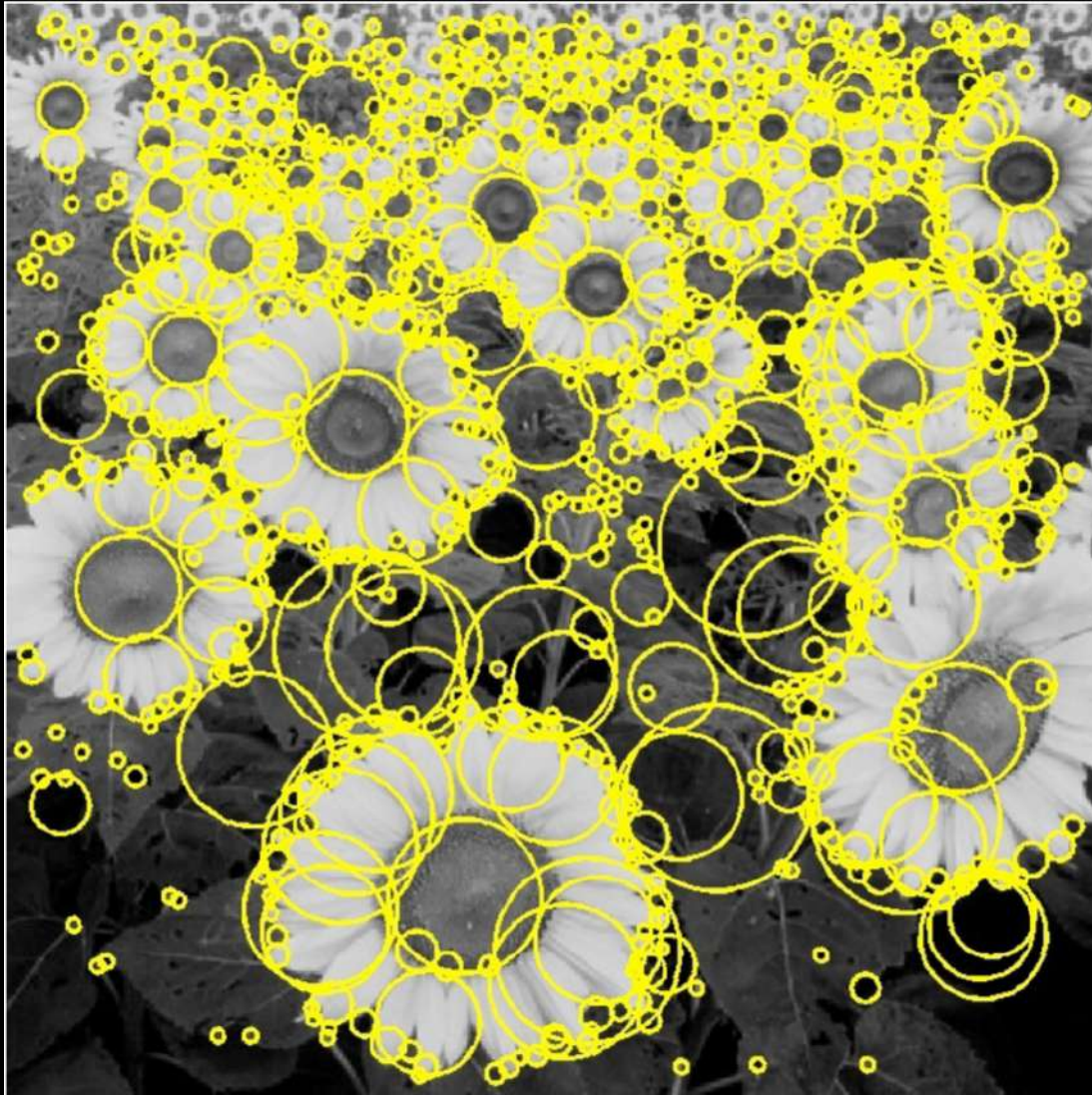
- How do we find the blobs in the image?

# Multi-scale blob detection in images

- Find the local extrema (minima/maxima) by looking at all neighbors across scales.



# Multi-scale blob detection in images



# Questions?

# Reading material next lecture:

- **Article:**
  - *Distinctive Image Features from Scale-Invariant Keypoints*, David G. Lowe, IJCV 2004.
  - <https://www.cs.ubc.ca/~lowe/papers/ijcv04.pdf>
- Section 7.1.2 Feature descriptors, in Szeliski book
- Video lecture Mubarak Shah: <https://www.youtube.com/watch?v=NPcMS49V5hg>