Detectors and Descriptors

EECS 442 – David Fouhey

Fall 2019, University of Michigan

http://web.eecs.umich.edu/~fouhey/teaching/EECS442_F19/

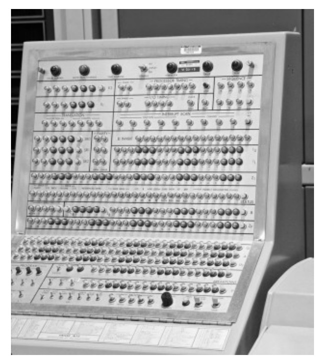
Goal

How big is this image as a vector?

389x600 = 233,400 dimensions **(big)**

Applications To Have In Mind

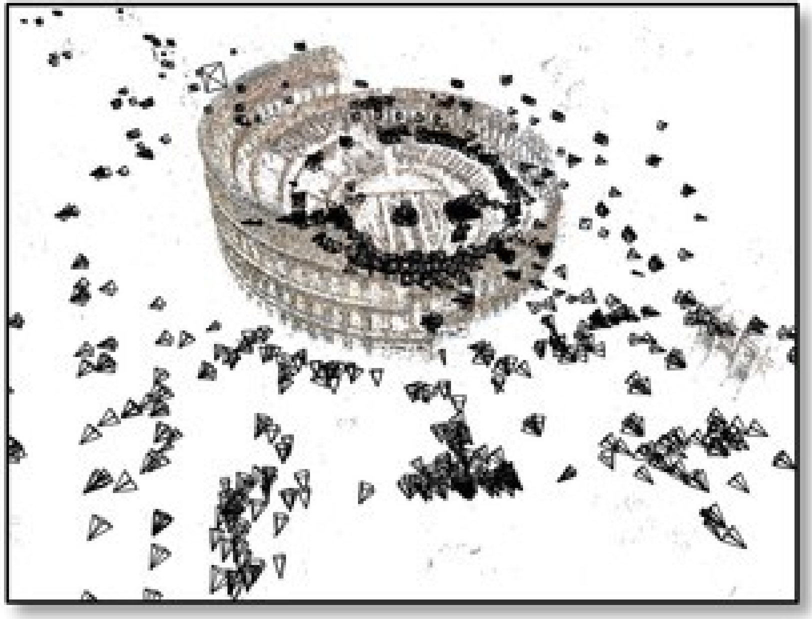
Part of the same photo?



Same computer from another angle?

Applications To Have In Mind

Building a 3D Reconstruction Out Of Images



Slide Credit: N. Seitz

Applications To Have In Mind

Stitching photos taken at different angles

One Familiar Example

Given two images: how do you align them?

One (Hopefully Familiar) Solution

```
for y in range(-ySearch,ySearch+1):
    for x in range(-xSearch,xSearch+1):
        #Touches all HxW pixels!
        check_alignment_with_images()
```

One Motivating Example

Given these images: how do you align them?

These aren't off by a small 2D translation but instead by a 3D rotation + translation of the camera.

Photo credit: M. Brown, D. Lowe

One (Hopefully Familiar) Solution

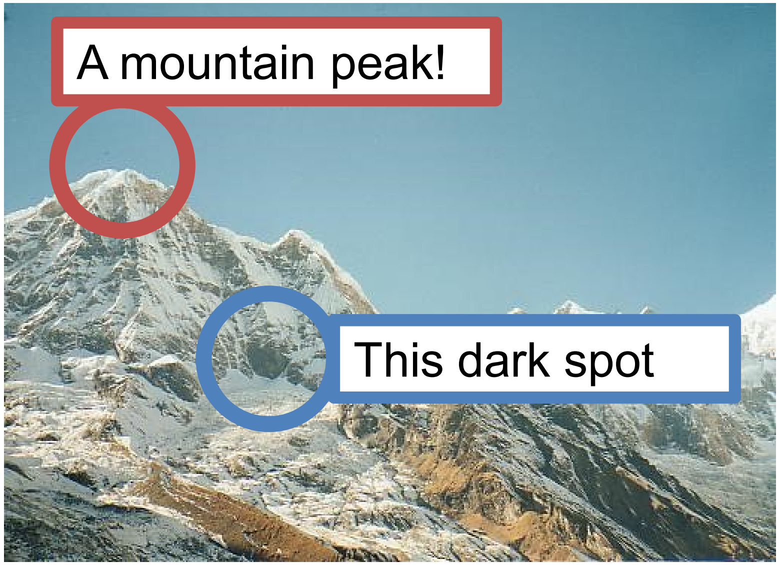
```
for y in yRange:
    for x in xRange:
        for z in zRange:
            for xRot in xRotVals:
                for yRot in yRotVals:
                    for zRot in zRotVals:
                        #touches all HxW pixels!
                        check_alignment_with_images()
```

This code should make you really <u>unhappy</u>

Note: this actually isn't even the full number of parameters; it's actually 8 for loops.

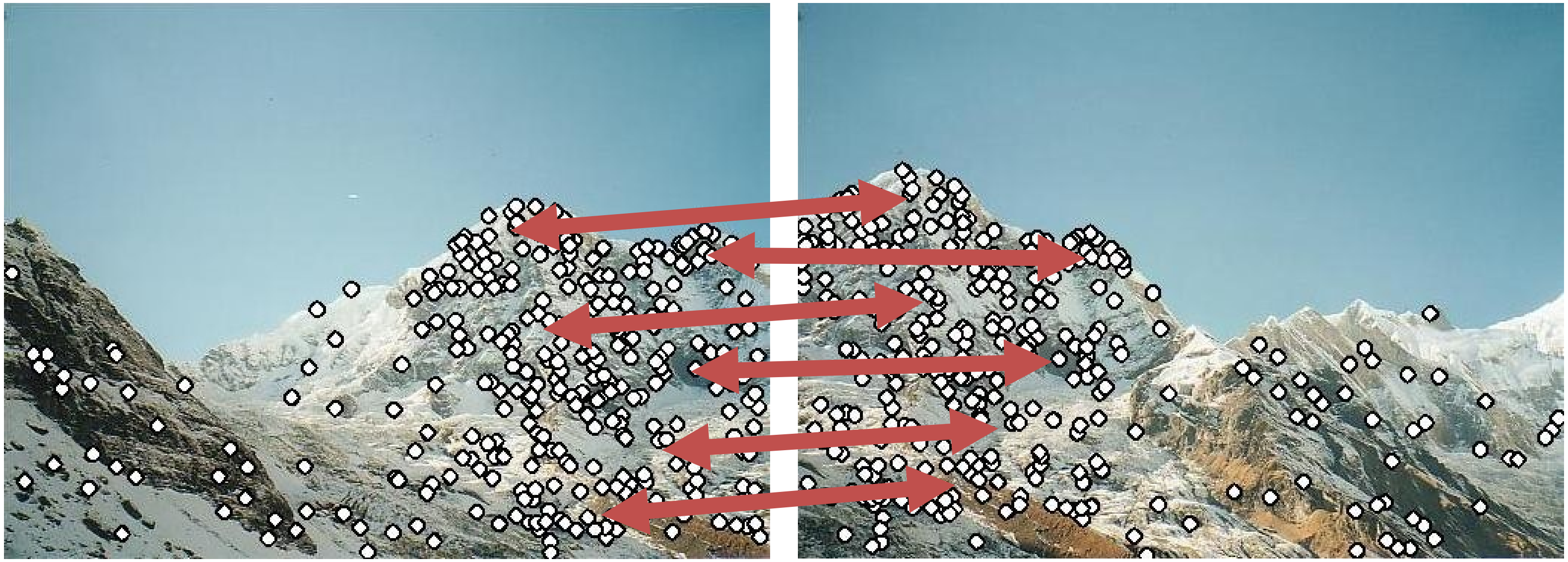
An Alternate Approach

Given these images: how would **<u>you</u>** align them?



An Alternate Approach

Finding and Matching



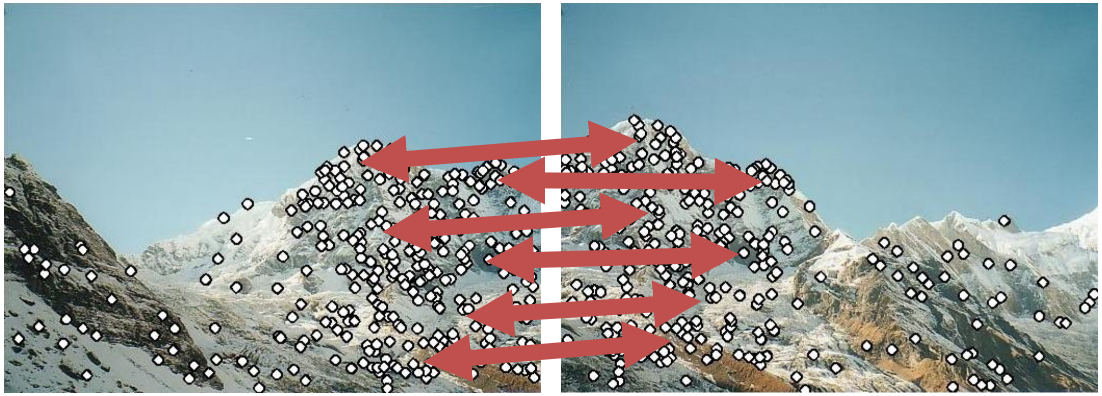
1: find corners+features

2: match based on local image data

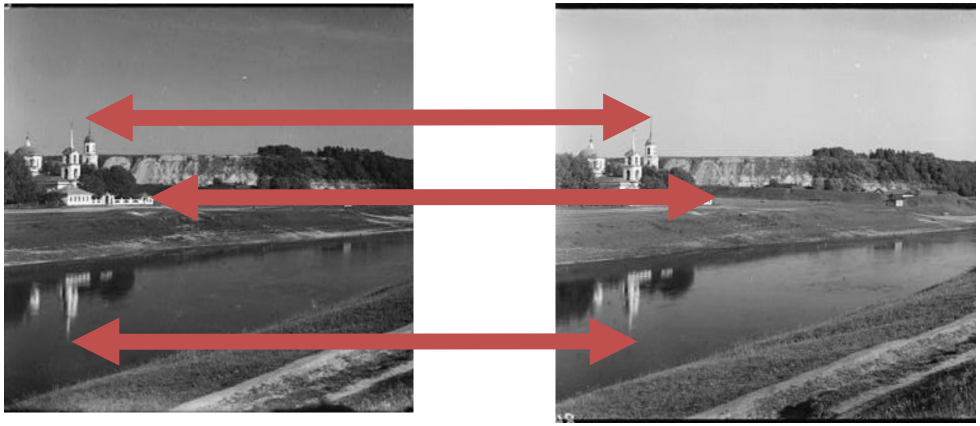
Slide Credit: S. Lazebnik, original figure: M. Brown, D. Lowe

What Now?

Given pairs **p1**,**p2** of correspondence, **how do I align?**

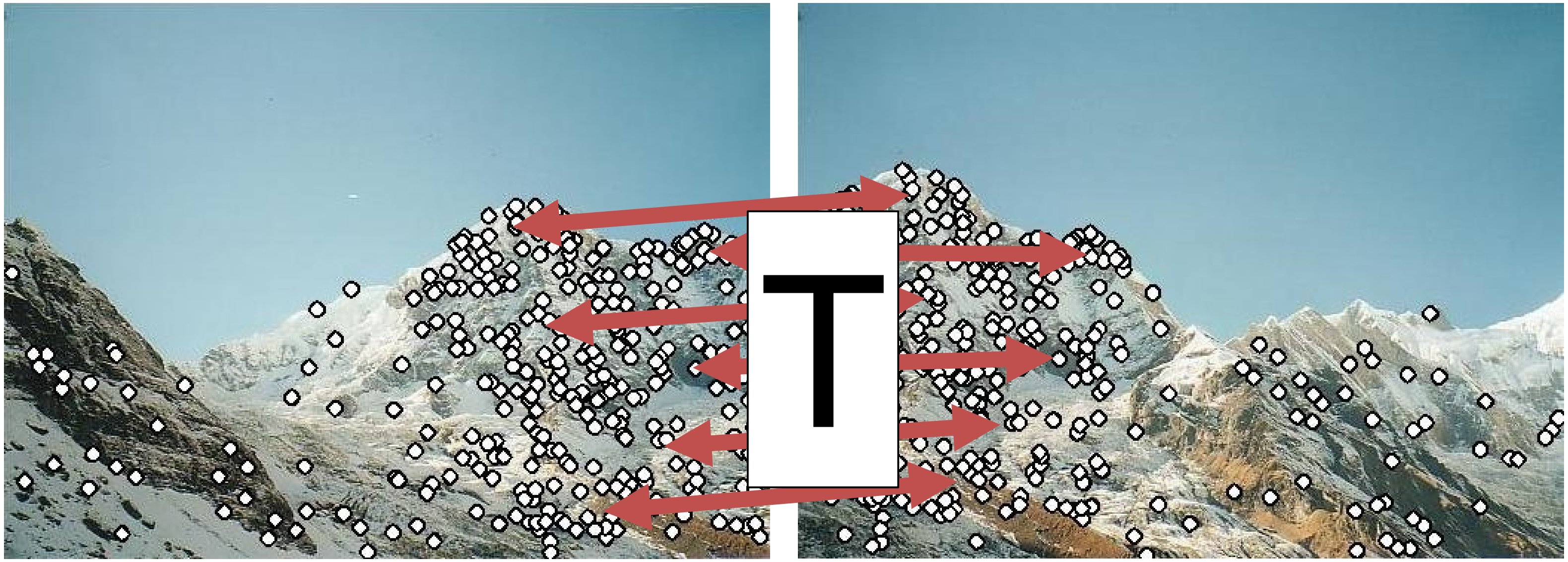


Consider translation-only case from HW1.



An Alternate Approach

Solving for a Transformation



3: Solve for transformation T (e.g. such that **p1 ≡ T p2**) that fits the matches well

Note the homogeneous coordinates, you'll see them again.

Slide Credit: S. Lazebnik, original figure: M. Brown, D. Lowe

An Alternate Approach

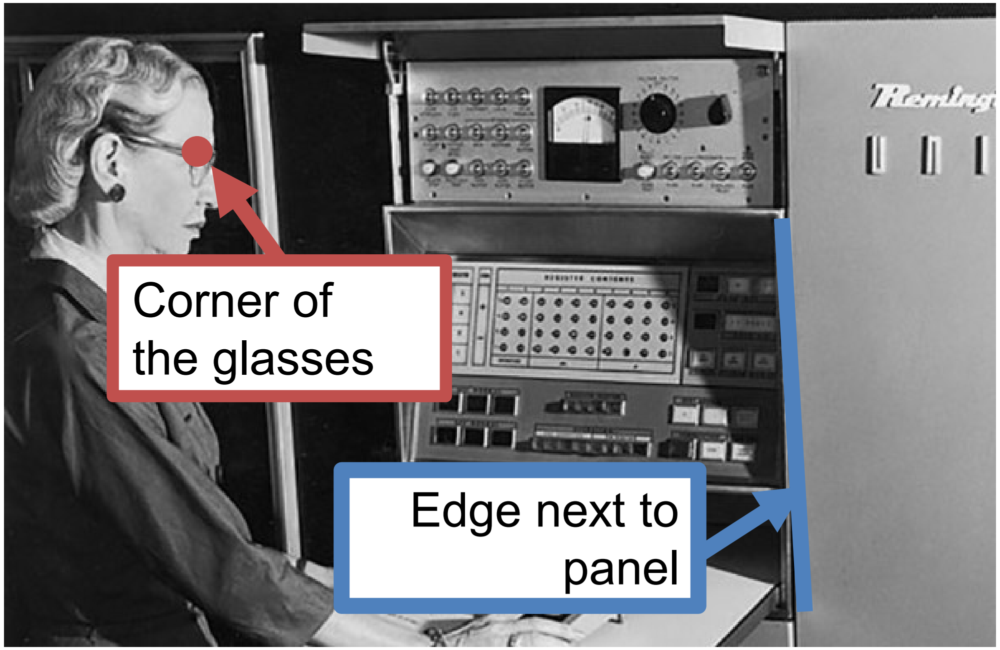
Blend Them Together

Key insight: we don't work with full image. We work with only parts of the image.

Photo Credit: M. Brown, D. Lowe

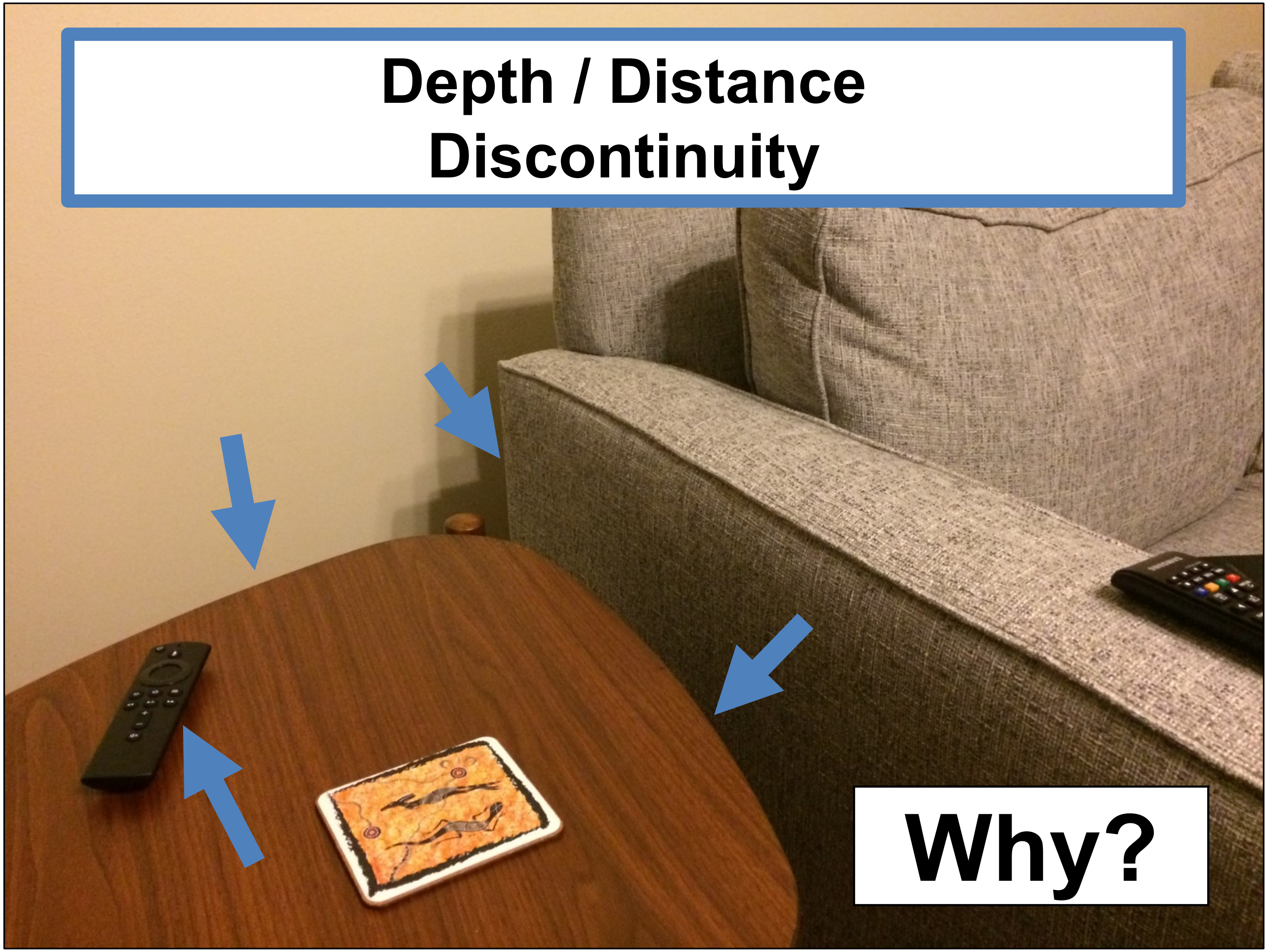
Today

Finding edges (part 1) and corners (part 2) in images.

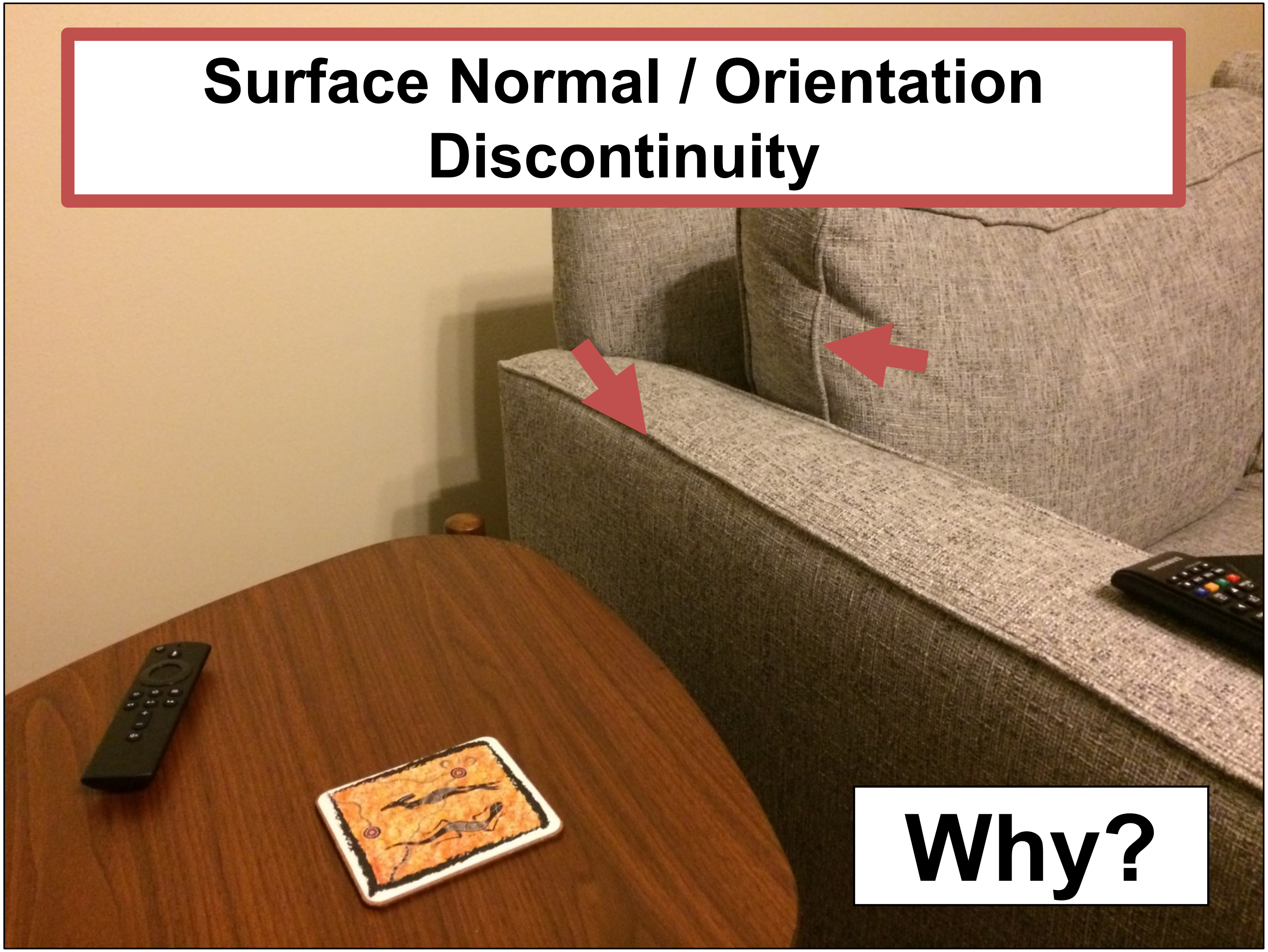


Where do Edges Come From?

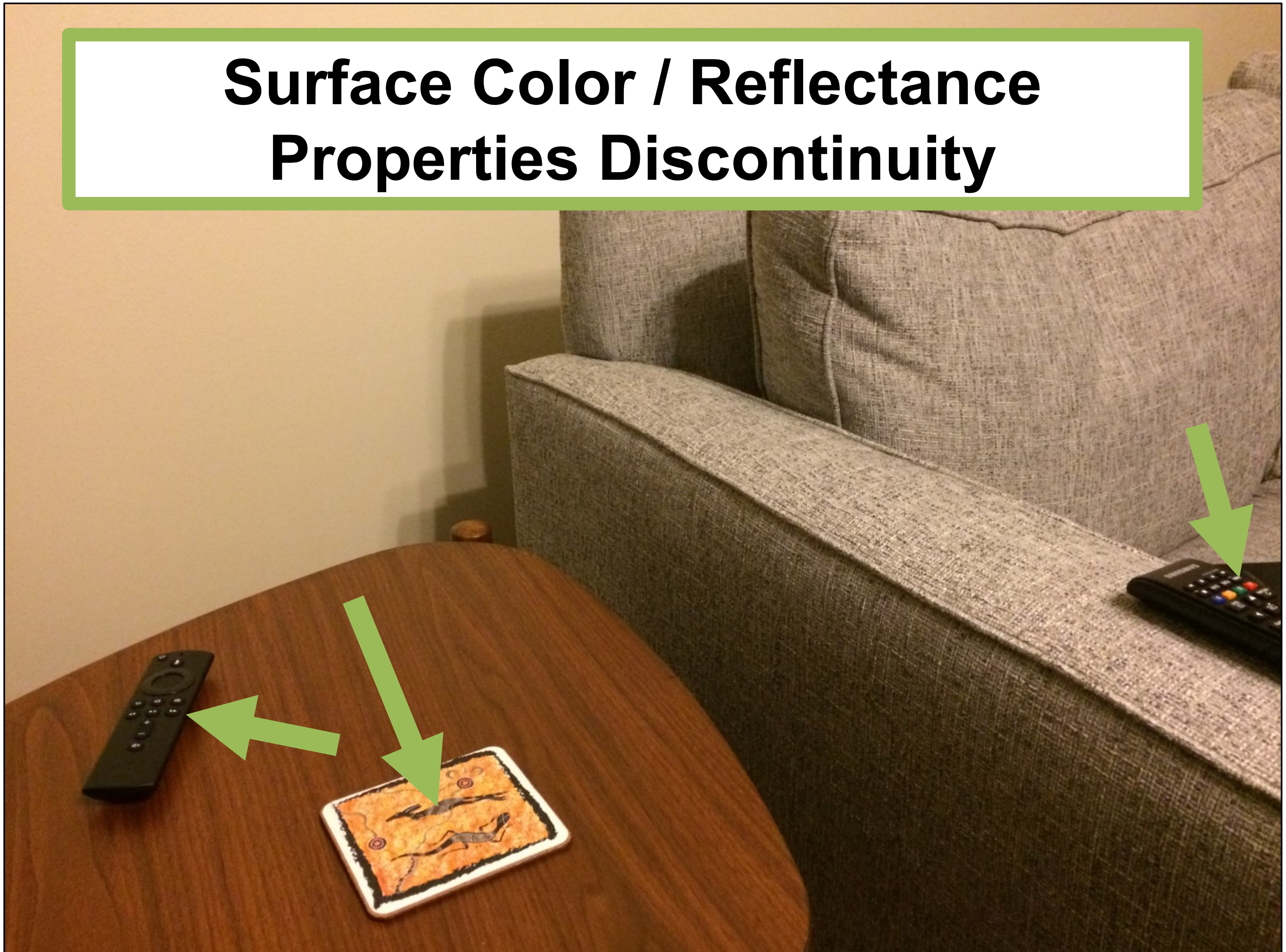
Where do Edges Come From?



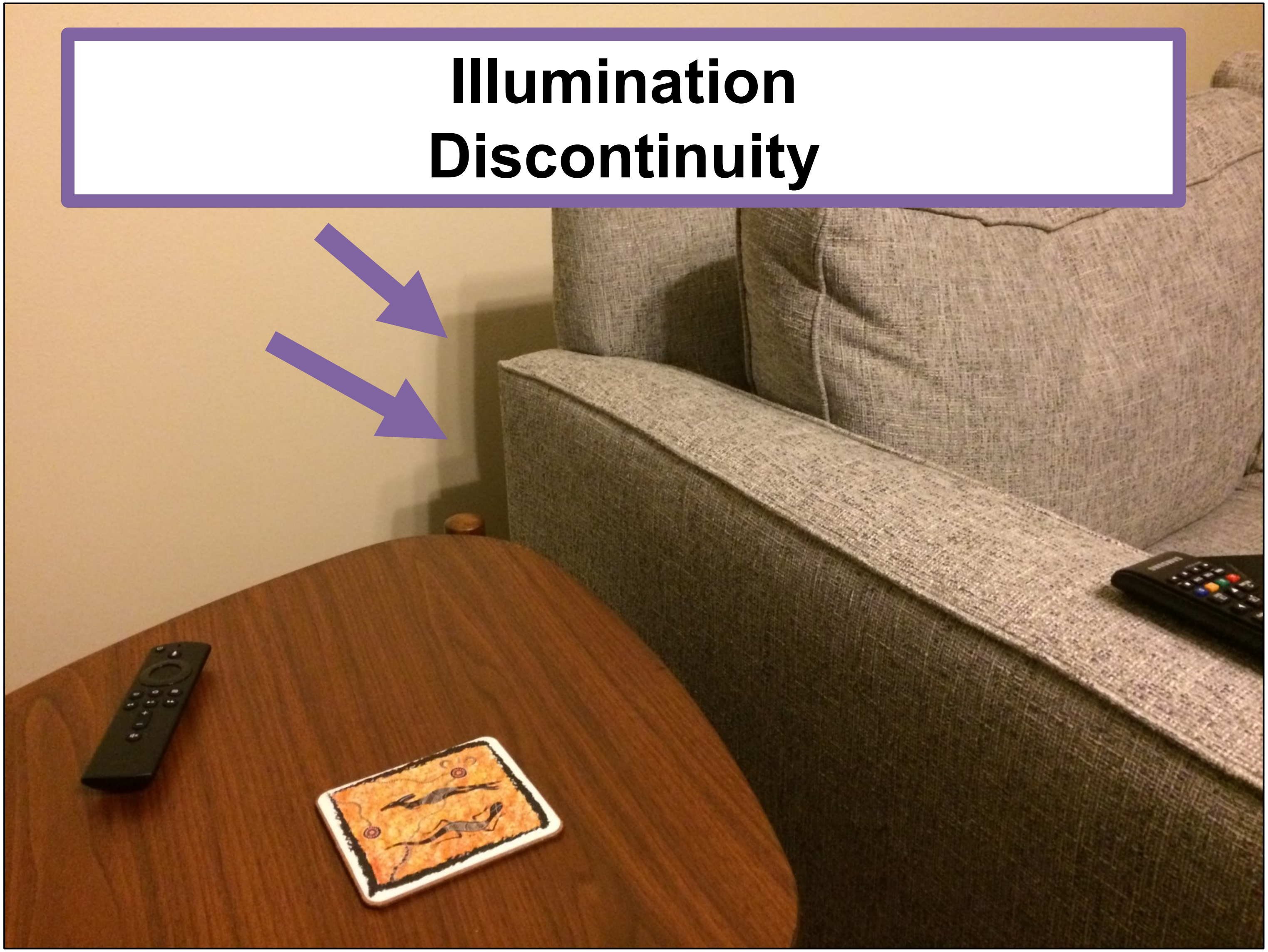
Where do Edges Come From?



Where do Edges Come From?



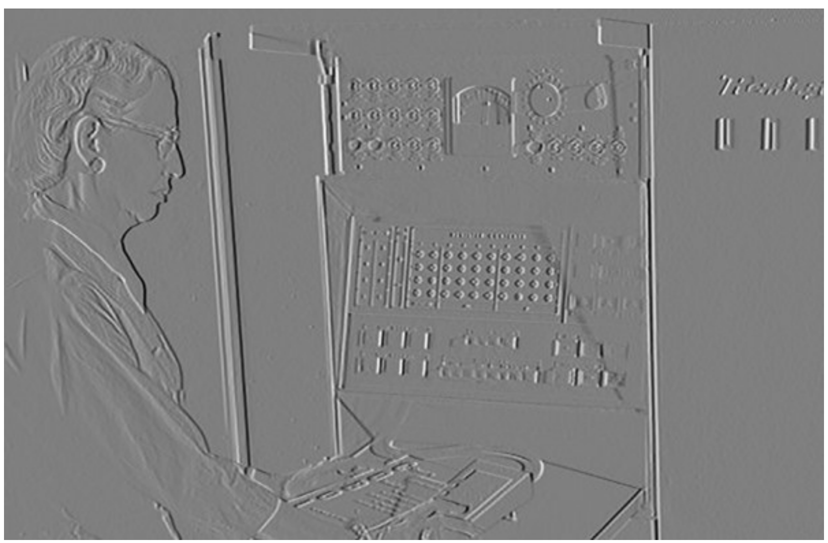
Where do Edges Come From?



Last Time

-1	0	1

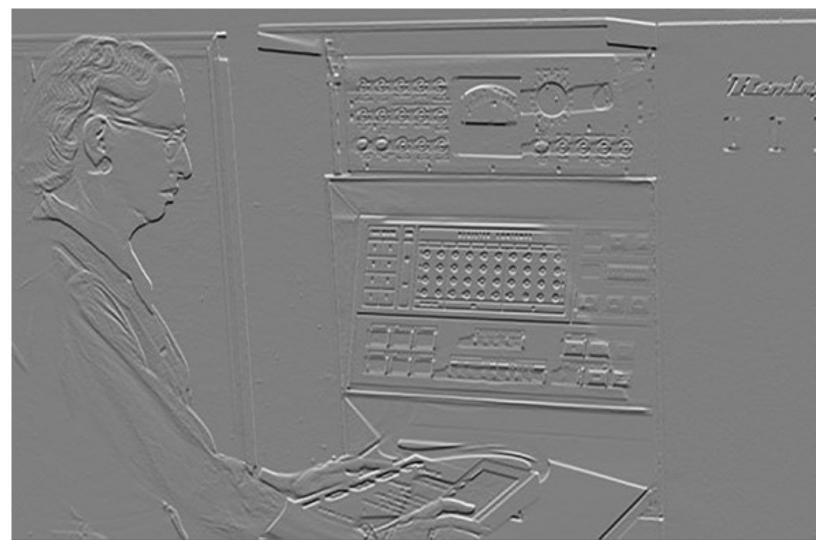
Ix



-1	0	1

T

Iy



Derivatives

Remember derivatives?

Derivative: rate at which a function f(x) changes at a point as well as the direction that increases the function

Given quadratic function f(x)

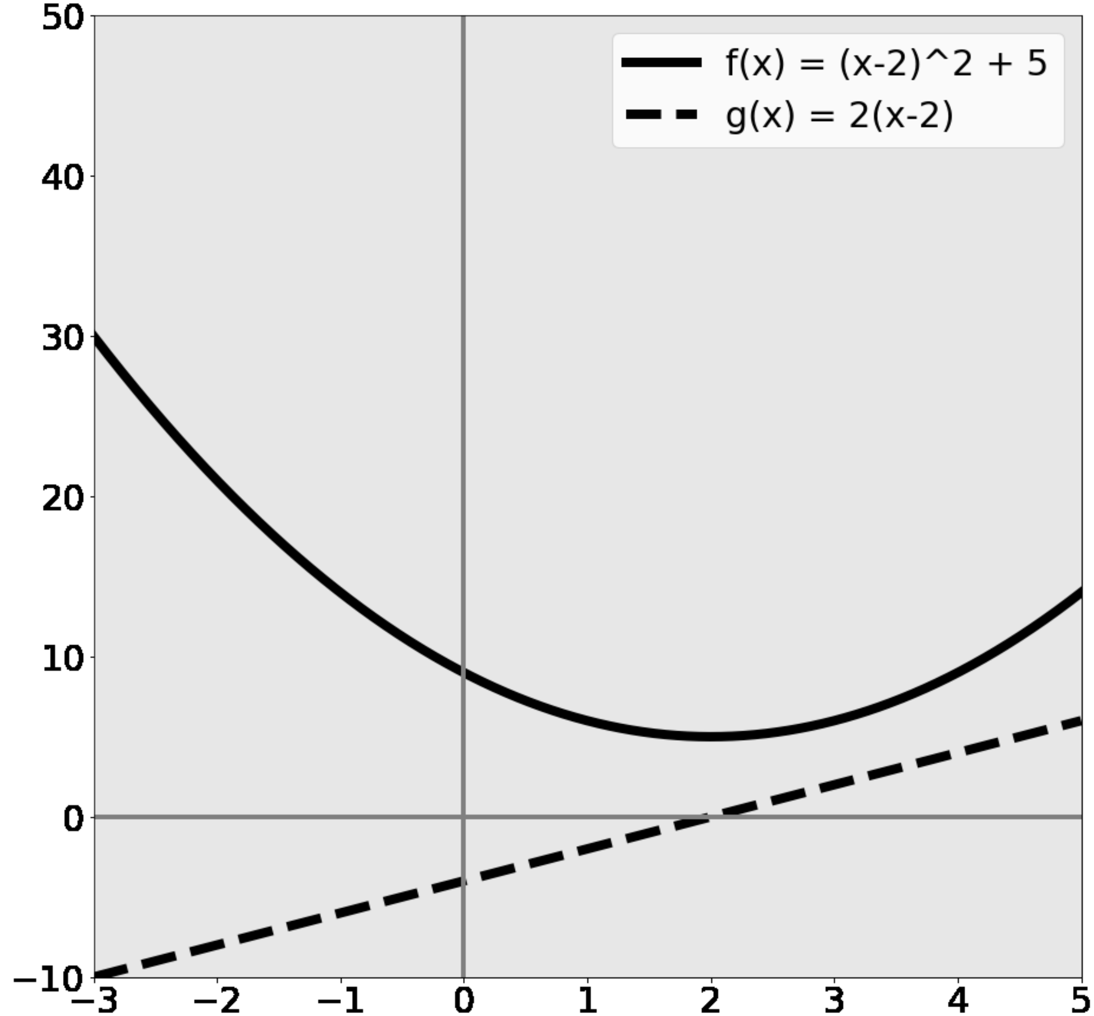
$$f(x, y) = (x - 2)^2 + 5$$

$f(x)$ is function

$$g(x) = f'(x)$$

aka

$$g(x) = \frac{d}{dx} f(x)$$



Given quadratic function f(x)

$$f(x, y) = (x - 2)^2 + 5$$

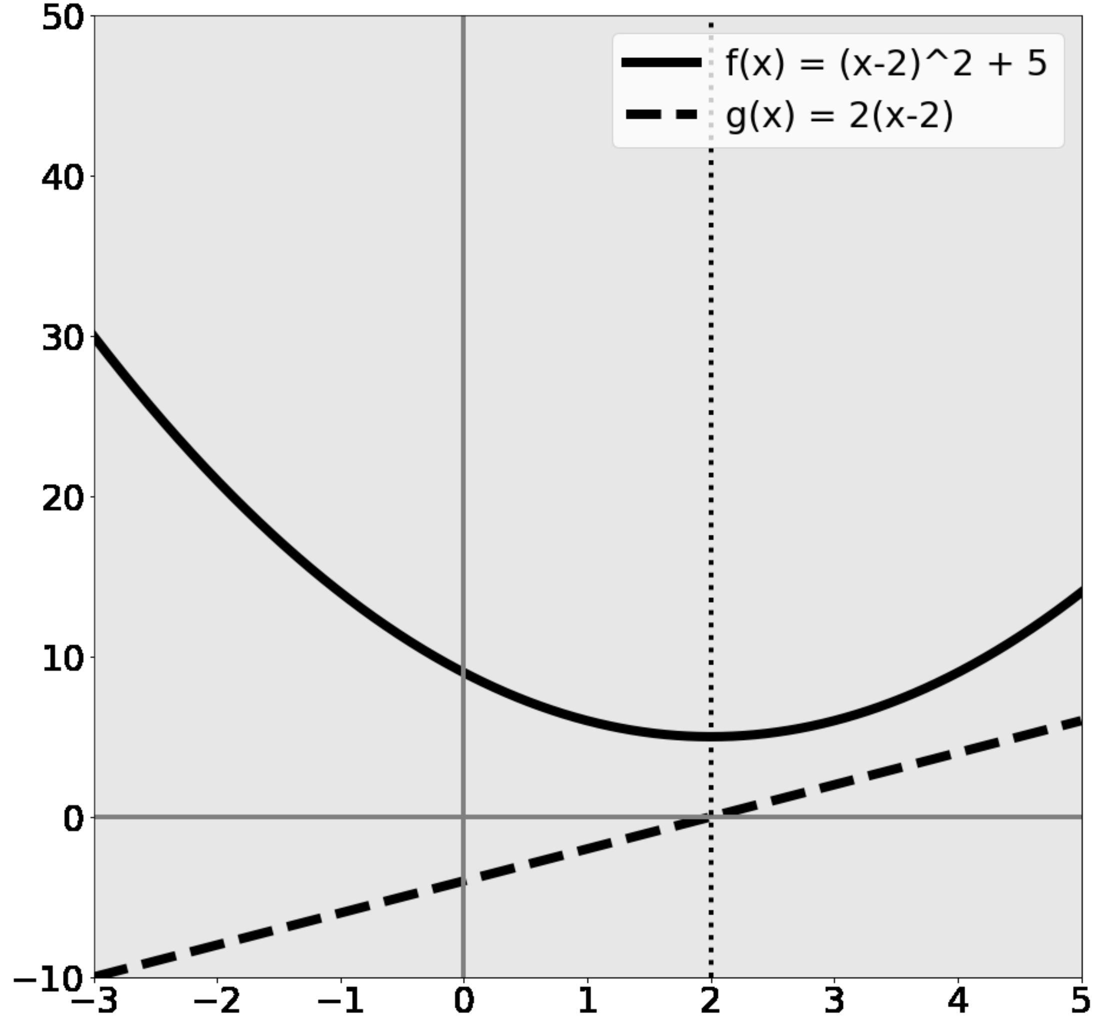
What's special about x=2?

$f(x)$ minim. at 2

$g(x) = 0$ at 2

a = minimum of f → $g(a) = 0$

Reverse is ***not true***



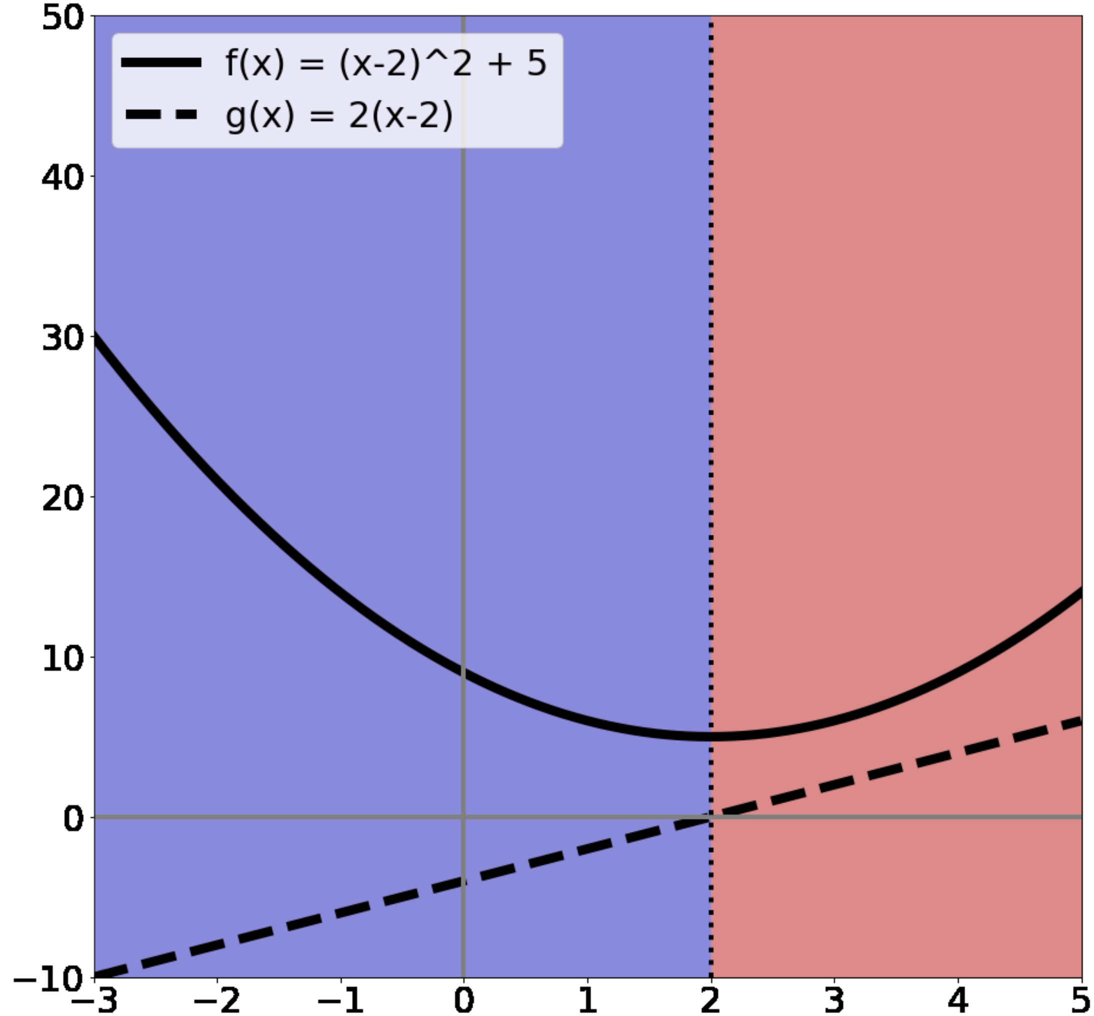
Rates of change

$$f(x, y) = (x - 2)^2 + 5$$

Suppose I want to increase f(x) by changing x:

Blue area: move left
Red area: move right

Derivative tells you direction of ascent and rate



What Calculus Should I Know

- Really need intuition
- Need chain rule
- Rest you should look up / use a computer algebra system / use a cookbook
- Partial derivatives (and that's it from multivariable calculus)

Partial Derivatives

- Pretend other variables are constant, take a derivative. That's it.
- Make our function a function of two variables

$$f(x) = (x-2)^2 + 5$$

$$\frac{\partial}{\partial x} f(x) = 2(x-2) * 1 = 2(x-2)$$

$$f_2(x,y) = (x-2)^2 + 5 + \boxed{(y+1)^2}$$

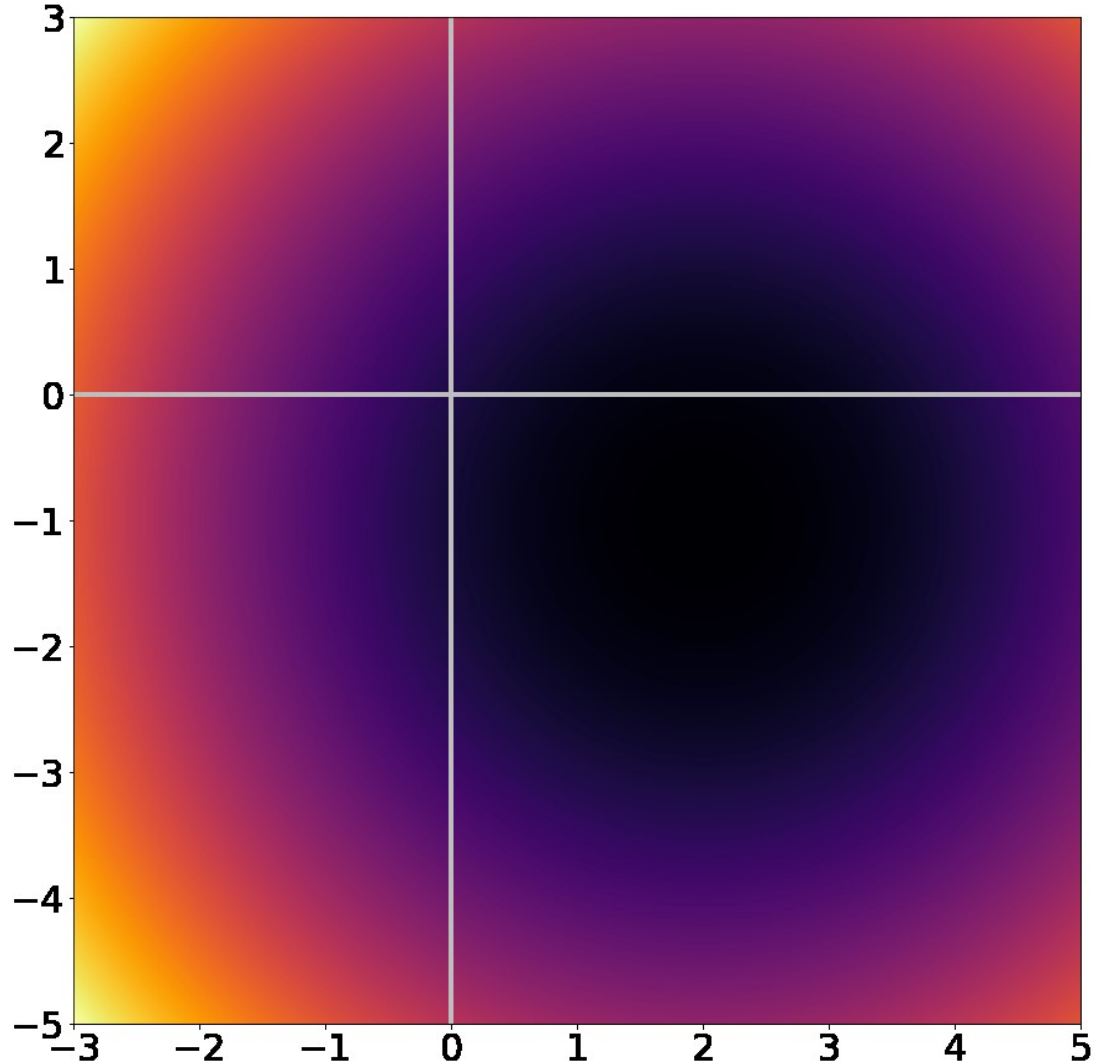
Pretend it's constant → derivative = 0

$$\frac{\partial}{\partial x} f_2(x) = 2(x-2)$$

Zooming Out

$$f_2(x, y) = (x - 2)^2 + 5 + (y + 1)^2$$

Dark = f(x,y) low
Bright = f(x,y) high



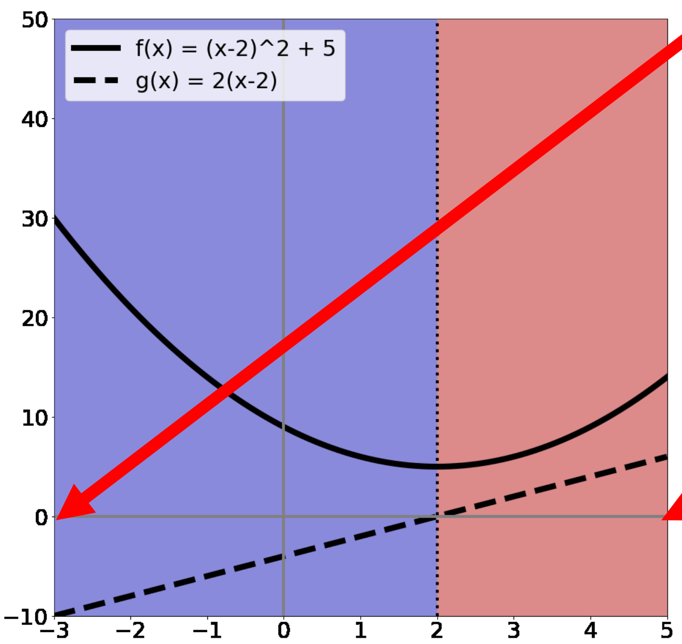
Taking a slice of

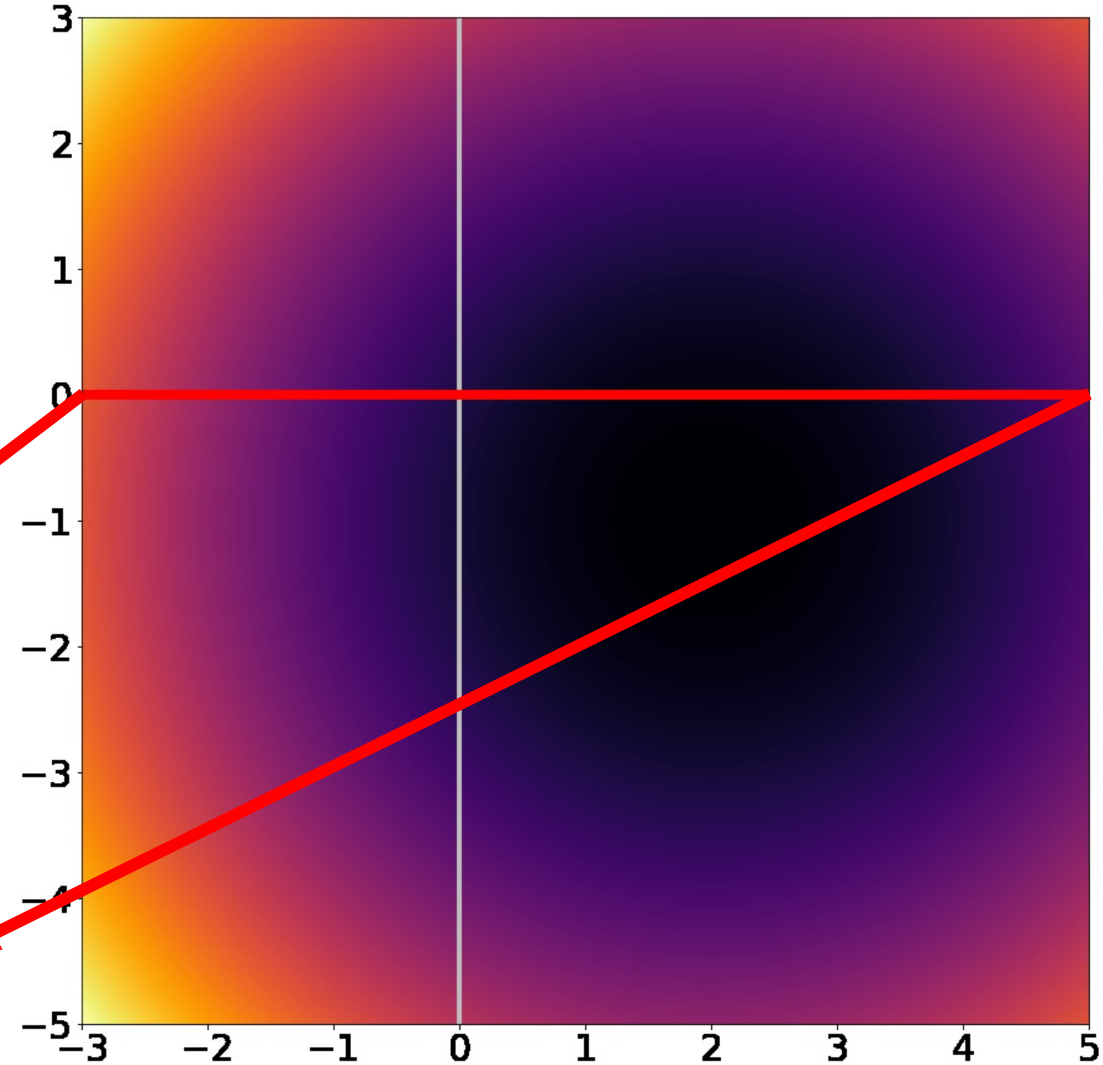
$$f_2(x,y) = (x-2)^2 + 5 + (y+1)^2$$

Slice of y=0 is the function from before:

$$f(x) = (x-2)^2 + 5$$

$$f'(x) = 2(x-2)$$

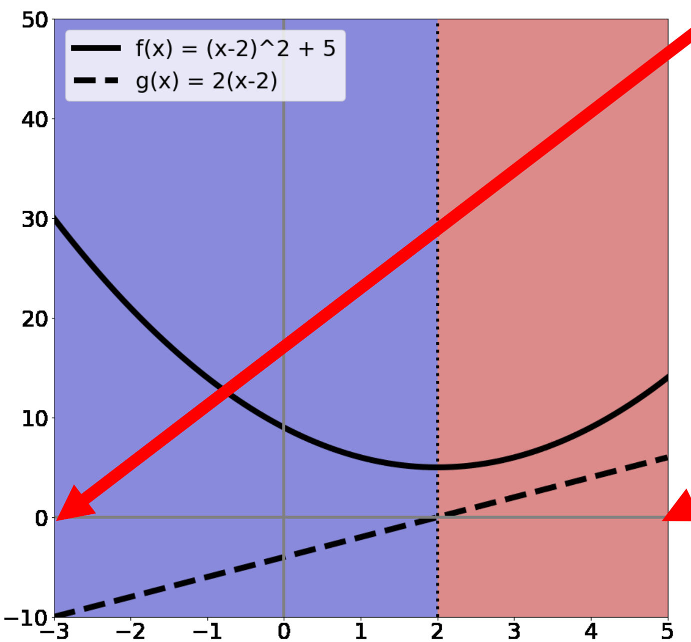


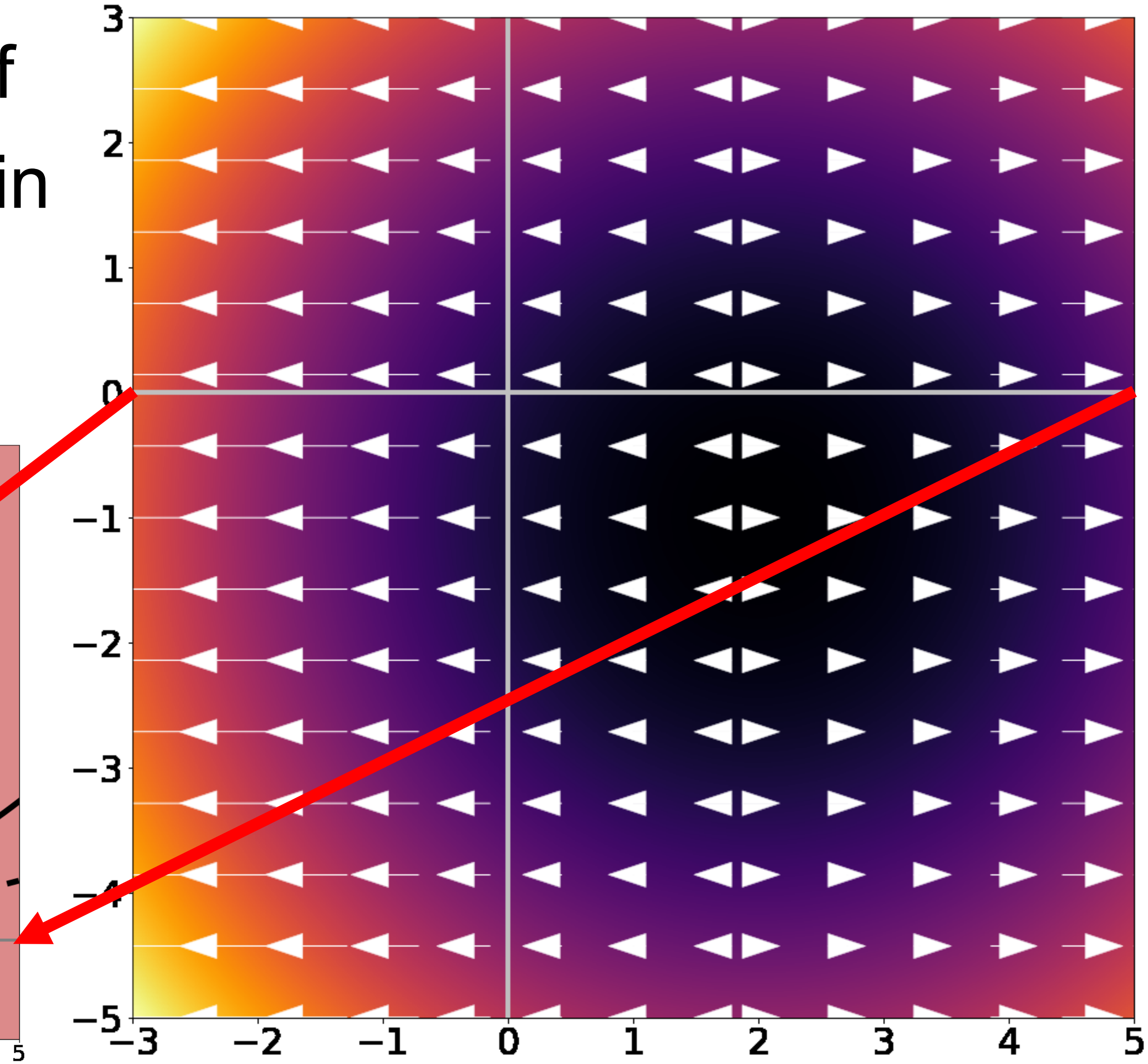


Taking a slice of

$$f_2(x, y) = (x-2)^2 + 5 + (y+1)^2$$

$\frac{\partial}{\partial x} f_2(x, y)$ is rate of change & direction in x dimension





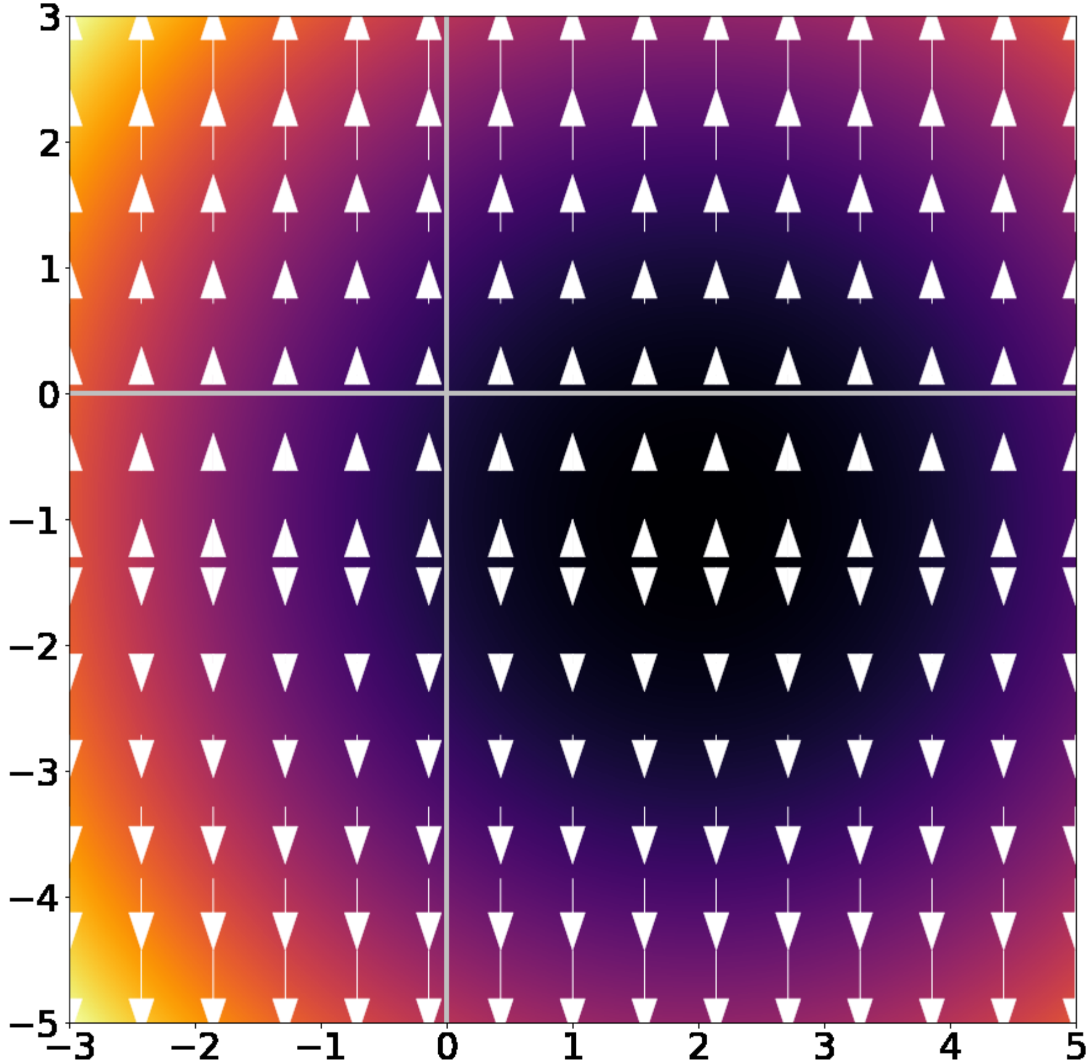
Zooming Out

$$f_2(x, y) = (x-2)^2 + 5 + (y+1)^2$$

$\frac{\partial}{\partial y} f_2(x, y)$ is

$2(y+1)$

and is the rate of change & direction in y dimension



Zooming Out

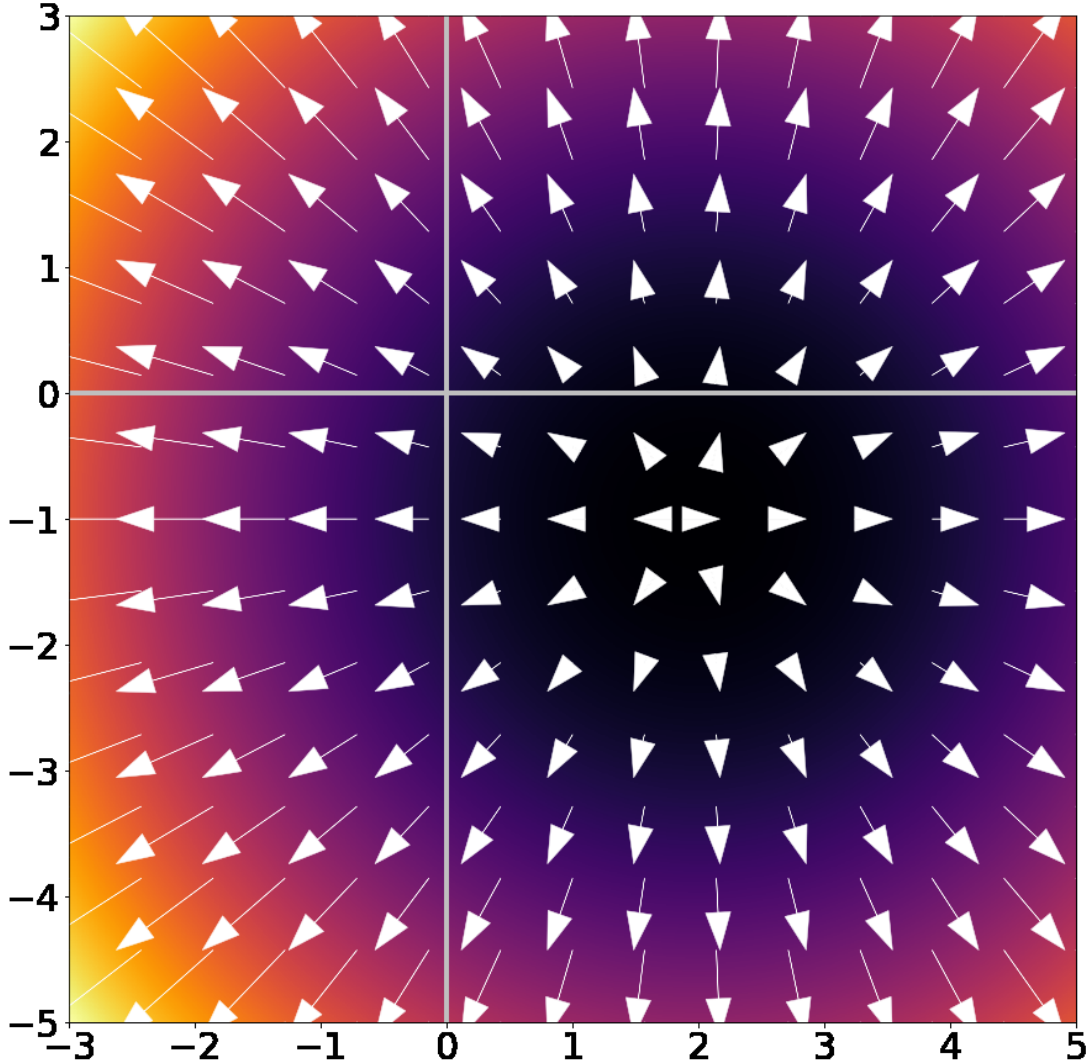
$$f_2(x, y) = (x-2)^2 + 5 + (y+1)^2$$

Gradient/Jacobian: Making a vector of

$$\nabla_f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

gives rate and direction of change.

Arrows point OUT of minimum / basin.



What Should I Know?

- Gradients are simply partial derivatives per-dimension: if $\boldsymbol{x}$ in $f(\boldsymbol{x})$ has n dimensions, $\nabla_f(x)$ has n dimensions
- Gradients point in direction of ascent and tell the rate of ascent
- If a is minimum of $f(\boldsymbol{x}) \rightarrow \nabla_{\mathrm{f}}(\mathrm{a}) = \mathbf{0}$
- Reverse is not true, especially in high-dimensional spaces

Last Time

$$(Ix^2 + Iy^2)^{1/2}$$

Why Does This Work?

Image is function f(x,y)

Remember:

$$\frac{\partial f(x,y)}{\partial x} = \lim_{\epsilon \to 0} \frac{f(x+\epsilon,y) - f(x,y)}{\epsilon}$$

Approximate:

-1	1

$$\frac{\partial f(x,y)}{\partial x} \approx \frac{f(x+1,y) - f(x,y)}{1}$$

Another one:

-1	0	1

$$\frac{\partial f(x,y)}{\partial x} \approx \frac{f(x+1,y) - f(x-1,y)}{2}$$

Other Differentiation Operations

	Horizontal	Vertical
Prewitt	$\begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$
Sobel	$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$

Why might people use these compared to [-1,0,1]?

Images as Functions or Points

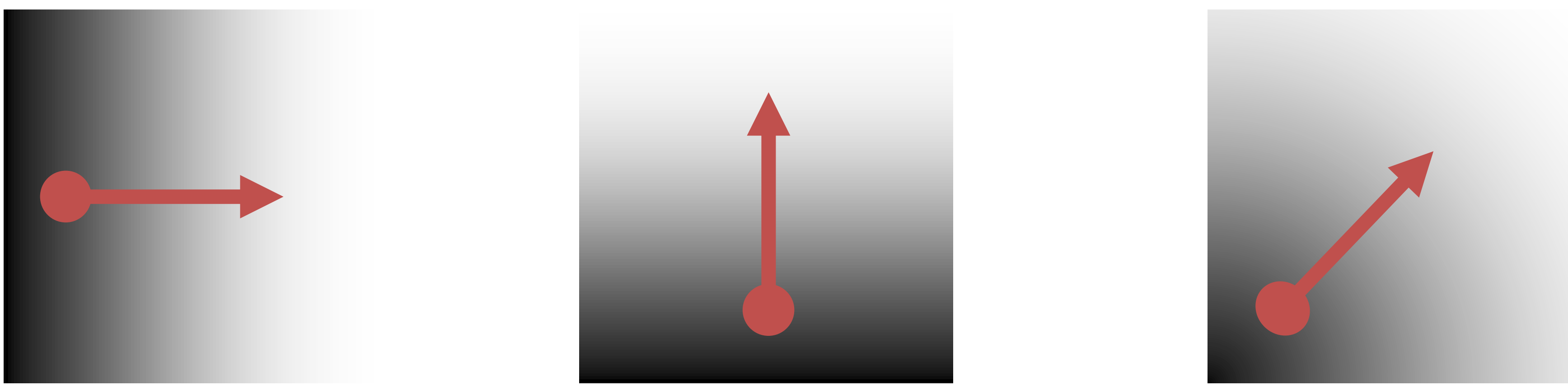
Key idea: can treat image as a point in $R^{(HxW)}$ or as a function of x,y.

$$\nabla I(x,y) = \begin{bmatrix} \frac{\partial I}{\partial x}(x,y) \\ \\ \frac{\partial I}{\partial y}(x,y) \end{bmatrix}$$

How much the intensity of the image changes as you go horizontally at (x,y)
(Often called Ix)

Image Gradient Direction

Some gradients



$$\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$$

$$\nabla f = \left[0, \frac{\partial f}{\partial y}\right]$$

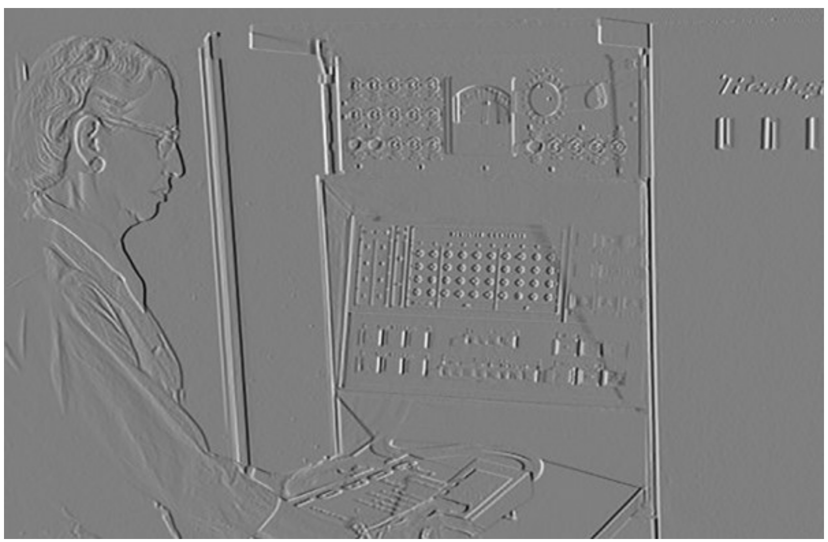
$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

Figure Credit: S. Seitz

Image Gradient

Gradient: direction of maximum change.
What’s the relationship to edge direction?

Ix



Iy

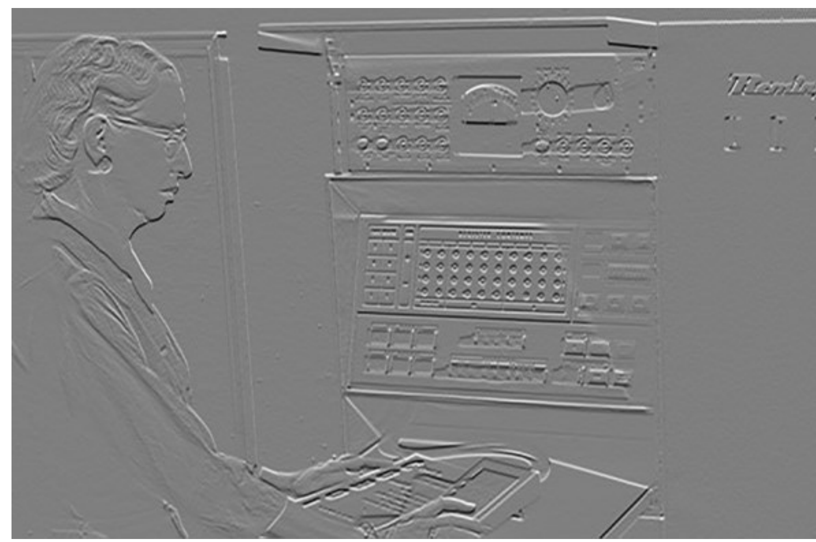
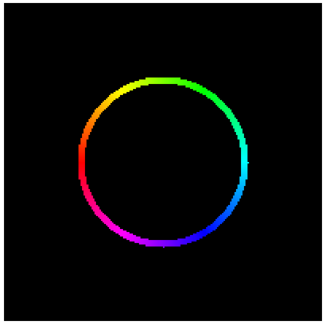


Image Gradient

$(Ix^2 + Iy^2)^{1/2}$: magnitude

Image Gradient

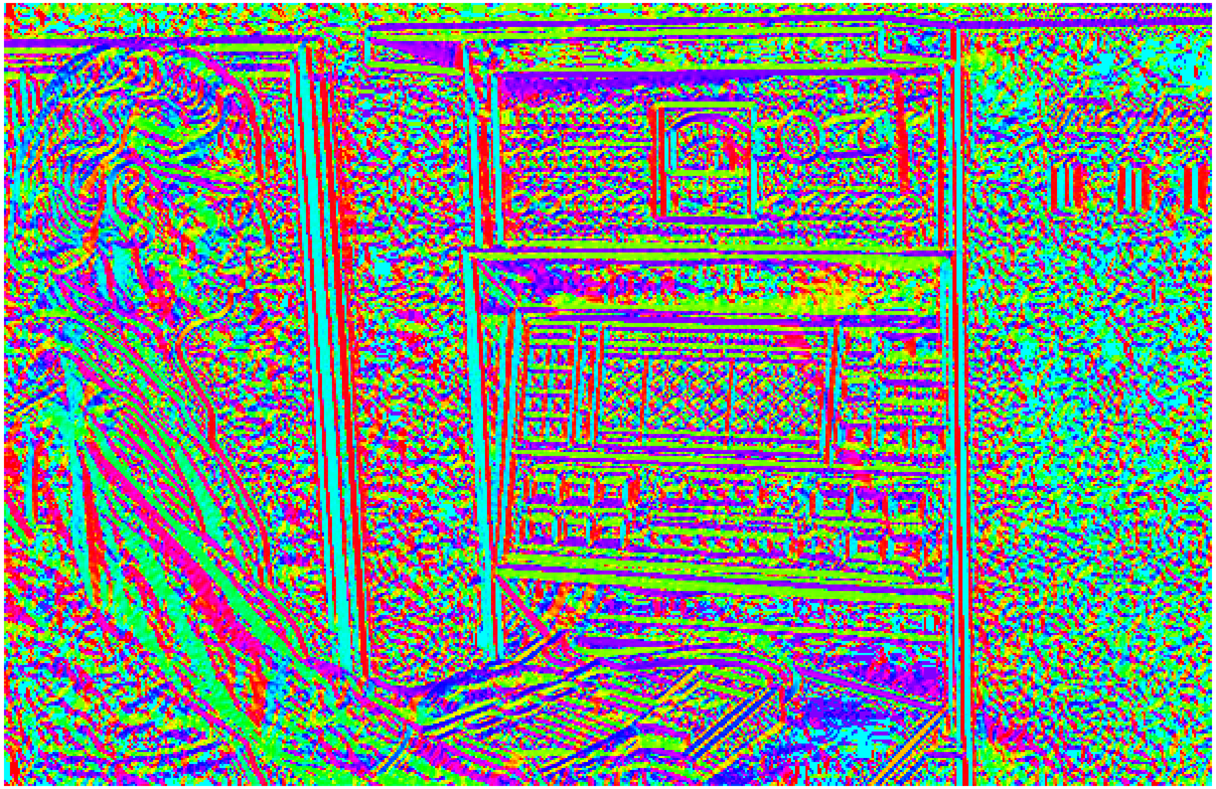
atan2(Iy,Ix): orientation

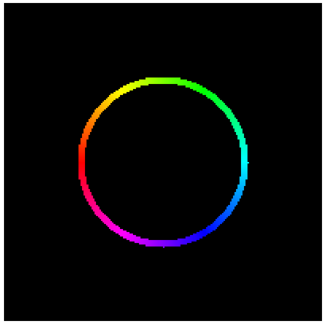


I'm making the lightness equal to gradient magnitude

Image Gradient

atan2(Iy,Ix): orientation



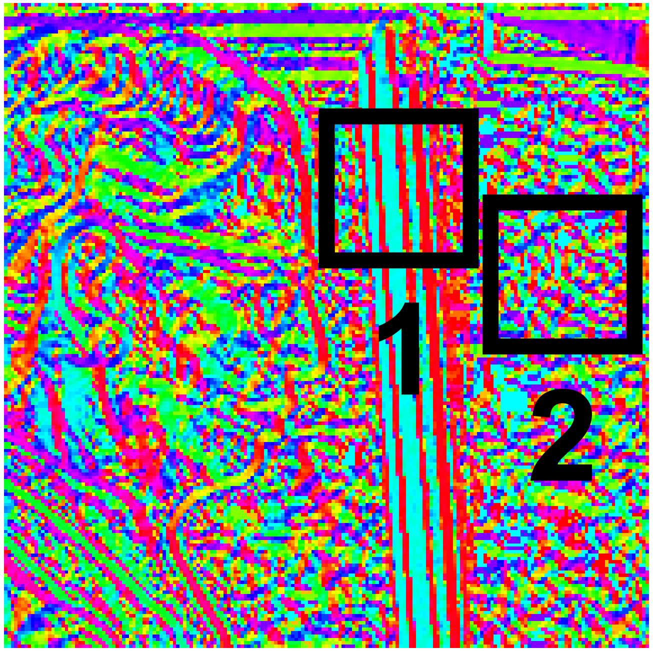


Now I'm showing *all* the gradients

Image Gradient

atan2(Iy,Ix): orientation

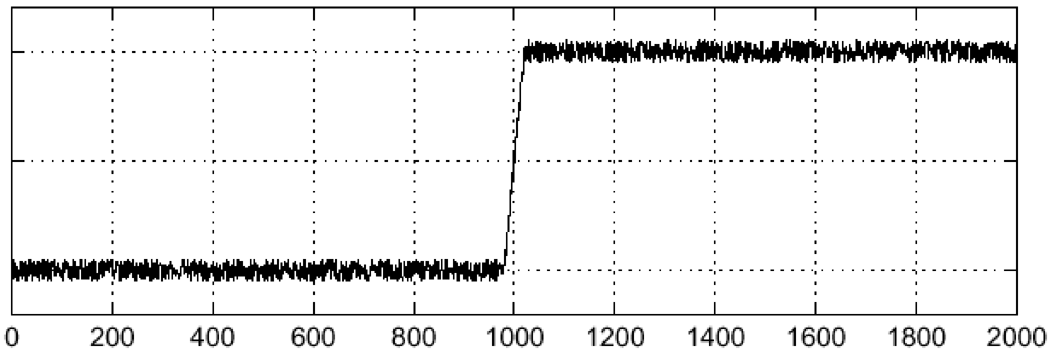
Why is there structure at 1 and not at 2?



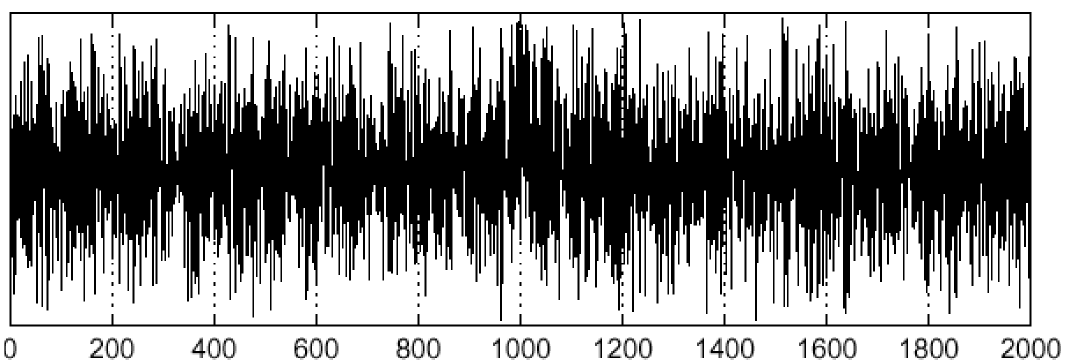
Noise

Consider a row of f(x,y) (i.e., fix y)

$f(x)$



$\frac{d}{dx}f(x)$



Slide Credit: S. Seitz

Noise

Conv. image + per-pixel noise with

-1	0	1

$I_{i,j} =$ True image $\quad \epsilon_{i,j} \sim N(0, \sigma^2)$

$$D_{i,j} = (I_{i,j+1} + \epsilon_{i,j+1}) - (I_{i,j-1} + \epsilon_{i,j-1})$$

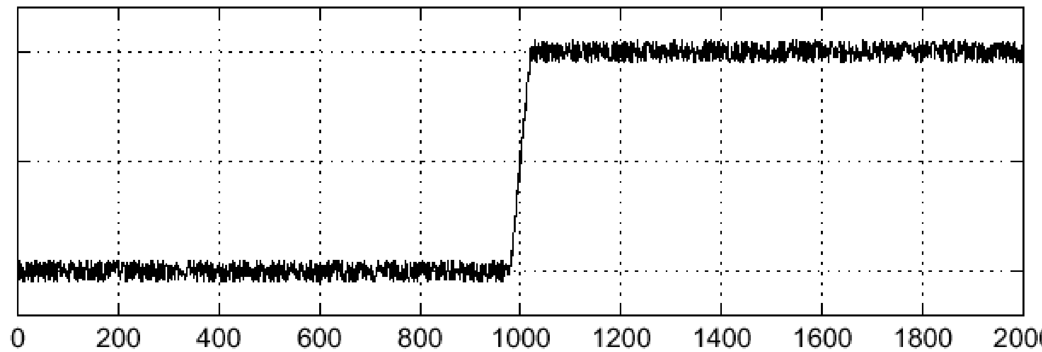
$$D_{i,j} = \underbrace{(I_{i,j+1} - I_{i,j-1})}_{\text{True difference}} + \underbrace{\epsilon_{i,j+1} - \epsilon_{i,j-1}}_{\text{Sum of 2 Gaussians}}$$

$\epsilon_{i,j} - \epsilon_{k,l} \sim N(0, 2\sigma^2) \rightarrow$ Variance doubles!

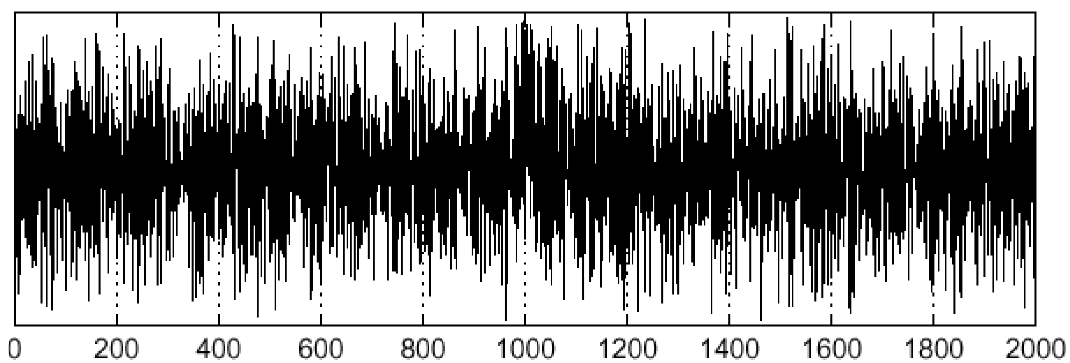
Noise

Consider a row of f(x,y) (i.e., make y constant)

$f(x)$



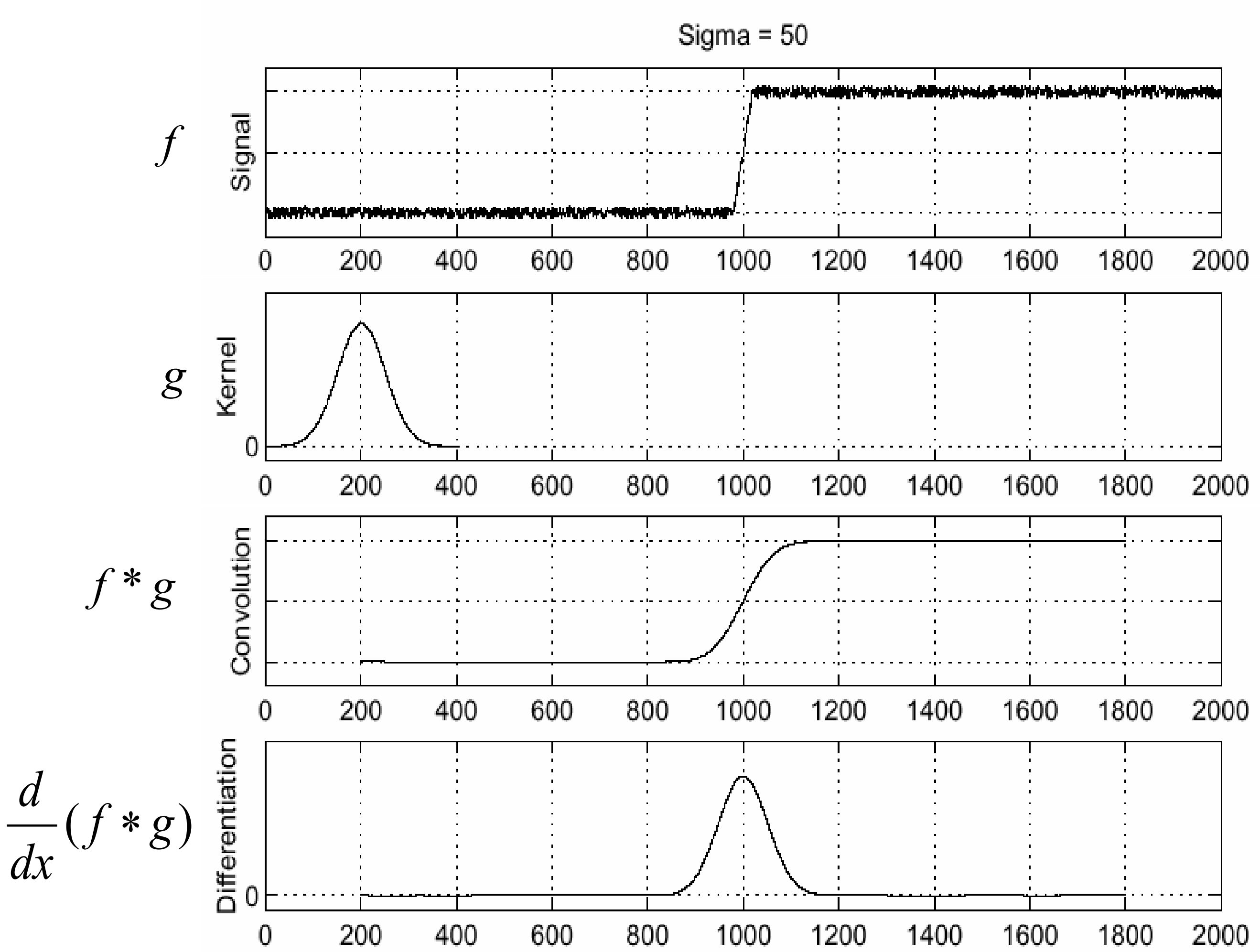
$\frac{d}{dx}f(x)$



How can we use the last class to fix this?

Slide Credit: S. Seitz

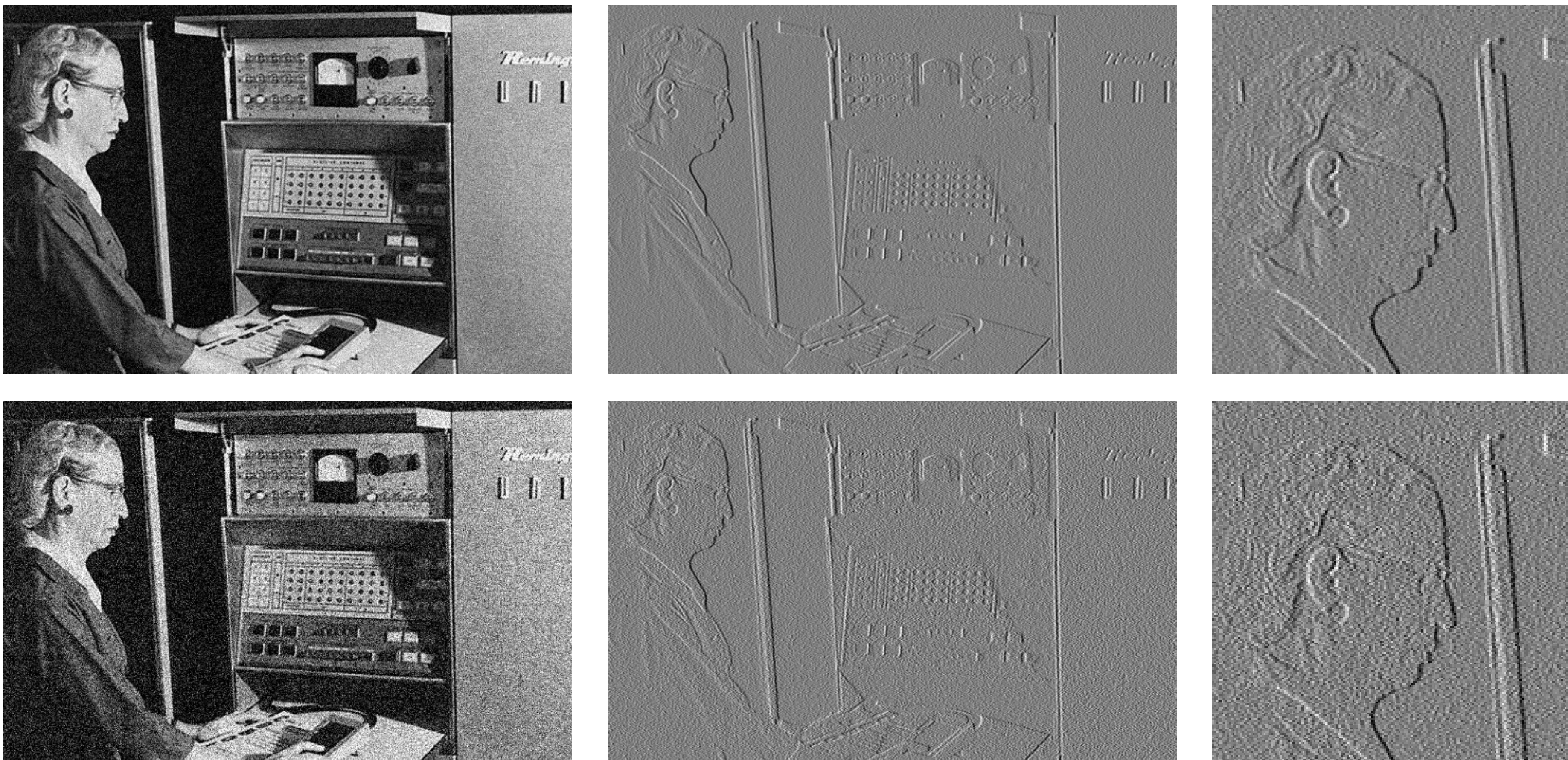
Handling Noise



Slide Credit: S. Seitz

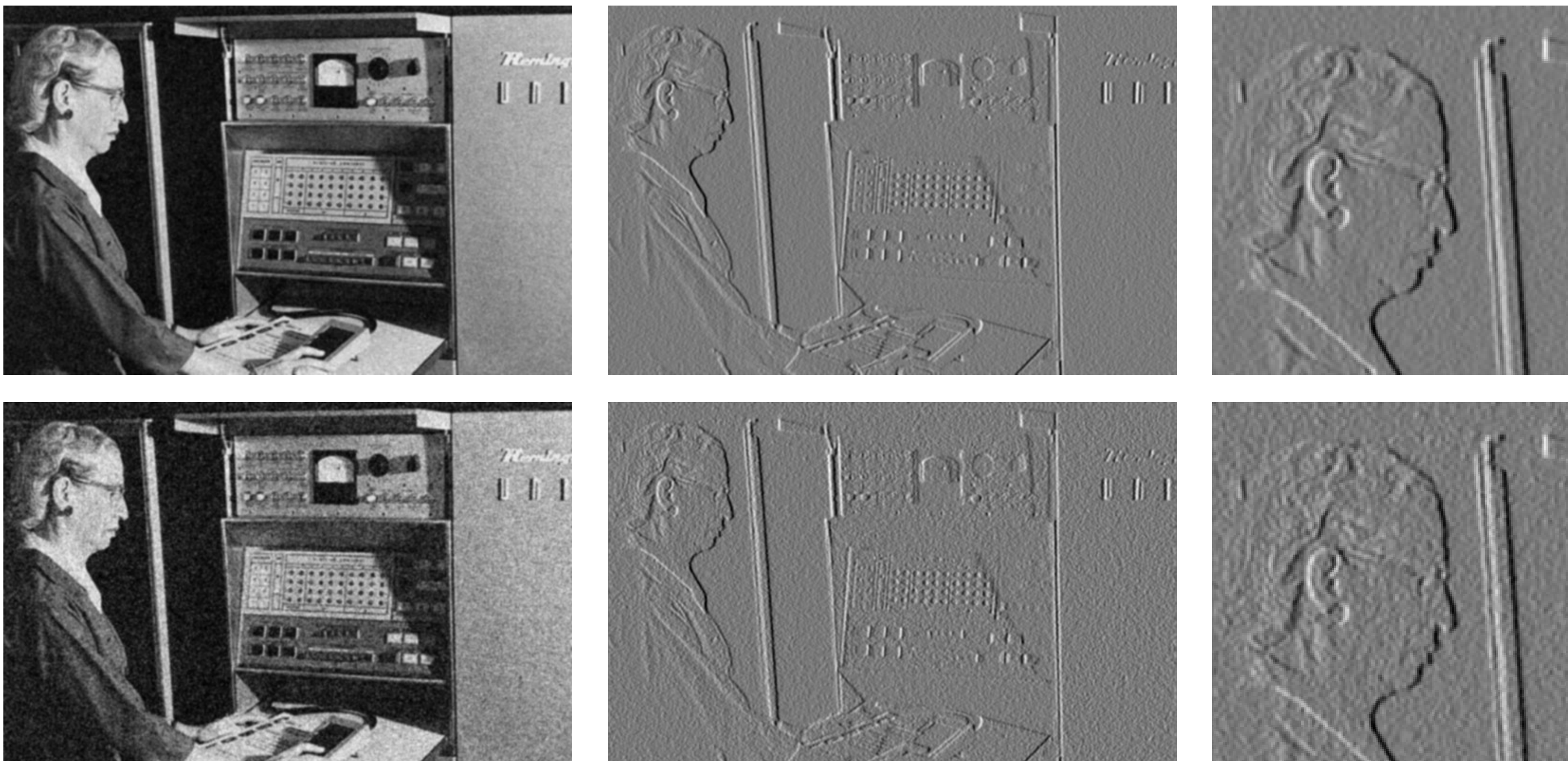
Noise in 2D

Noisy Input | Ix via [-1,01] | Zoom



Noise + Smoothing

Smoothed Input | Ix via [-1,01] | Zoom



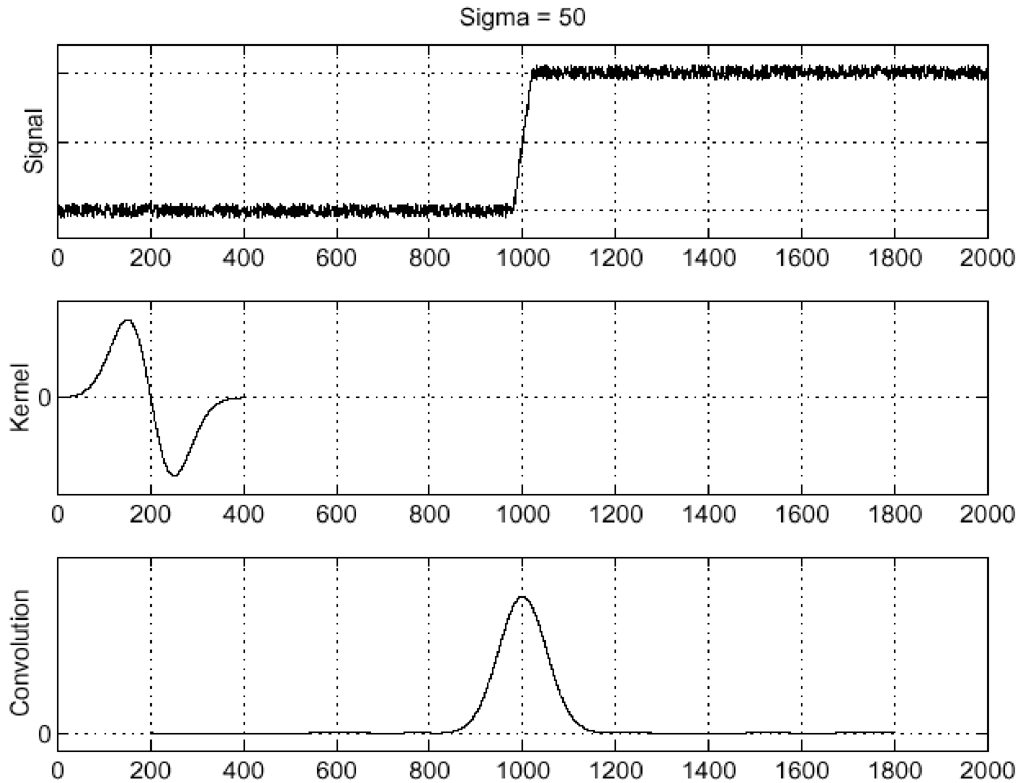
Let’s Make It One Pass (1D)

$$\frac{d}{dx}(f * g) = f * \frac{d}{dx} g$$

f

$\frac{d}{dx} g$

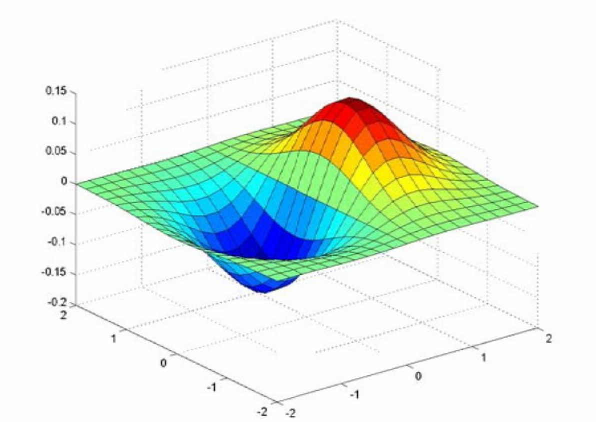
$f * \frac{d}{dx} g$

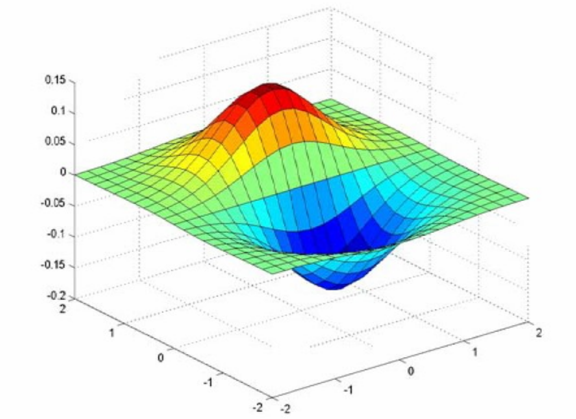


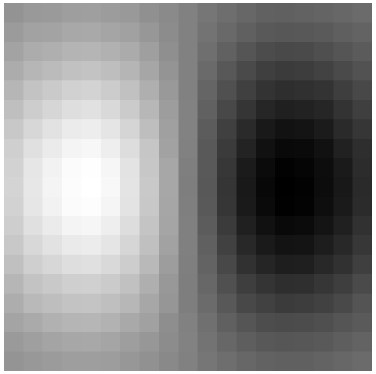
Slide Credit: S. Seitz

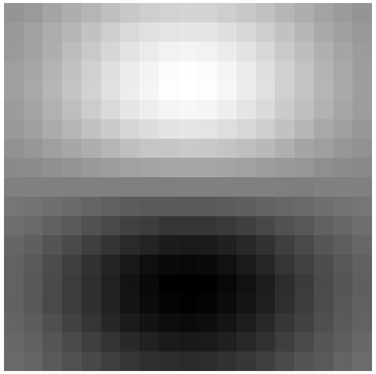
Let's Make It One Pass (2D)

Gaussian Derivative Filter







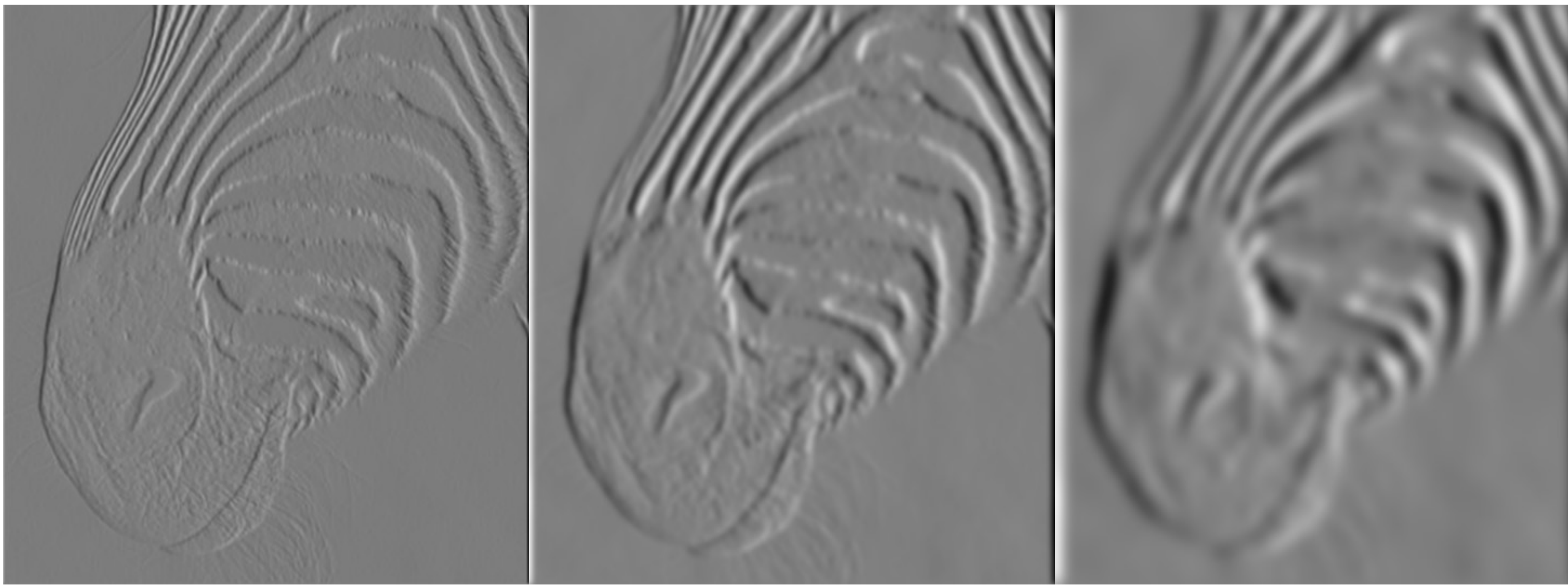


Which one finds the X direction?

Slide Credit: L. Lazebnik

Applying the Gaussian Derivative

1 pixel 3 pixels 7 pixels

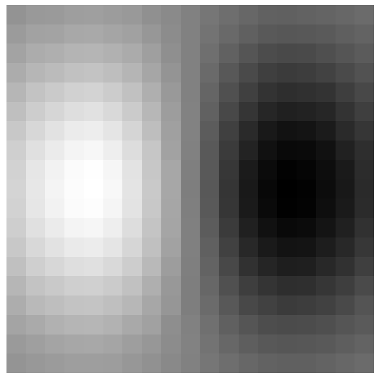


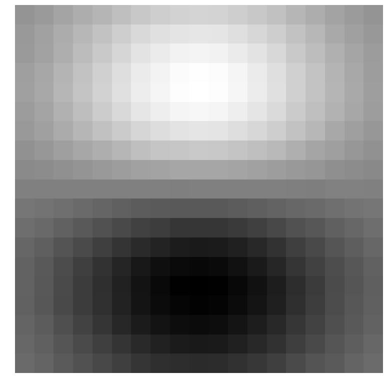
Removes noise, but blurs edge

Slide Credit: D. Forsyth

Compared with the Past

Gaussian Derivative



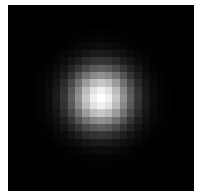
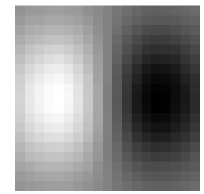
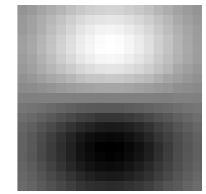


Sobel Filter

$$\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \qquad \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

Why would anybody use the bottom filter?

Filters We've Seen

	Smoothing	Derivative
		 
Example	Gaussian	Deriv. of gauss
Goal	Remove noise	Find edges
Only +?	**Yes**	**No**
Sums to	1	0

Why sum to 1 or 0, intuitively?

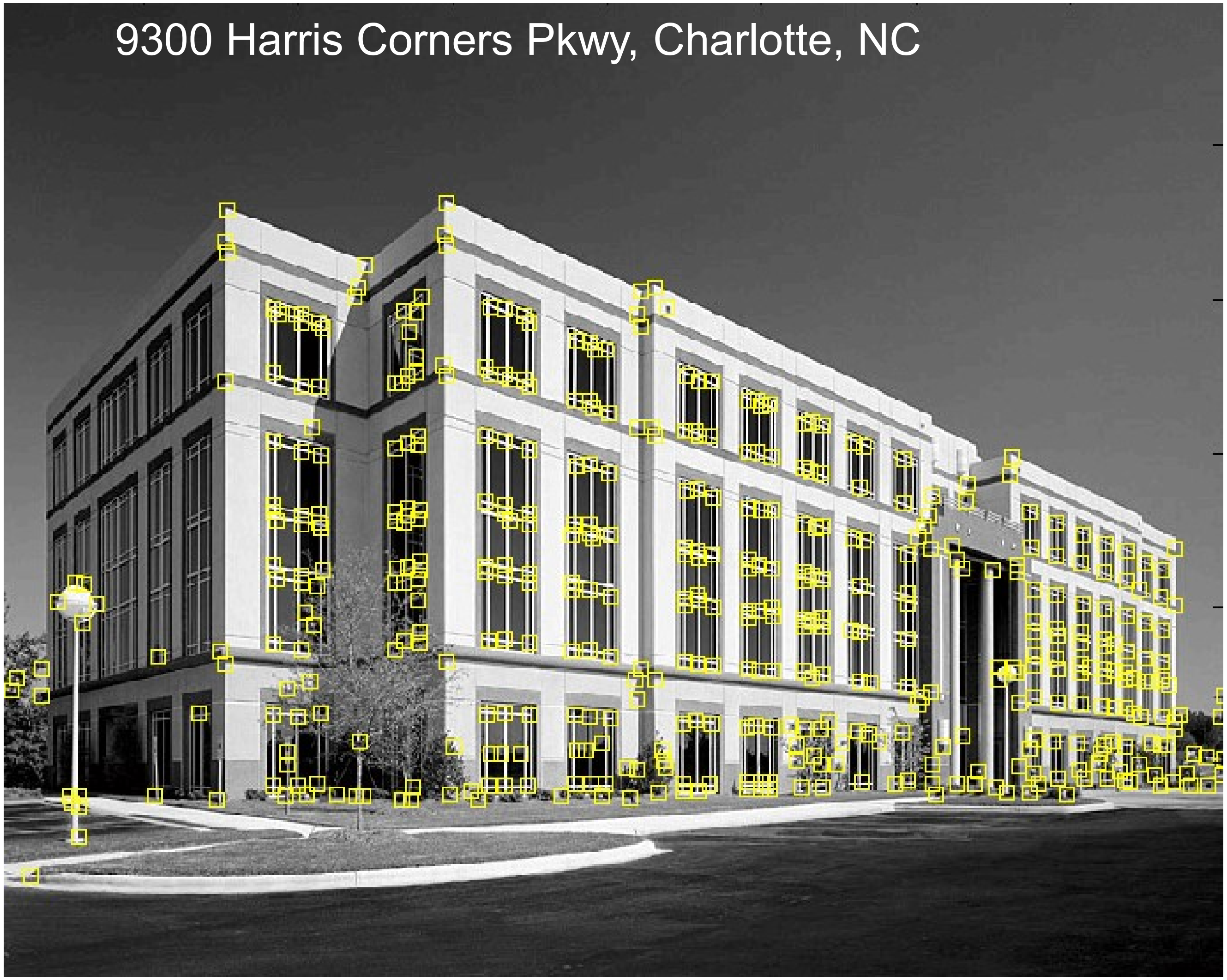
Slide Credit: J. Deng

Problems

Image | human segmentation | gradient magnitude

Still an active area of research

Corners



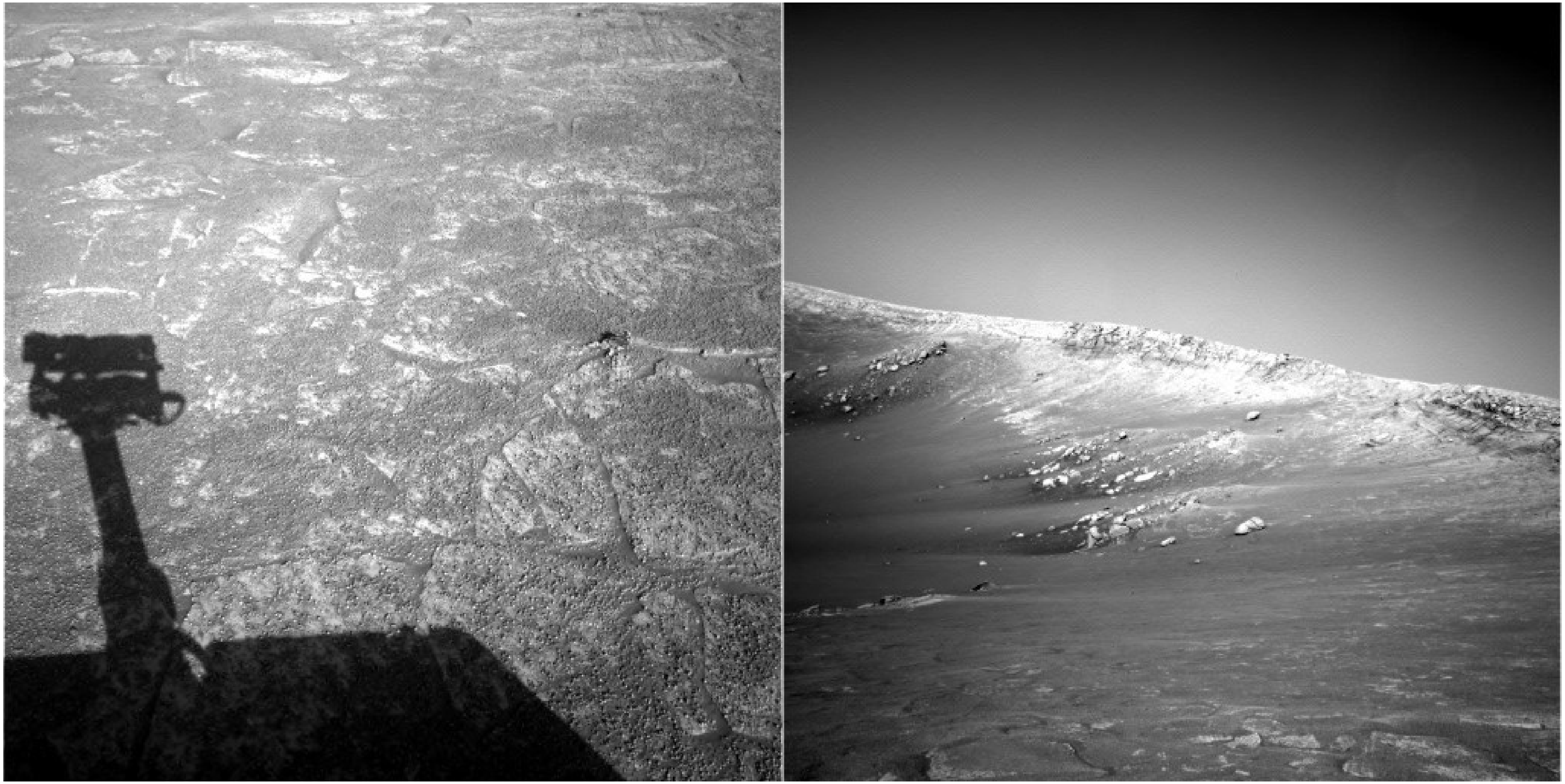
Slide Credit: S. Lazebnik

Desirables

- Repeatable: should find same things even with distortion
- Saliency: each feature should be distinctive
- Compactness: shouldn’t just be all the pixels
- Locality: should only depend on local image data

Property list: S. Lazebnik

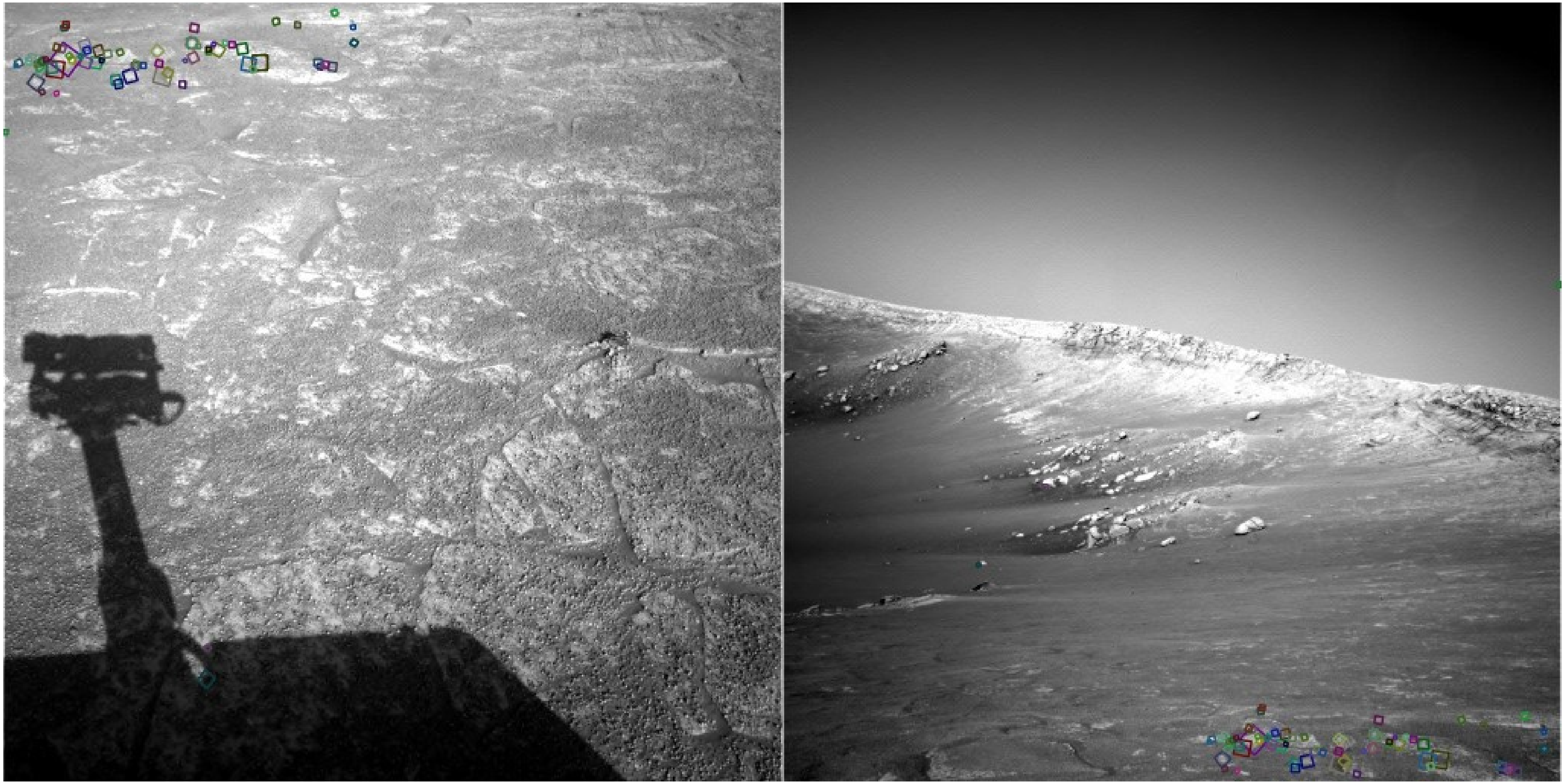
Example



Can you find the correspondences?

Slide credit: N. Snavely

Example Matches

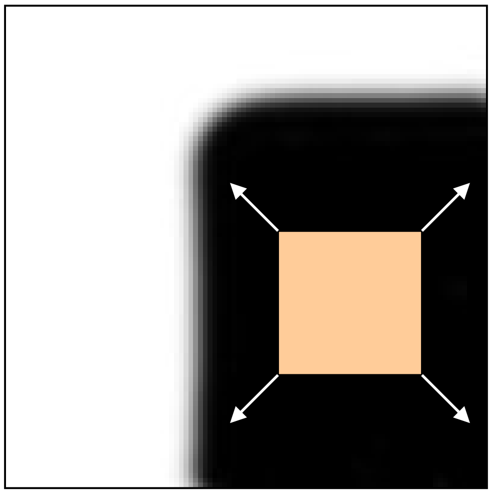


Look for the colored squares

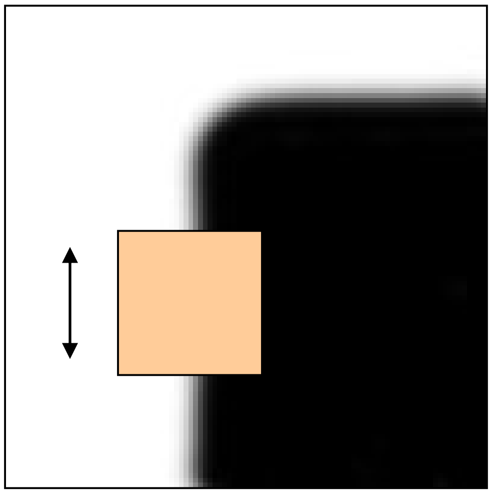
Slide credit: N. Snavely

Basic Idea

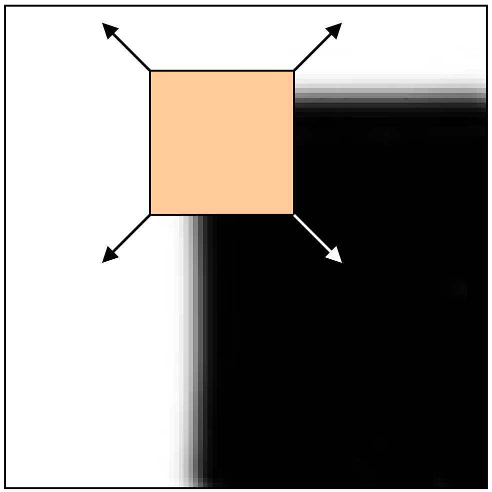
Should see where we are based on small window, or any shift → big intensity change.



"flat" region:
no change in all directions



"edge":
no change along the edge direction



"corner":
significant change in all directions

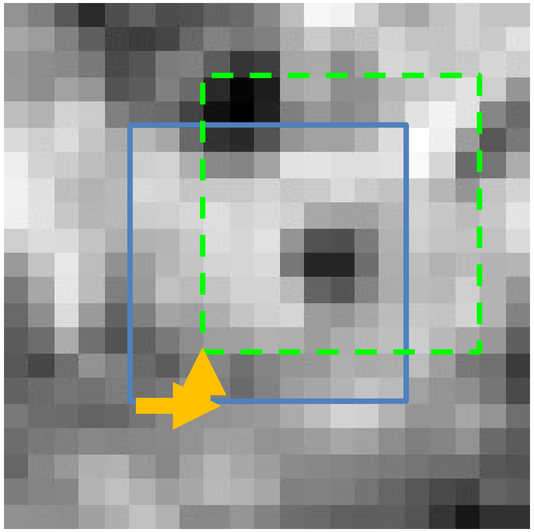
Slide Credit: S. Lazebnik

Formalizing Corner Detection

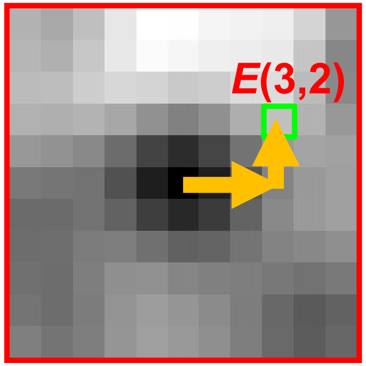
Sum of squared differences between image and image shifted u,v pixels over.

$$E(u,v) = \sum_{(x,y)\in W} \left(I[x+u, y+v] - I[x,y]\right)^2$$

Image I(x,y)



Plot of E(u,v)



Slide Credit: S. Lazebnik

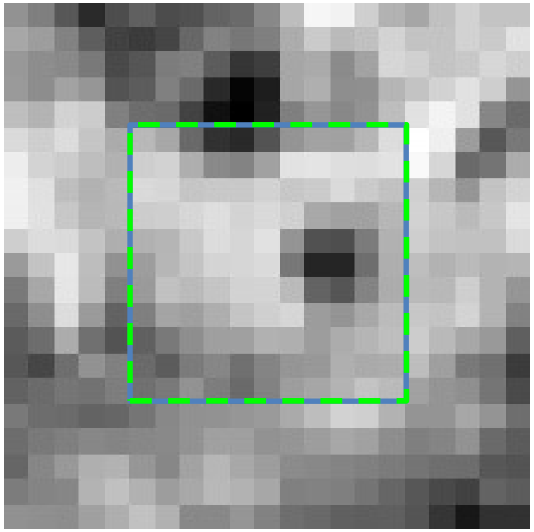
Formalizing Corner Detection

Sum of squared differences between image and image shifted u,v pixels over.

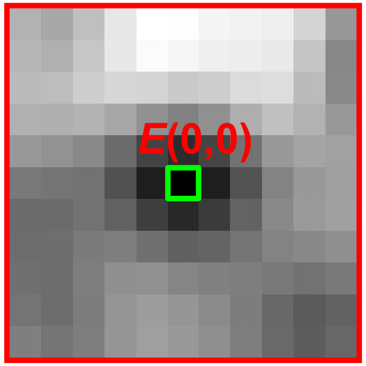
$$E(u,v) = \sum_{(x,y)\in W} (I[x+u, y+v] - I[x,y])^2$$

What's the value of E(0,0)?

Image I(x,y)



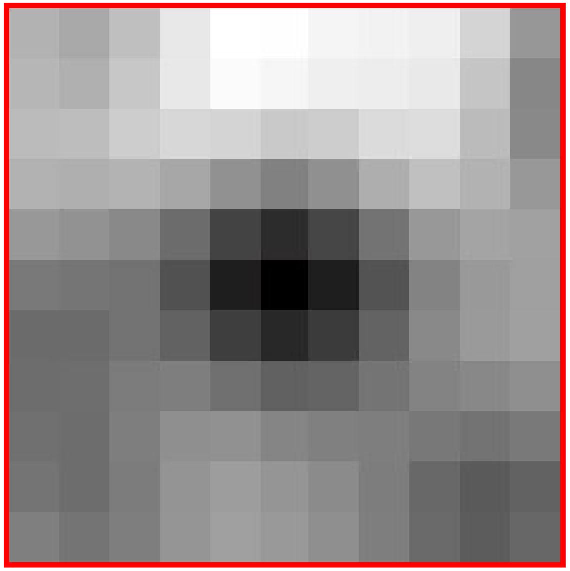
Plot of E(u,v)



Slide Credit: S. Lazebnik

Formalizing Corner Detection

Can compute E[u,v] for any window and u,v.
But we'd like an simpler function of u,v.



Slide Credit: S. Lazebnik

Aside: Taylor Series for Images

Recall Taylor Series:

$$f(x+d) \approx f(x) + \frac{\partial f}{\partial x} d$$

Do the same with images, treating them as function of x, y

$$I(x+u, y+v) \approx I(x,y) + I_x u + I_y v$$

Formalizing Corner Detection

$$E(u,v) = \sum_{(x,y)\in W} (I[x+u, y+v] - I[x,y])^2$$

Taylor series expansion for I at every single point in window

$$\approx \sum_{(x,y)\in W} \left(I[x,y] + I_x[x,y]u + I_y[x,y]v - I[x,y]\right)^2$$

Cancel

$$= \sum_{(x,y)\in W} \left(I_x[x,y]u + I_y[x,y]v\right)^2$$

Expand

$$= \sum_{(x,y)\in W} I_x u^2 + 2I_x I_y uv + I_y^2 v^2$$

For brevity: Ix = Ix at point (x,y), Iy = Iy at point (x,y)

Formalizing corner Detection

By linearizing image, we can approximate E(u,v) with quadratic function of u and v

$$E(u,v) \approx \sum_{(x,y)\in W} \left(I_x^2 u^2 + 2 I_x I_y uv + I_y^2 v^2 \right)$$

$$= [u,v]\boldsymbol{M}[u,v]^T$$

$$\boldsymbol{M} = \begin{bmatrix} \sum_{x,y\in W} I_x^2 & \sum_{x,y\in W} I_x I_y \\ \sum_{x,y\in W} I_x I_y & \sum_{x,y\in W} I_y^2 \end{bmatrix}$$

M is called the second moment matrix

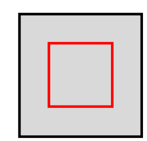
Intuitively what is M?

Pretend for now gradients are either vertical or horizontal at a pixel (so Ix Iy = 0)

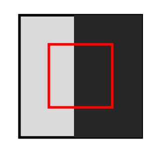
Obviously Wrong!

$$\boldsymbol{M} = \begin{bmatrix} \sum_{x,y \in W} I_x^2 & \sum_{x,y \in W} I_x I_y \\ \sum_{x,y \in W} I_x I_y & \sum_{x,y \in W} I_y^2 \end{bmatrix} = \begin{bmatrix} a & 0 \\ 0 & b \end{bmatrix}$$

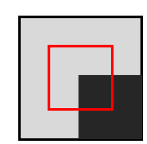
If a,b are both small: flat



If one is big, one is small: edge



If a,b both big: corner



Review: Quadratic Forms

Suppose have symmetric matrix **M,** scalar a, vector [u,v]:

$$E([u,v]) = [u,v]\boldsymbol{M}[u,v]^T$$

Then the isocontour / slice-through of F, i.e.

$$E([u,v]) = a$$

is an ellipse.

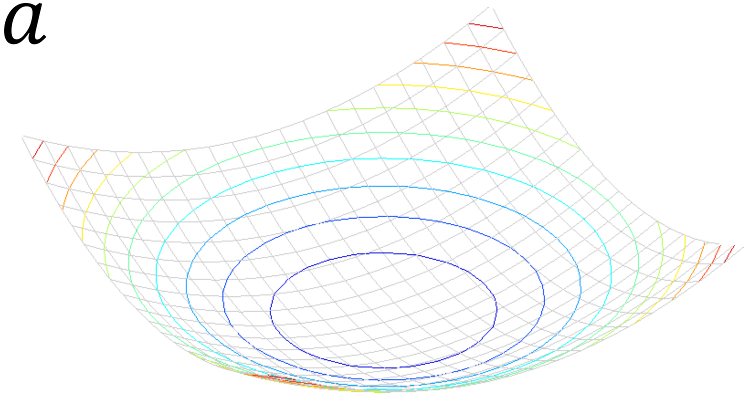


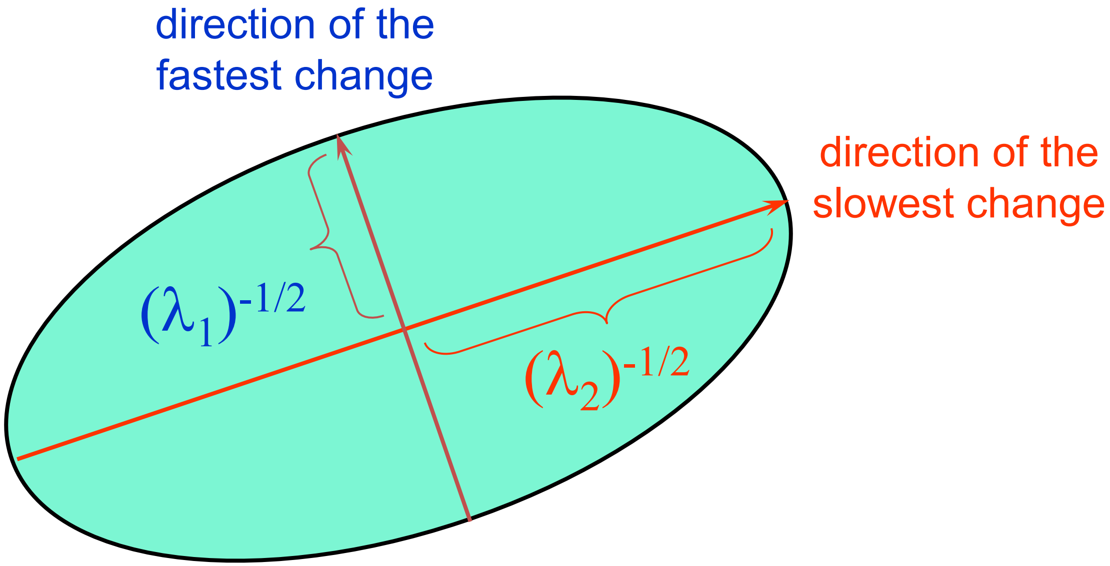
Diagram credit: S. Lazebnik

Review: Quadratic Forms

We can look at the shape of this ellipse by decomposing M into a rotation + scaling

$$\boldsymbol{M} = \boldsymbol{R}^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \boldsymbol{R}$$

What are λ_1 and λ_2?



Slide credit: S. Lazebnik

Interpreting The Matrix M

The second moment matrix tells us how quickly the image changes and in which directions.

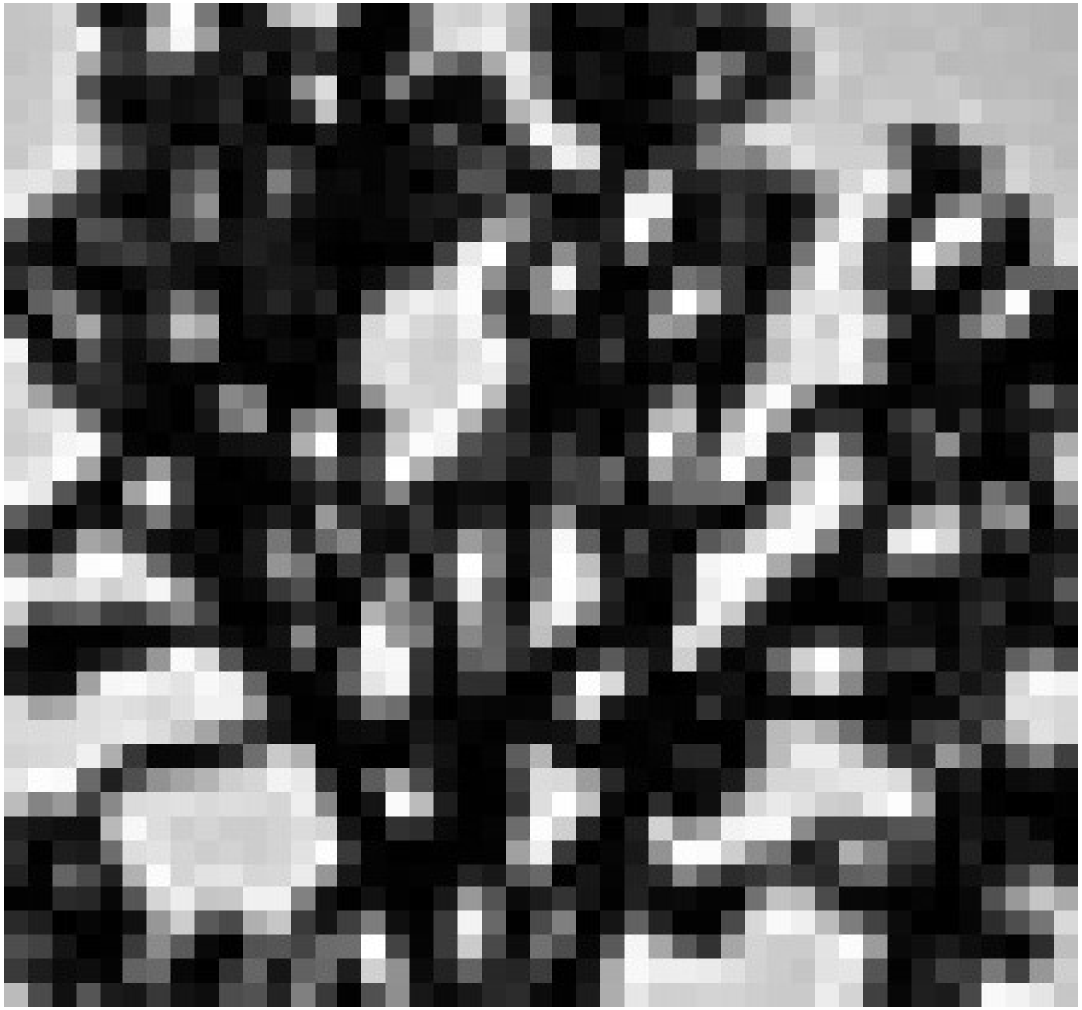
Can compute at each pixel

Directions

$$\boldsymbol{M} = \begin{bmatrix} \sum_{x,y \in W} I_x^2 & \sum_{x,y \in W} I_x I_y \\ \sum_{x,y \in W} I_x I_y & \sum_{x,y \in W} I_y^2 \end{bmatrix} = \boldsymbol{R}^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \boldsymbol{R}$$

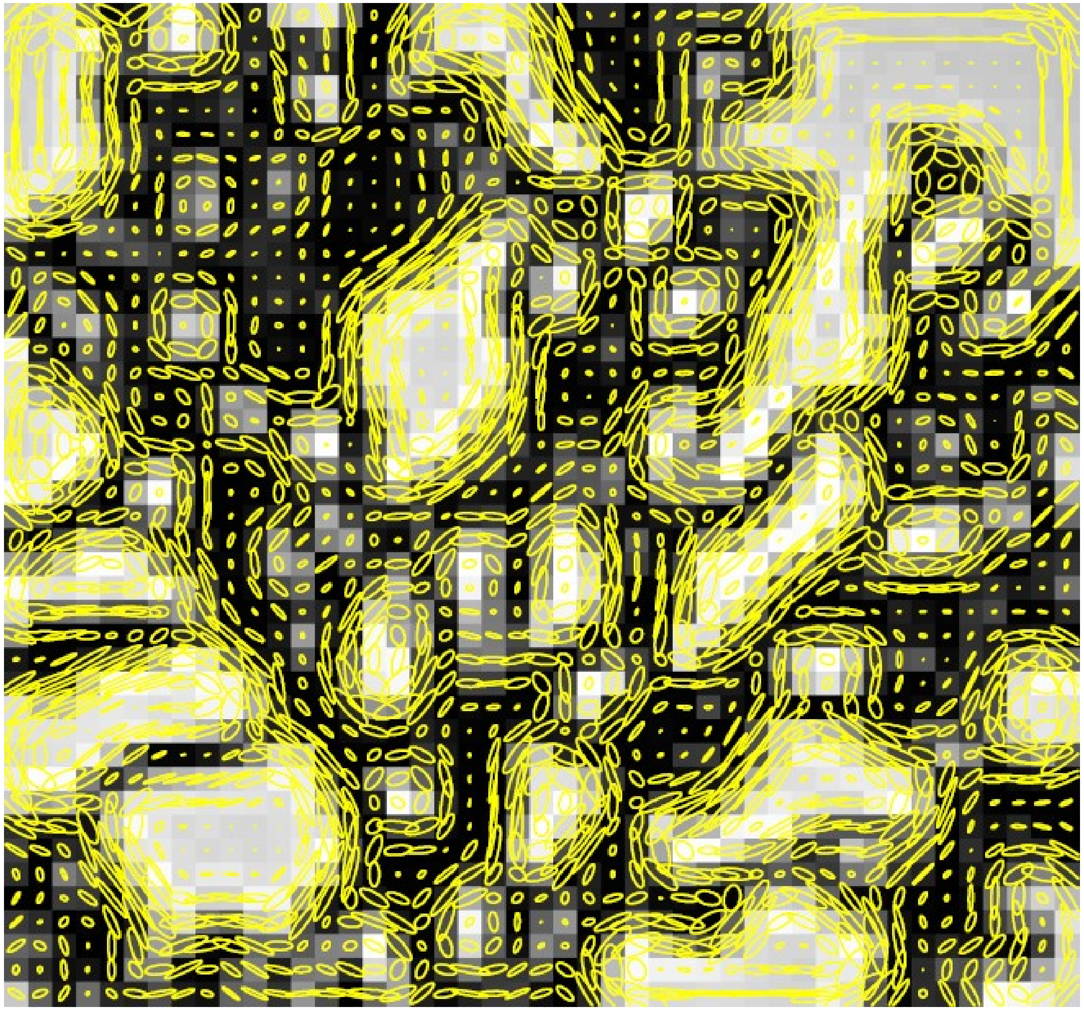
Amounts

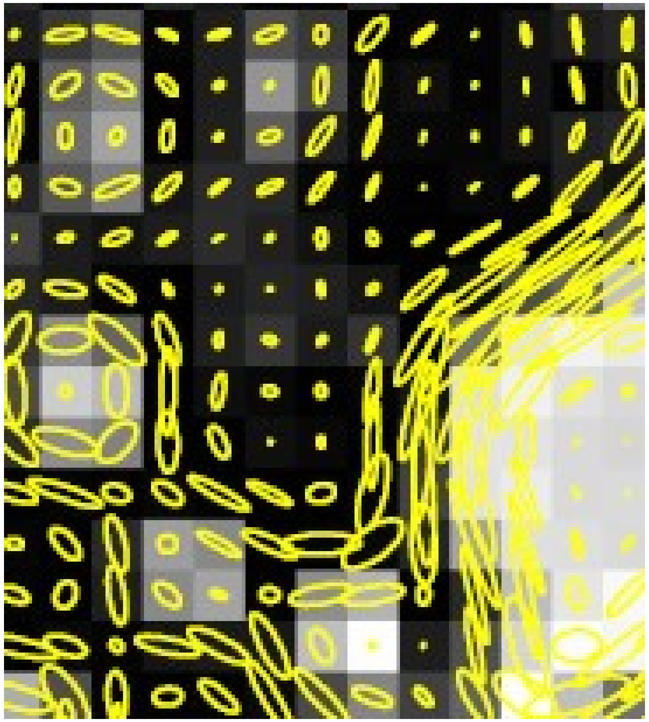
Visualizing M



Slide credit: S. Lazebnik

Visualizing M

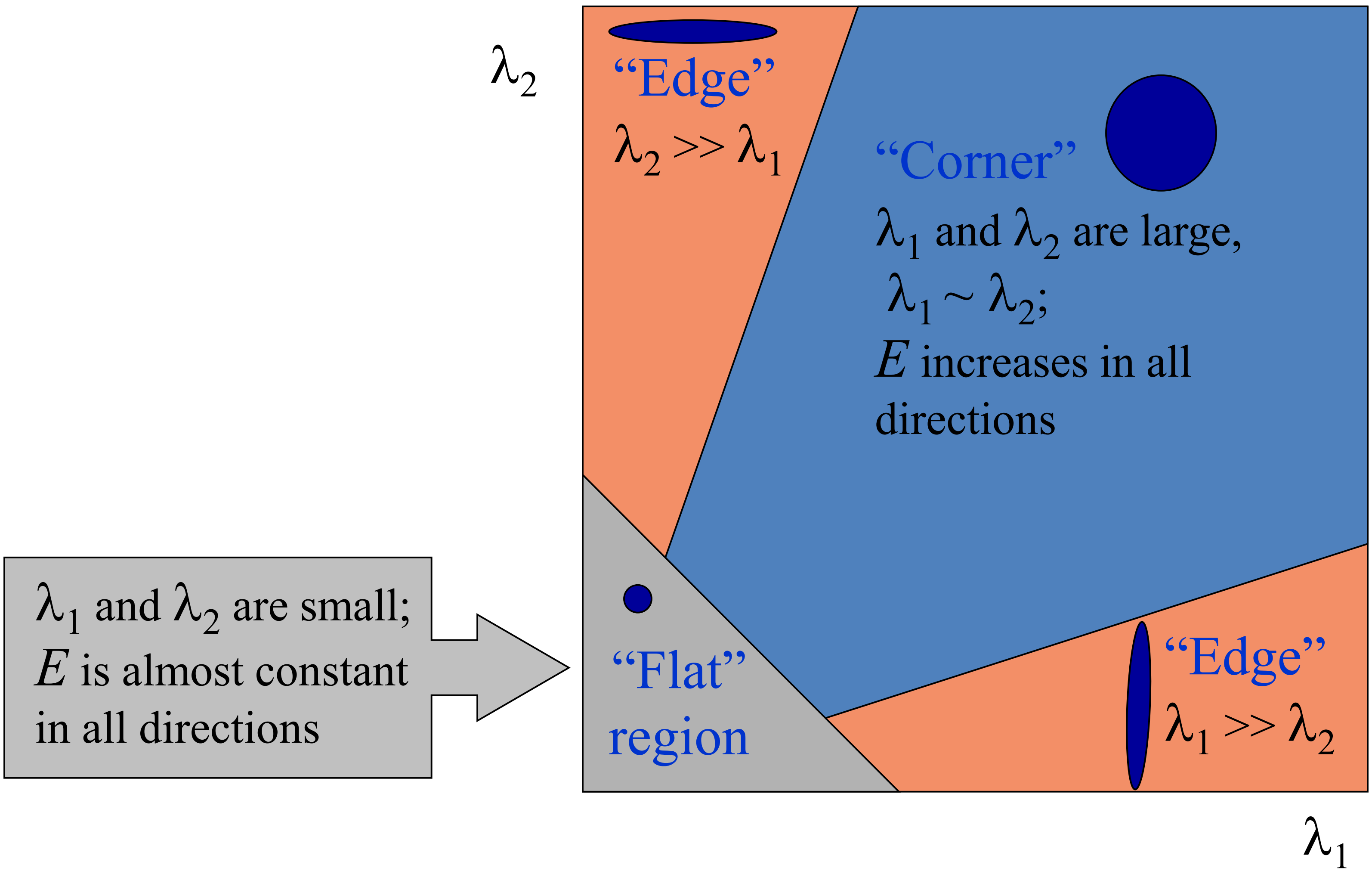




Technical note: M is often best *visualized* by first taking inverse, so long edge of ellipse goes along edge

Slide credit: S. Lazebnik

Interpreting Eigenvalues of M

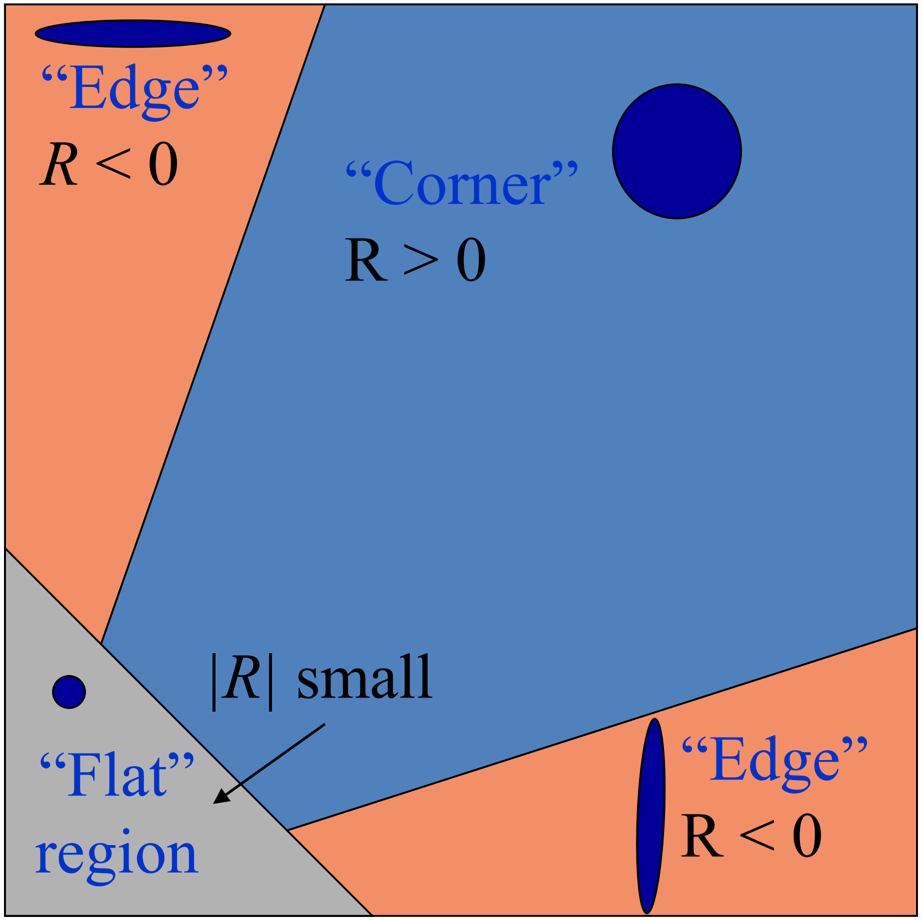


Slide credit: S. Lazebnik; Note: this refers to previous ellipses, not original M ellipse. Other slides on the internet may vary

Putting Together The Eigenvalues

$$R = \det(\boldsymbol{M}) - \alpha\, trace(\boldsymbol{M})^2$$
$$= \lambda_1\lambda_2 - \alpha(\lambda_1 + \lambda_2)^2$$

α: constant (0.04 to 0.06)



Slide credit: S. Lazebnik; Note: this refers to previous ellipses, not original M ellipse. Other slides on the internet may vary

In Practice

1. Compute partial derivatives Ix, Iy per pixel
2. Compute **M** at each pixel, using Gaussian weighting w

$$\boldsymbol{M} = \begin{bmatrix} \sum_{x,y \in W} w(x,y) I_x^2 & \sum_{x,y \in W} w(x,y) I_x I_y \\ \sum_{x,y \in W} w(x,y) I_x I_y & \sum_{x,y \in W} w(x,y) I_y^2 \end{bmatrix}$$

C.Harris and M.Stephens. [“A Combined Corner and Edge Detector.”] *Proceedings of the 4th Alvey Vision Conference*: pages 147—151, 1988.

Slide credit: S. Lazebnik

In Practice

1. Compute partial derivatives Ix, Iy per pixel
2. Compute **M** at each pixel, using Gaussian weighting w
3. Compute response function R

$$R = \det(\boldsymbol{M}) - \alpha \, trace(\boldsymbol{M})^2$$
$$= \lambda_1 \lambda_2 - \alpha(\lambda_1 + \lambda_2)^2$$

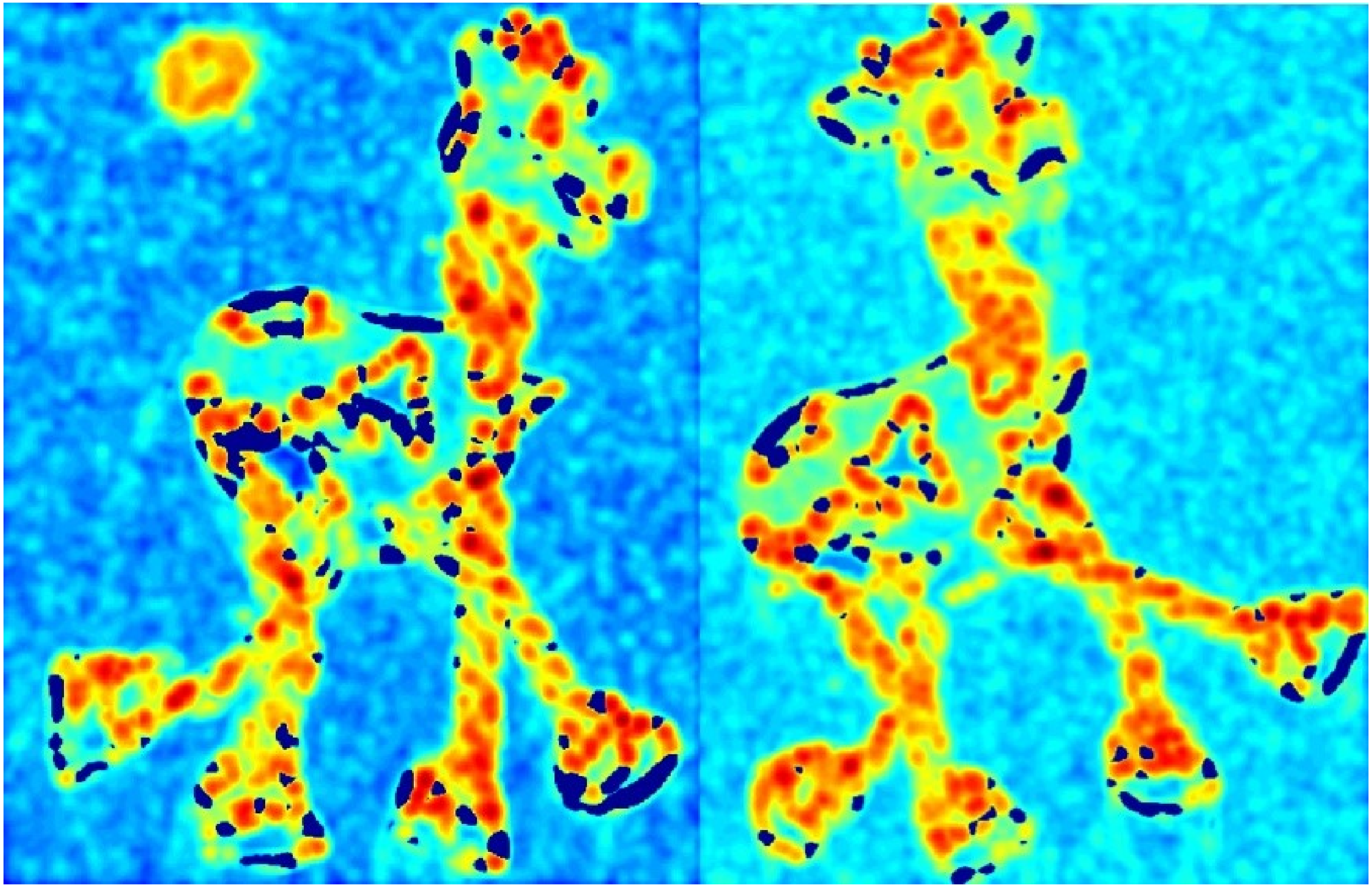
C.Harris and M.Stephens. "A Combined Corner and Edge Detector." *Proceedings of the 4th Alvey Vision Conference*: pages 147—151, 1988.

Slide credit: S. Lazebnik

Computing R

Slide credit: S. Lazebnik

Computing R



Slide credit: S. Lazebnik

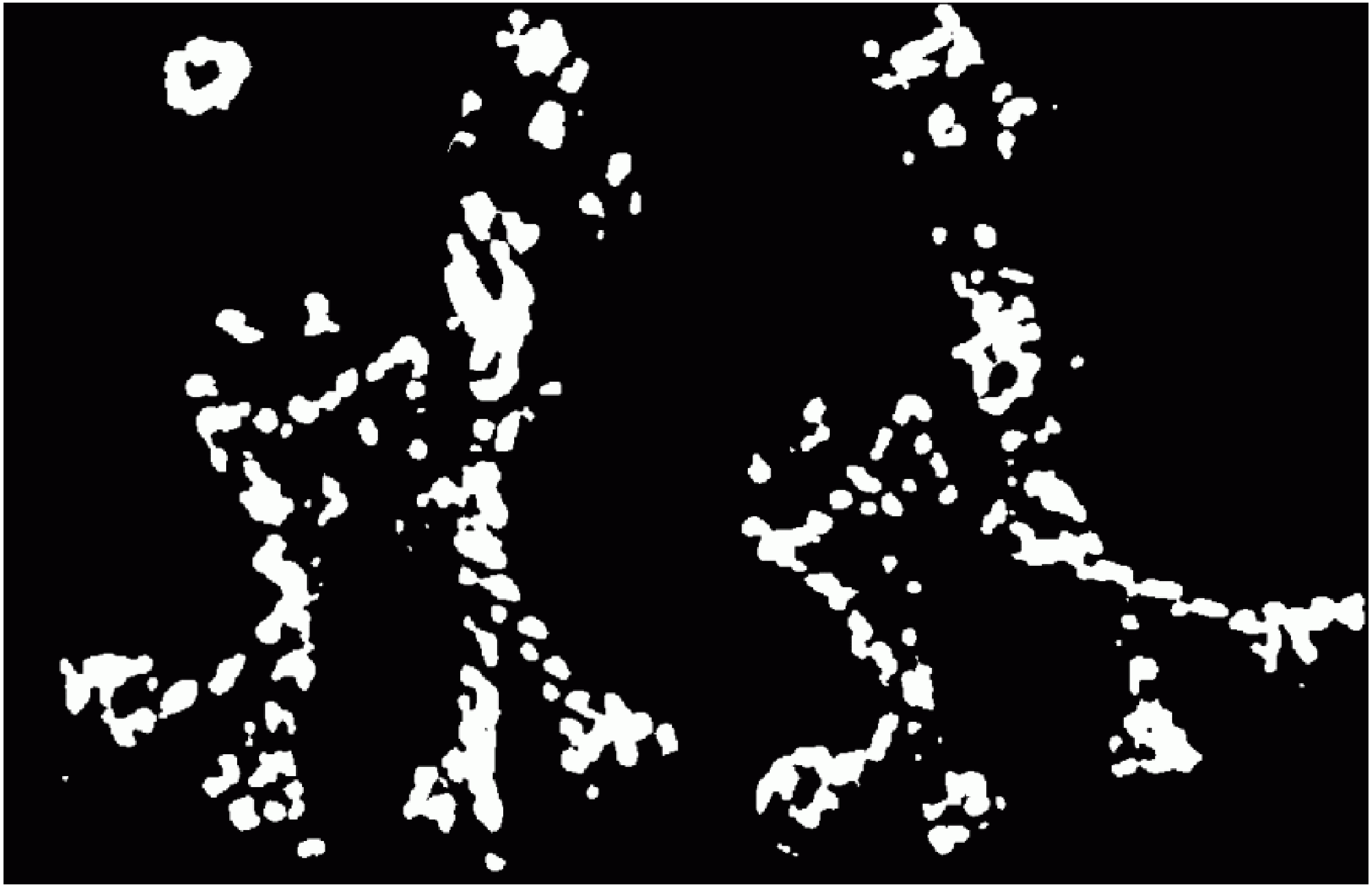
In Practice

1. Compute partial derivatives Ix, Iy per pixel
2. Compute **M** at each pixel, using Gaussian weighting w
3. Compute response function R
4. Threshold R

C.Harris and M.Stephens. “A Combined Corner and Edge Detector.” *Proceedings of the 4th Alvey Vision Conference*: pages 147—151, 1988.

Slide credit: S. Lazebnik

Thresholded R



Slide credit: S. Lazebnik

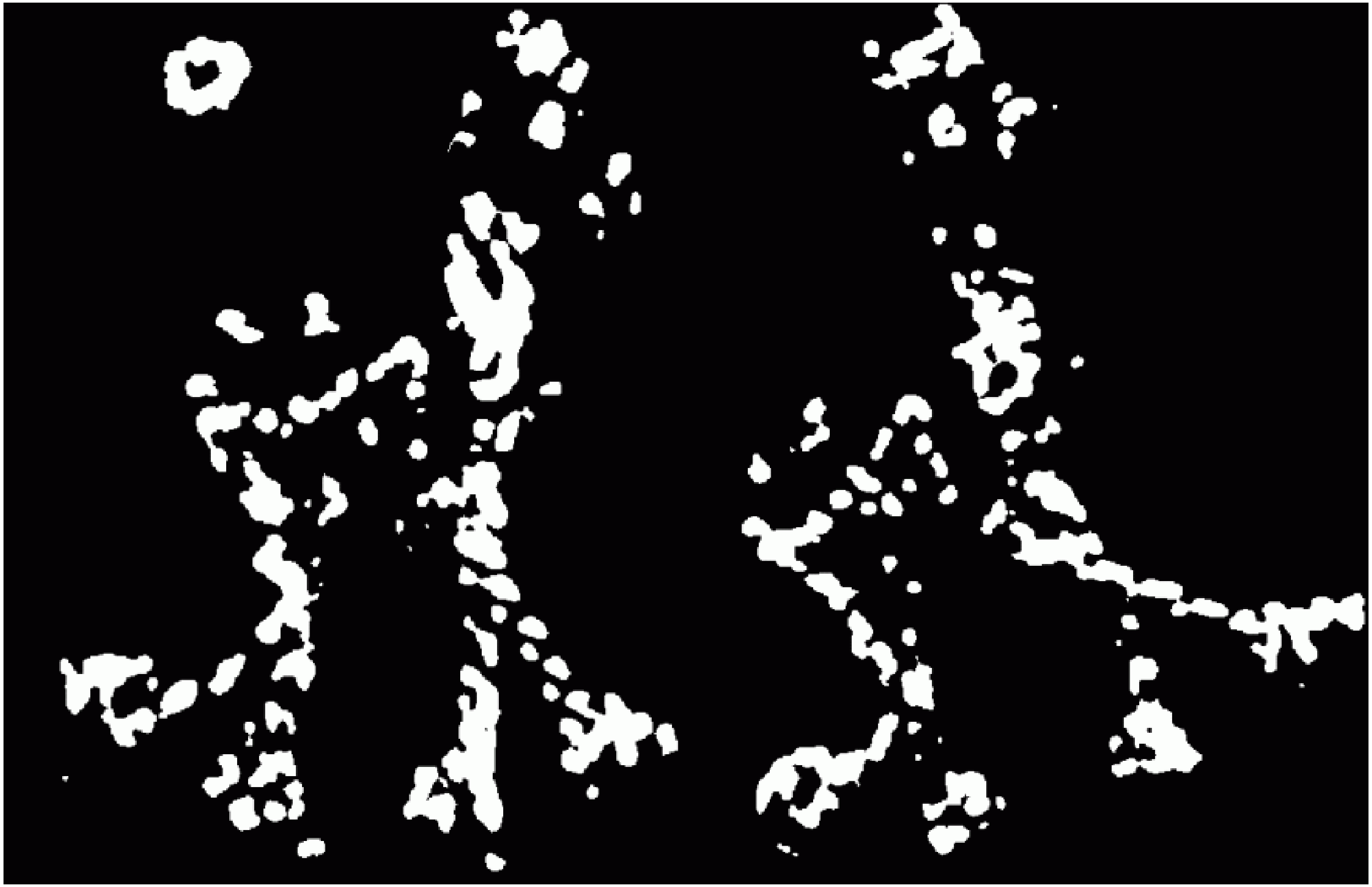
In Practice

1. Compute partial derivatives Ix, Iy per pixel
2. Compute **M** at each pixel, using Gaussian weighting w
3. Compute response function R
4. Threshold R
5. Take only local maxima (called non-maxima suppression)

C.Harris and M.Stephens. "A Combined Corner and Edge Detector." *Proceedings of the 4th Alvey Vision Conference*: pages 147—151, 1988.

Slide credit: S. Lazebnik

Thresholded, NMS R



Slide credit: S. Lazebnik

Final Results

Slide credit: S. Lazebnik

Desirable Properties

If our detectors are repeatable, they should be:

- **Invariant** to some things: image is transformed and corners remain the same
- **Covariant/equivariant** with some things: image is transformed and corners transform with it.

Slide credit: S. Lazebnik

Recall Motivating Problem

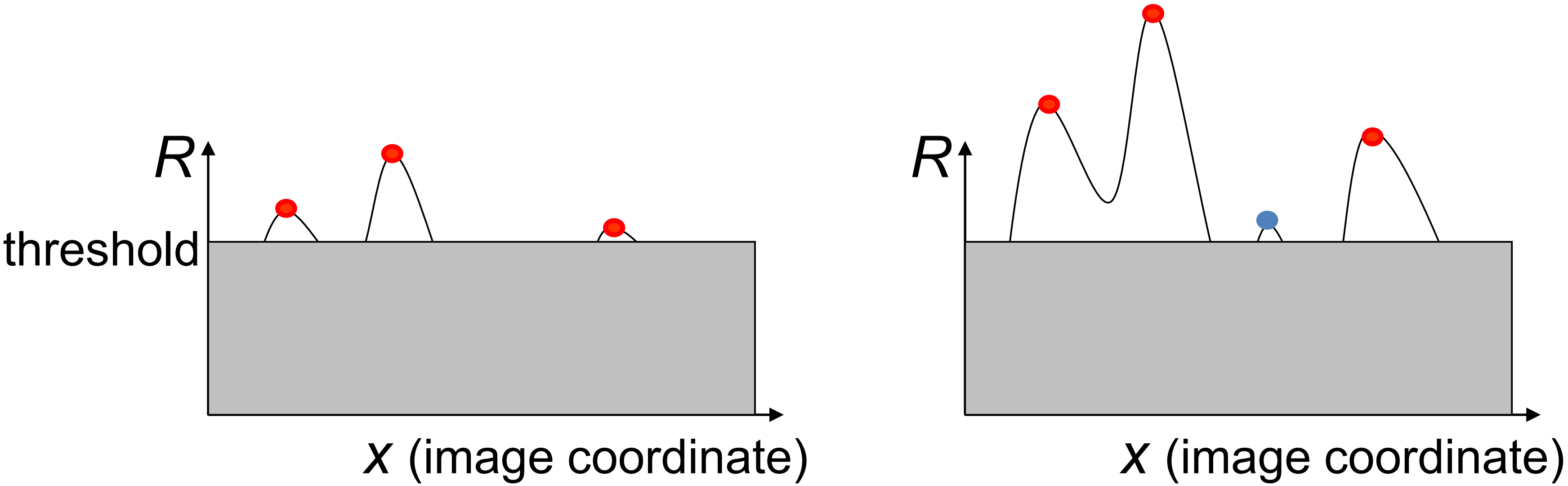
Images may be different in lighting and geometry

Affine Intensity Change

$$I_{new} = aI_{old} + b$$

M only depends on derivatives, so b is irrelevant

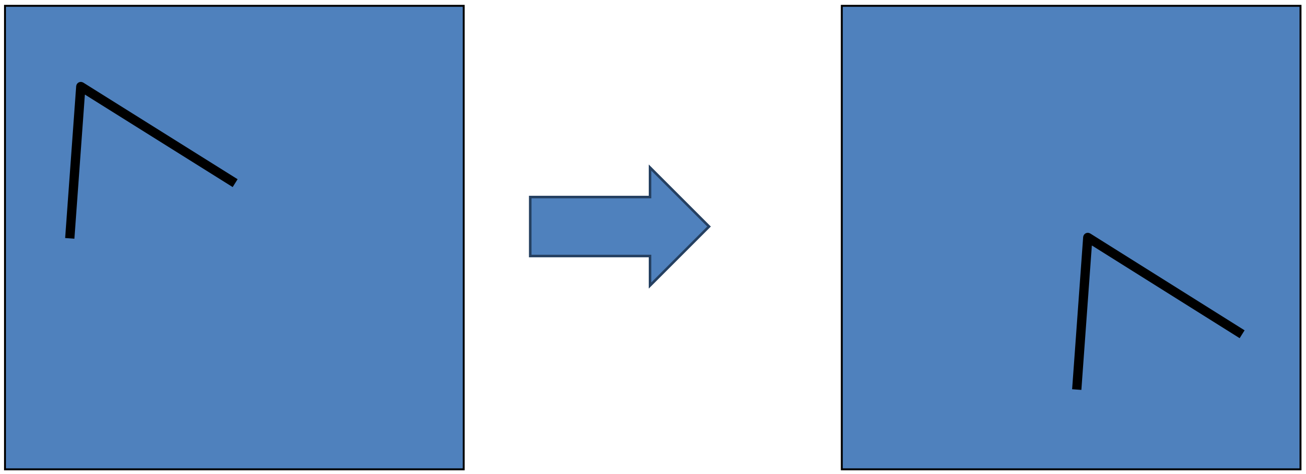
But a scales derivatives and there's a threshold



Partially invariant to affine intensity changes

Slide credit: S. Lazebnik

Image Translation

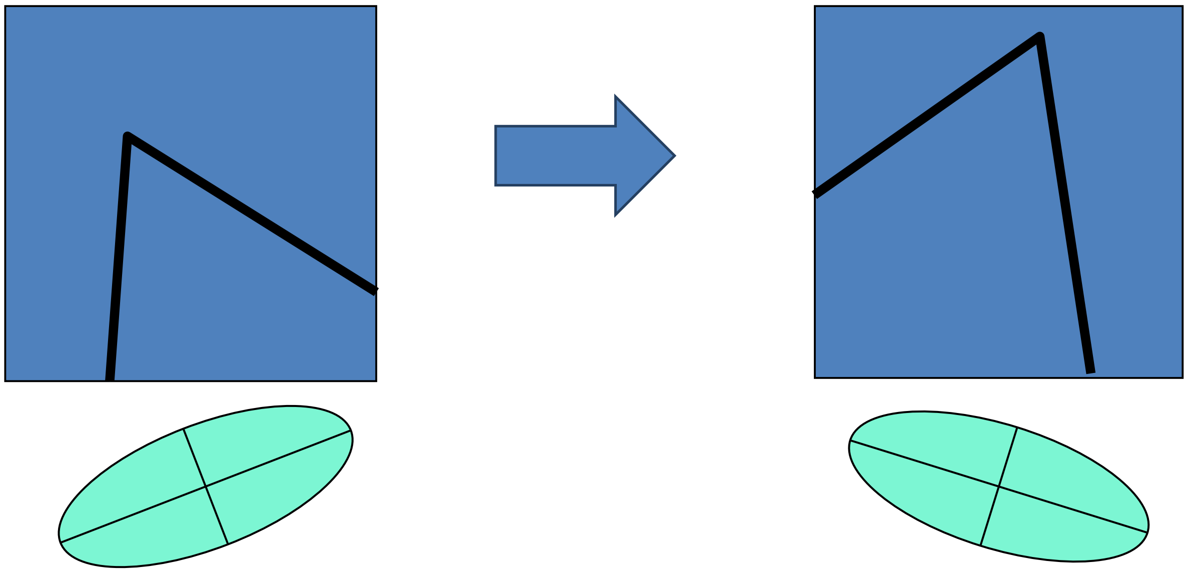


All done with convolution. Convolution is translation invariant.

Equivariant with translation

Slide credit: S. Lazebnik

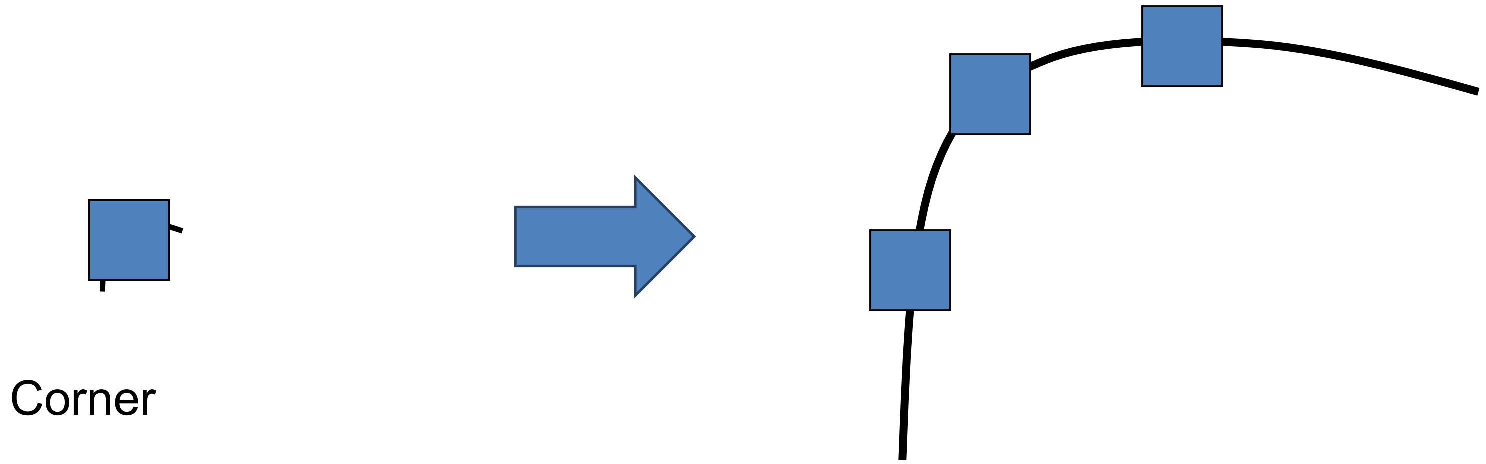
Image Rotation



Rotations just cause the corner rotation to change. Eigenvalues remain the same.

Equivariant with rotation

Image Scaling



One pixel can become many pixels and vice-versa.

Not equivariant with scaling