Finding Edges

- Edges reveal much about images
- Edge representations can be seen as information compression (because boundary is fewer pixels than the inside)
- Edges are the result of many different things
  - simple material change (step edge, corners)
  - illumination change (often soft, but not always)
  - shading edges and bar edges in inside corners
- An edge is basically where the images changes---hence finding images is studying changes (differentiation)

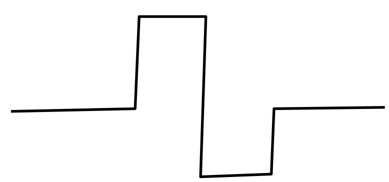
Differentiation and convolution

- Recall $$\frac{\partial f}{\partial x} = \lim_{\varepsilon \to 0}\left(\frac{f(x+\varepsilon, y)}{\varepsilon} - \frac{f(x,y)}{\varepsilon}\right)$$

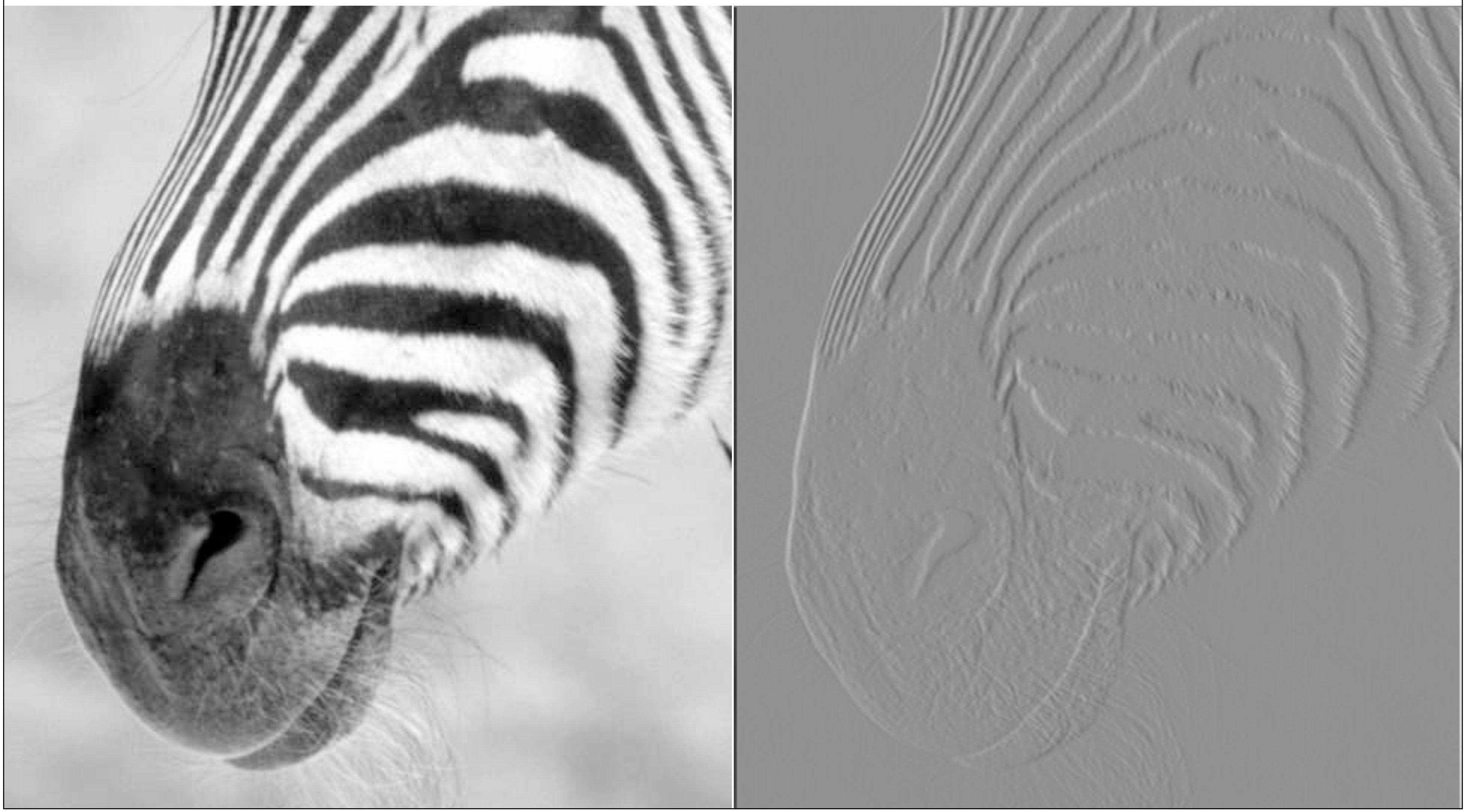
- This is linear and shift invariant, so must be the result of a convolution.

- We could approximate this as $$\frac{\partial f}{\partial x} \approx \frac{f(x_{n+1}, y) - f(x_n, y)}{\Delta x}$$

- This is convolution by



Finite differences (x-direction)



Noise

- Simplest noise model
  - independent stationary additive Gaussian noise
  - the noise value at each pixel is given by an independent draw from the same normal probability distribution

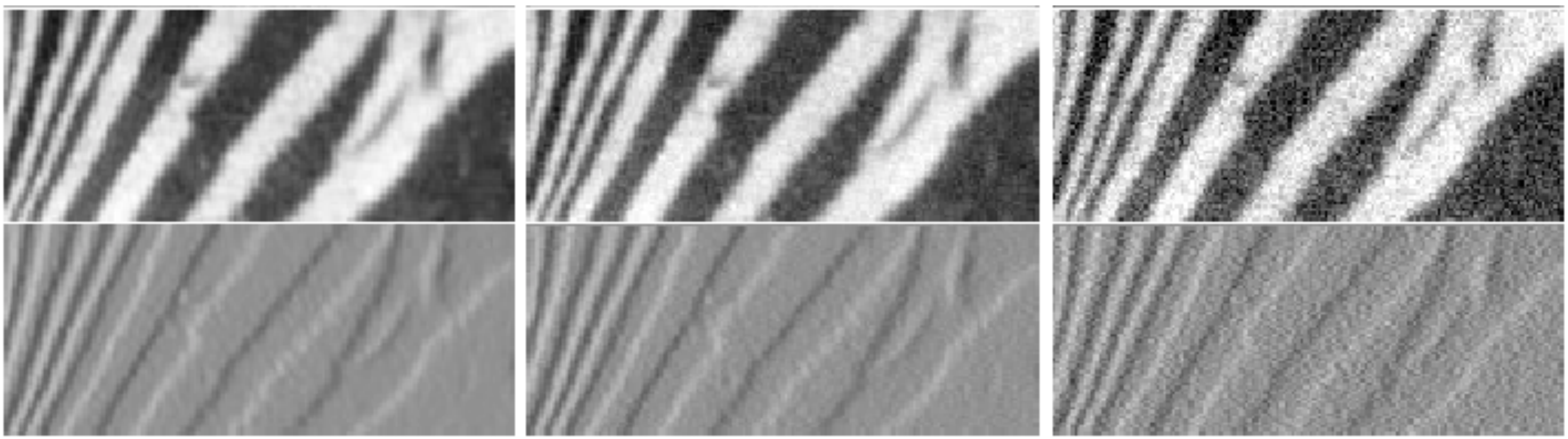
image with added
Gaussian noise
(sigma=1)

image with added
Gaussian noise
(sigma=16)

Finite differences and noise

- Finite difference filters respond strongly to noise
  - Noise is not correlated across adjacent pixels, but the pixels tend to be correlated
  - Thus differences lock onto the noise!
- The larger the noise, the bigger such a response

Finite differences responding to noise



Increasing noise ----->

(zero mean additive gaussian noise)

Smoothing reduces noise

- Generally expect pixels to “be like” their neighbors
  - surfaces turn slowly
  - relatively few reflectance changes

- Generally expect noise processes to be **independent** from pixel to pixel

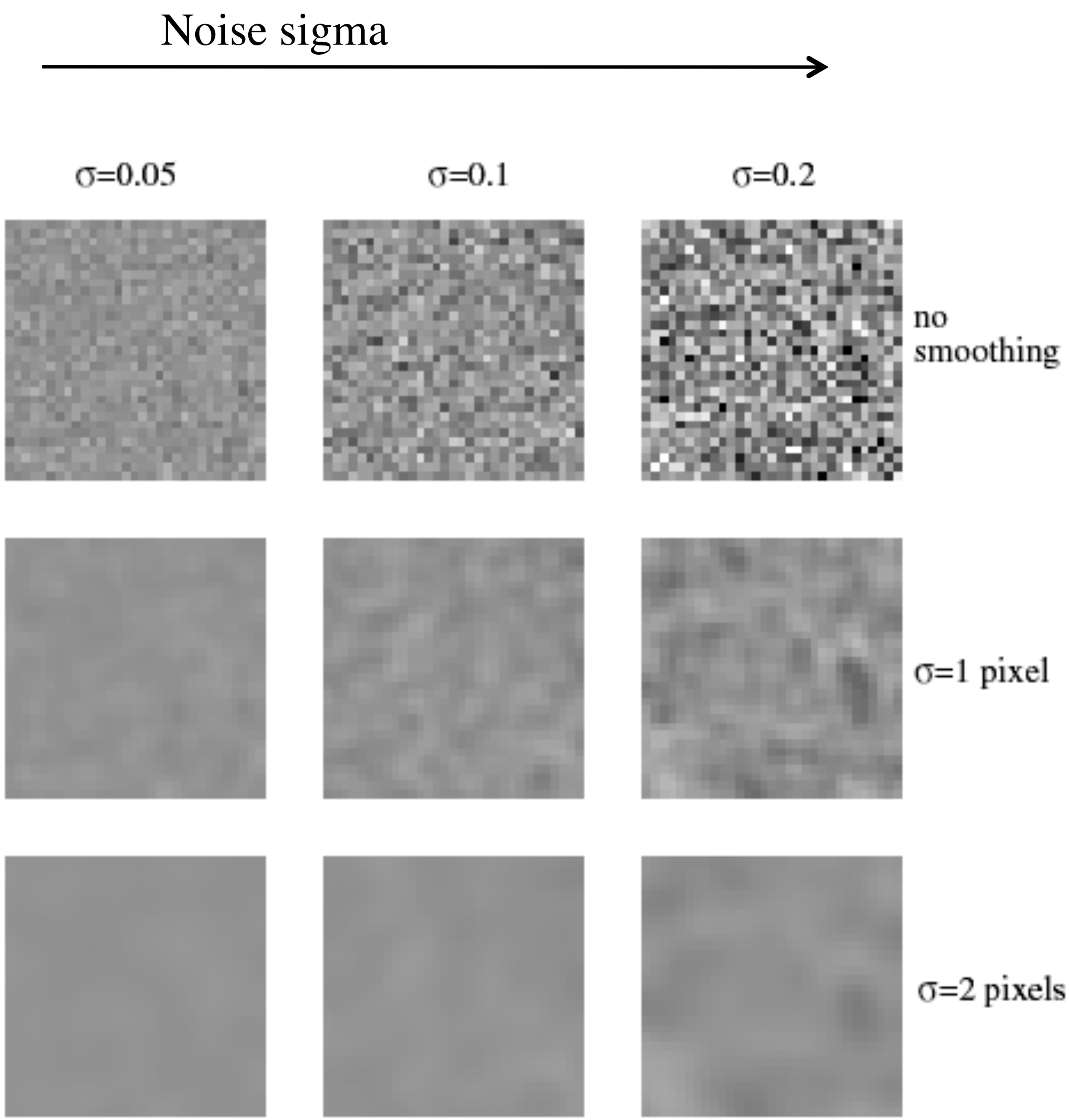
- Implies that some kind of averaging or smoothing suppresses noise, for appropriate noise models

Smoothing reduces noise

- Degree of smoothing <==> scale
  - the parameter in the symmetric Gaussian
  - as this parameter goes up, more pixels are involved in the average
  - and the image gets more blurred
  - and noise is more effectively suppressed

The effects of smoothing

Each row shows smoothing with gaussians of different width; each column shows different realizations of an image of gaussian noise.



Median Filtering

- Using a Gaussian to remove noise assumes a well behaved noise process (sensitive to outliers).
- A more robust method is to replace a pixel with the median of the ones in a window (median filtering)
- This filter is non-linear!
  - We give up lots of nice properties

Gradients and edges

- Sources of points of sharp change in an image:
  - change in reflectance
  - change in object
  - change in illumination
  - noise!
- Sometimes called **edge points**

- General strategy
  - determine image gradient
  - mark points where gradient magnitude is particularly large compared to that of neighbors
  - attempt to promote linked edge points

Reminder

- The gradient is a vector made of two components
  - 1) The (smoothed) difference in X (from one convolution) for the first component
  - 2) The (smoothed) difference in Y (from a different convolution) as the second component

- The magnitude of the gradient vector is a measure of edge strength

- The direction of the gradient vector gives us a direction perpendicular to the edge direction.

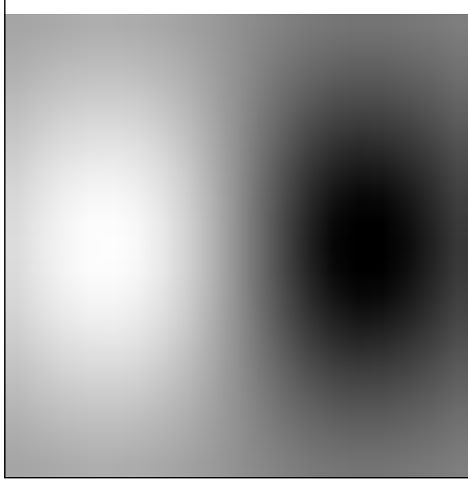
Gradient magnitudes of zebra at two different scales

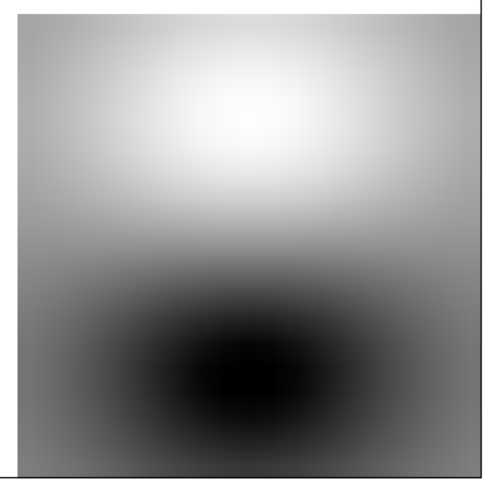
Three major issues:

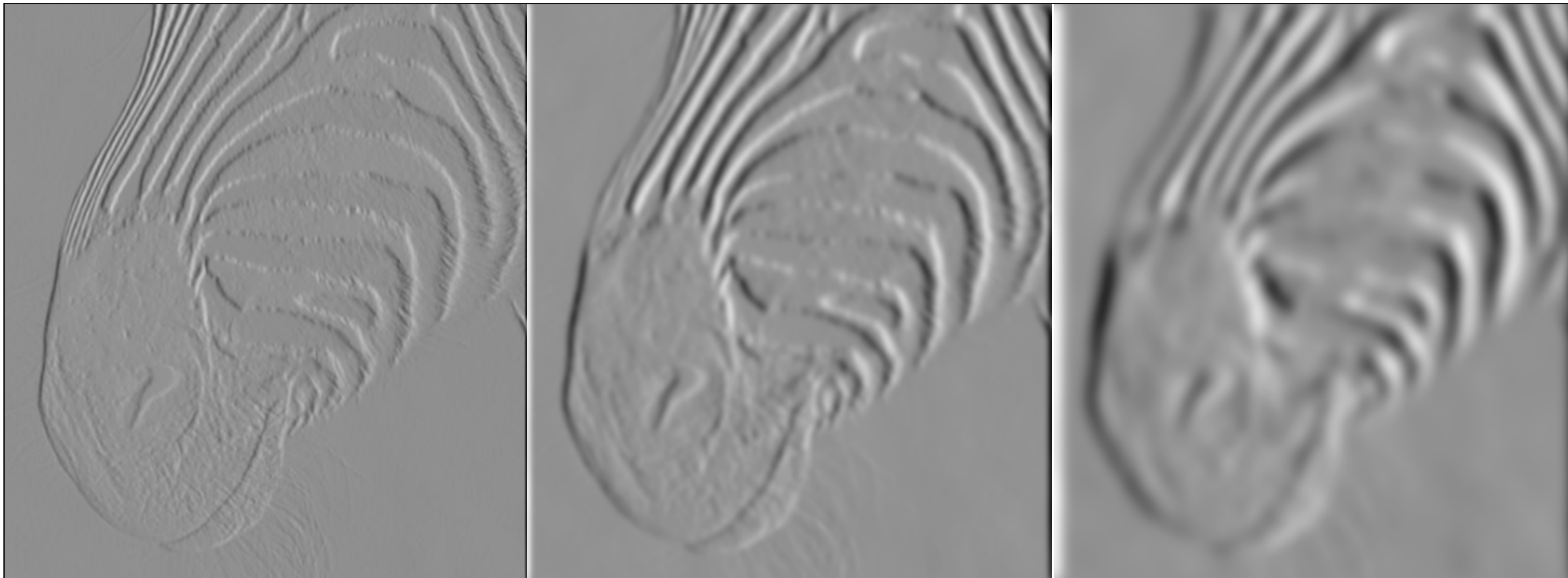
1) The gradient magnitude at different scales is different; which one should we choose?
2) The gradient magnitude is large throughout thick trail; how do we identify the actual edge location?
3) How do we link the relevant points up into curves?

Smoothing and Differentiation

- Issue: noise
  - so we smooth before differentiation
  - this suggests a convolution to smooth, then a convolution to differentiate
  - but we can use a derivative of Gaussian filter
    - because differentiation is convolution, and convolution is associative







1 pixel

3 pixels

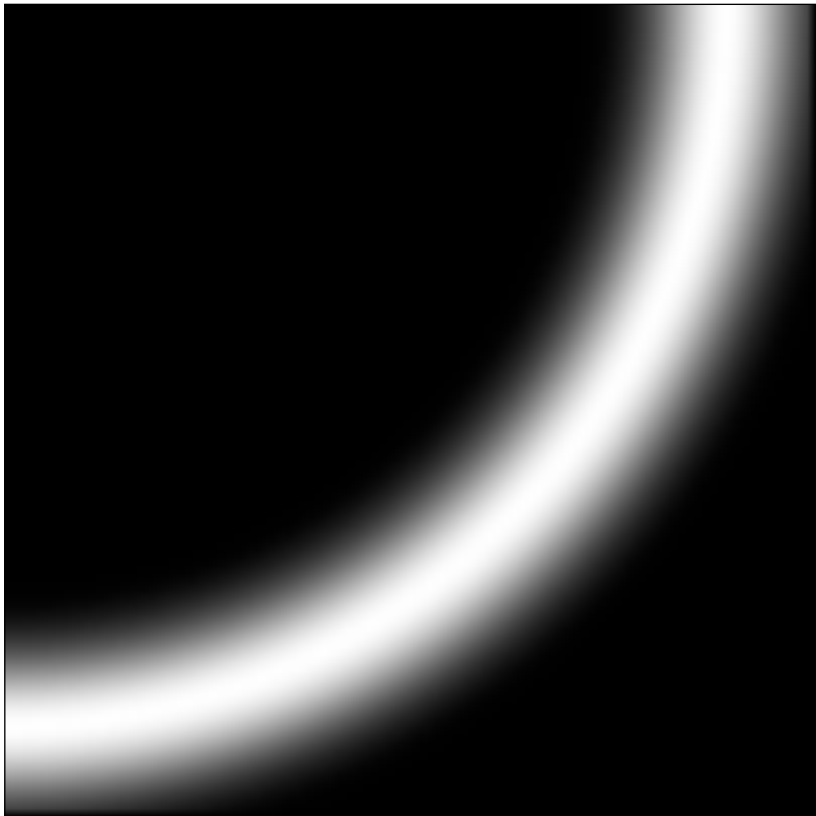
7 pixels

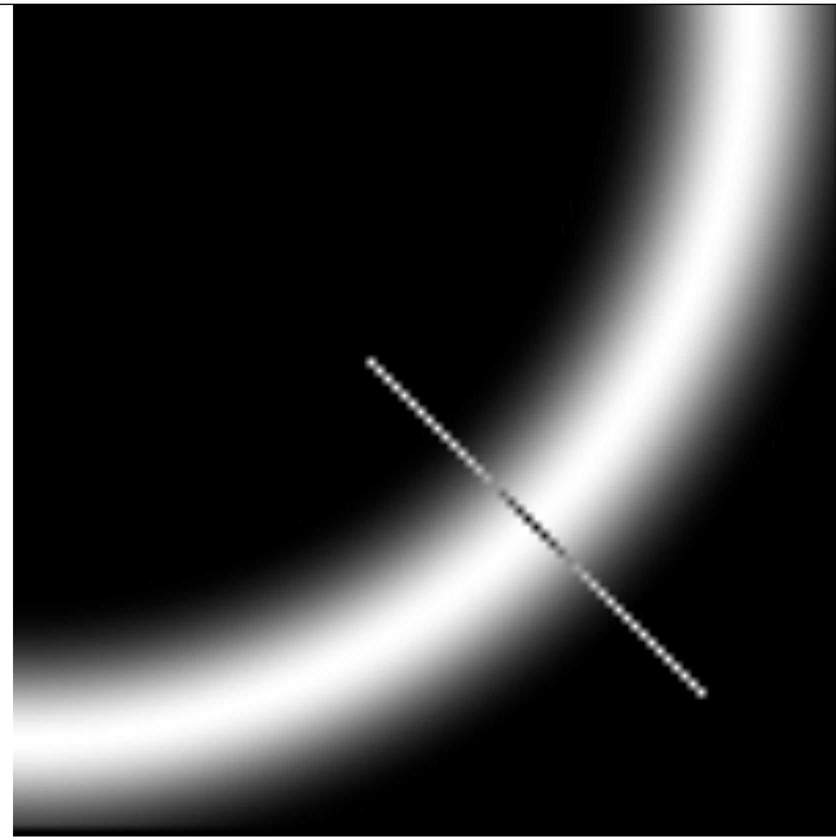
Horizontal derivative magnitude at different scales

The scale affects the estimates and the semantics of the edges recovered.

Non-maximal suppression (alg 8.2)

- Given a scale, how do we find edge points?
- If we set a threshold, then either lots of points near the edge are accepted, or none are.





We wish to mark points along the curve where the gradient magnitude is biggest in the gradient direction (best edge points).

We can do this by looking for a maximum along a slice normal to the curve (non-maximum suppression).

These points should form a curve.