

# Non-Linear Filtering and Hough Transform

# Overview of today's lecture

New in lecture 4:

- Non-Linear Filtering
- Finding boundaries.
- Line fitting.
- Line parameterizations.
- Hough transform.
- Hough circles.
- Some applications.

# Slide credits

Most of these slides were adapted from:

- Kris Kitani (15-463, Fall 2016).

Some slides were inspired or taken from:

- Fredo Durand (MIT).
- James Hays (Georgia Tech).

# Non-Linear Filtering

# Effect of smoothing filters

5x5

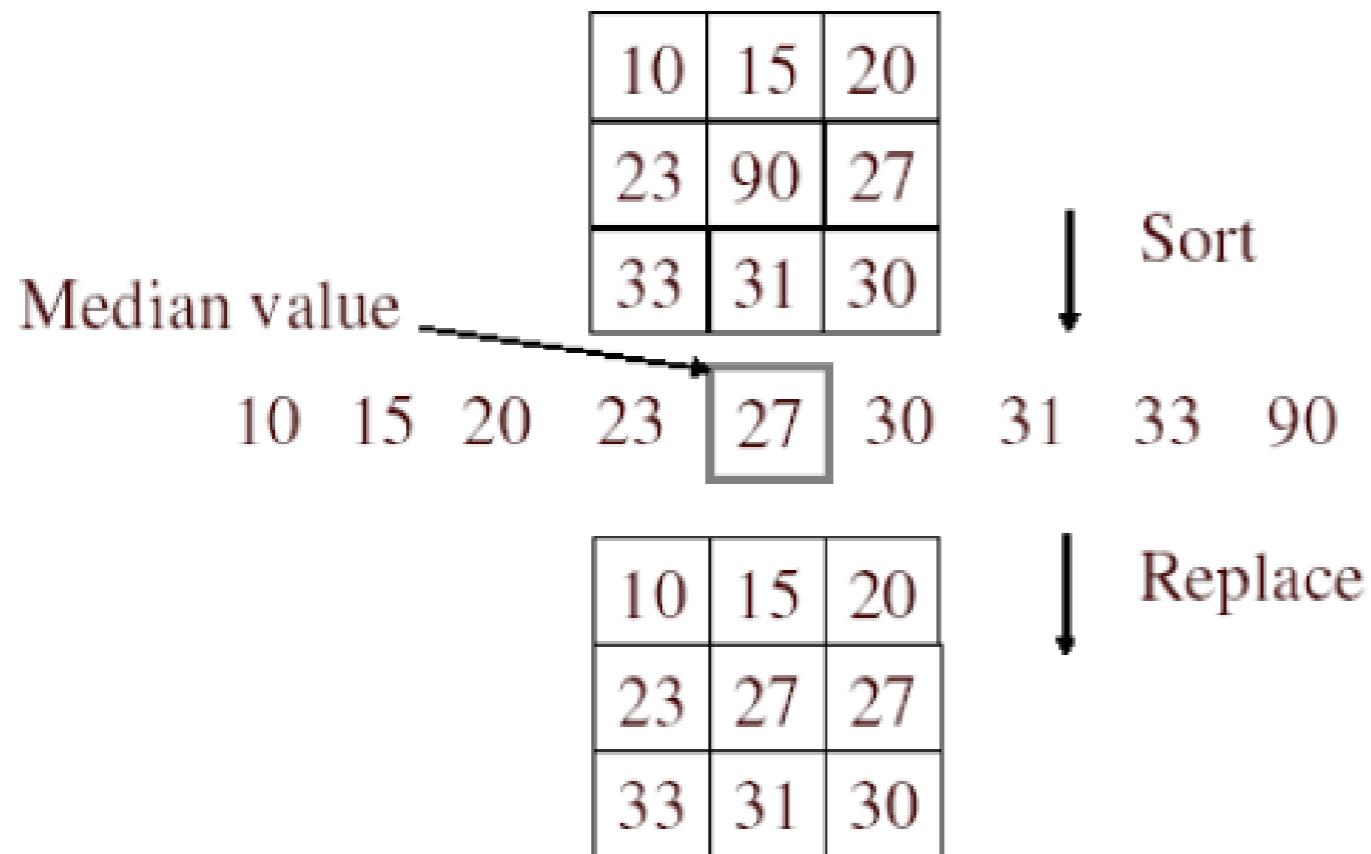


Additive Gaussian noise



Salt and pepper noise

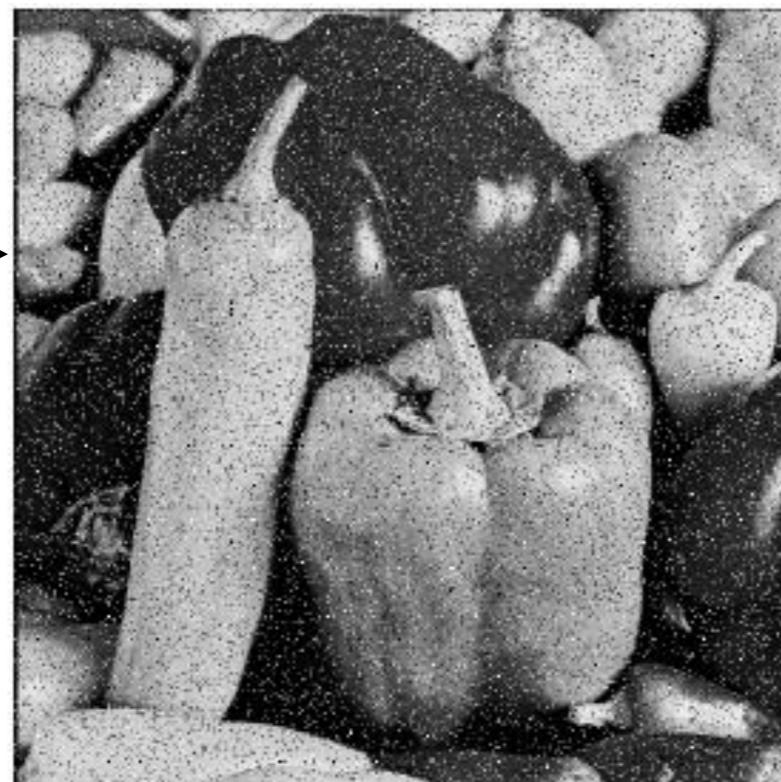
# Median filter



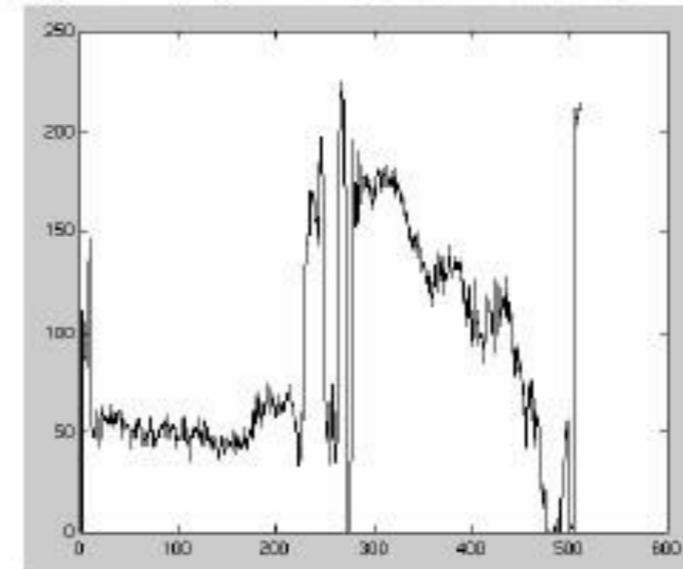
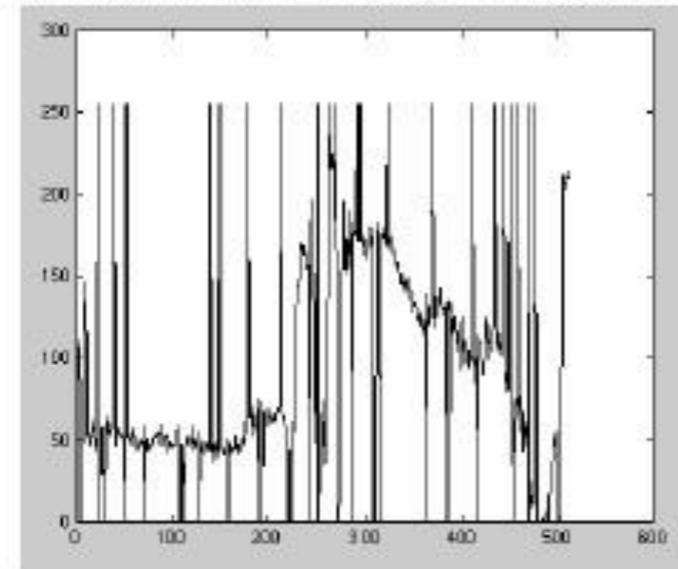
- No new pixel values introduced
- Removes spikes: good for impulse, salt & pepper noise
- Non-linear filter

# Median filter

Salt and  
pepper noise



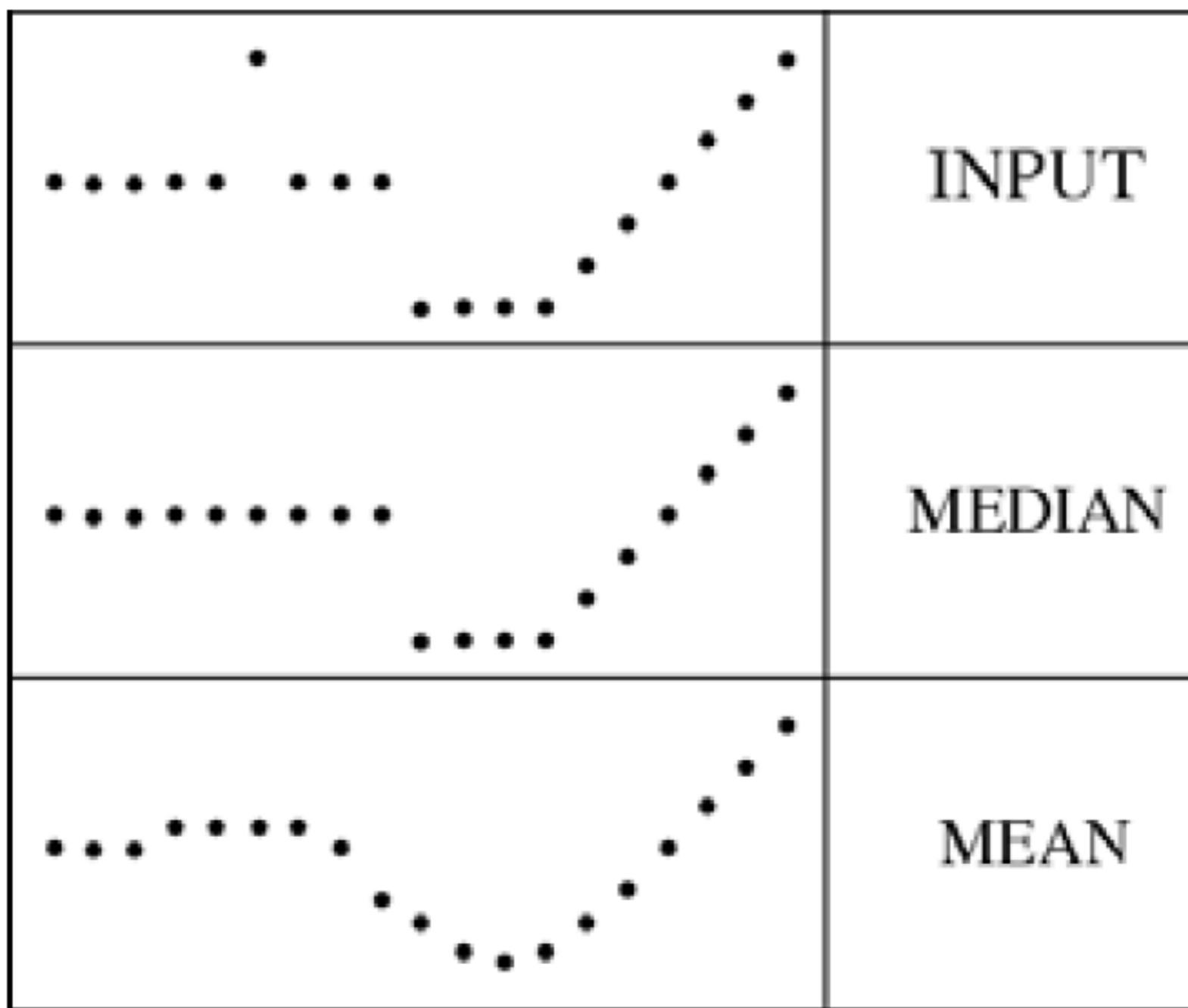
Median  
filtered



Plots of a row of the image

# Median filter

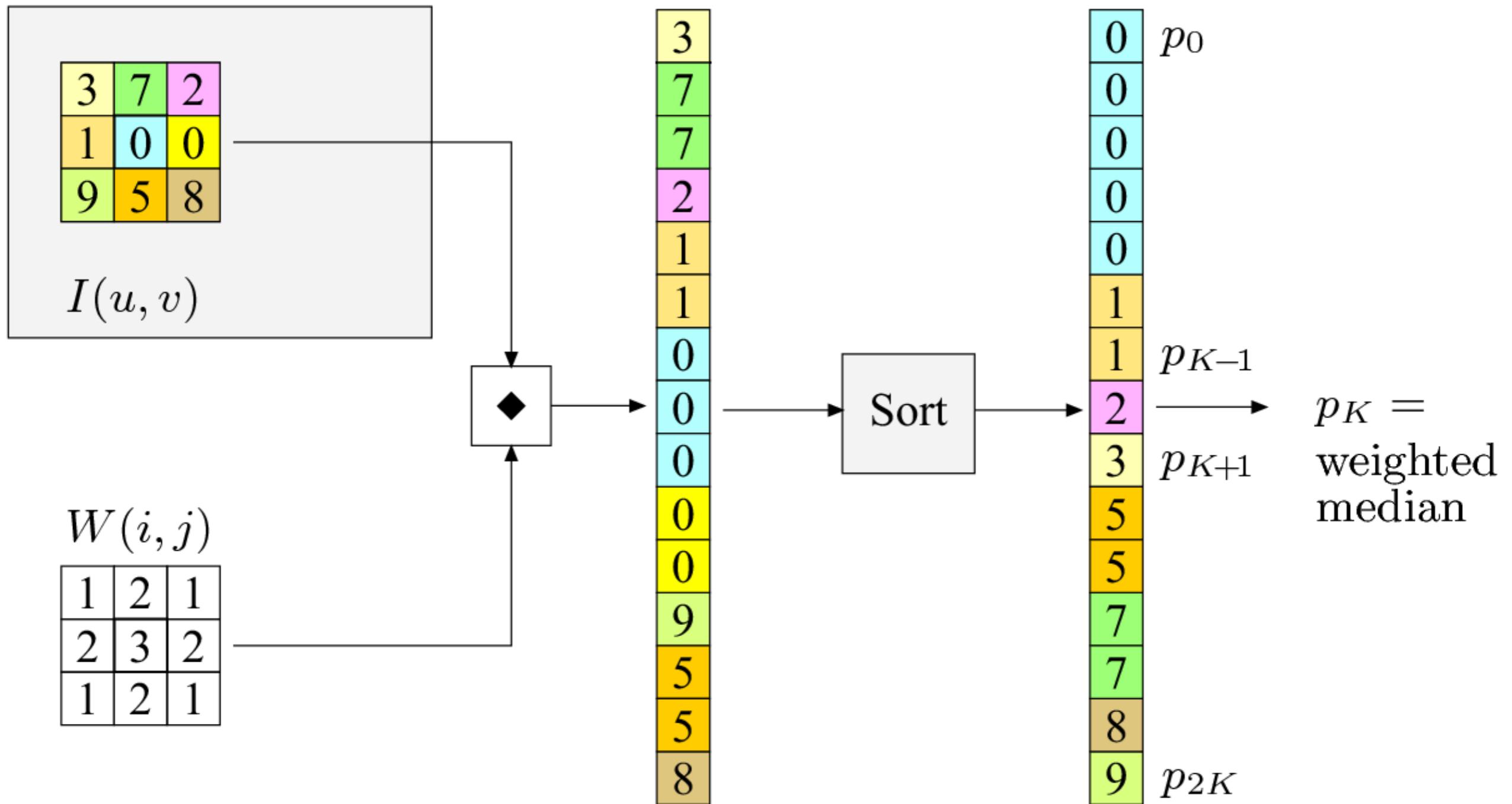
- Median filter is edge preserving



# Weighted Median Filter

- What if we want to apply median filter while giving higher weights to some pixels than others?
- Solution: Replicate pixels values in proportion to their weight → Weighted Median Filter
- Note that weights have to be integers

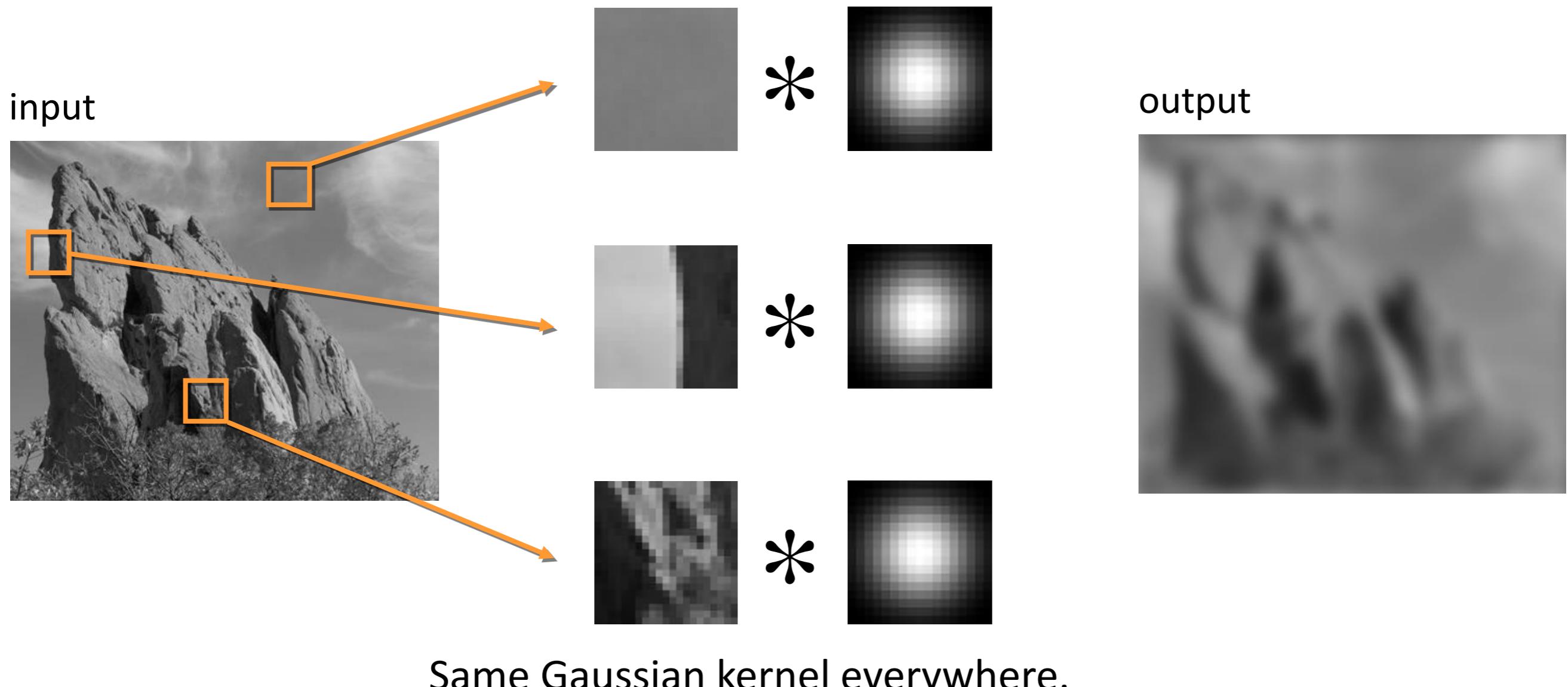
# Weighted Median Filter



# Bilateral Filtering

- What if want to remove Gaussian noise without blurring details of the image?
- Bilateral filtering smoothens an image with a degree inversely proportional to the local contrast

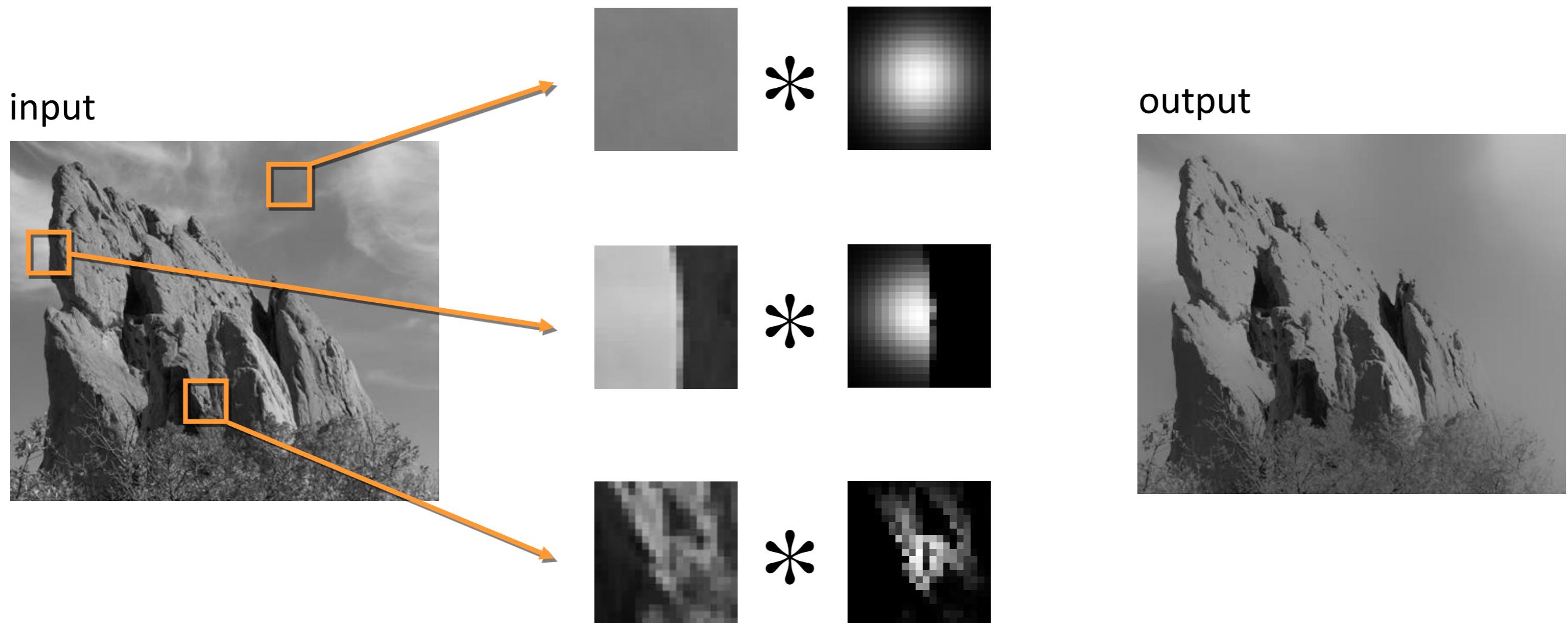
# Blur Comes from Averaging across Edges



# Bilateral Filter

[Aurich 95, Smith 97, Tomasi 98]

## No Averaging across Edges



The kernel shape depends on the image content.

# Bilateral Filter Definition: an Additional Edge Term

Same idea: **weighted average of pixels.**

$$BF[I]_p = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(|I_p - I_q|) I_q$$

new  
not new  
new

normalization factor      *space* weight      *range* weight

$I$

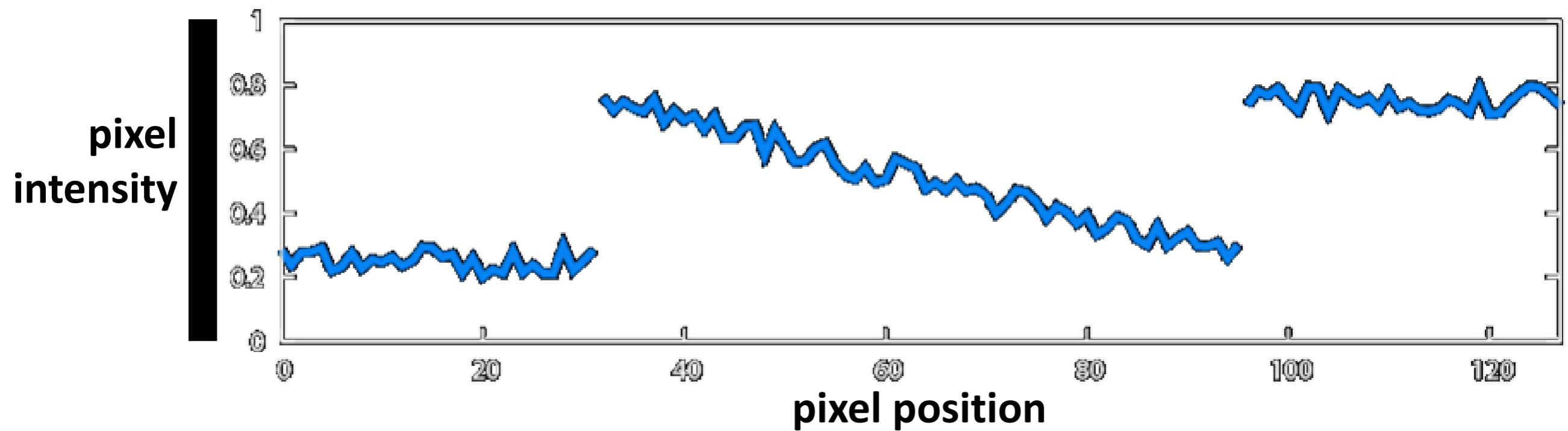
$t$

# Illustration a 1D Image

- 1D image = line of pixels

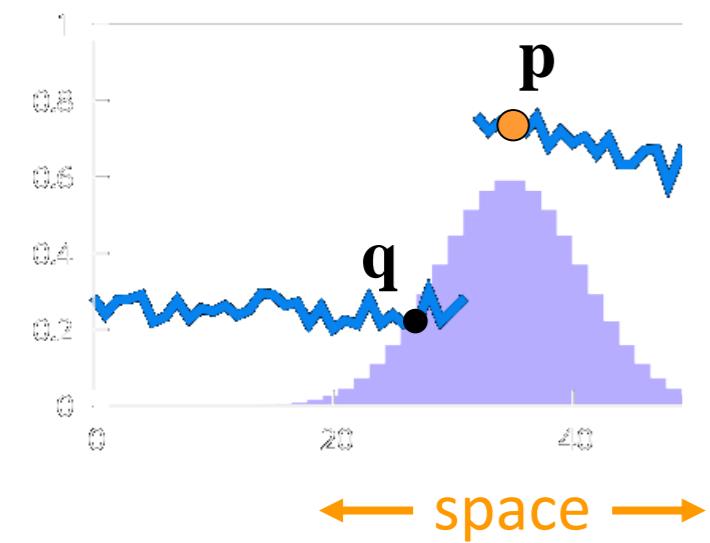


- Better visualized as a plot



# Gaussian Blur and Bilateral Filter

## Gaussian blur

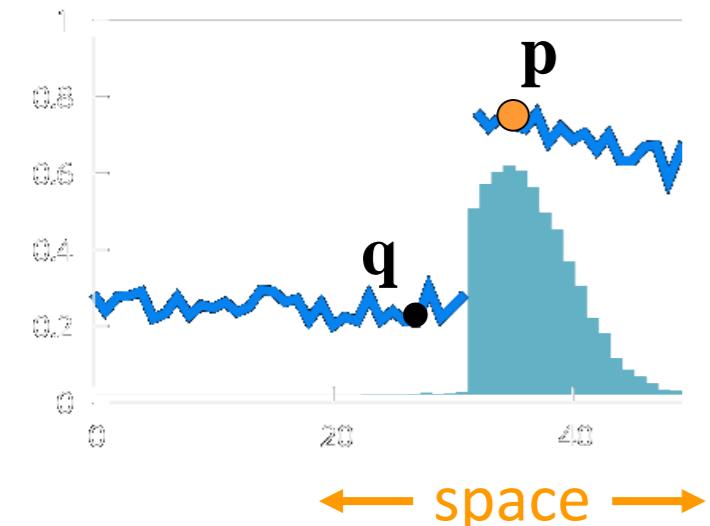


$$GB[I]_p = \sum_{q \in S} G_\sigma(\|p - q\|) I_q$$

space

## Bilateral filter

[Aurich 95, Smith 97, Tomasi 98]



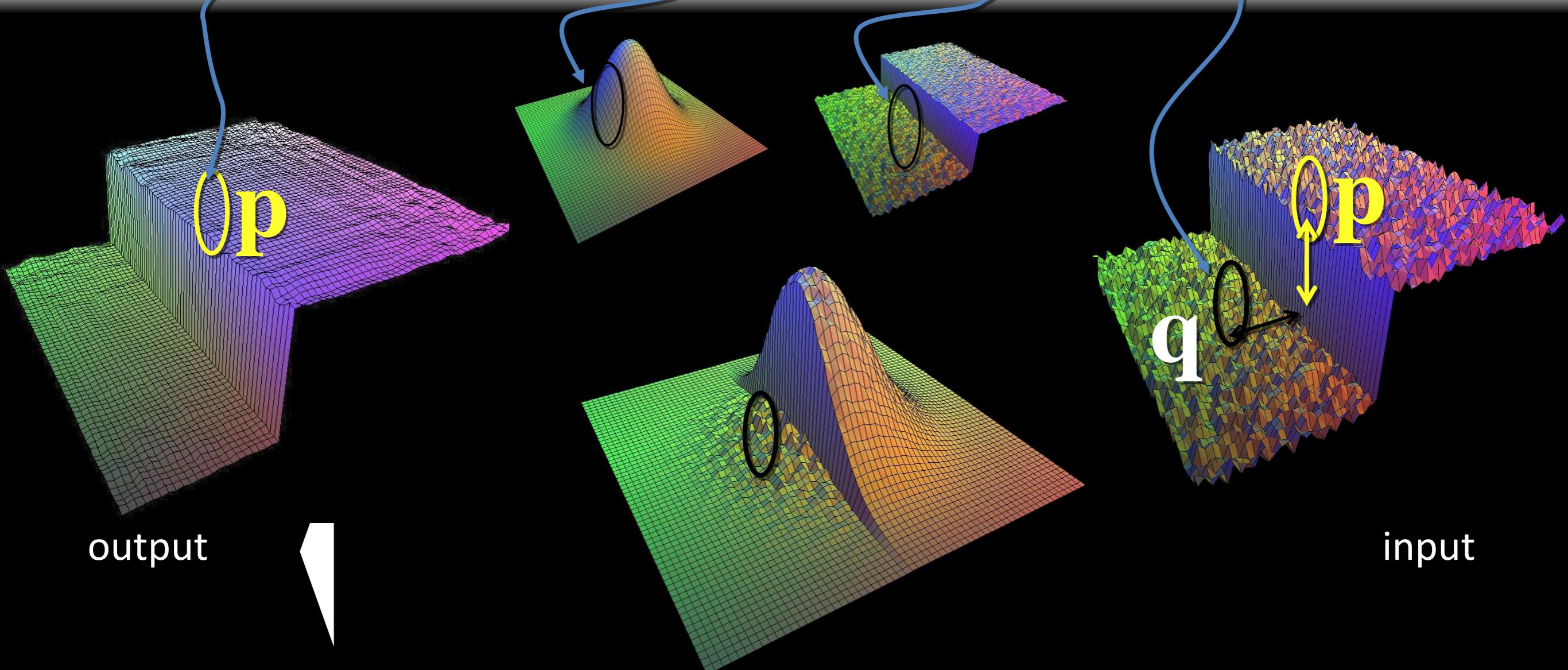
$$BF[I]_p = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(|I_p - I_q|) I_q$$

normalization

space      range

# Bilateral Filter on a Height Field

$$BF[I]_p = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(|I_p - I_q|) I_q$$



# Space and Range Parameters

$$BF[I]_p = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_s}(||p - q||) G_{\sigma_r}(|I_p - I_q|) I_q$$


- space  $\sigma_s$  : spatial extent of the kernel, size of the considered neighborhood.
- range  $\sigma_r$  : “minimum” amplitude of an edge

# Exploring the Parameter Space



input

$\sigma_s = 2$



$\sigma_r = 0.1$



$\sigma_r = 0.25$

$\sigma_r = \infty$   
(Gaussian blur)



$\sigma_s = 6$



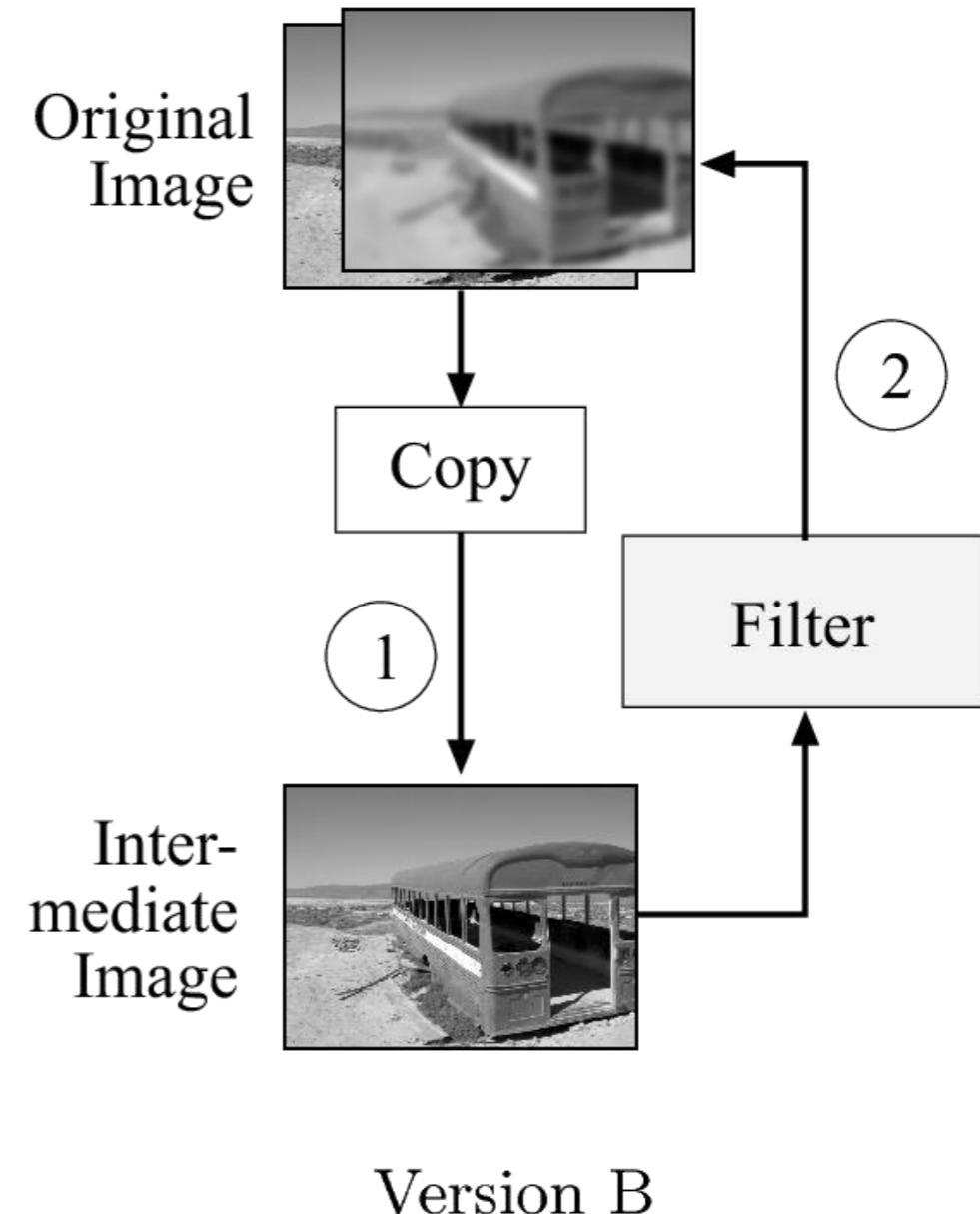
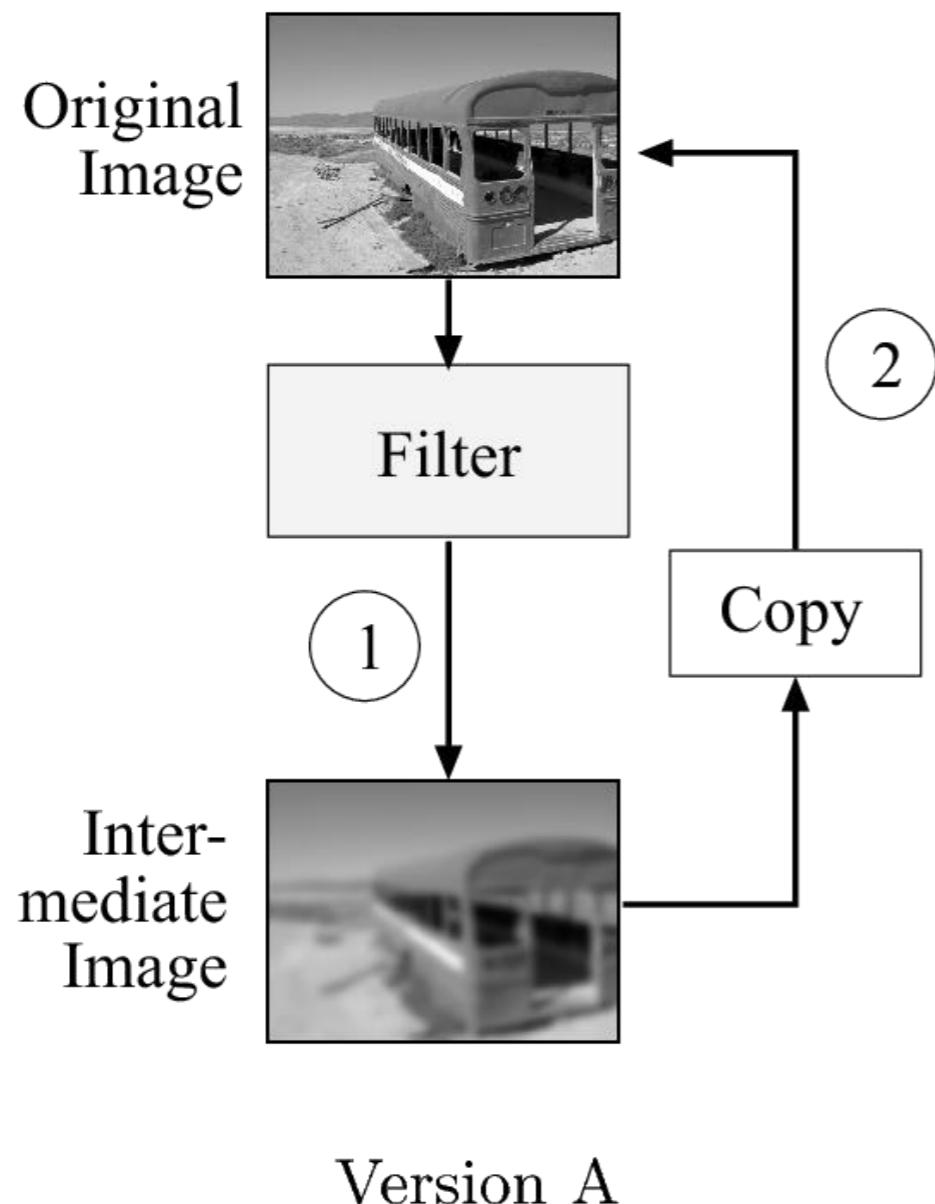
$\sigma_s = 18$



# Practical Issue in Filtering

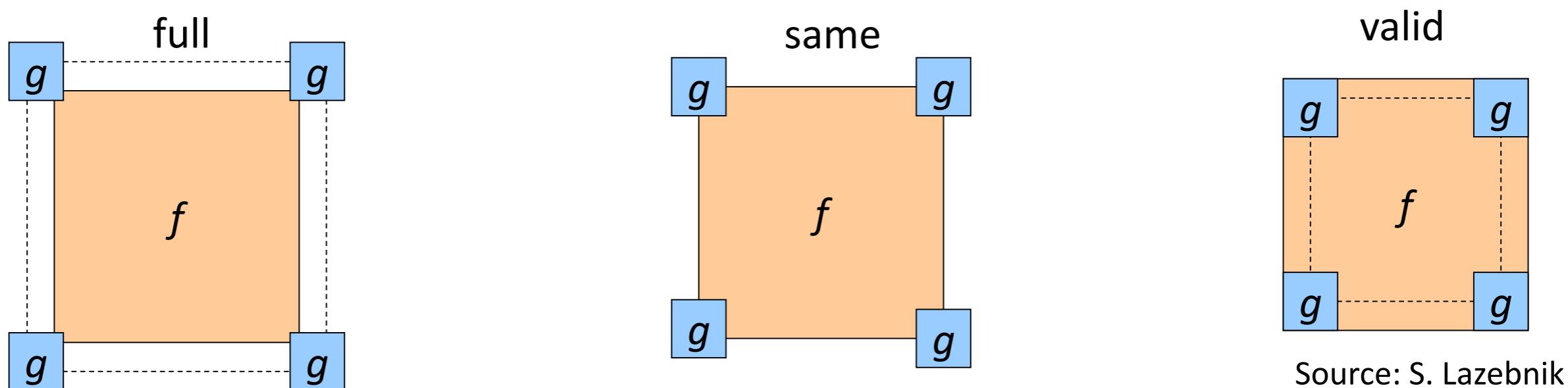
- Making temp copy of input image
- Handling image boundary pixels

# Filtering: Using Temp Copy of Input



# Filtering: Boundary Issues

- What is the size of the output filtered image?
- MATLAB: output size / “shape” options
  - *shape* = ‘full’: output size is sum of sizes of f and g
  - *shape* = ‘same’: output size is same as f
  - *shape* = ‘valid’: output size is difference of sizes of f and g
- OpenCV: only ‘same’ mode supported
  - Use `copyMakeBorder()` for ‘full’ mode
  - Set ROI for ‘valid’ mode



# Filtering: Boundary Issues

- What about near the edge?
  - the filter window falls off the edge of the image
  - need to extrapolate
  - methods:
    - clip filter (black)
      - borderType = BORDER\_CONSTANT
    - wrap around
      - borderType = BORDER\_WRAP
    - copy edge
      - borderType = BORDER\_REPLICATE
    - reflect across edge
      - borderType = BORDER\_REFLECT\_101



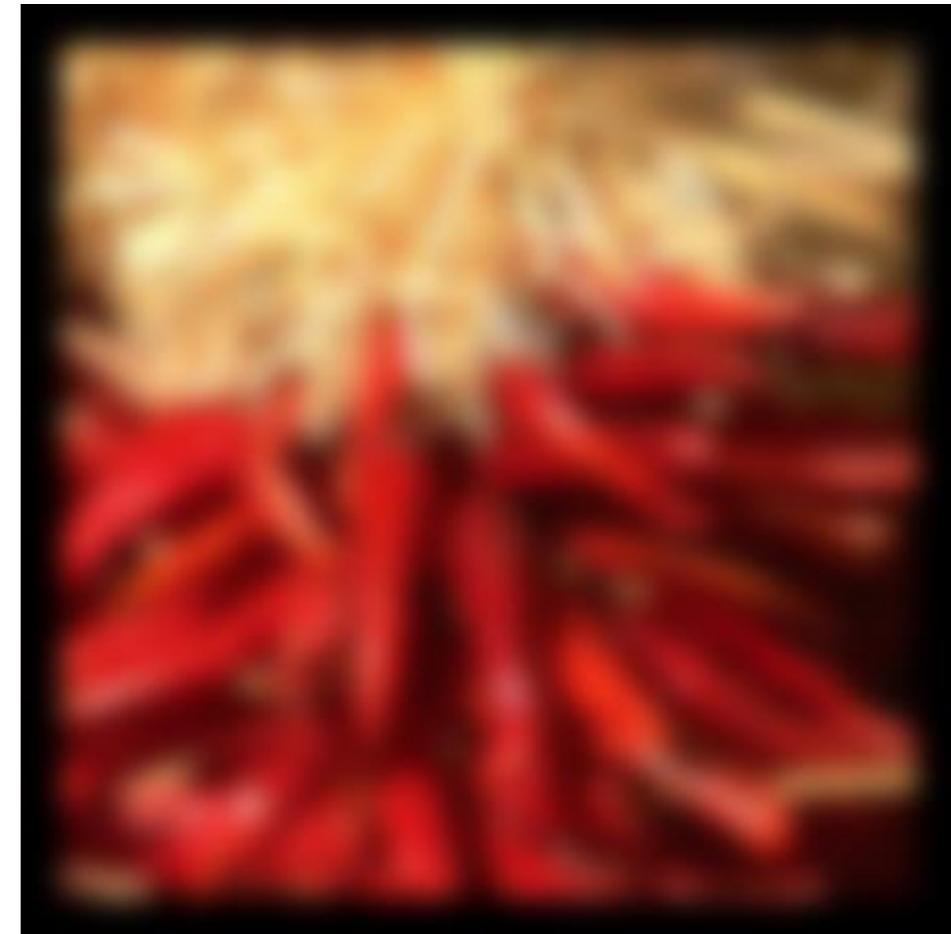
# Filtering: Boundary Issues

- What about near the edge?
  - the filter window falls off the edge of the image
  - need to extrapolate
  - methods:
    - **clip filter (black)**
      - borderType = BORDER\_CONSTANT
    - wrap around
      - borderType = BORDER\_WRAP
    - copy edge
      - borderType = BORDER\_REPLICATE
    - reflect across edge
      - borderType = BORDER\_REFLECT\_101



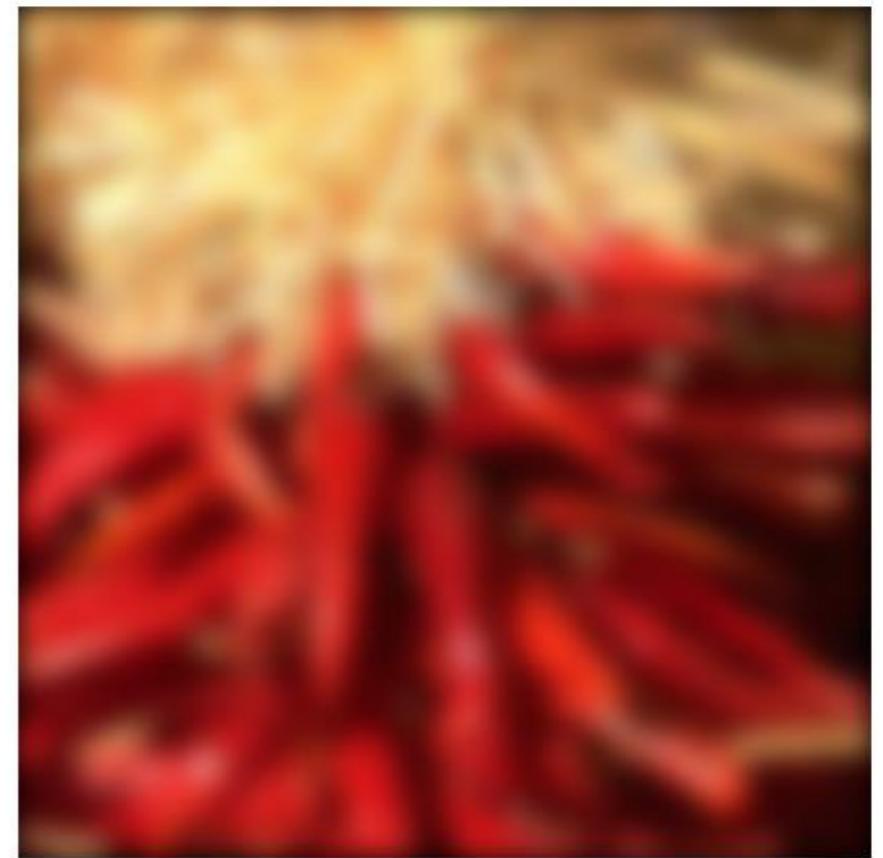
# Filtering: Boundary Issues

- What about near the edge?
  - the filter window falls off the edge of the image
  - need to extrapolate
  - methods:
    - **clip filter (black)**
      - borderType = BORDER\_CONSTANT
    - wrap around
      - borderType = BORDER\_WRAP
    - copy edge
      - borderType = BORDER\_REPLICATE
    - reflect across edge
      - borderType = BORDER\_REFLECT\_101



# Filtering: Boundary Issues

- What about near the edge?
  - the filter window falls off the edge of the image
  - need to extrapolate
  - methods:
    - **clip filter (black)**
      - borderType = BORDER\_CONSTANT
    - wrap around
      - borderType = BORDER\_WRAP
    - copy edge
      - borderType = BORDER\_REPLICATE
    - reflect across edge
      - borderType = BORDER\_REFLECT\_101



# Filtering: Boundary Issues

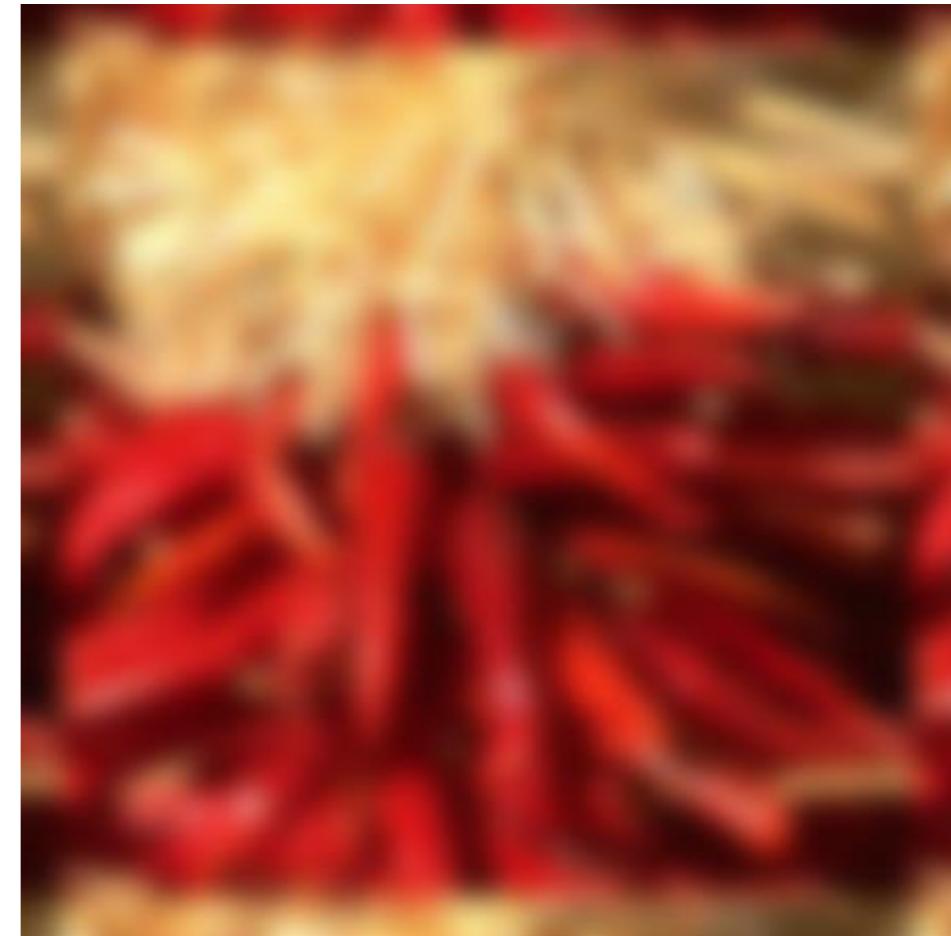
- What about near the edge?
  - the filter window falls off the edge of the image
  - need to extrapolate
  - methods:
    - clip filter (black)
      - borderType = BORDER\_CONSTANT
    - **wrap around**
      - borderType = BORDER\_WRAP
    - copy edge
      - borderType = BORDER\_REPLICATE
    - reflect across edge
      - borderType = BORDER\_REFLECT\_101



Source: S. Marschner

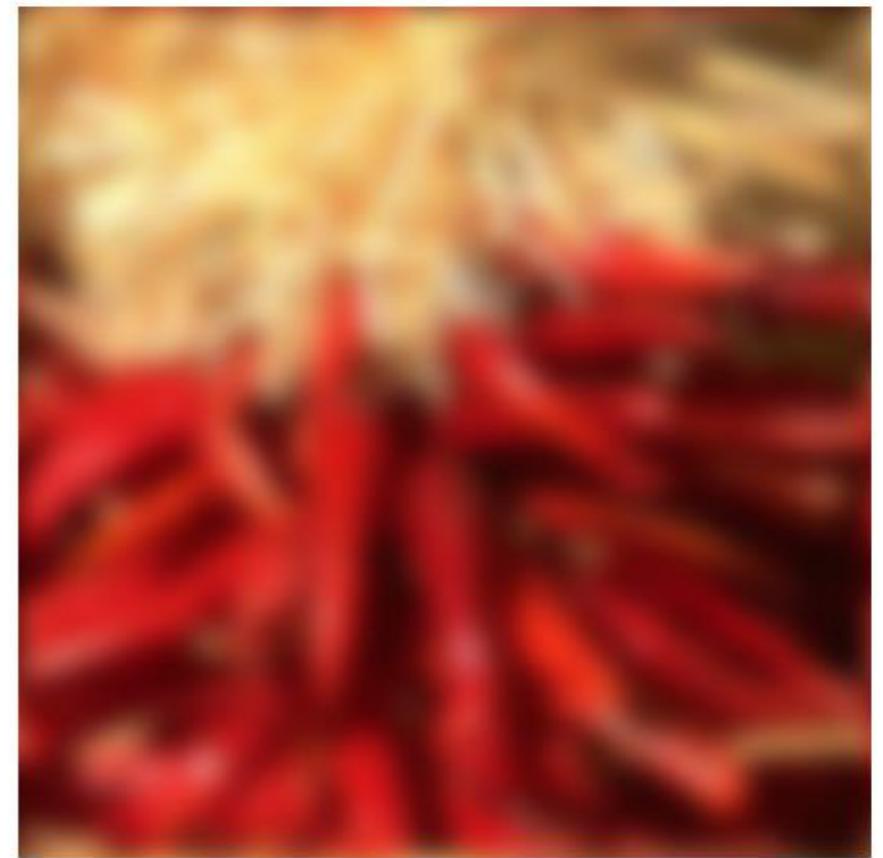
# Filtering: Boundary Issues

- What about near the edge?
  - the filter window falls off the edge of the image
  - need to extrapolate
  - methods:
    - clip filter (black)
      - borderType = BORDER\_CONSTANT
    - **wrap around**
      - borderType = BORDER\_WRAP
    - copy edge
      - borderType = BORDER\_REPLICATE
    - reflect across edge
      - borderType = BORDER\_REFLECT\_101



# Filtering: Boundary Issues

- What about near the edge?
  - the filter window falls off the edge of the image
  - need to extrapolate
  - methods:
    - clip filter (black)
      - borderType = BORDER\_CONSTANT
    - **wrap around**
      - borderType = BORDER\_WRAP
    - copy edge
      - borderType = BORDER\_REPLICATE
    - reflect across edge
      - borderType = BORDER\_REFLECT\_101



# Filtering: Boundary Issues

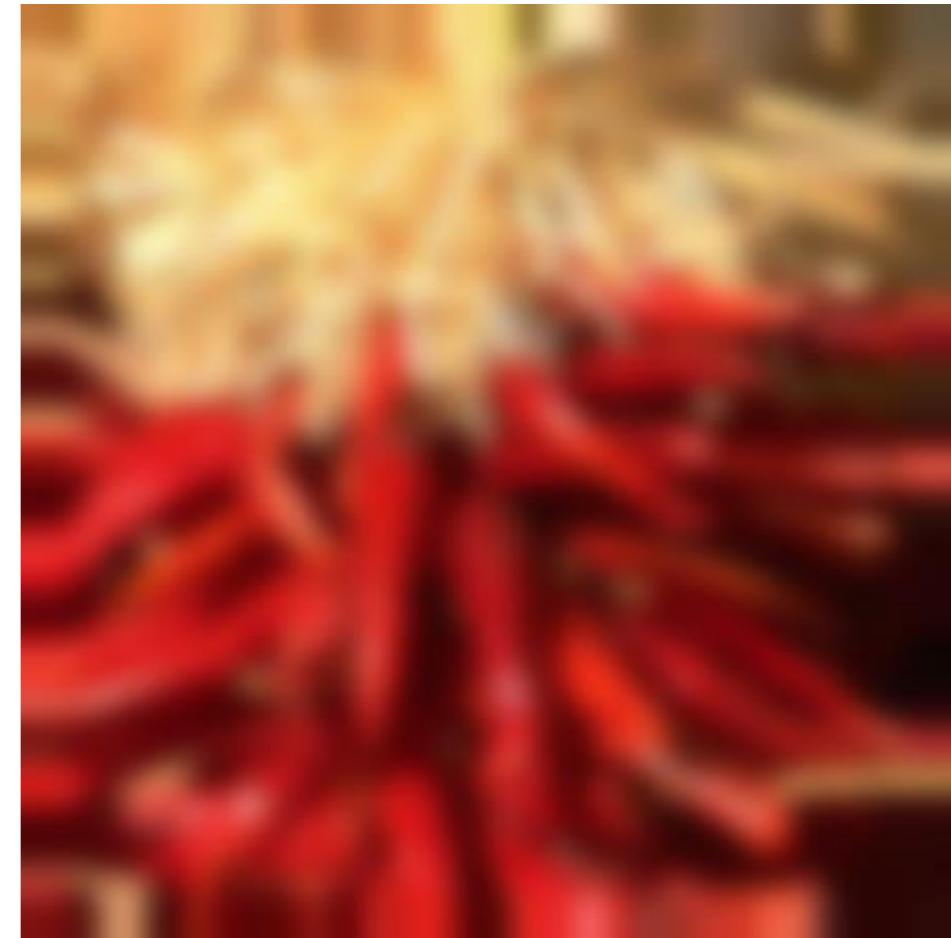
- What about near the edge?
  - the filter window falls off the edge of the image
  - need to extrapolate
  - methods:
    - clip filter (black)
      - borderType = BORDER\_CONSTANT
    - wrap around
      - borderType = BORDER\_WRAP
    - **copy edge**
      - borderType = BORDER\_REPLICATE
    - reflect across edge
      - borderType = BORDER\_REFLECT\_101



Source: S. Marschner

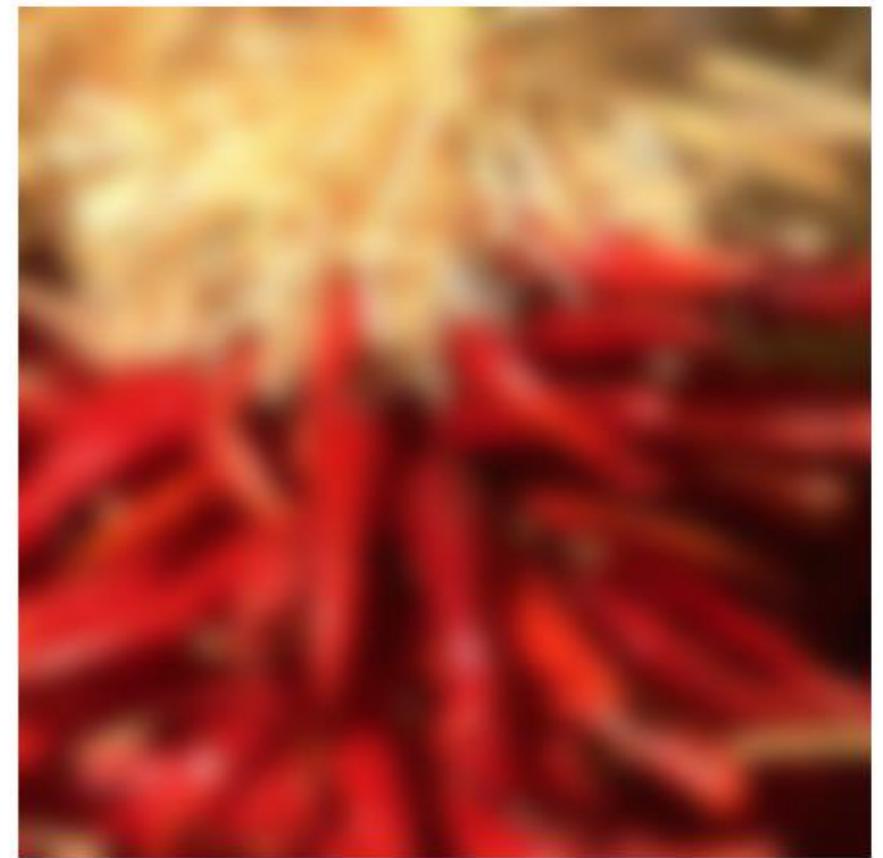
# Filtering: Boundary Issues

- What about near the edge?
  - the filter window falls off the edge of the image
  - need to extrapolate
  - methods:
    - clip filter (black)
      - borderType = BORDER\_CONSTANT
    - wrap around
      - borderType = BORDER\_WRAP
    - **copy edge**
      - borderType = BORDER\_REPLICATE
    - reflect across edge
      - borderType = BORDER\_REFLECT\_101



# Filtering: Boundary Issues

- What about near the edge?
  - the filter window falls off the edge of the image
  - need to extrapolate
  - methods:
    - clip filter (black)
      - borderType = BORDER\_CONSTANT
    - wrap around
      - borderType = BORDER\_WRAP
    - **copy edge**
      - borderType = BORDER\_REPLICATE
    - reflect across edge
      - borderType = BORDER\_REFLECT\_101



# Filtering: Boundary Issues

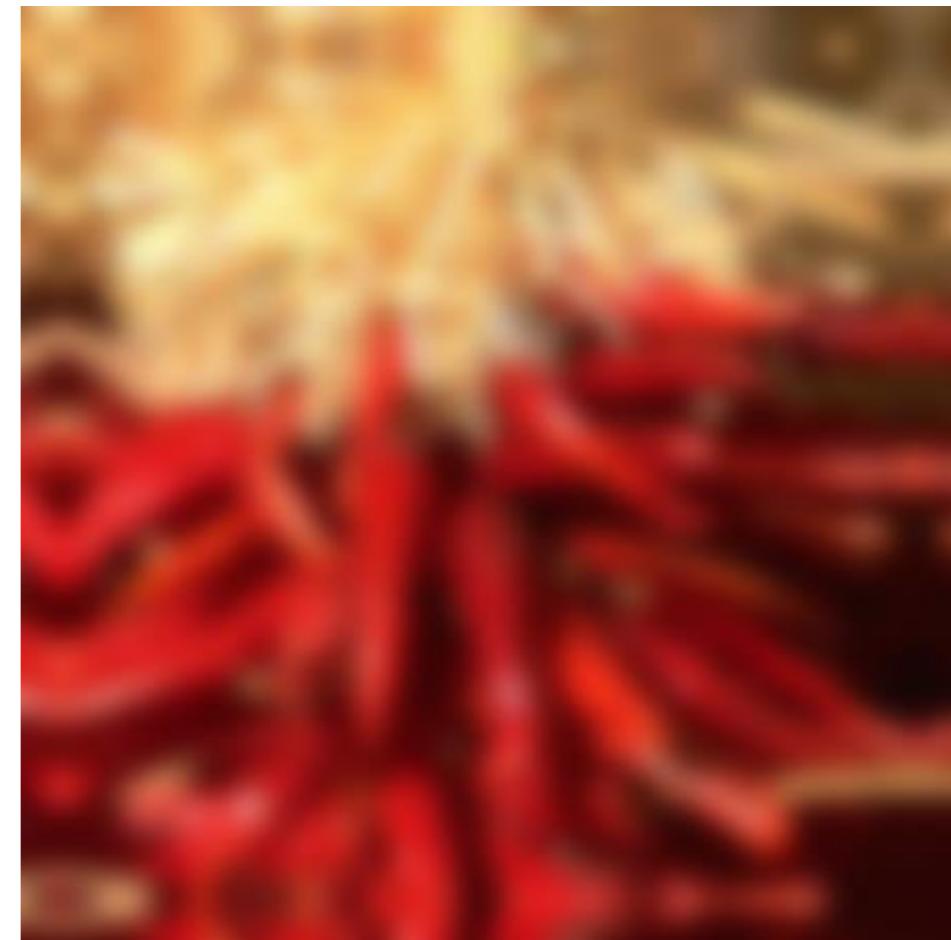
- What about near the edge?
  - the filter window falls off the edge of the image
  - need to extrapolate
  - methods:
    - clip filter (black)
      - borderType = BORDER\_CONSTANT
    - wrap around
      - borderType = BORDER\_WRAP
    - copy edge
      - borderType = BORDER\_REPLICATE
    - **reflect across edge**
      - borderType = BORDER\_REFLECT\_101



Source: S. Marschner

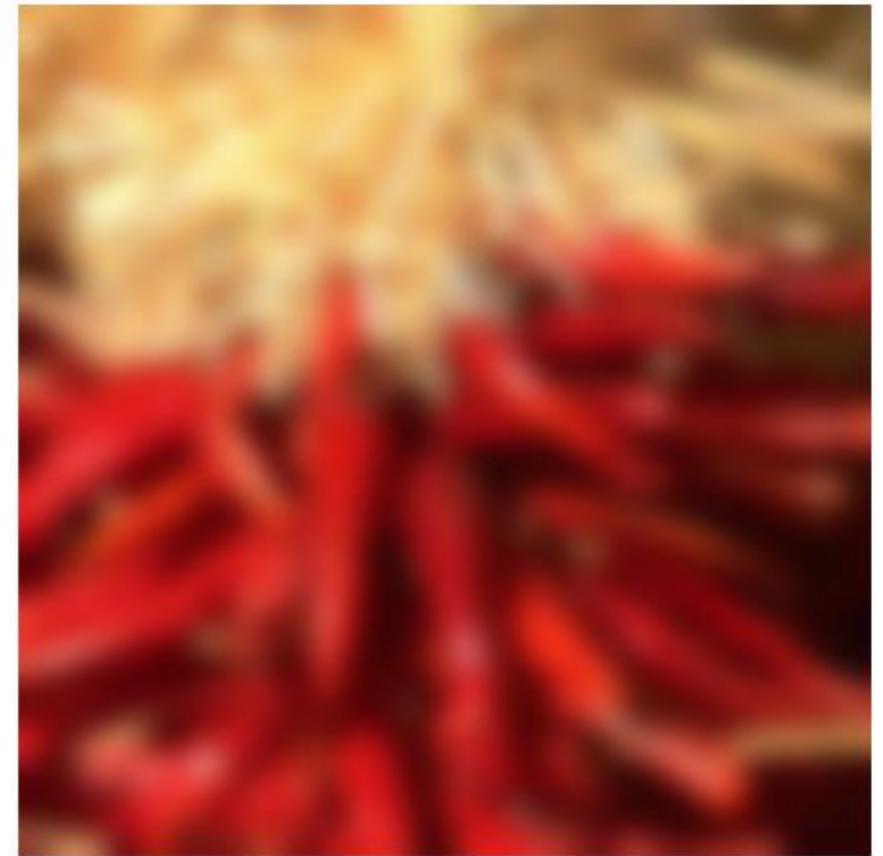
# Filtering: Boundary Issues

- What about near the edge?
  - the filter window falls off the edge of the image
  - need to extrapolate
  - methods:
    - clip filter (black)
      - borderType = BORDER\_CONSTANT
    - wrap around
      - borderType = BORDER\_WRAP
    - copy edge
      - borderType = BORDER\_REPLICATE
    - **reflect across edge**
      - borderType = BORDER\_REFLECT\_101



# Filtering: Boundary Issues

- What about near the edge?
  - the filter window falls off the edge of the image
  - need to extrapolate
  - methods:
    - clip filter (black)
      - borderType = BORDER\_CONSTANT
    - wrap around
      - borderType = BORDER\_WRAP
    - copy edge
      - borderType = BORDER\_REPLICATE
    - **reflect across edge**
      - borderType = BORDER\_REFLECT\_101



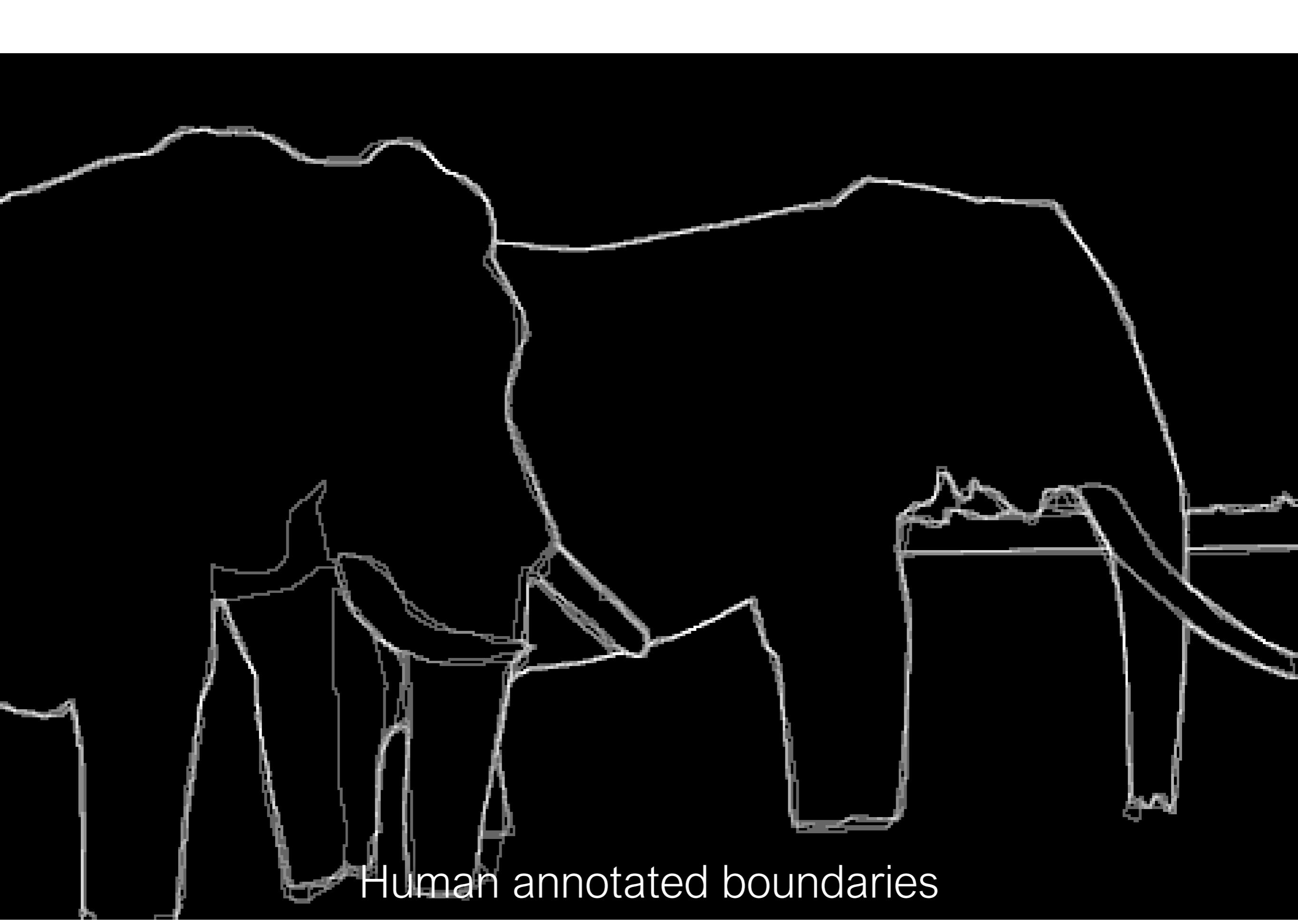
# Summary

- Linear Filtering
  - Smoothing filters
    - Box filters
    - Gaussian filters
  - Difference filters
    - Sharpening filter
  - Relationship with convolution
  - Separability
- Non-linear filtering
  - Median filter
  - Weighted median filter
  - Bilateral filtering
- Practical Issues

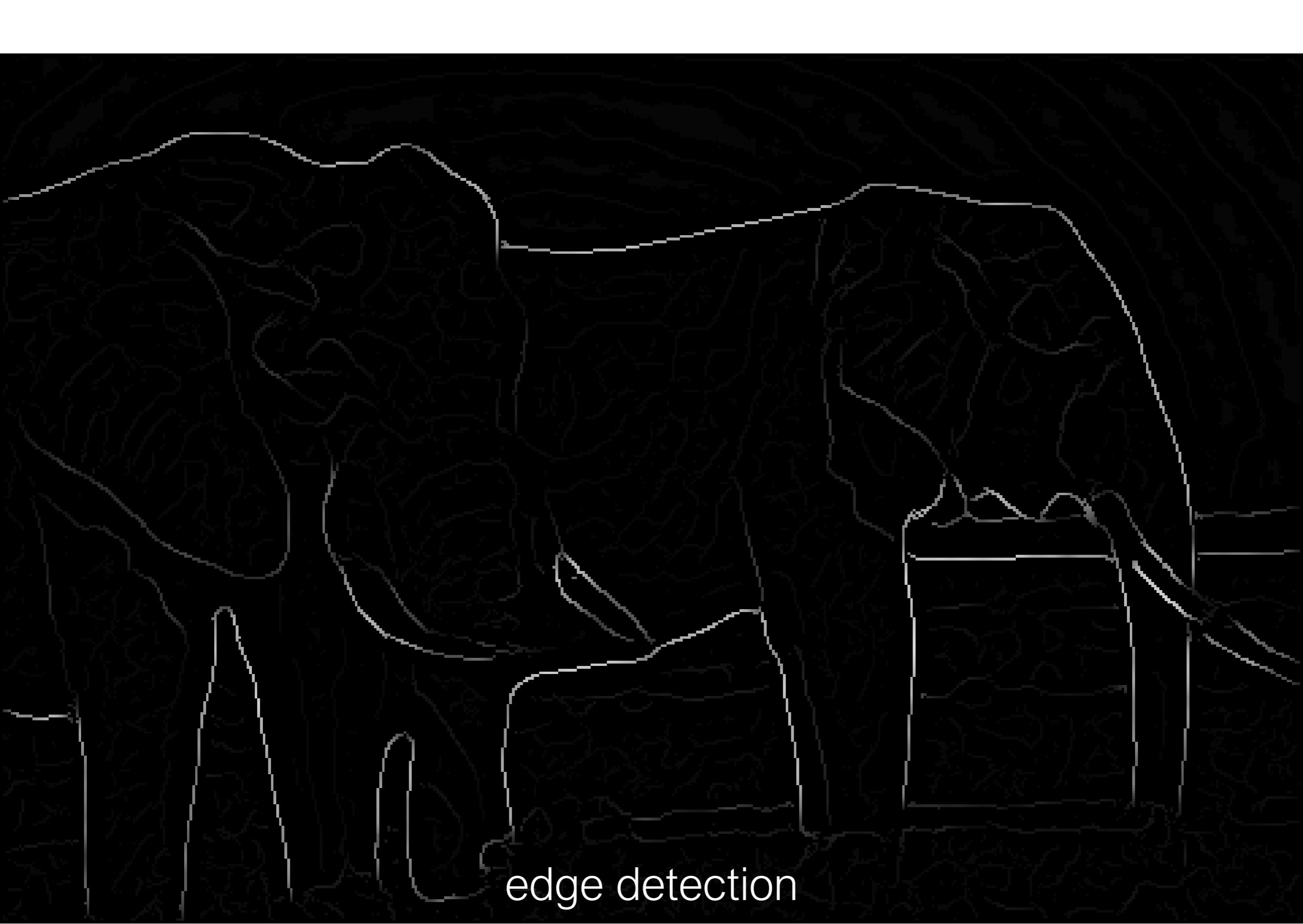
# Finding boundaries

Where are the object boundaries?

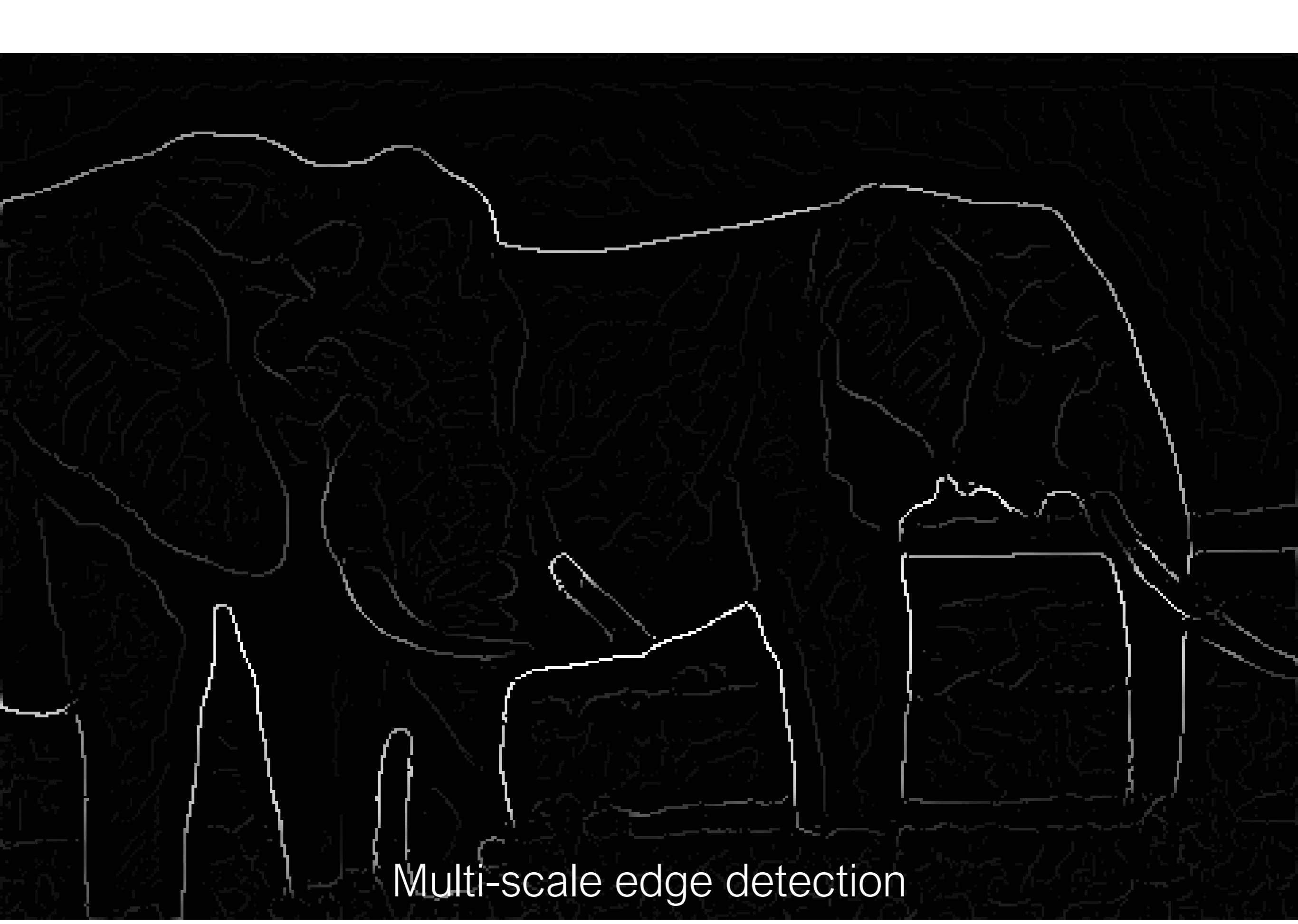




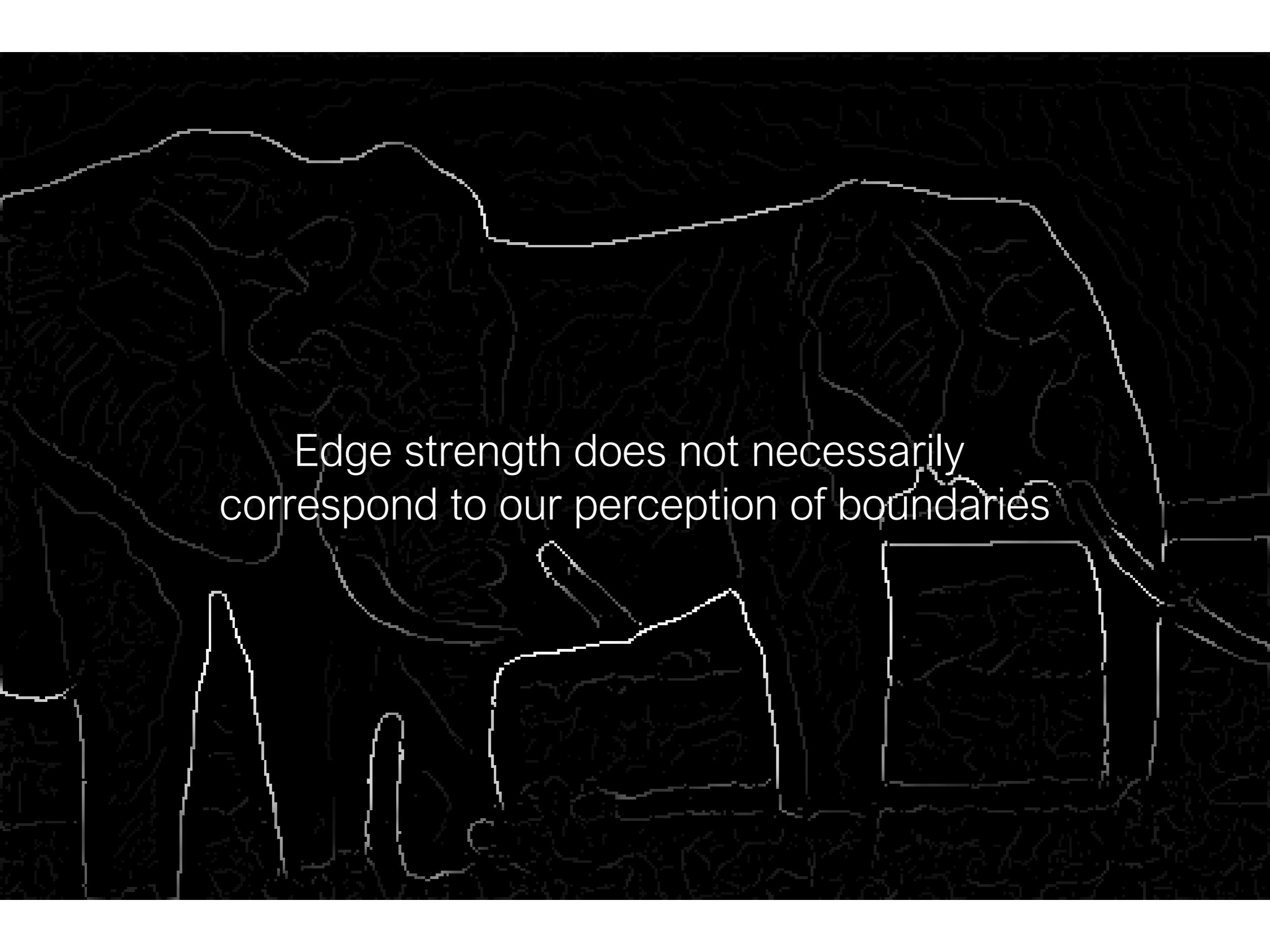
Human annotated boundaries



edge detection



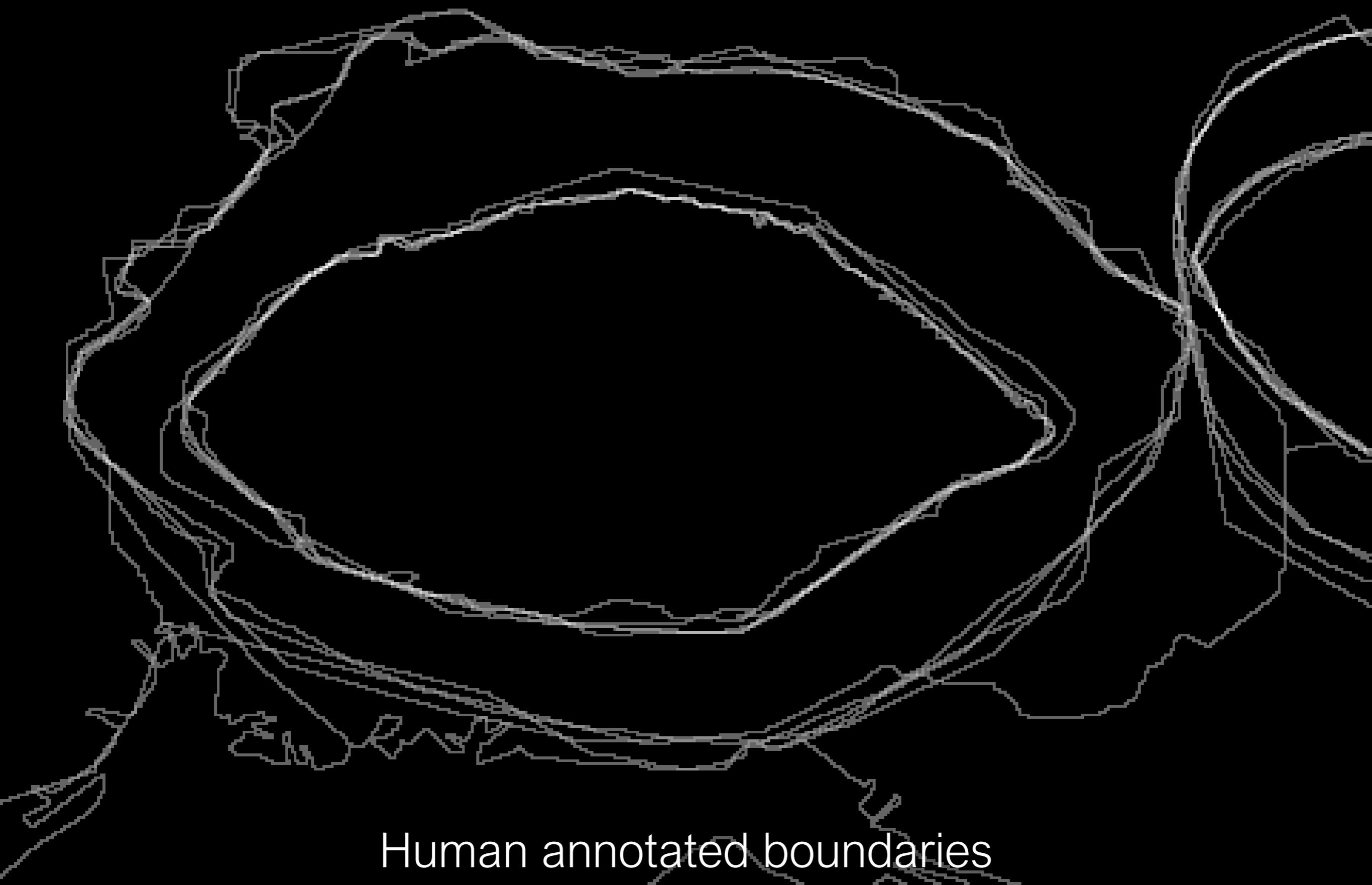
Multi-scale edge detection



Edge strength does not necessarily correspond to our perception of boundaries

Where are the object boundaries?

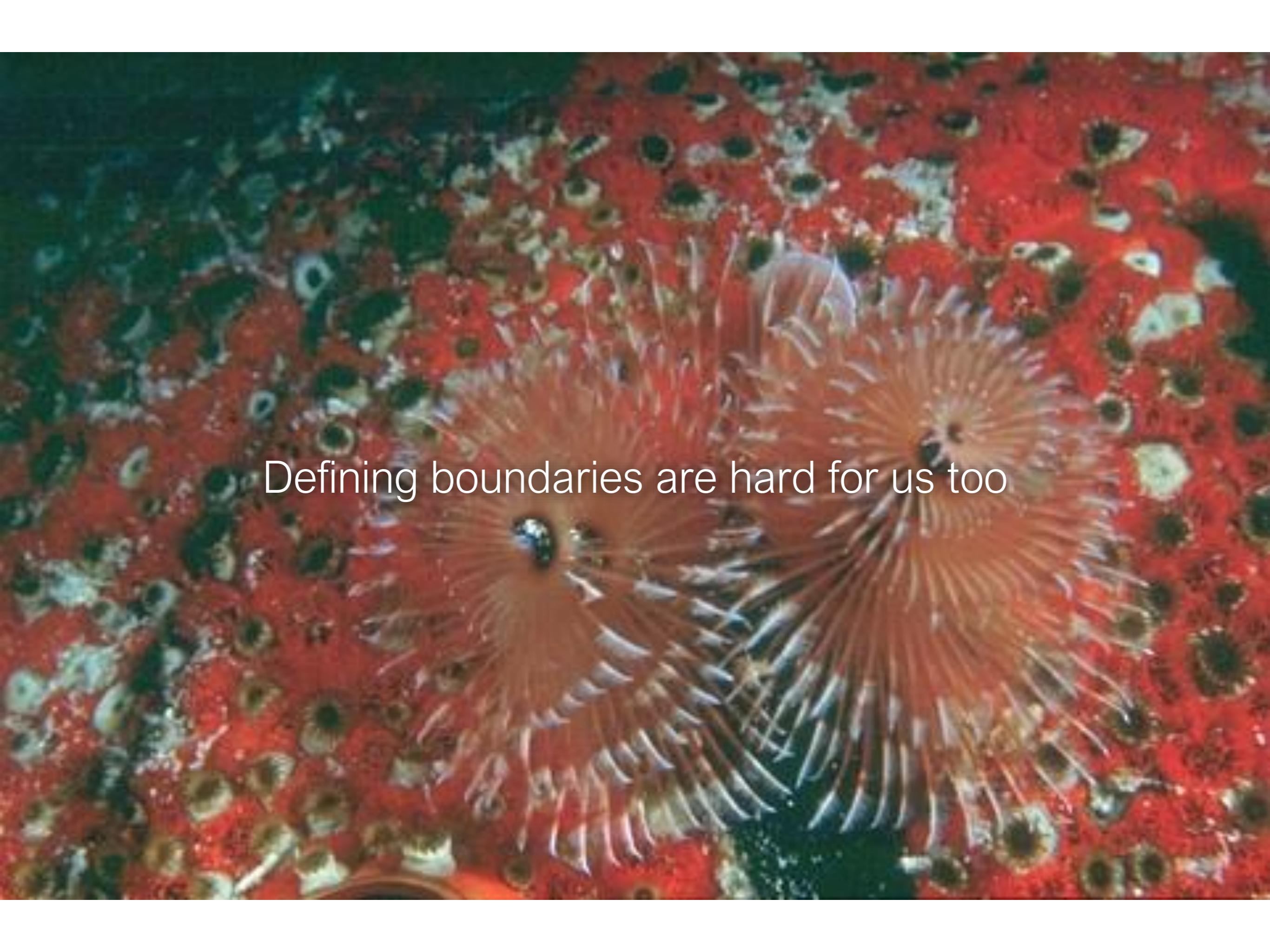




Human annotated boundaries

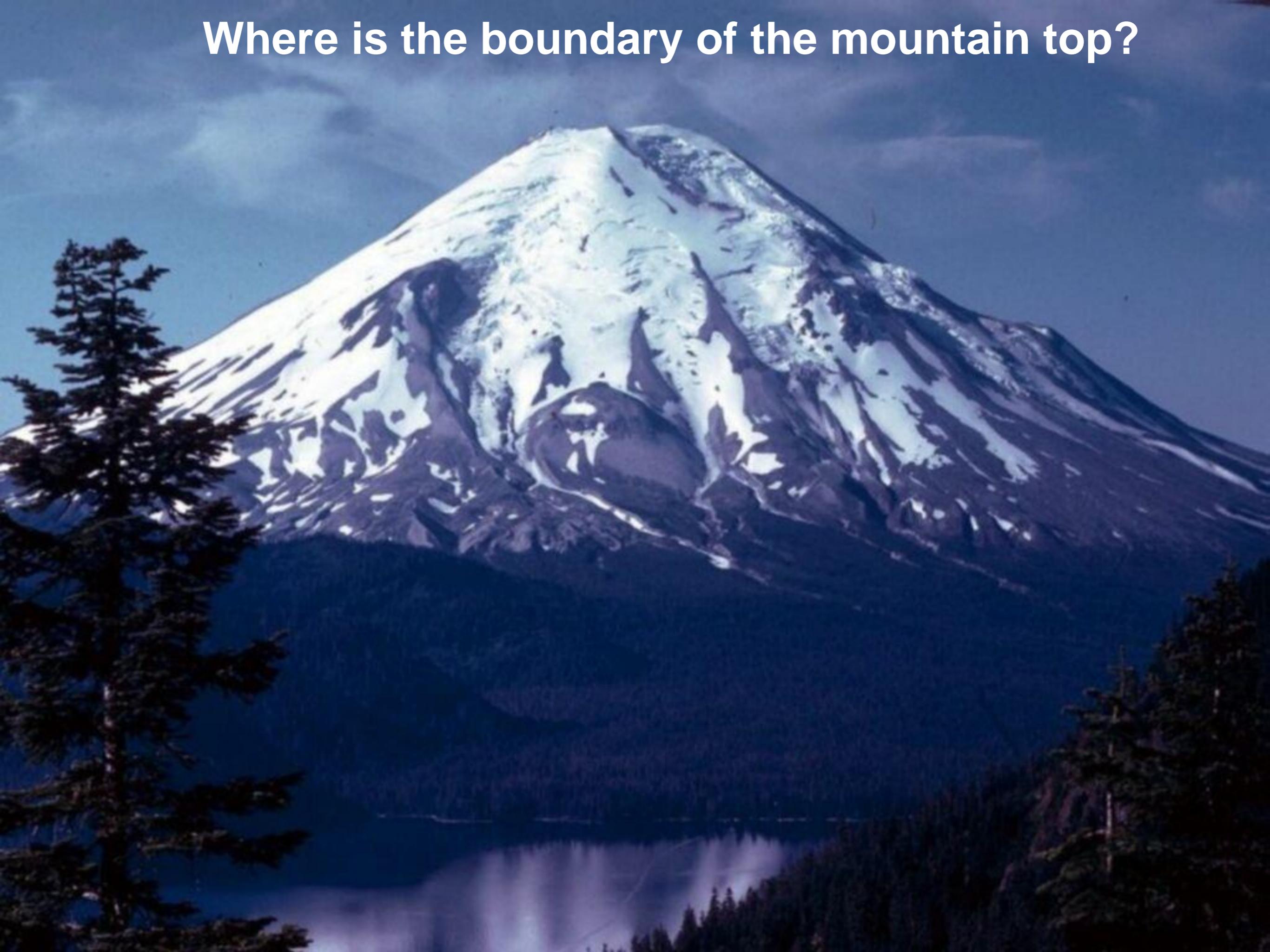


edge detection



Defining boundaries are hard for us too

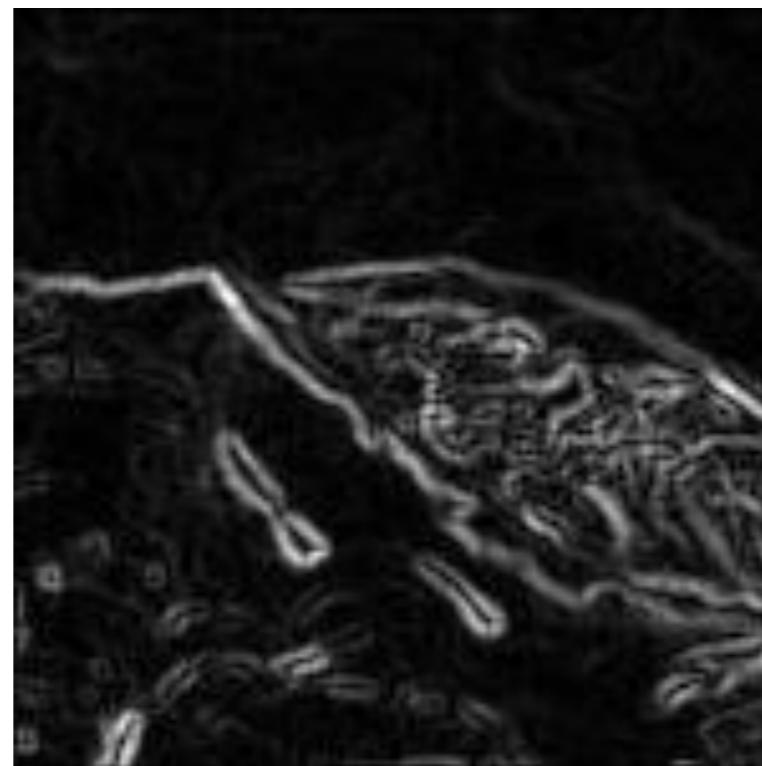
Where is the boundary of the mountain top?



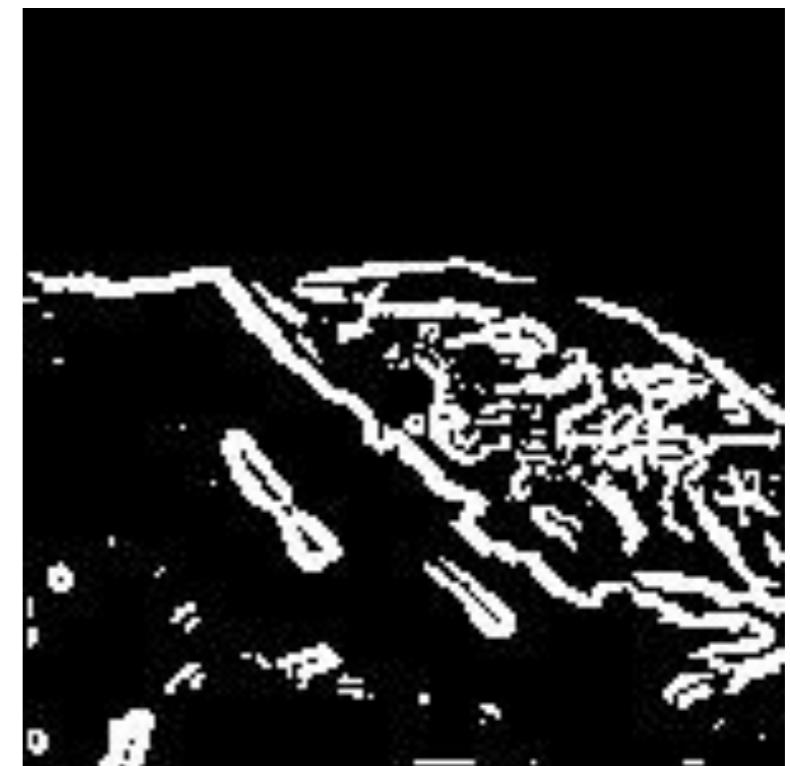
# Lines are hard to find



Original image



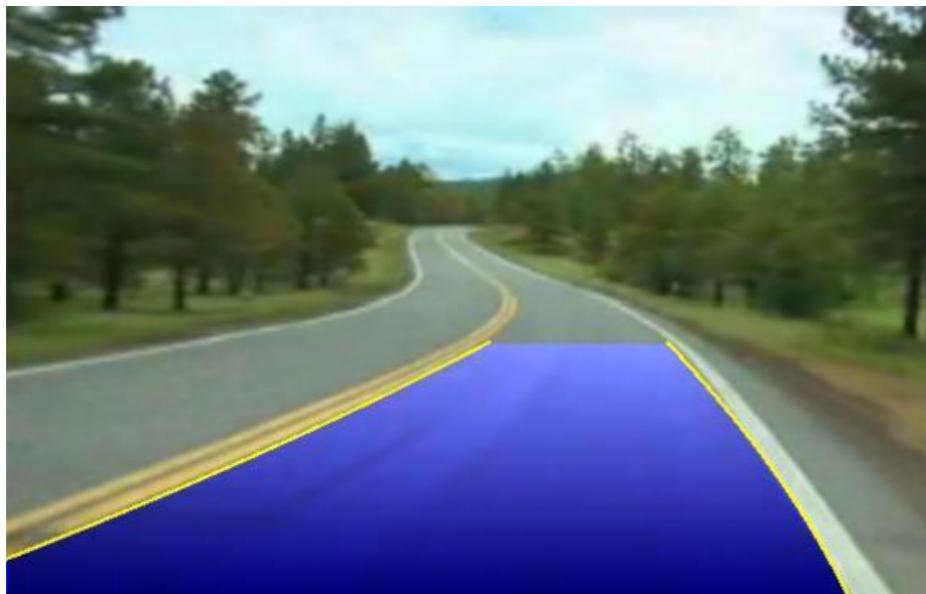
Edge detection



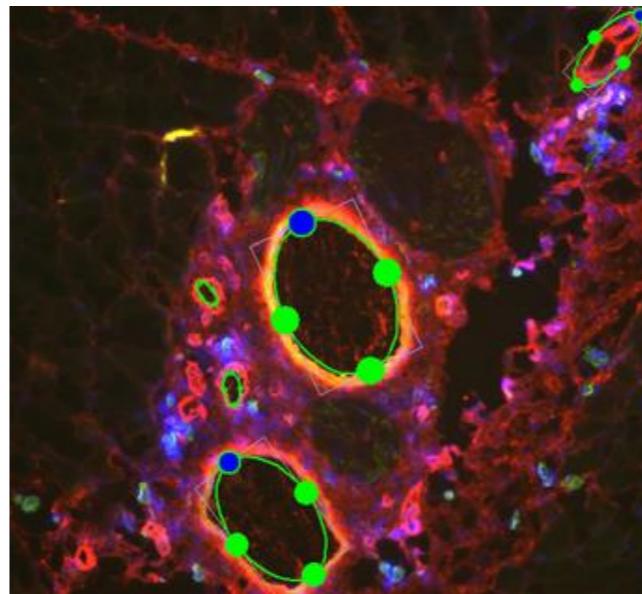
Thresholding

Noisy edge image  
Incomplete boundaries

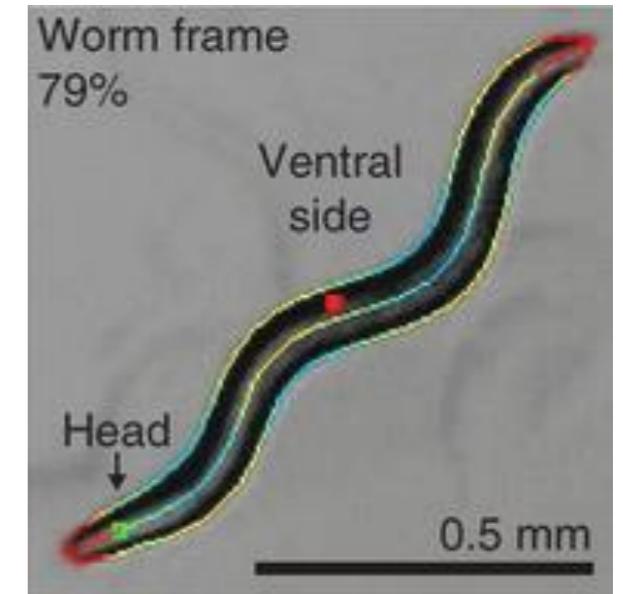
# Applications



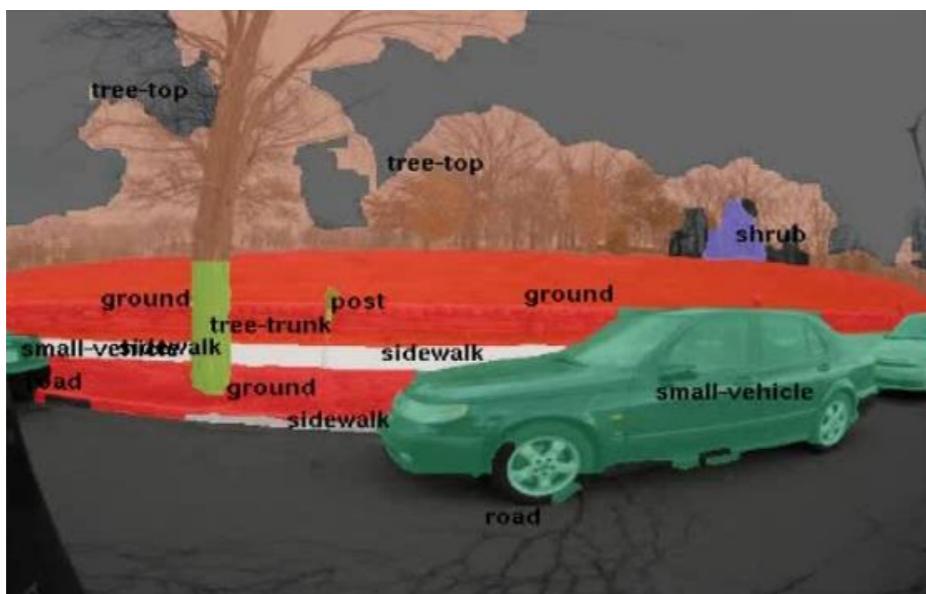
Autonomous Vehicles  
(lane line detection)



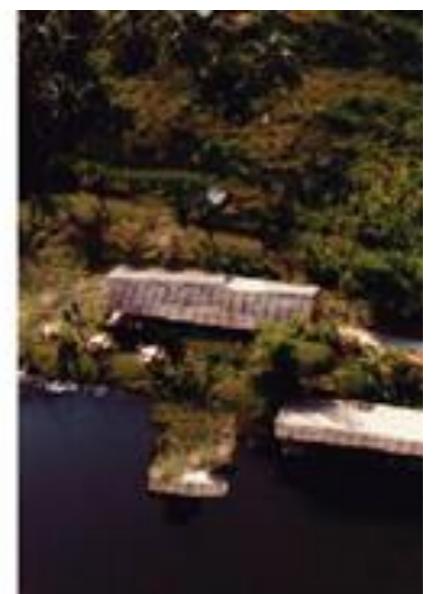
tissue engineering  
(blood vessel counting)



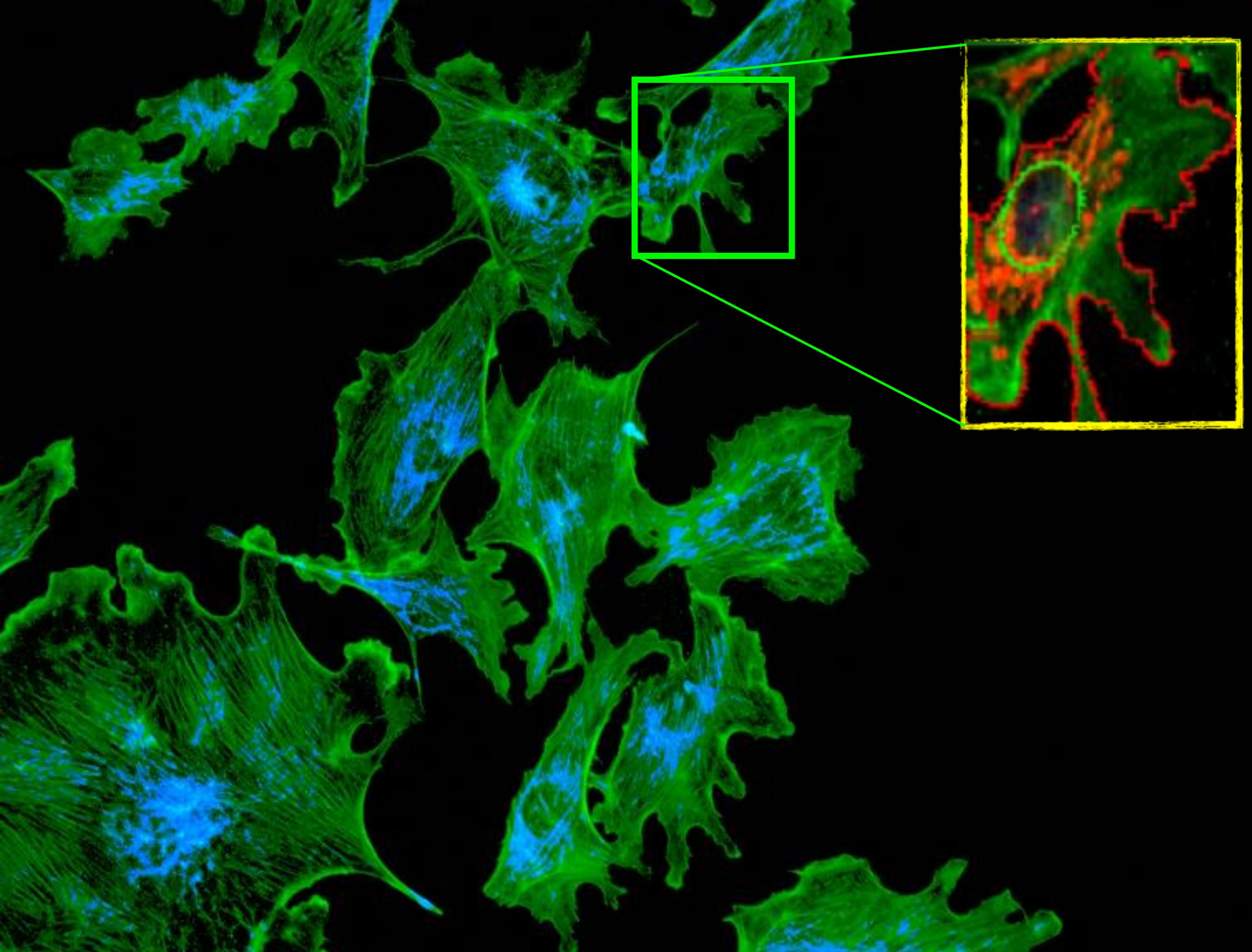
behavioral genetics  
(earthworm contours)



Autonomous Vehicles  
(semantic scene segmentation)



Computational Photography  
(image inpainting)



# Line fitting

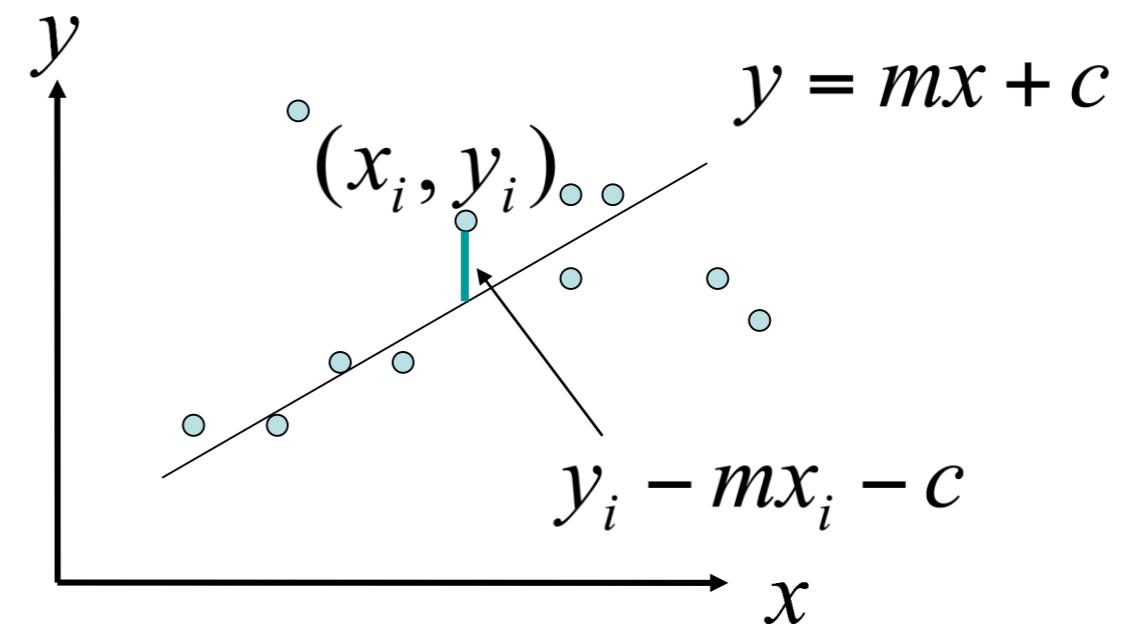
# Line fitting

Given: Many  $(x_i, y_i)$  pairs

Find: Parameters  $(m, c)$

Minimize: Average square distance:

$$E = \sum_i \frac{(y_i - mx_i - c)^2}{N}$$



# Line fitting

Given: Many  $(x_i, y_i)$  pairs

Find: Parameters  $(m, c)$

Minimize: Average square distance:

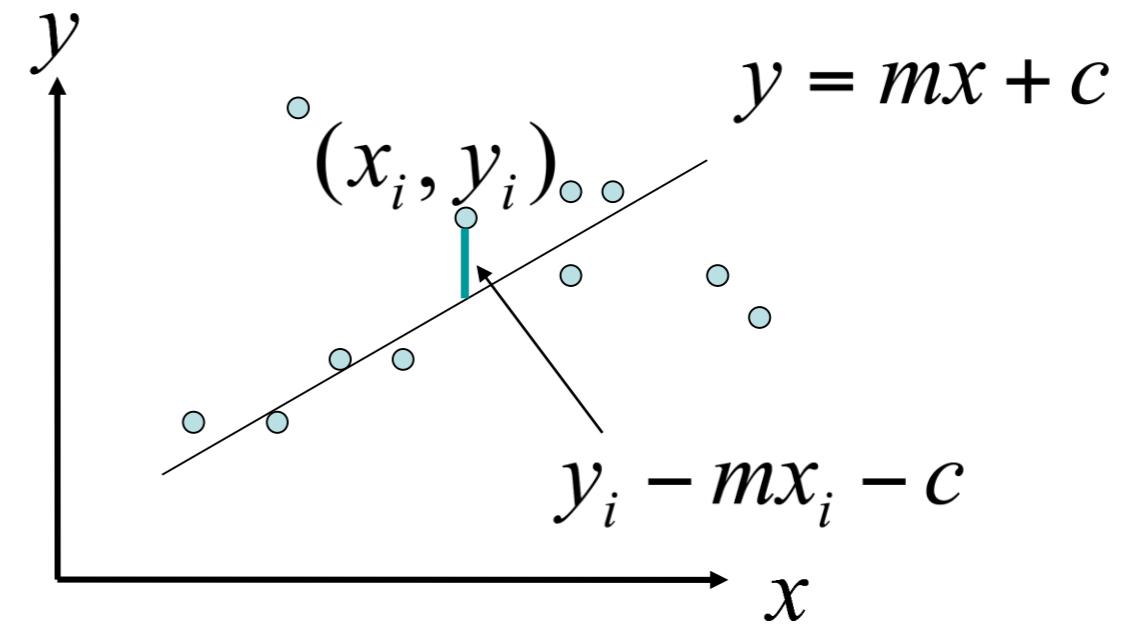
$$E = \sum_i \frac{(y_i - mx_i - c)^2}{N}$$

Using:

$$\frac{\partial E}{\partial m} = 0 \quad \& \quad \frac{\partial E}{\partial c} = 0$$

Note:

$$\bar{y} = \frac{\sum_i y_i}{N} \quad \bar{x} = \frac{\sum_i x_i}{N}$$



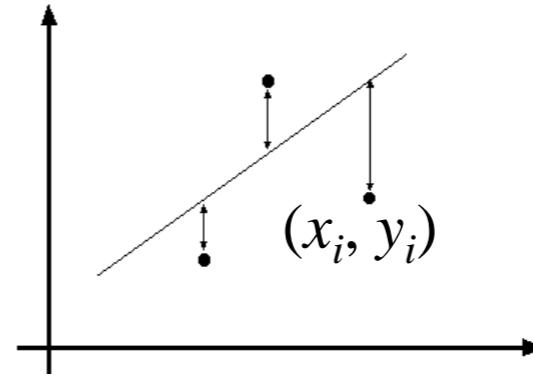
$$c = \bar{y} - m \bar{x}$$

$$m = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sum_i (x_i - \bar{x})^2}$$

*What are some problems with the approach?*

Data:  $(x_1, y_1), \dots, (x_n, y_n)$

Line equation:  $y_i = m x_i + b$



Find  $(m, b)$  to minimize

$$E = \sum_{i=1}^n (y_i - mx_i - b)^2$$

$$Y = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \quad X = \begin{bmatrix} x_1 & 1 \\ \vdots & \vdots \\ x_n & 1 \end{bmatrix} \quad B = \begin{bmatrix} m \\ b \end{bmatrix}$$

$$E = \|Y - XB\|^2 = (Y - XB)^T(Y - XB) = Y^T Y - 2(XB)^T Y + (XB)^T(XB)$$

$$\frac{dE}{dB} = 2X^T XB - 2X^T Y = 0$$

$$X^T XB = X^T Y$$

Normal equations: least squares solution to  $XB=Y$

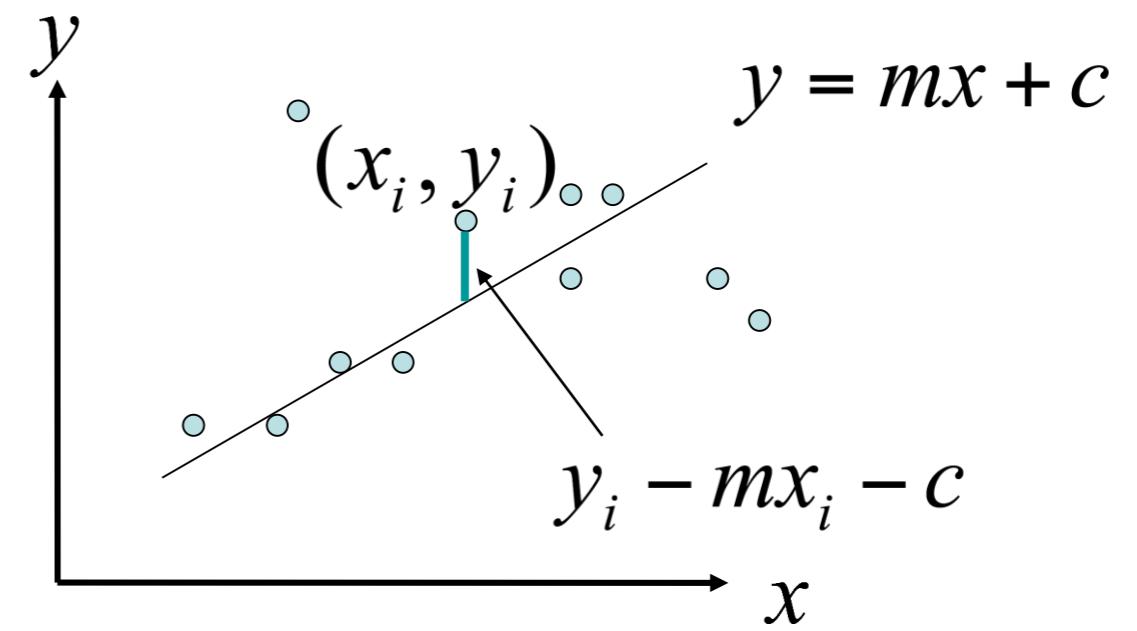
# Line fitting

Given: Many  $(x_i, y_i)$  pairs

Find: Parameters  $(m, c)$

Minimize: Average square distance:

$$E = \sum_i \frac{(y_i - mx_i - c)^2}{N}$$

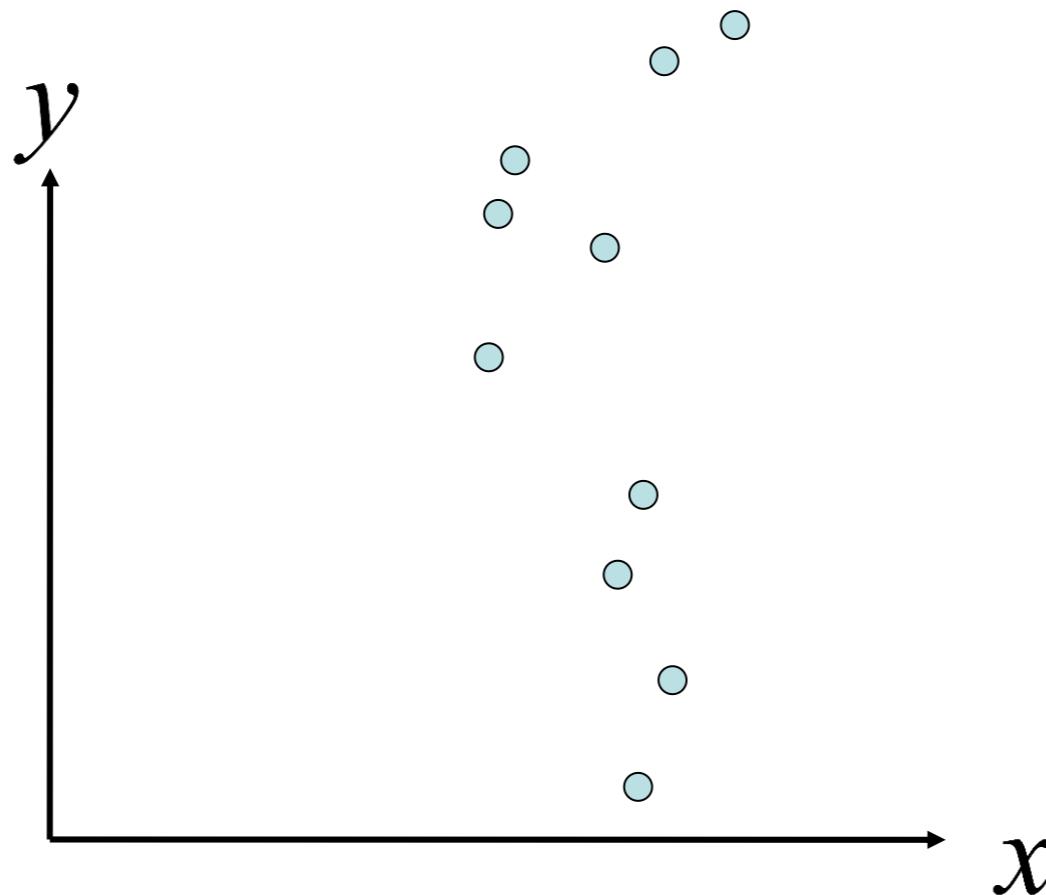


*How can we solve this minimization?*

# Problems with parameterizations

Where is the line that minimizes E?

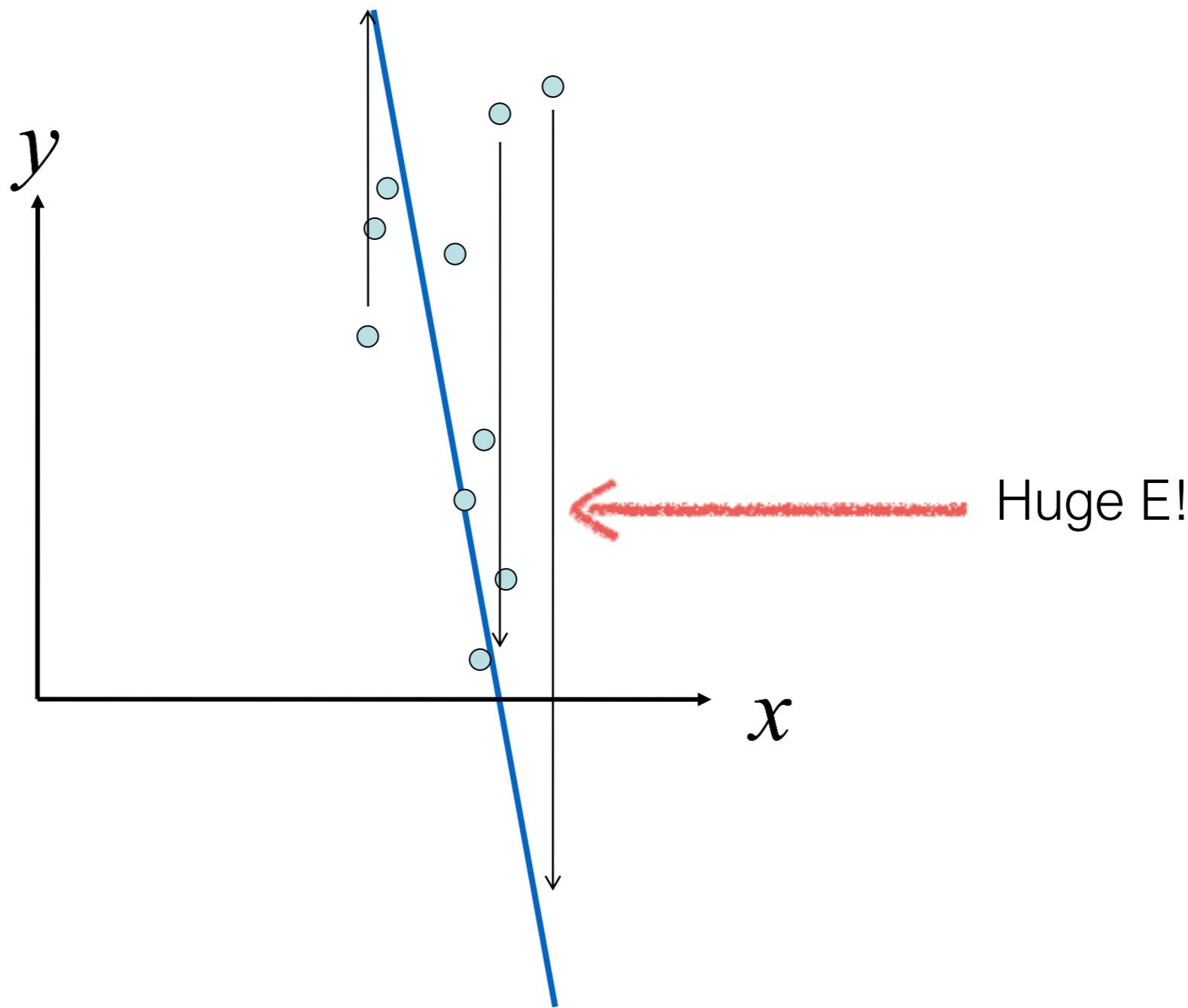
$$E = \sum_{i=1}^n (y_i - mx_i - b)^2$$



# Problems with parameterizations

Where is the line that minimizes E?

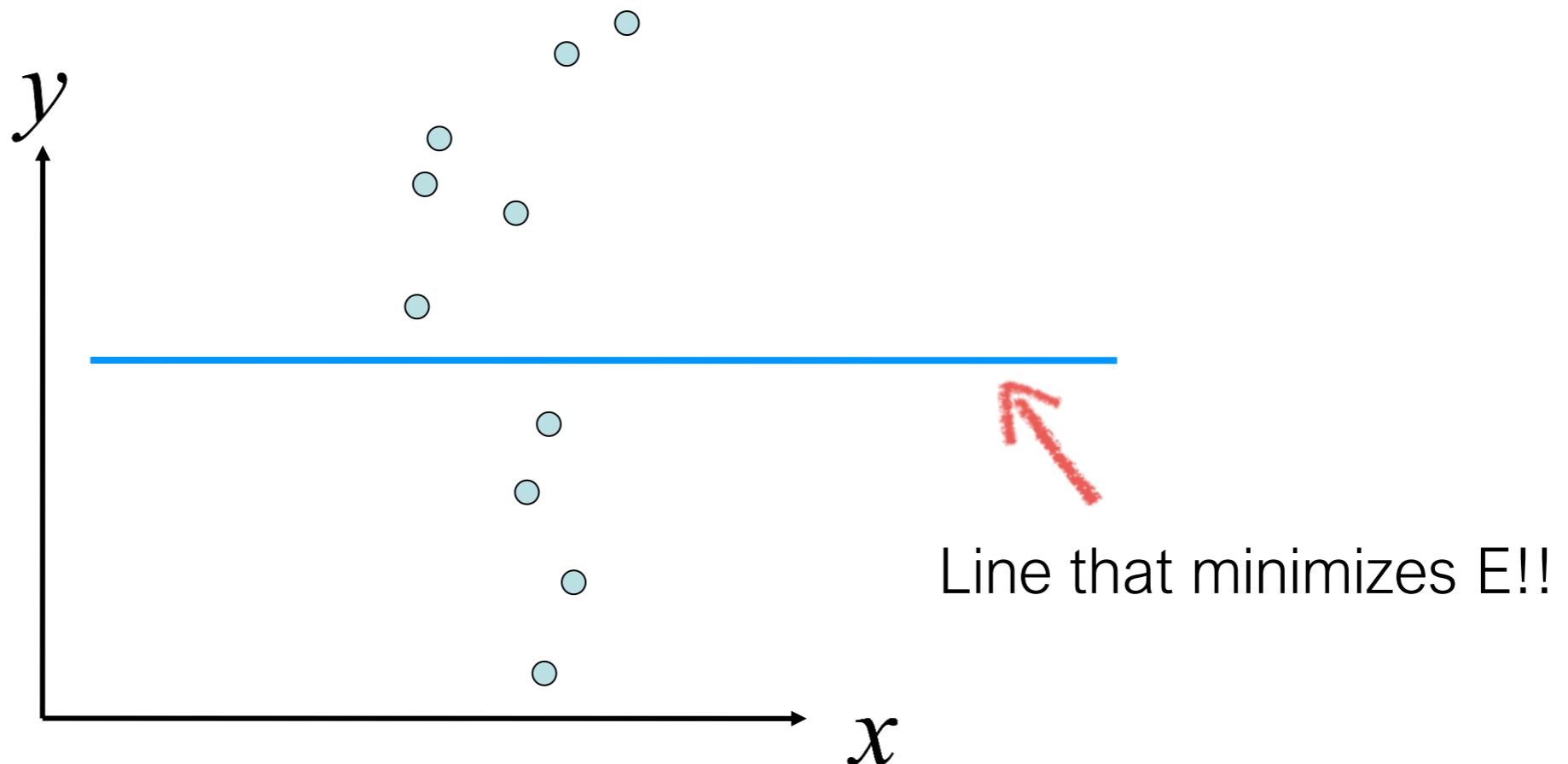
$$E = \sum_{i=1}^n (y_i - mx_i - b)^2$$



# Problems with parameterizations

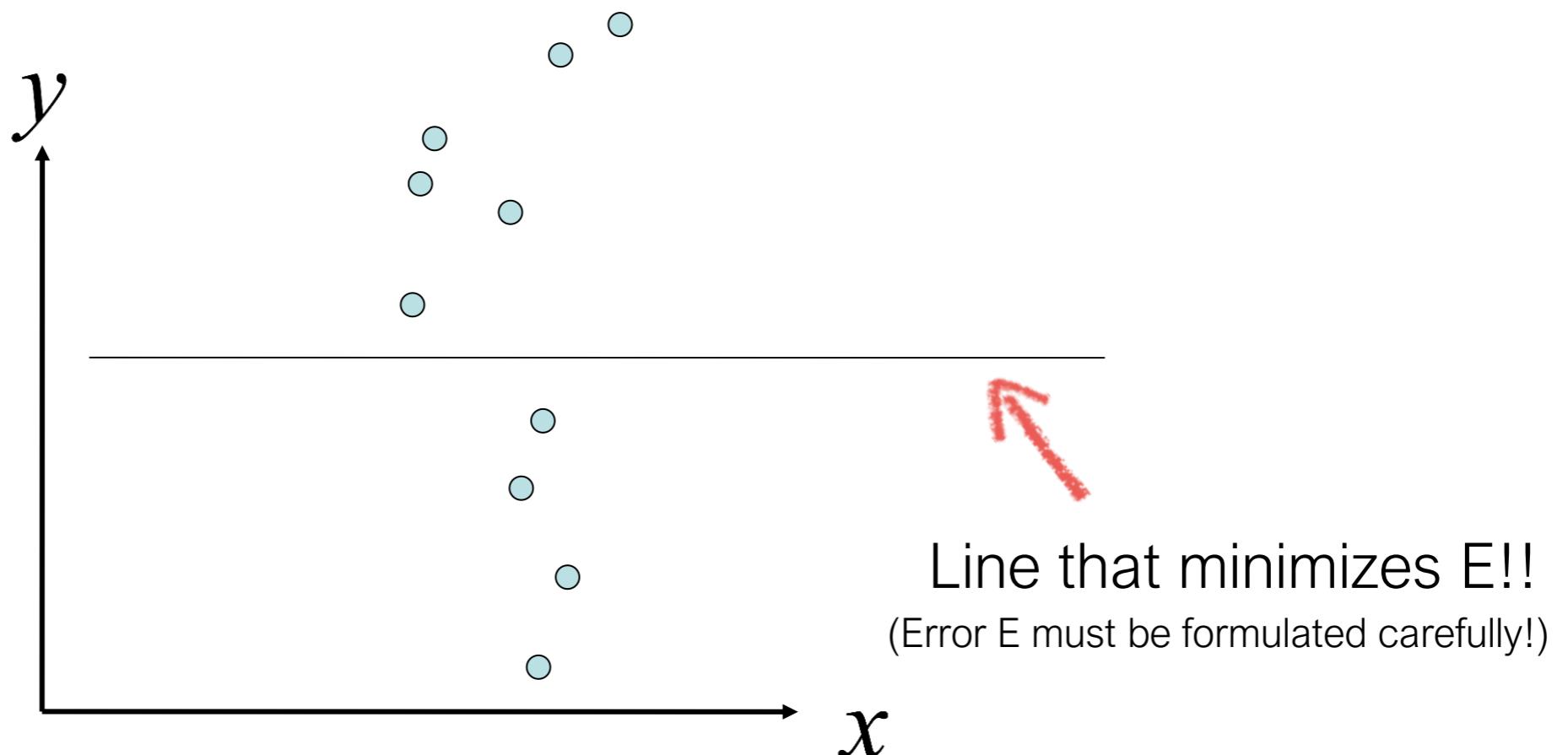
Where is the line that minimizes E?

$$E = \sum_{i=1}^n (y_i - mx_i - b)^2$$



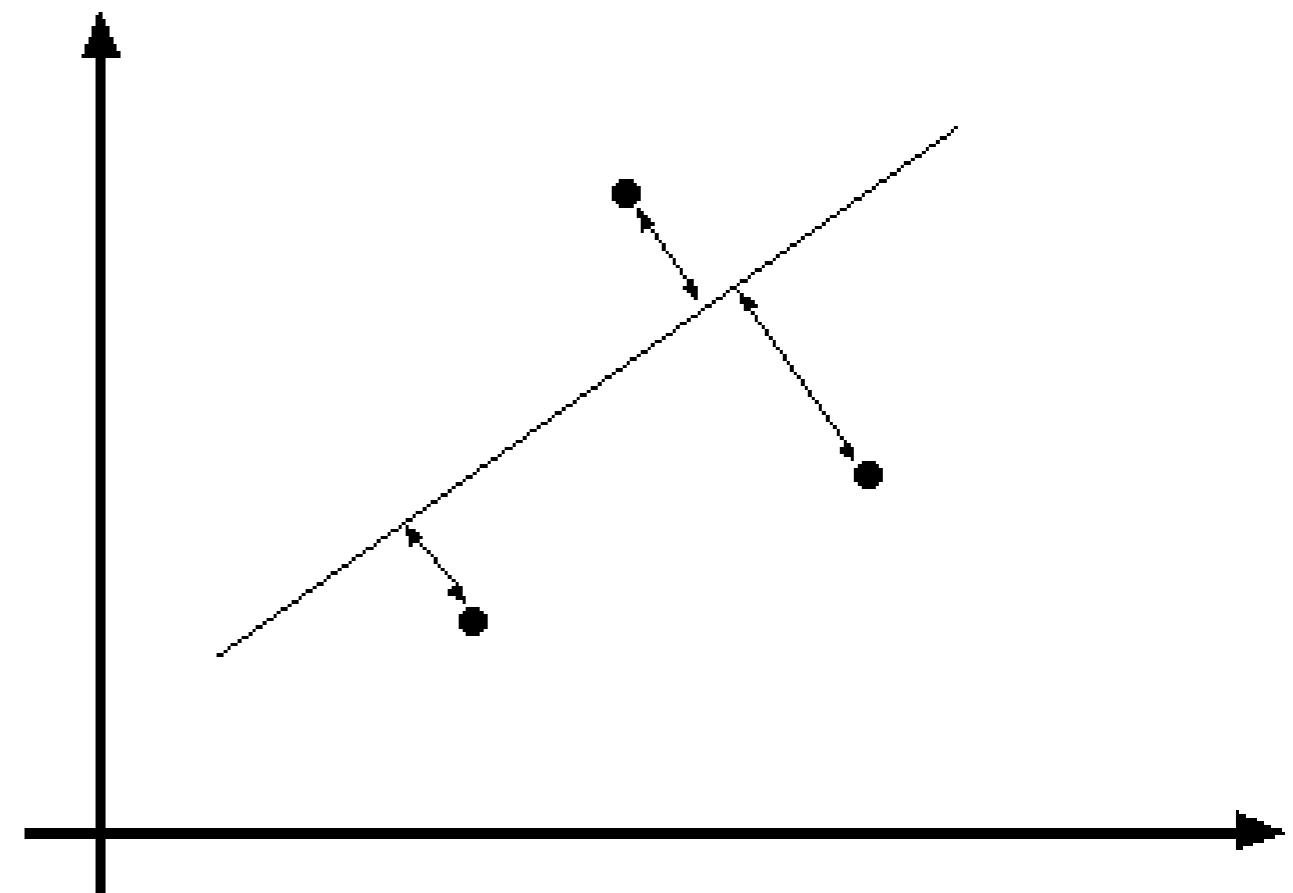
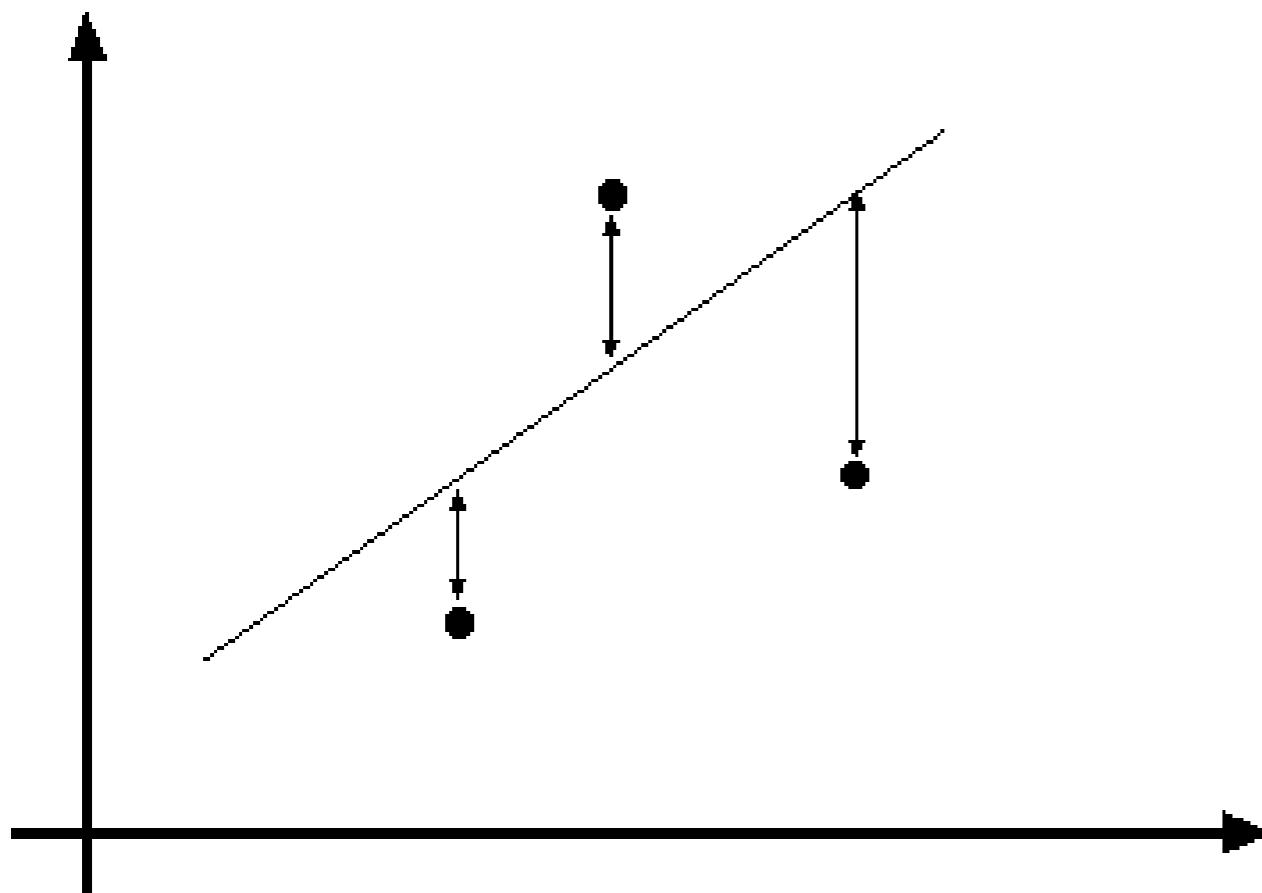
# Problems with parameterizations

Where is the line that minimizes E?



*How can we deal with this?*

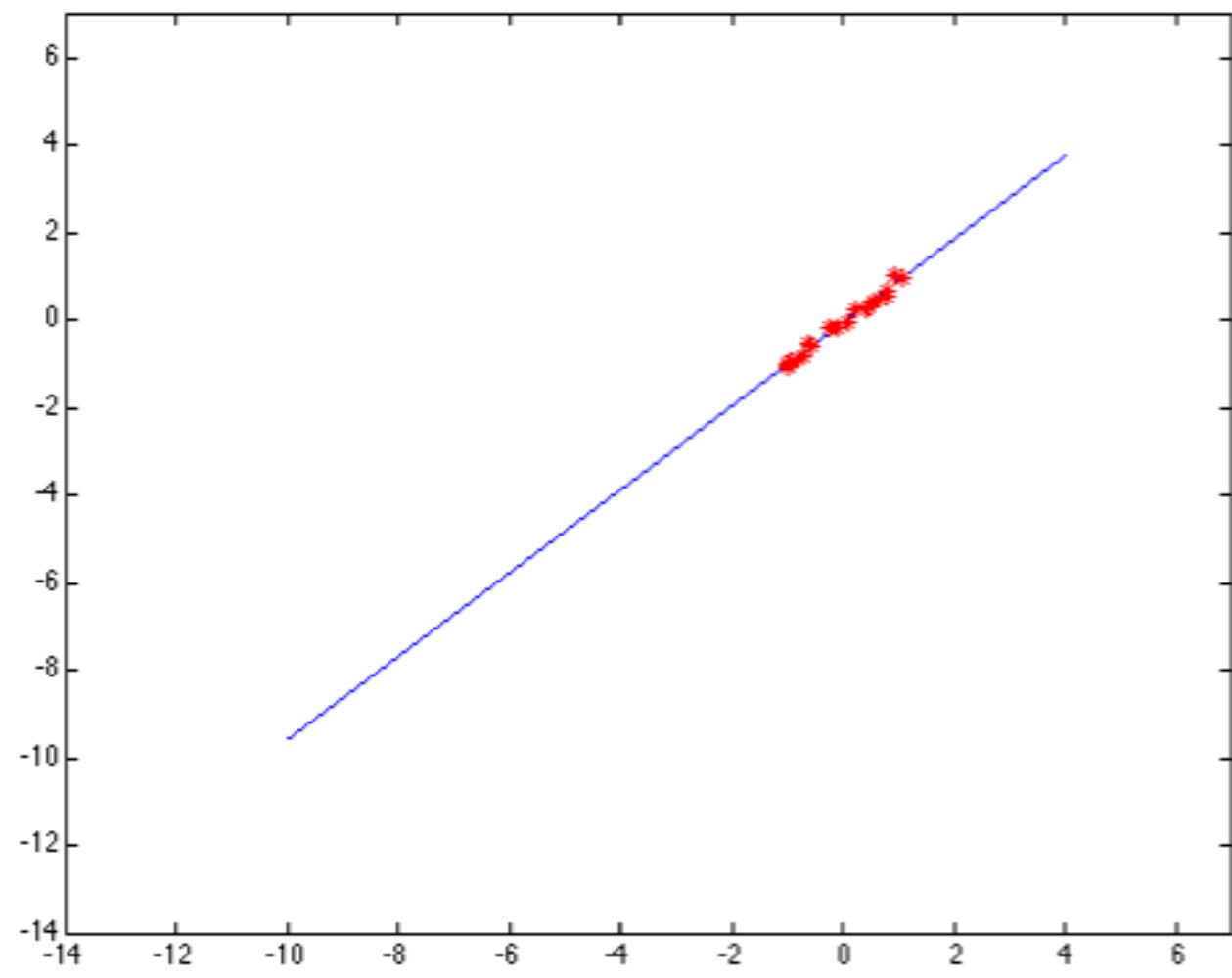
Line fitting is easily setup as a maximum likelihood problem  
... but choice of model is important



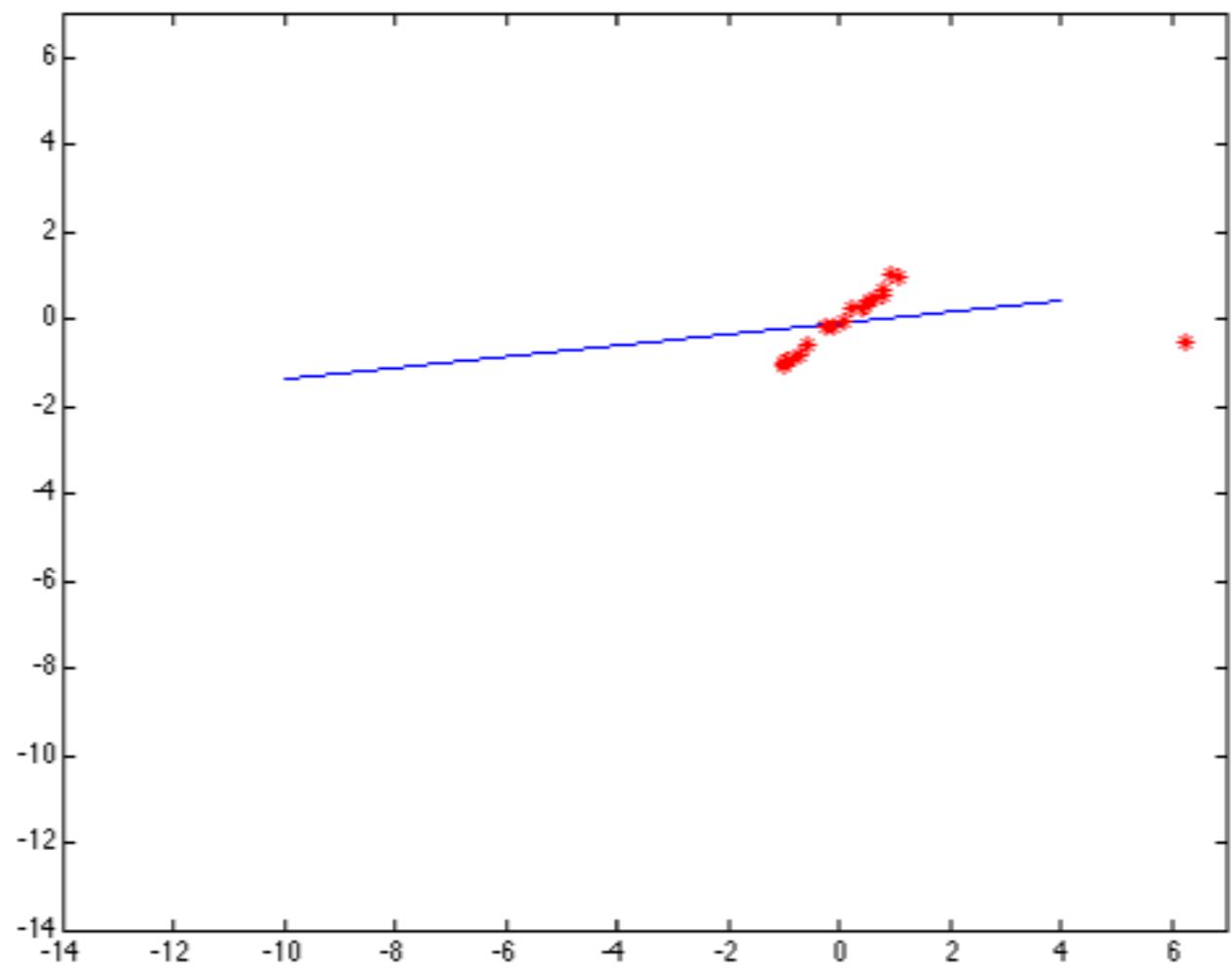
$$E = \sum_{i=1}^n (y_i - mx_i - b)^2$$

*What optimization are we solving here?*

# Problems with noise

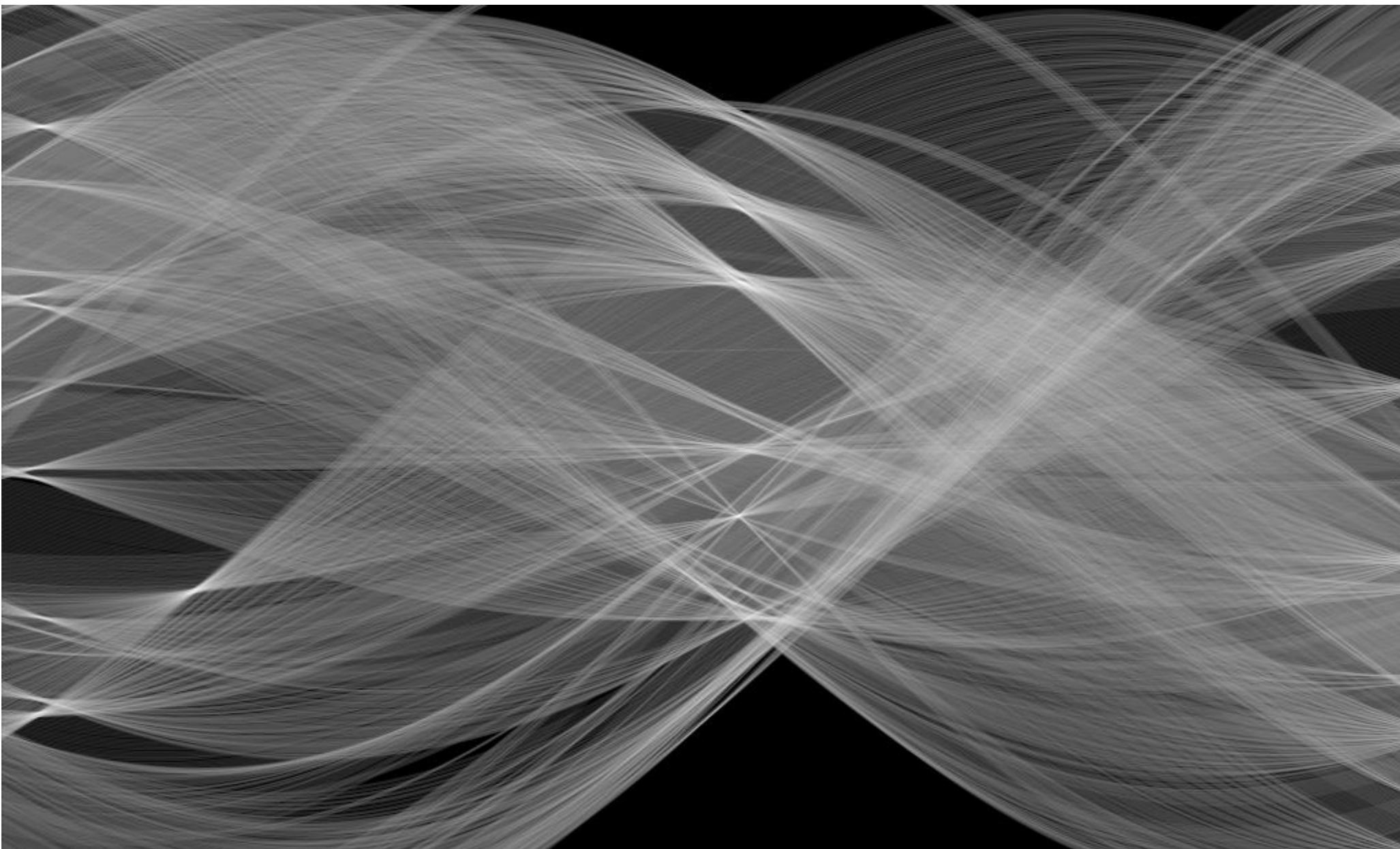


Least-squares error fit



Squared error heavily penalizes outliers

# Hough transform



# Model fitting is difficult because...

- **Extraneous data:** clutter or multiple models
  - We do not know what is part of the model?
  - Can we pull out models with a few parts from much larger amounts of background clutter?
- **Missing data:** only some parts of model are present
- **Noise**
- Cost:
  - It is not feasible to check all combinations of features by fitting a model to each possible subset

*So what can we do?*

# Line parameterizations

# Slope intercept form

$$y = mx + b$$

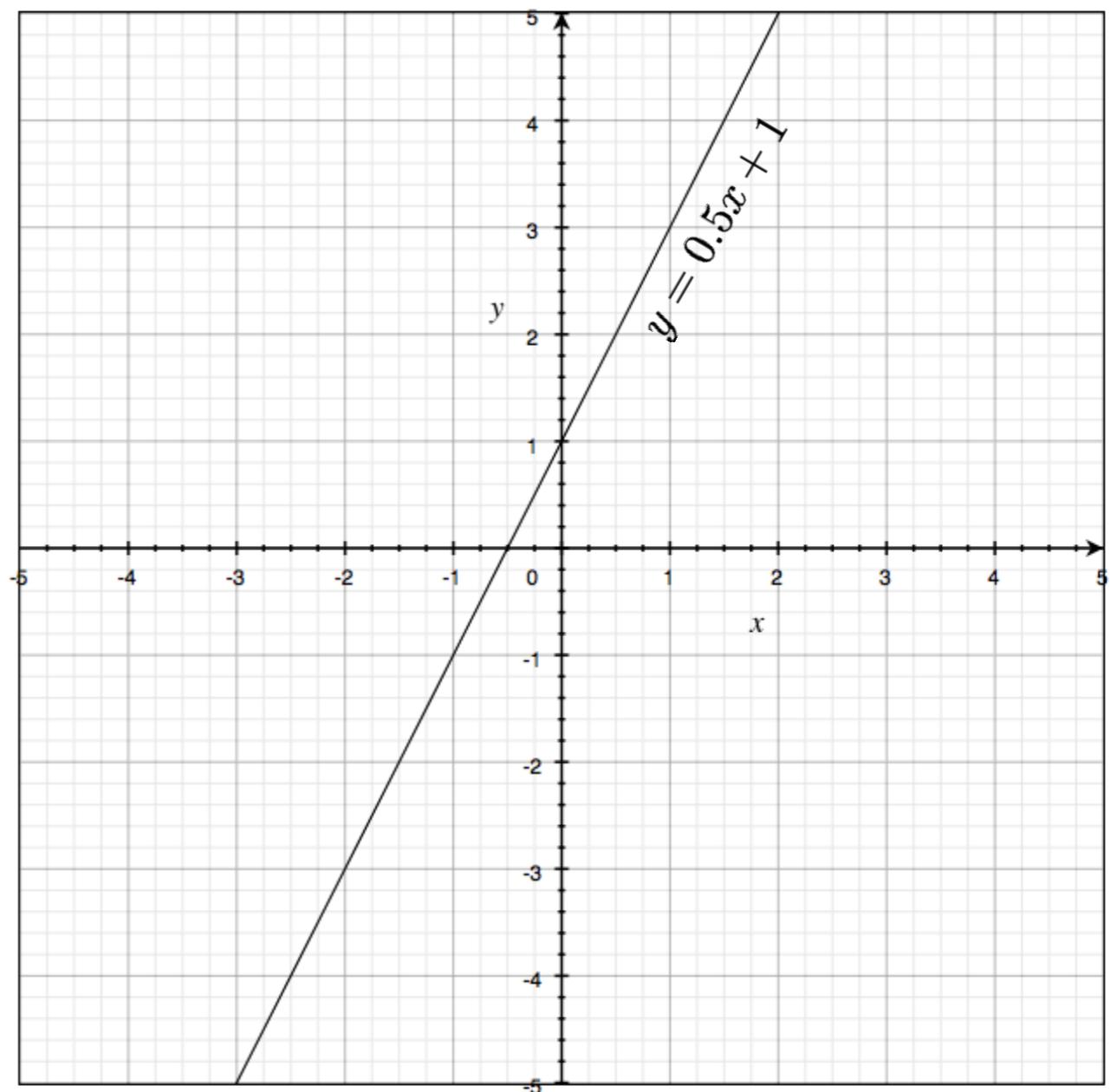

slope      y-intercept

*What are  $m$  and  $b$ ?*

# Slope intercept form

$$y = mx + b$$

↑                    ↑  
slope                y-intercept



# Double intercept form

$$\frac{x}{a} + \frac{y}{b} = 1$$

x-intercept                  y-intercept

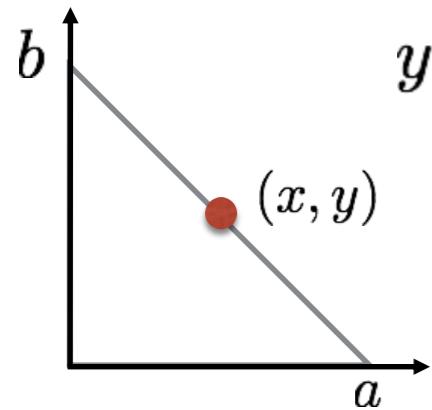
*What are x and y?*

# Double intercept form

$$\frac{x}{a} + \frac{y}{b} = 1$$

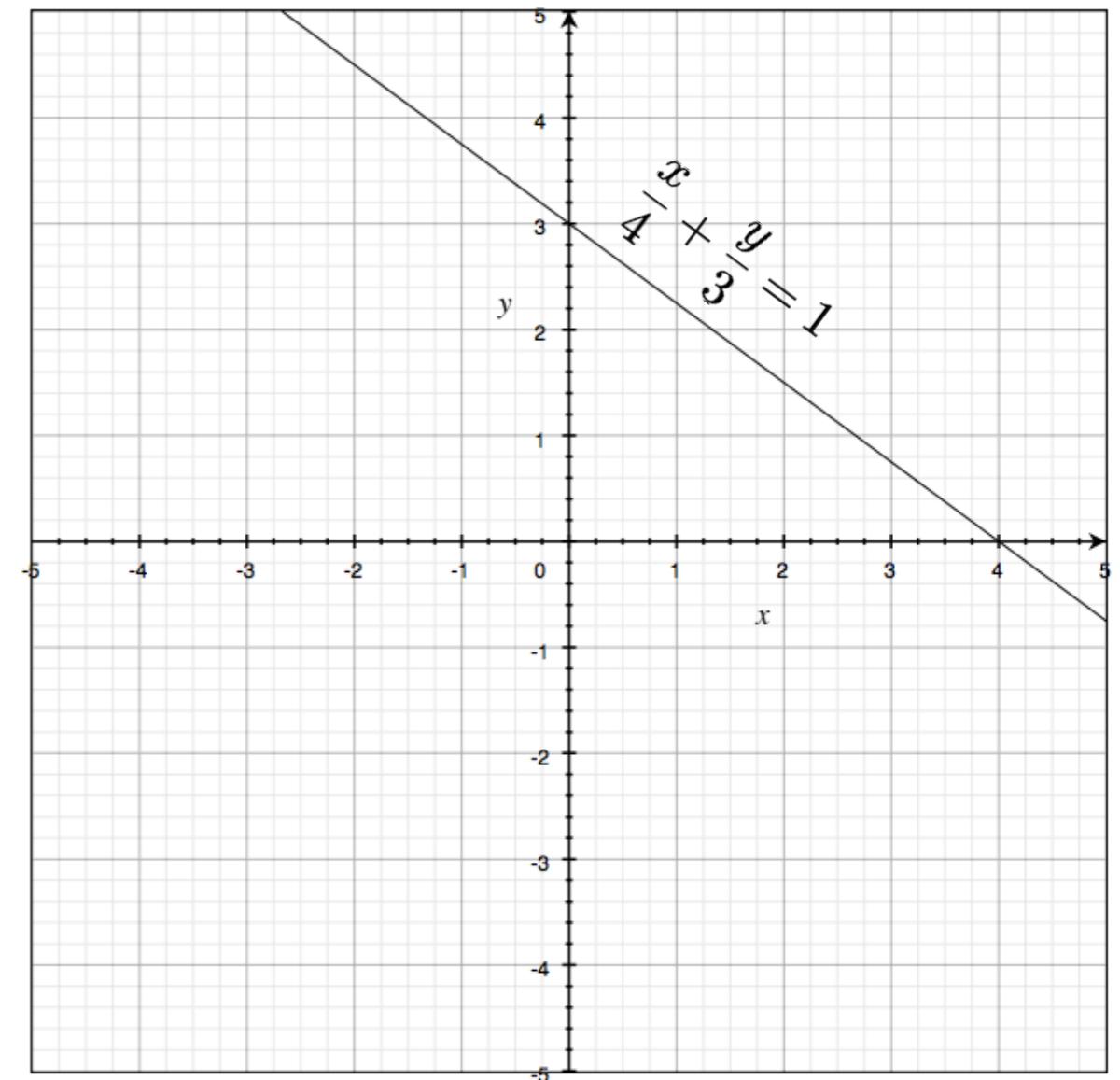
x-intercept      y-intercept

Derivation:



(Similar slope)  $\frac{y - b}{x - 0} = \frac{0 - y}{a - x}$

$$ya + yx - ba + bx = -yx$$
$$ya + bx = ba$$
$$\frac{y}{b} + \frac{x}{a} = 1$$



# Normal Form

$$x \cos \theta + y \sin \theta = \rho$$

*What are rho and theta?*

# Normal Form

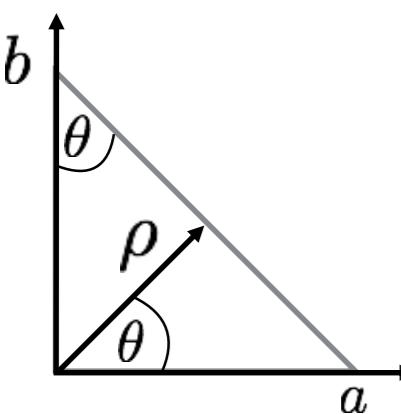
$$x \cos \theta + y \sin \theta = \rho$$

Derivation:

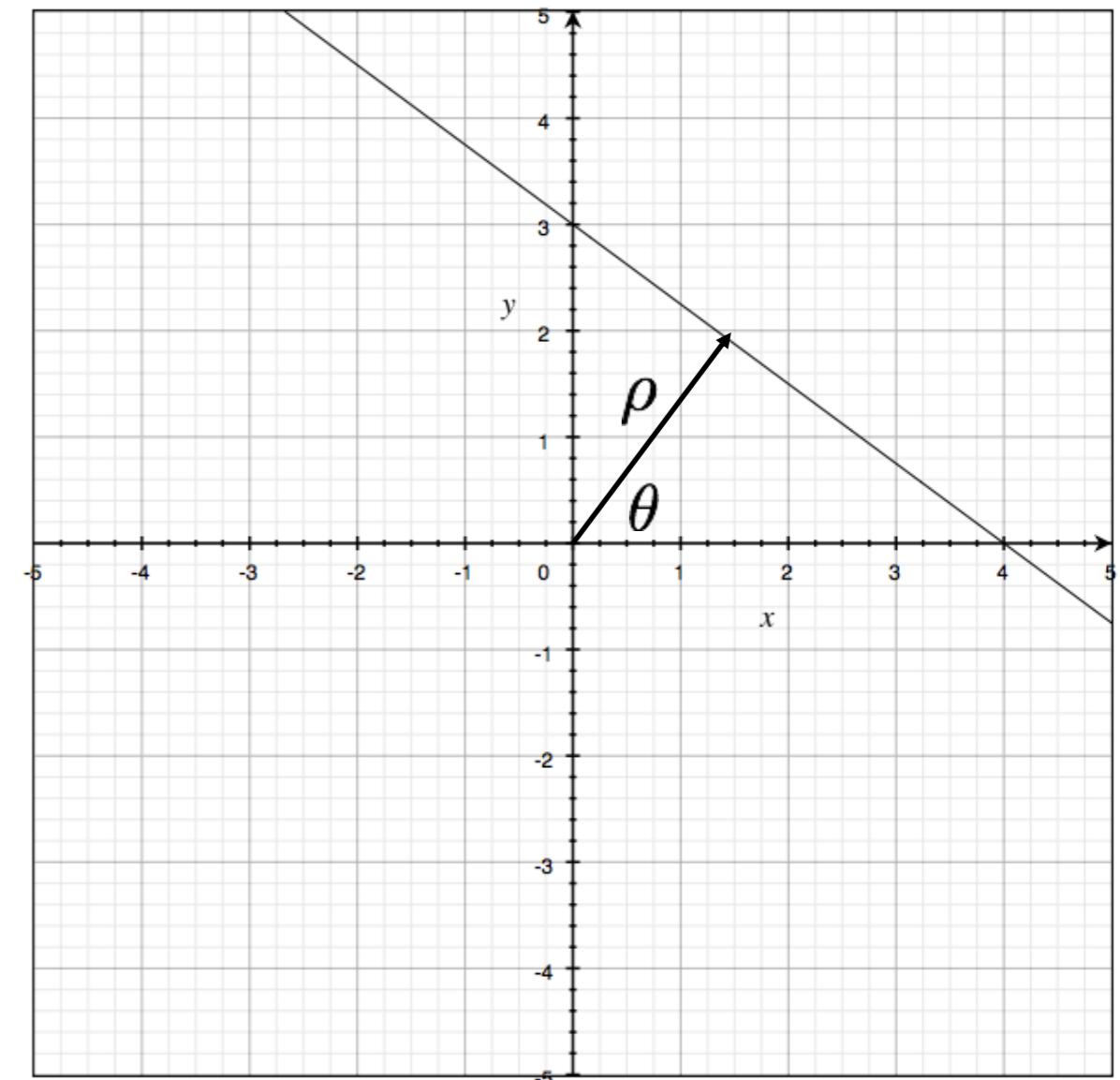
$$\cos \theta = \frac{\rho}{a} \rightarrow a = \frac{\rho}{\cos \theta}$$

$$\sin \theta = \frac{\rho}{b} \rightarrow b = \frac{\rho}{\sin \theta}$$

plug into:  $\frac{x}{a} + \frac{y}{b} = 1$



$$x \cos \theta + y \sin \theta = \rho$$



# Hough transform

- Generic framework for detecting a parametric model
- Edges don't have to be connected
- Lines can be occluded
- Key idea: edges **vote** for the possible models

# Image and parameter space

variables  
 $y = mx + b$   
parameters

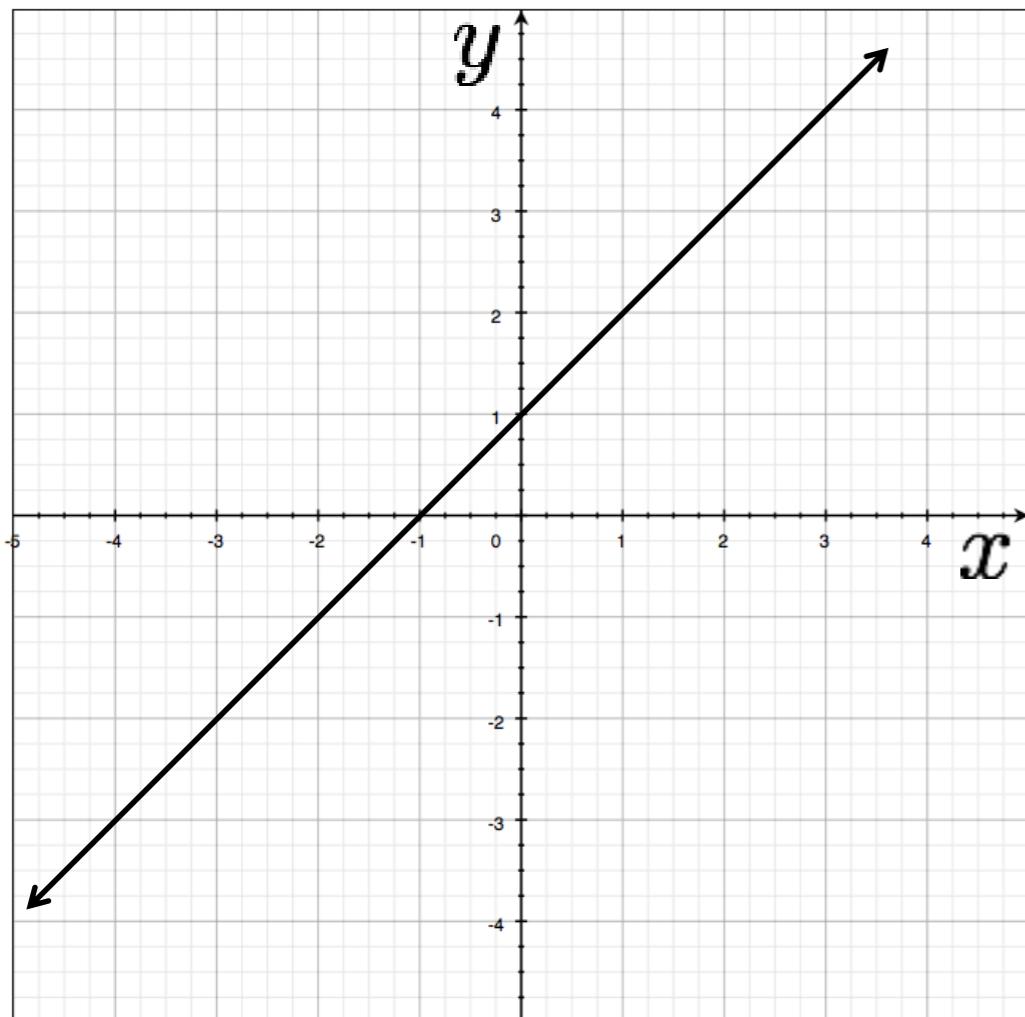
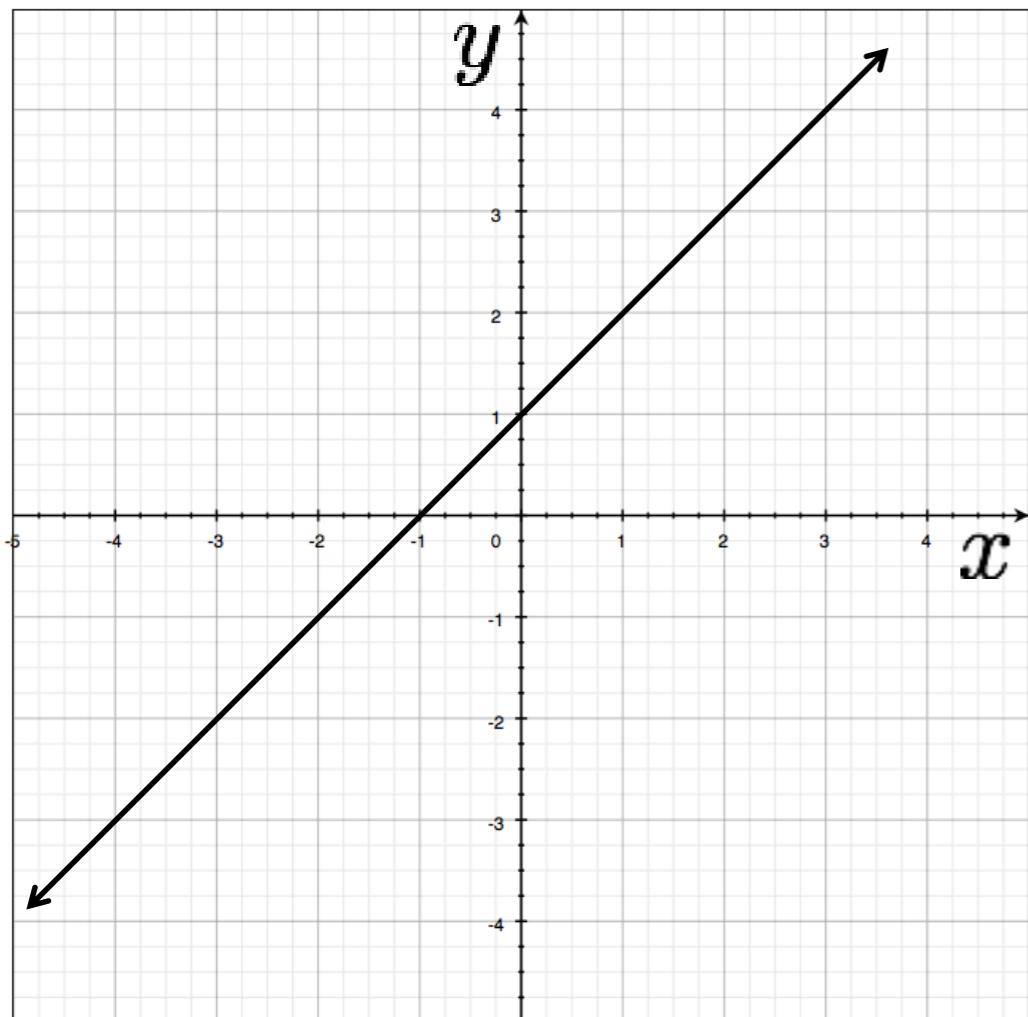


Image space

# Image and parameter space

variables  
 $y = mx + b$   
parameters



a line  
becomes a  
point

variables  
 $y - mx = b$   
parameters

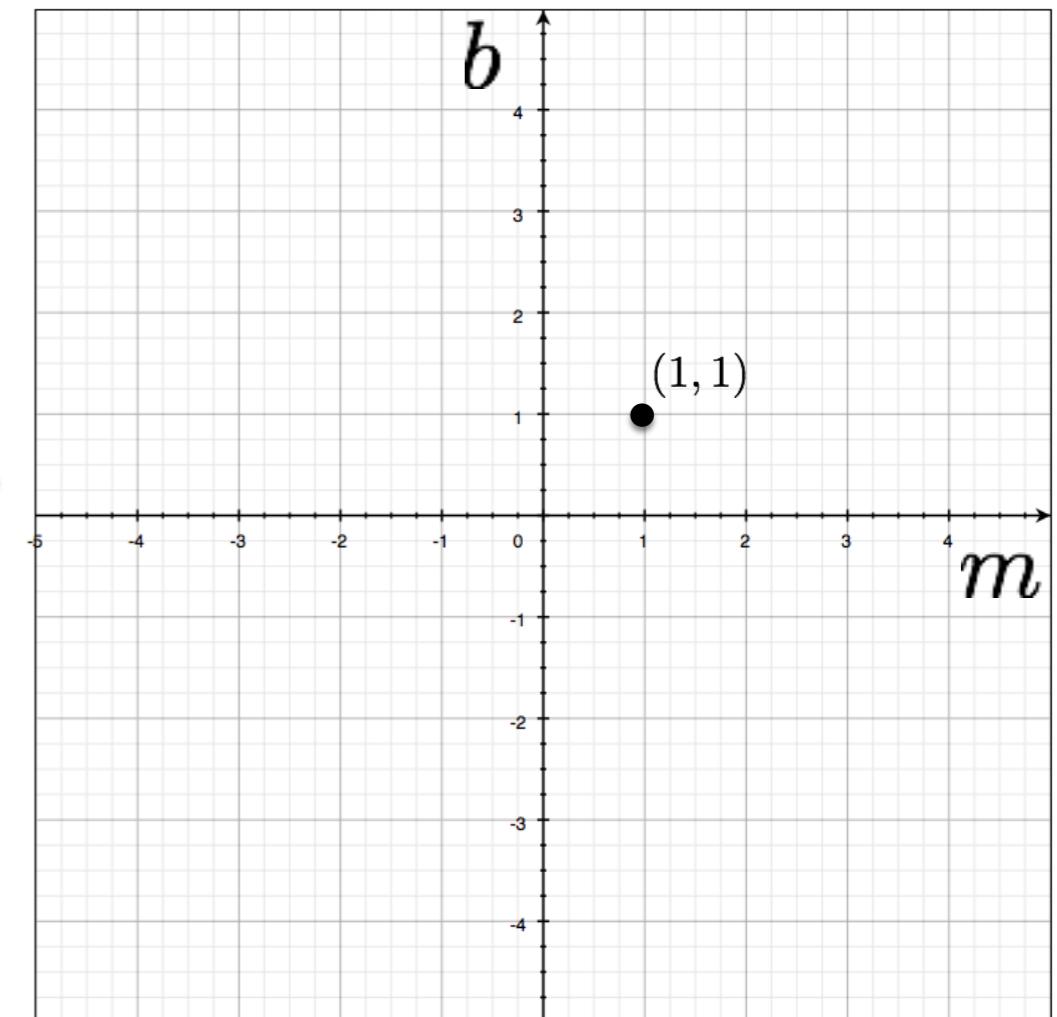


Image space

Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters

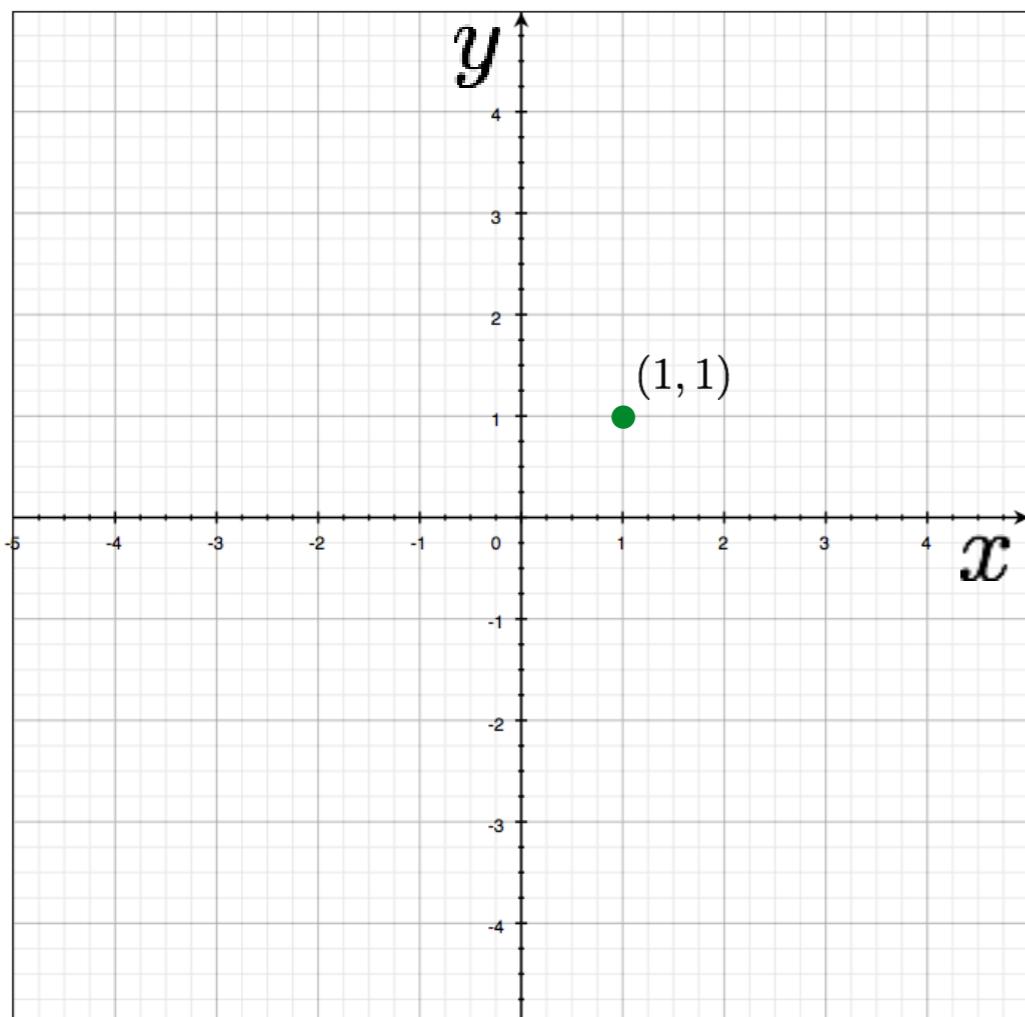
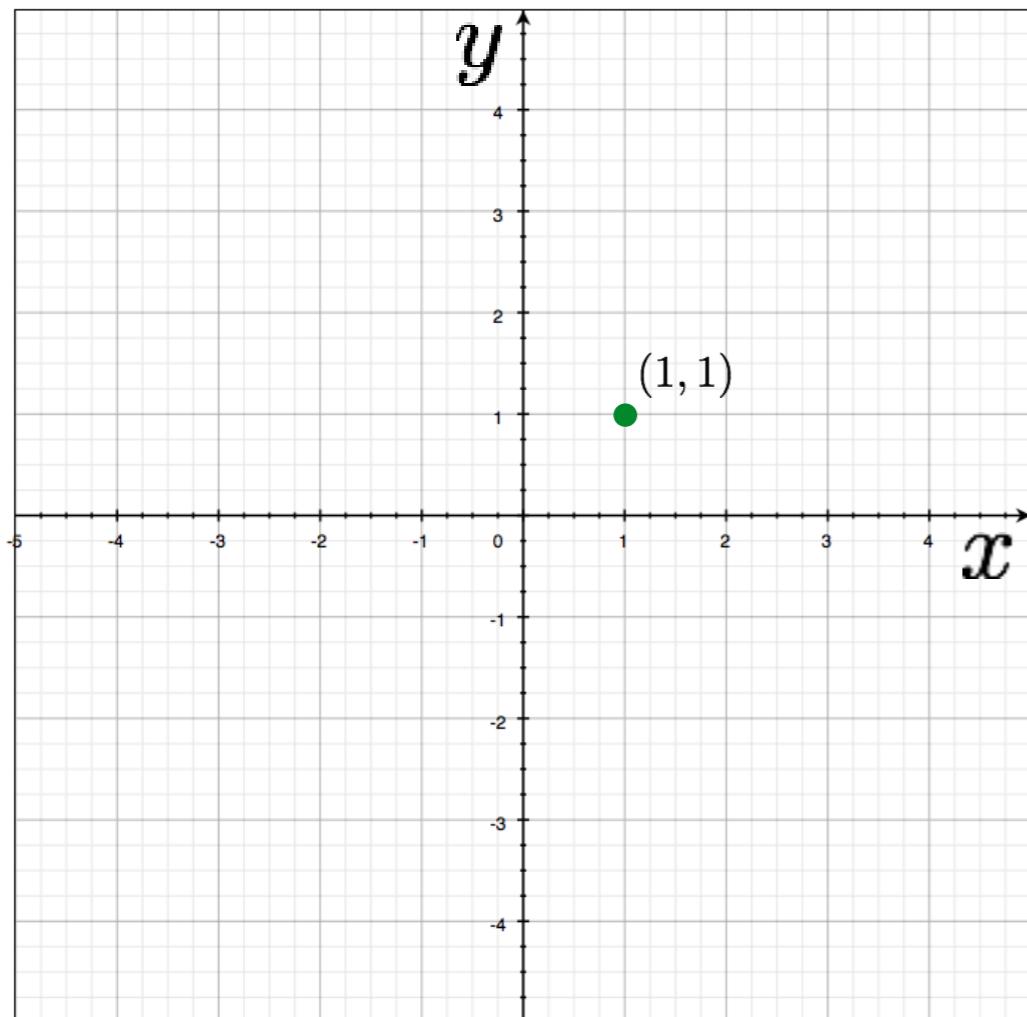


Image space

*What would a point in image space become in parameter space?*

# Image and parameter space

variables  
 $y = mx + b$   
parameters



a point becomes a line

variables  
 $y - mx = b$   
parameters

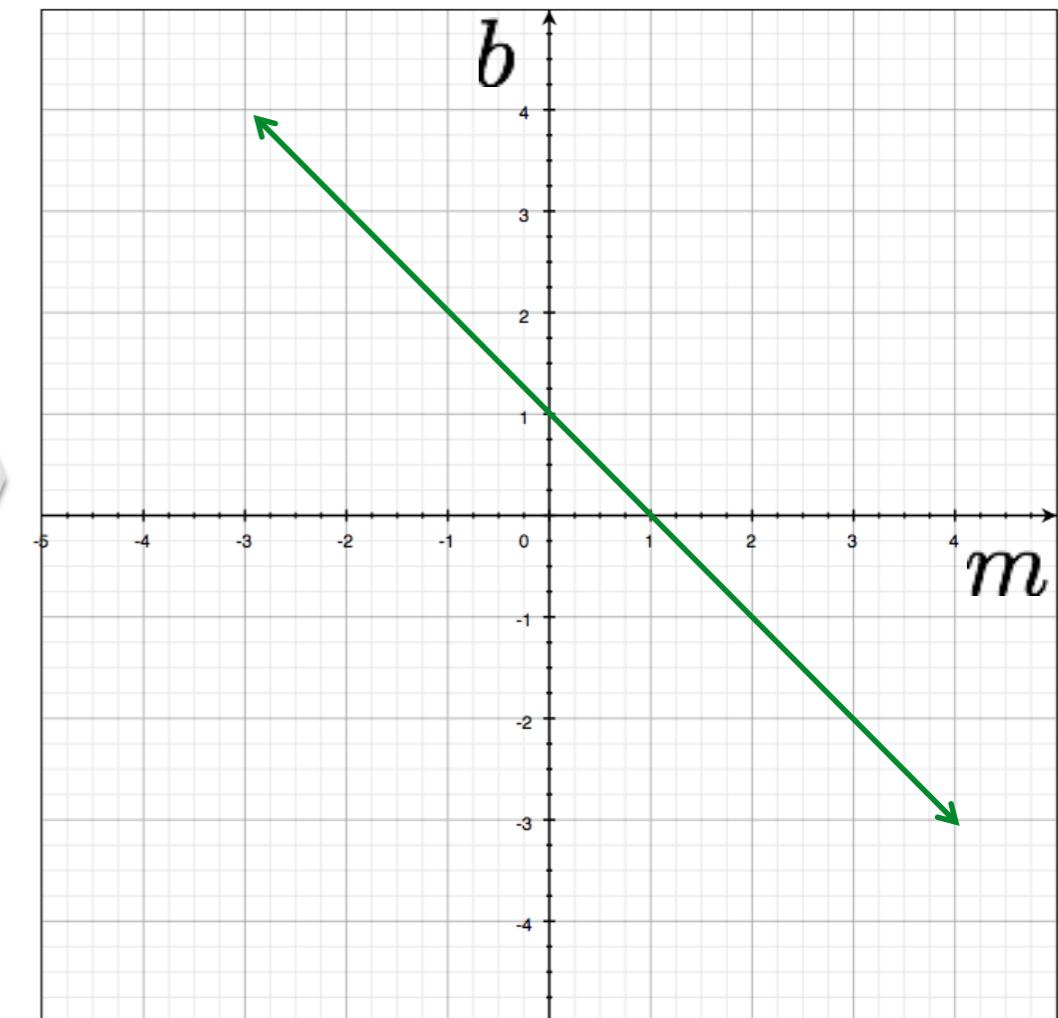
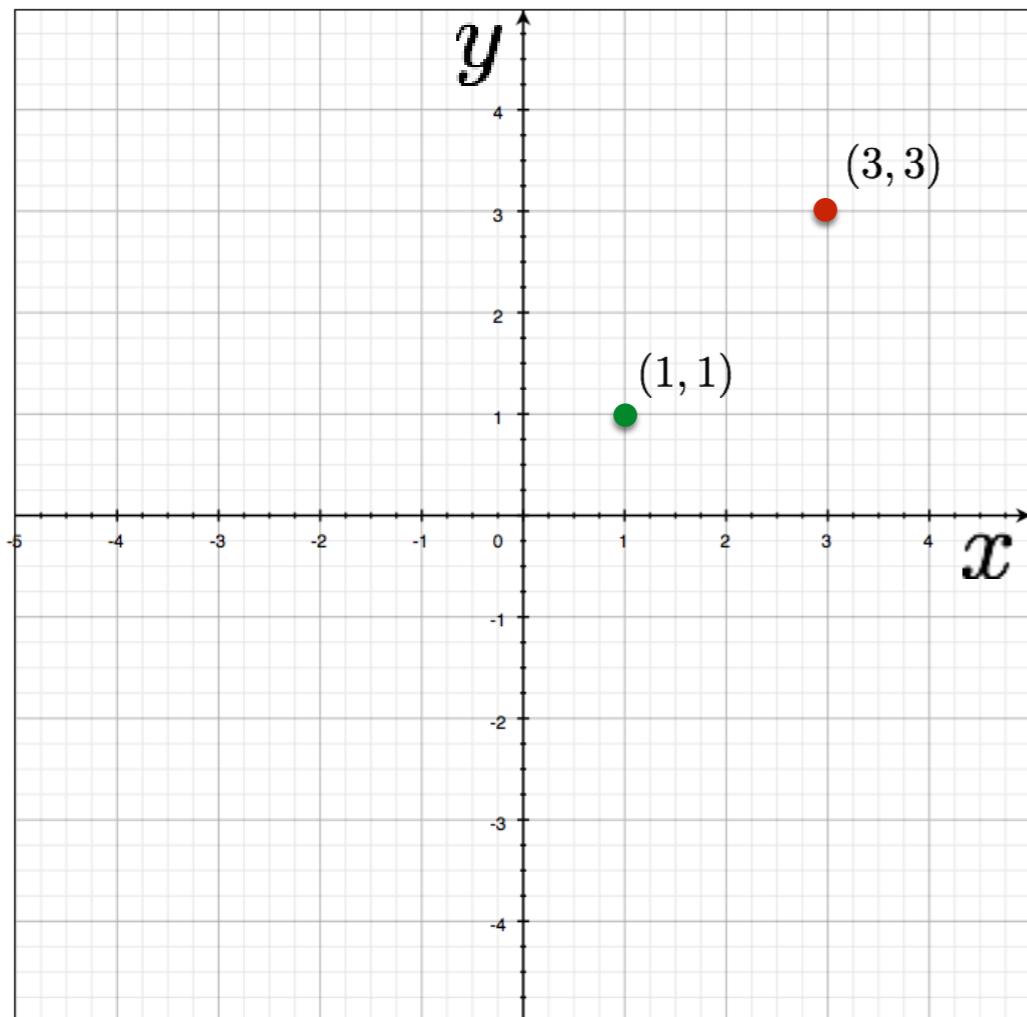


Image space

Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters



two points  
become  
?

variables  
 $y - mx = b$   
parameters

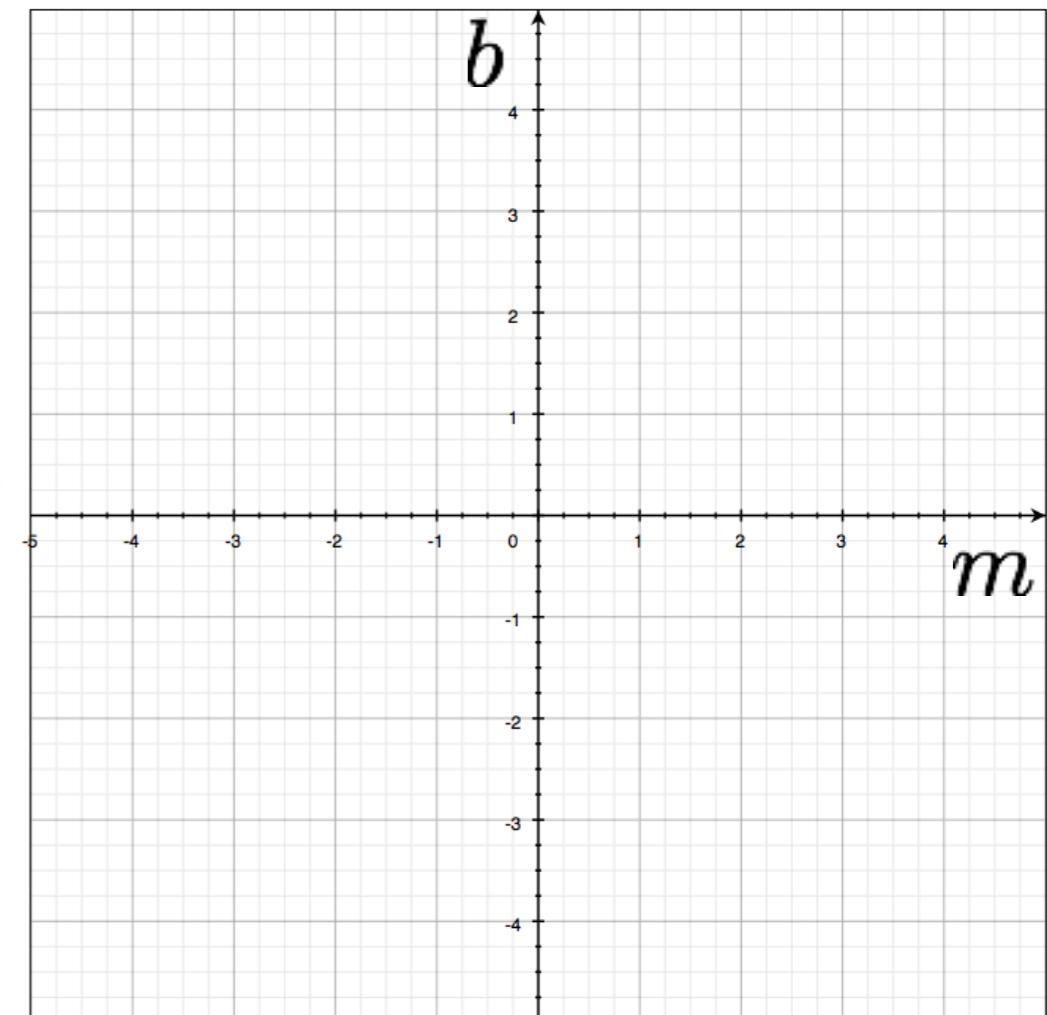
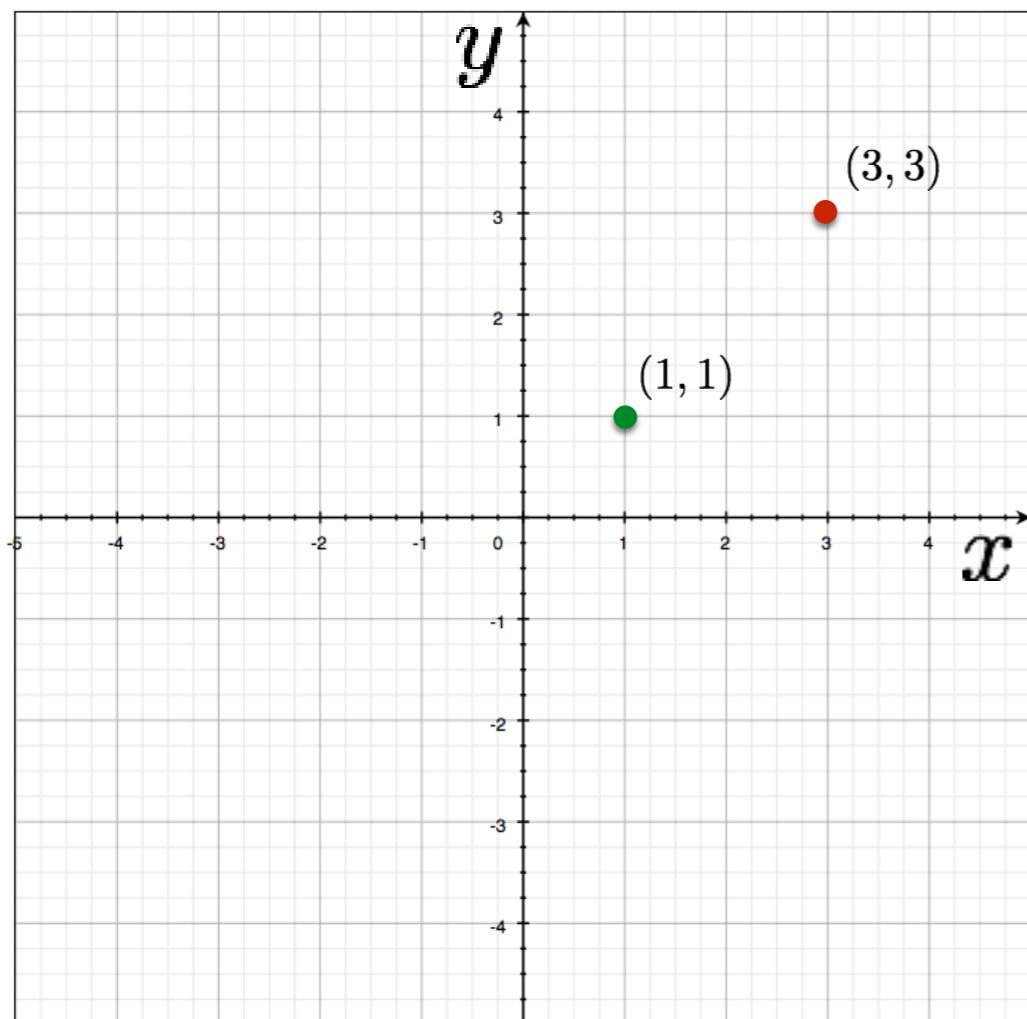


Image space

Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters



two points  
become  
?

variables  
 $y - mx = b$   
parameters

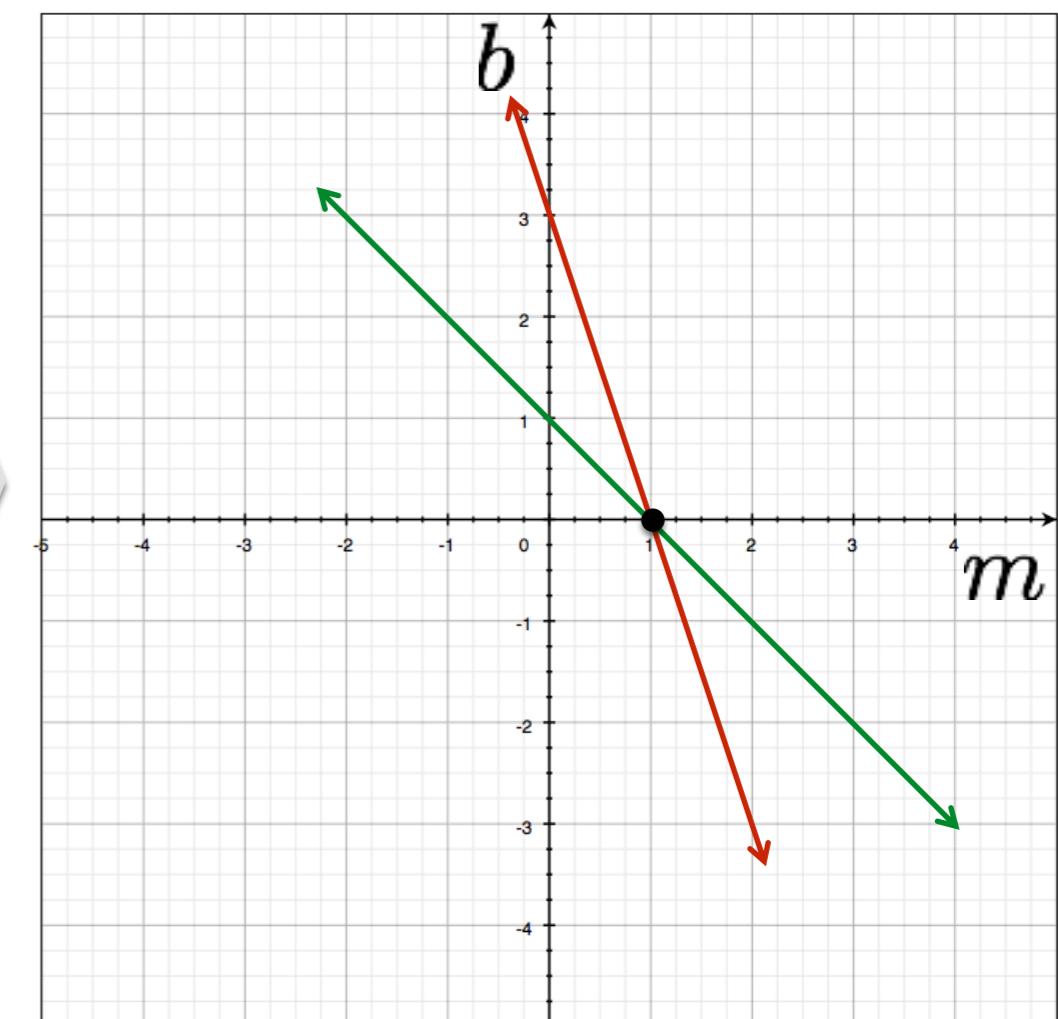
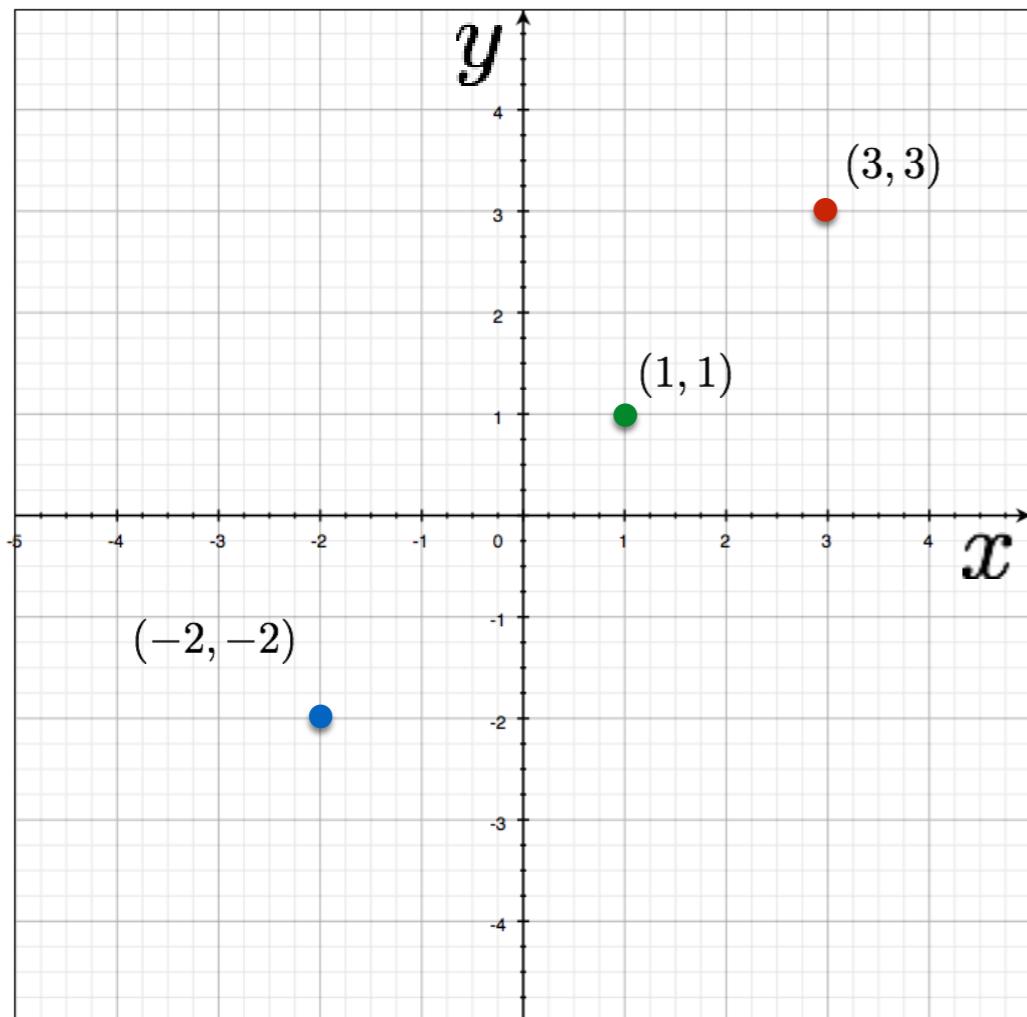


Image space

Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters



three points  
become  
?

variables  
 $y - mx = b$   
parameters

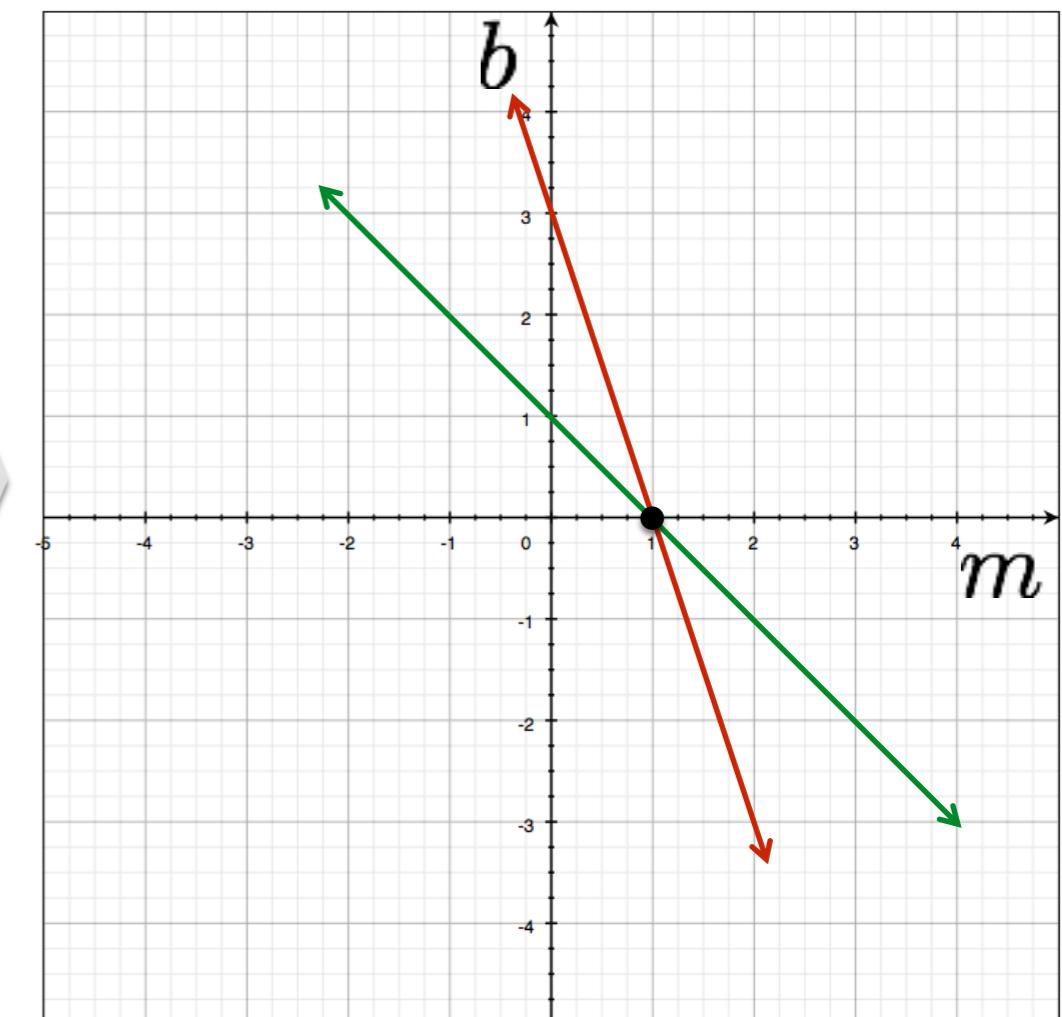
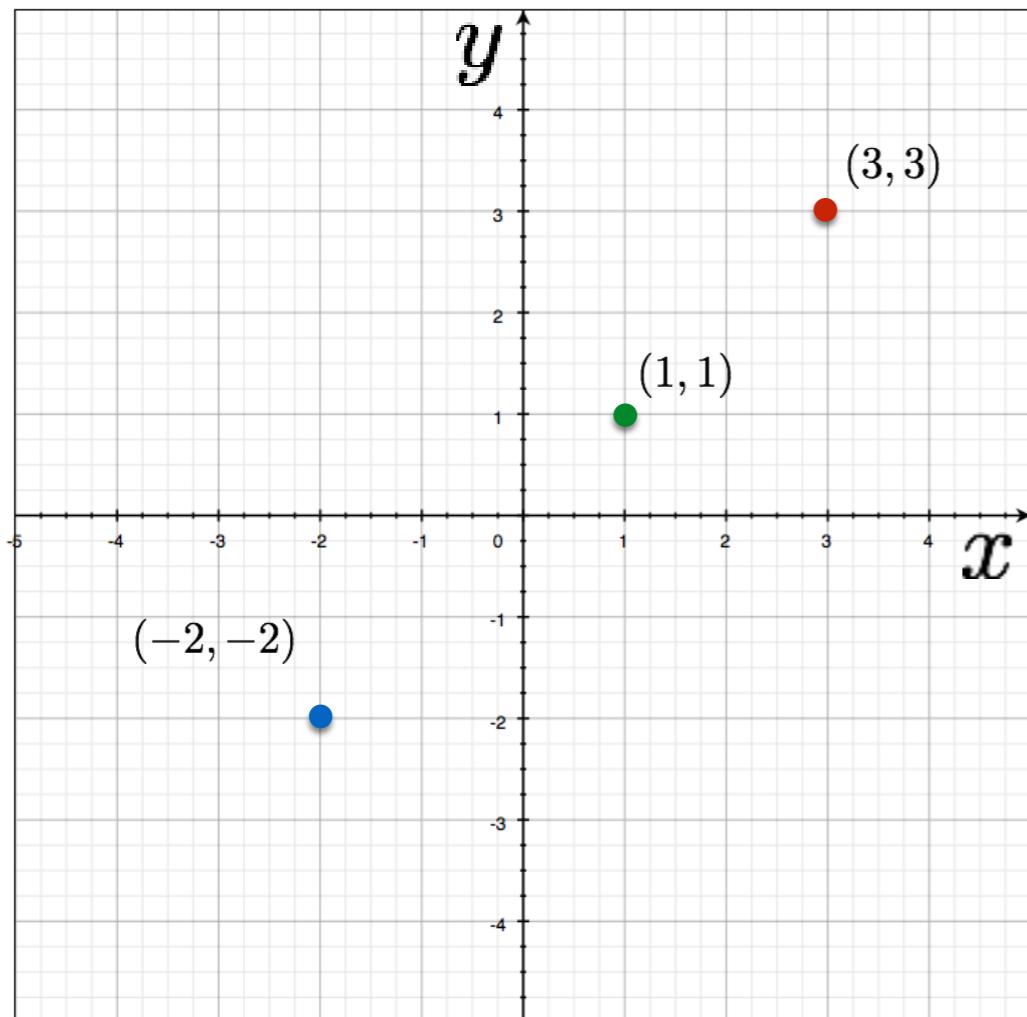


Image space

Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters



three points  
become  
?

variables  
 $y - mx = b$   
parameters

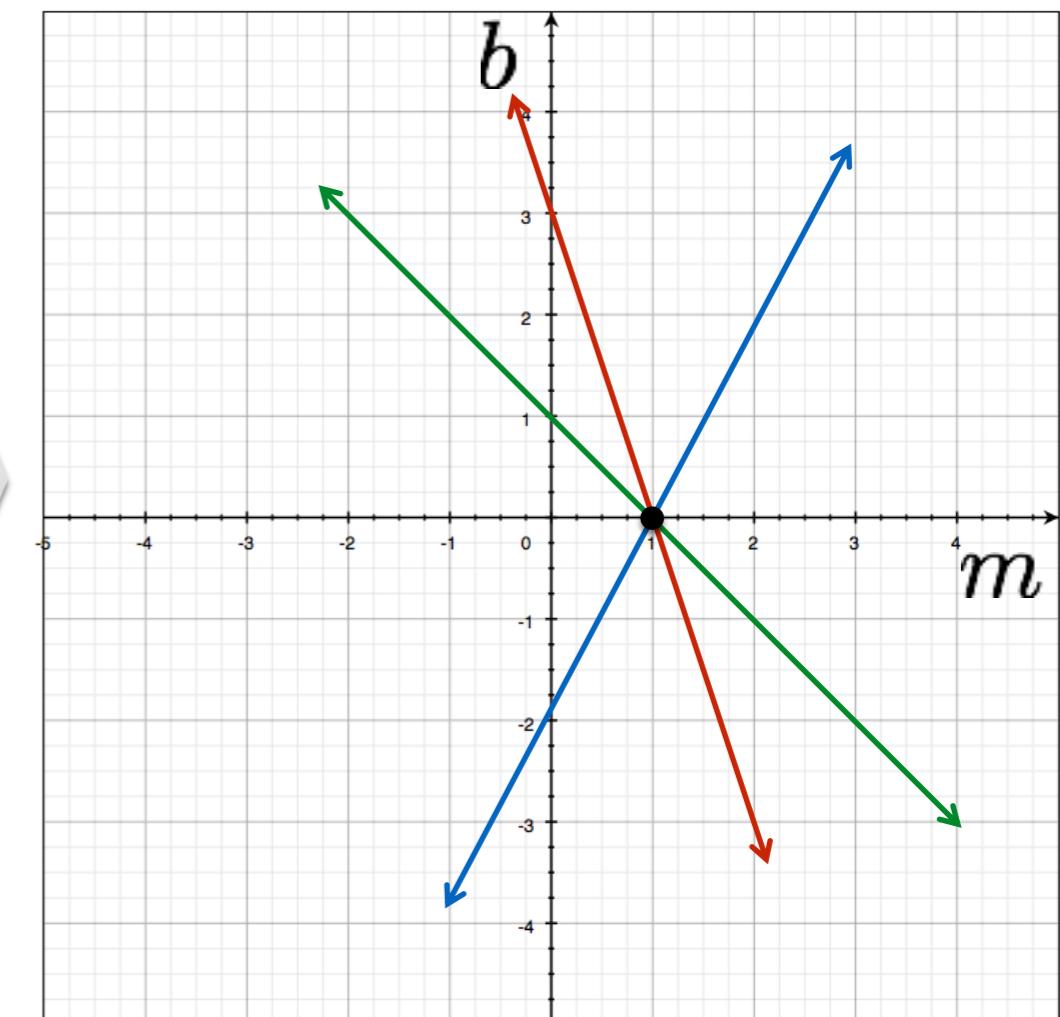
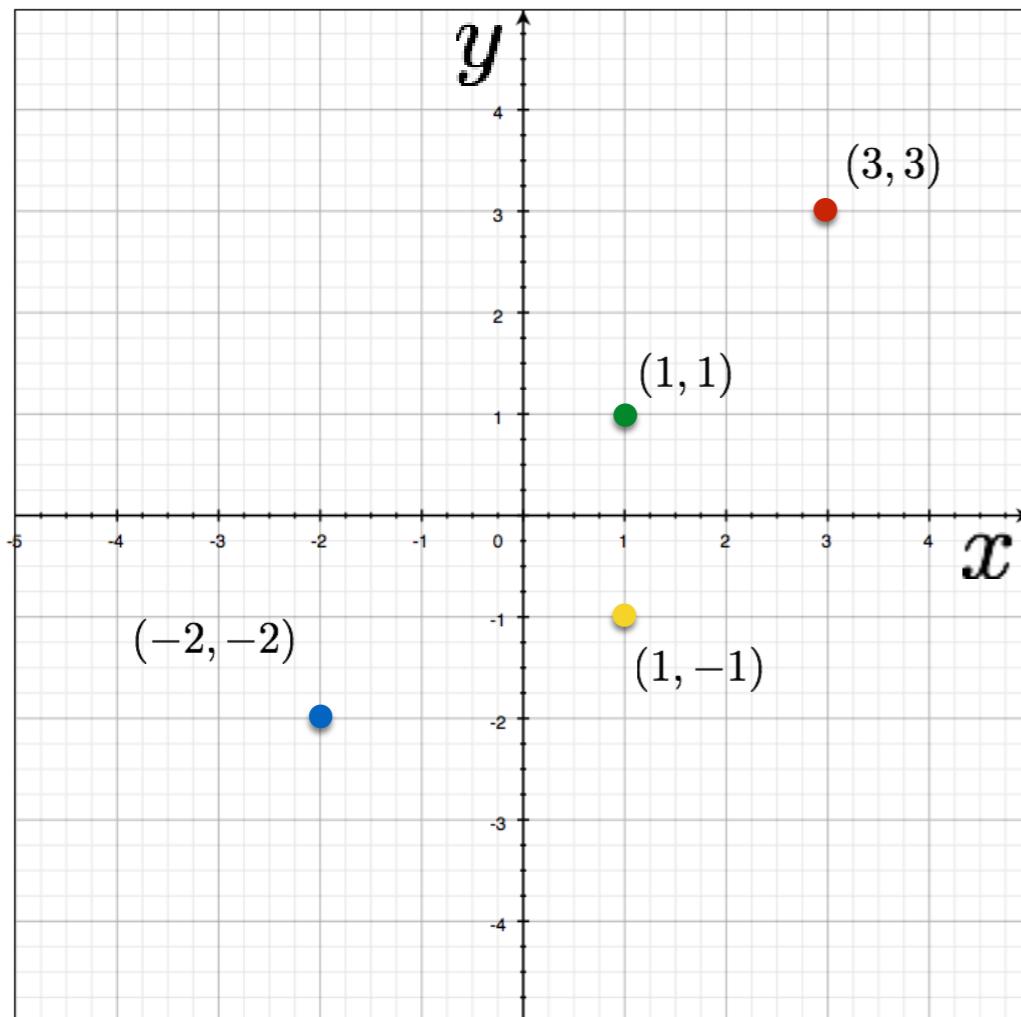


Image space

Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters



four points  
become  
?

variables  
 $y - mx = b$   
parameters

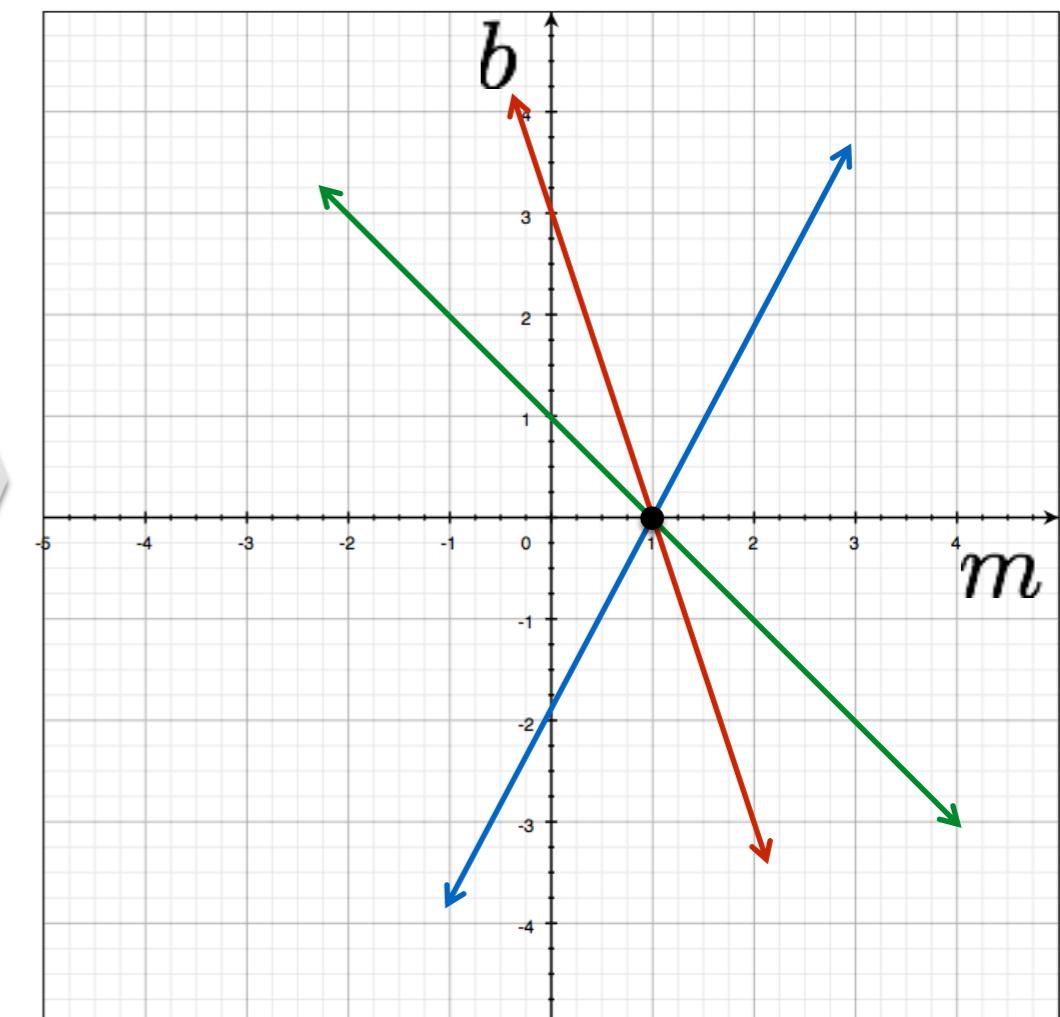
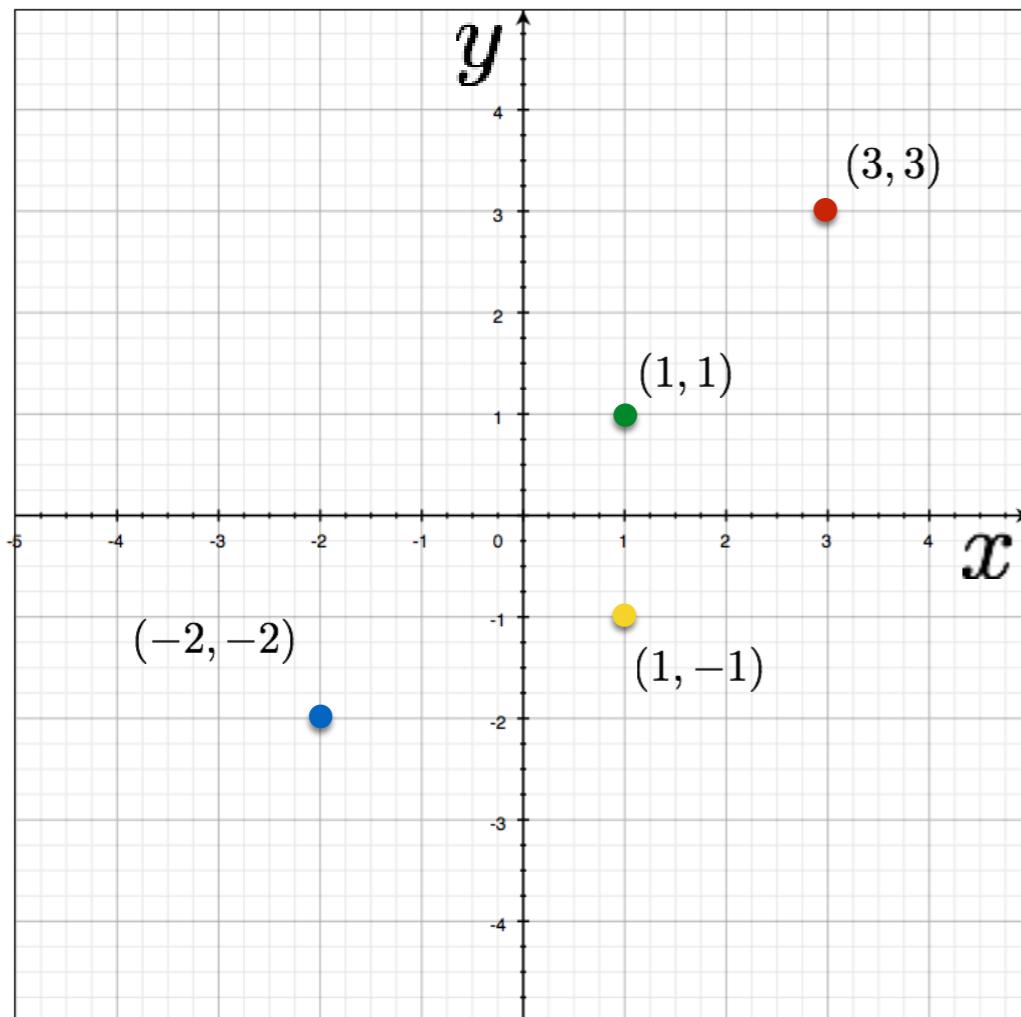


Image space

Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters



four points  
become  
?

variables  
 $y - mx = b$   
parameters

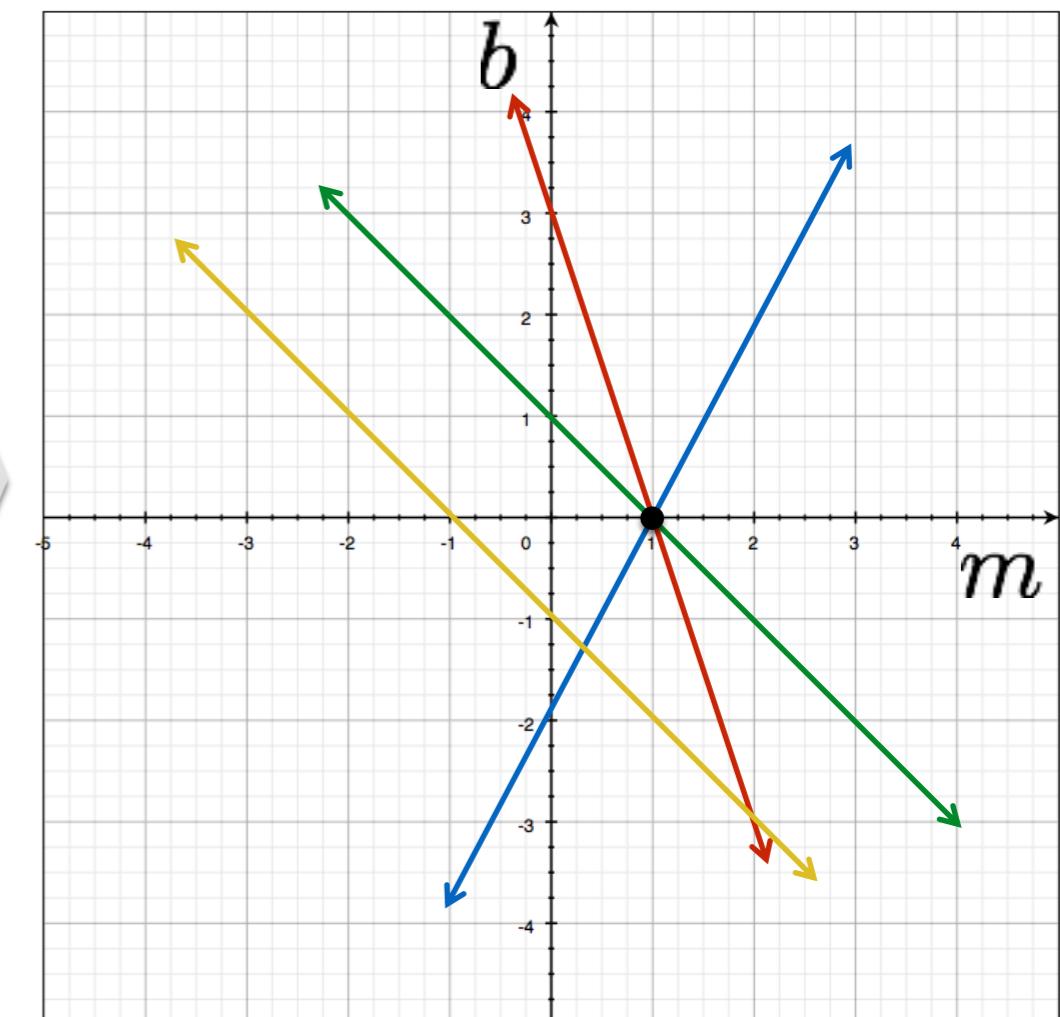


Image space

Parameter space

# How would you find the best fitting line?

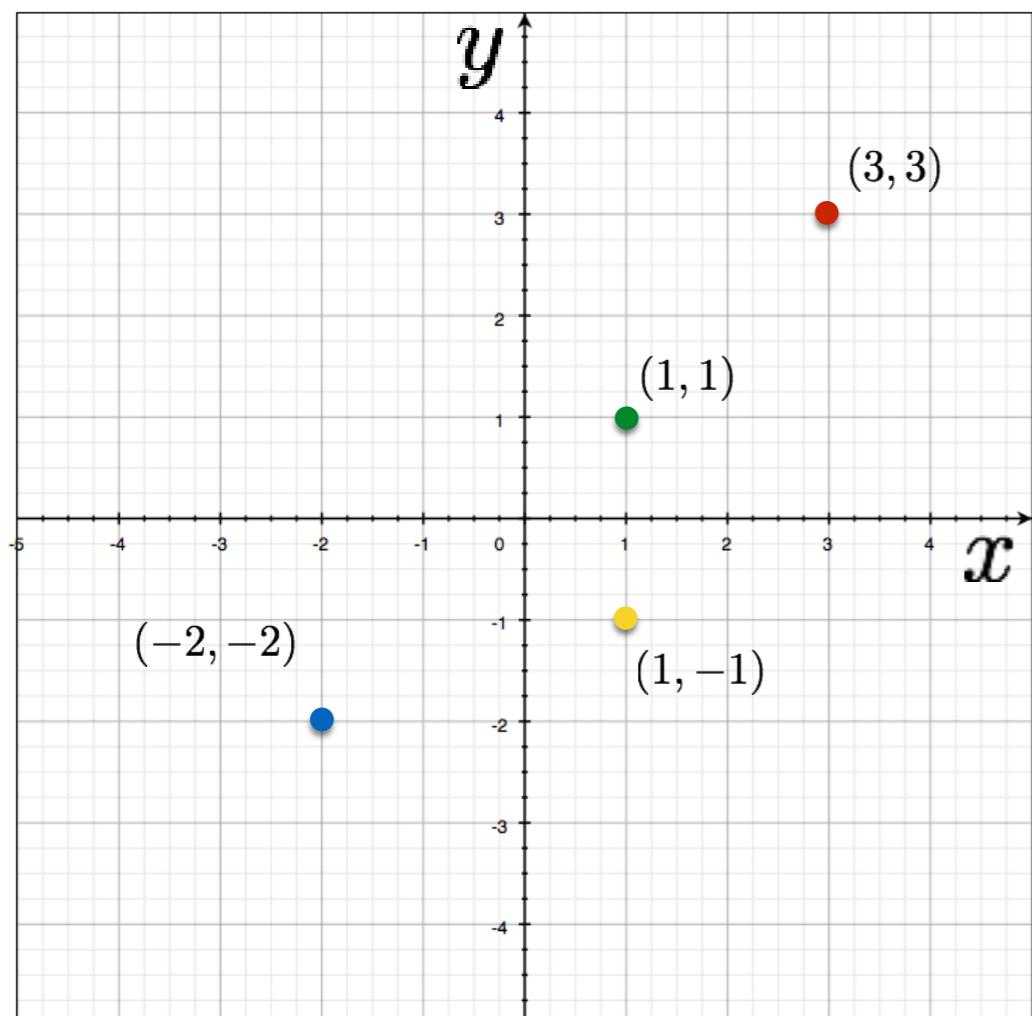
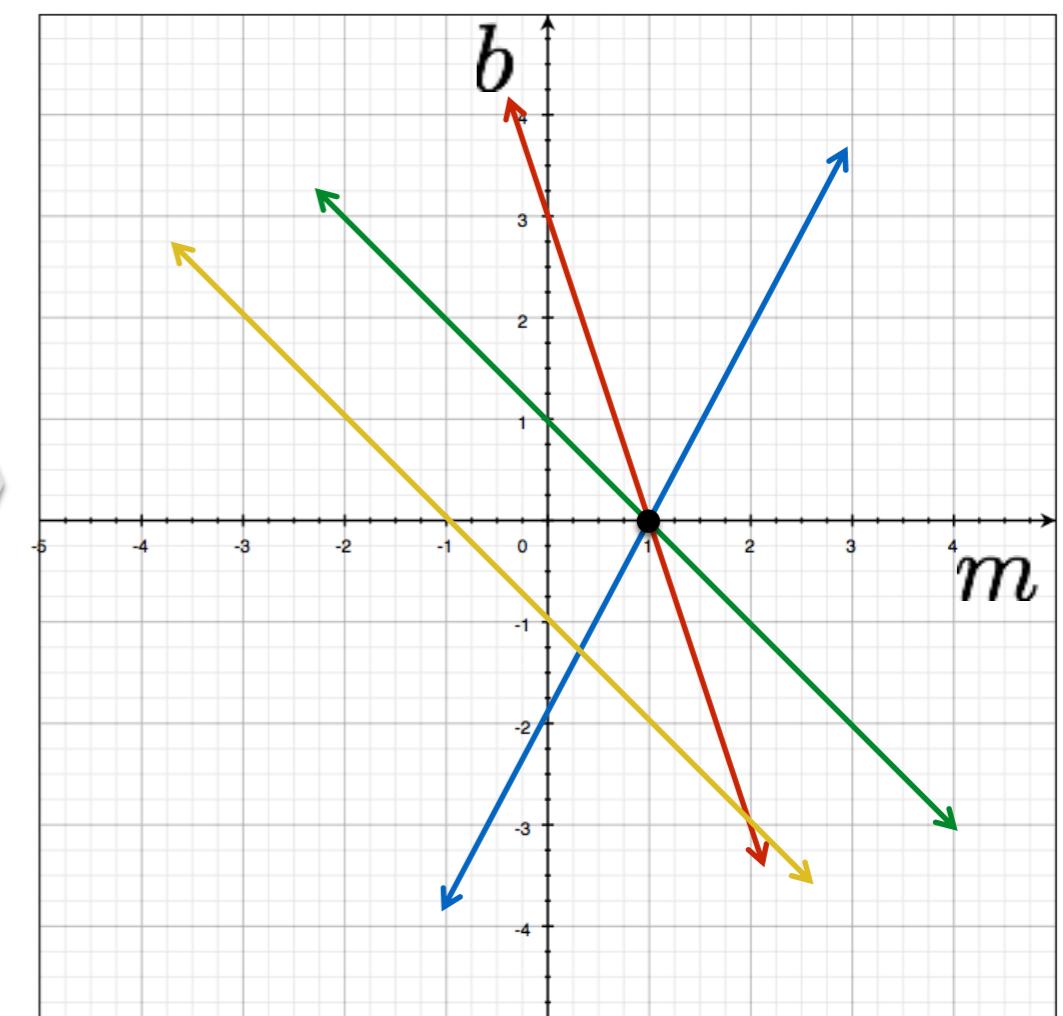


Image space



Parameter space

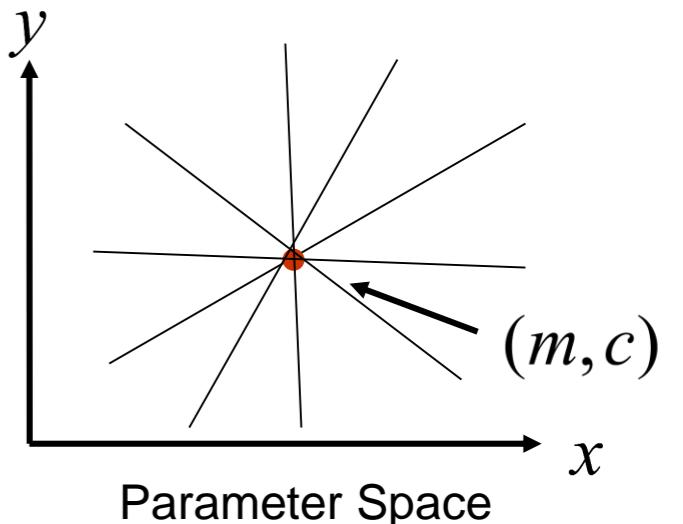
*Is this method robust to measurement noise?*

*Is this method robust to outliers?*

# Line Detection by Hough Transform

## Algorithm:

1. Quantize Parameter Space  $(m, c)$
2. Create Accumulator Array  $A(m, c)$
3. Set  $A(m, c) = 0 \quad \forall m, c$
4. For each image edge  $(x_i, y_i)$   
For each element in  $A(m, c)$   
If  $(m, c)$  lies on the line:  $c = -x_i m + y_i$   
Increment  $A(m, c) = A(m, c) + 1$
5. Find local maxima in  $A(m, c)$



A( $m, c$ )						
1					1	
	1			1		
		1	1			
					2	
		1	1			
	1			1		
1					1	

# Problems with parameterization

*How big does the accumulator need to be for the parameterization  $(m, c)$ ?*

A(m,c)

A 10x10 grid with the following numbered cells:

- (1, 1) = 1
- (2, 1) = 1
- (3, 1) = 1
- (4, 1) = 1
- (5, 1) = 1
- (6, 1) = 1
- (7, 1) = 1
- (8, 1) = 1
- (9, 1) = 1
- (10, 1) = 1
- (1, 2) = 1
- (2, 2) = 1
- (3, 2) = 1
- (4, 2) = 1
- (5, 2) = 1
- (6, 2) = 1
- (7, 2) = 1
- (8, 2) = 1
- (9, 2) = 1
- (10, 2) = 1
- (1, 3) = 1
- (2, 3) = 1
- (3, 3) = 1
- (4, 3) = 1
- (5, 3) = 1
- (6, 3) = 1
- (7, 3) = 1
- (8, 3) = 1
- (9, 3) = 1
- (10, 3) = 1
- (1, 4) = 1
- (2, 4) = 1
- (3, 4) = 1
- (4, 4) = 1
- (5, 4) = 1
- (6, 4) = 1
- (7, 4) = 1
- (8, 4) = 1
- (9, 4) = 1
- (10, 4) = 1
- (1, 5) = 1
- (2, 5) = 1
- (3, 5) = 1
- (4, 5) = 1
- (5, 5) = 1
- (6, 5) = 1
- (7, 5) = 1
- (8, 5) = 1
- (9, 5) = 1
- (10, 5) = 1
- (1, 6) = 1
- (2, 6) = 1
- (3, 6) = 1
- (4, 6) = 1
- (5, 6) = 1
- (6, 6) = 1
- (7, 6) = 1
- (8, 6) = 1
- (9, 6) = 1
- (10, 6) = 1
- (1, 7) = 1
- (2, 7) = 1
- (3, 7) = 1
- (4, 7) = 1
- (5, 7) = 1
- (6, 7) = 1
- (7, 7) = 1
- (8, 7) = 1
- (9, 7) = 1
- (10, 7) = 1
- (1, 8) = 1
- (2, 8) = 1
- (3, 8) = 1
- (4, 8) = 1
- (5, 8) = 1
- (6, 8) = 1
- (7, 8) = 1
- (8, 8) = 1
- (9, 8) = 1
- (10, 8) = 1
- (1, 9) = 1
- (2, 9) = 1
- (3, 9) = 1
- (4, 9) = 1
- (5, 9) = 1
- (6, 9) = 1
- (7, 9) = 1
- (8, 9) = 1
- (9, 9) = 1
- (10, 9) = 1
- (1, 10) = 1
- (2, 10) = 1
- (3, 10) = 1
- (4, 10) = 1
- (5, 10) = 1
- (6, 10) = 1
- (7, 10) = 1
- (8, 10) = 1
- (9, 10) = 1
- (10, 10) = 1

The number 2 is highlighted in red at position (5, 5).

# Problems with parameterization

*How big does the accumulator need to be for the parameterization  $(m, c)$ ?*

$A(m, c)$

1					1	
	1				1	
		1		1		
			2			
			1	1		
	1				1	
1					1	

The space of  $m$  is huge!

$$-\infty \leq m \leq \infty$$

The space of  $c$  is huge!

$$-\infty \leq c \leq \infty$$

# Better Parameterization

Use normal form:

$$x \cos \theta + y \sin \theta = \rho$$

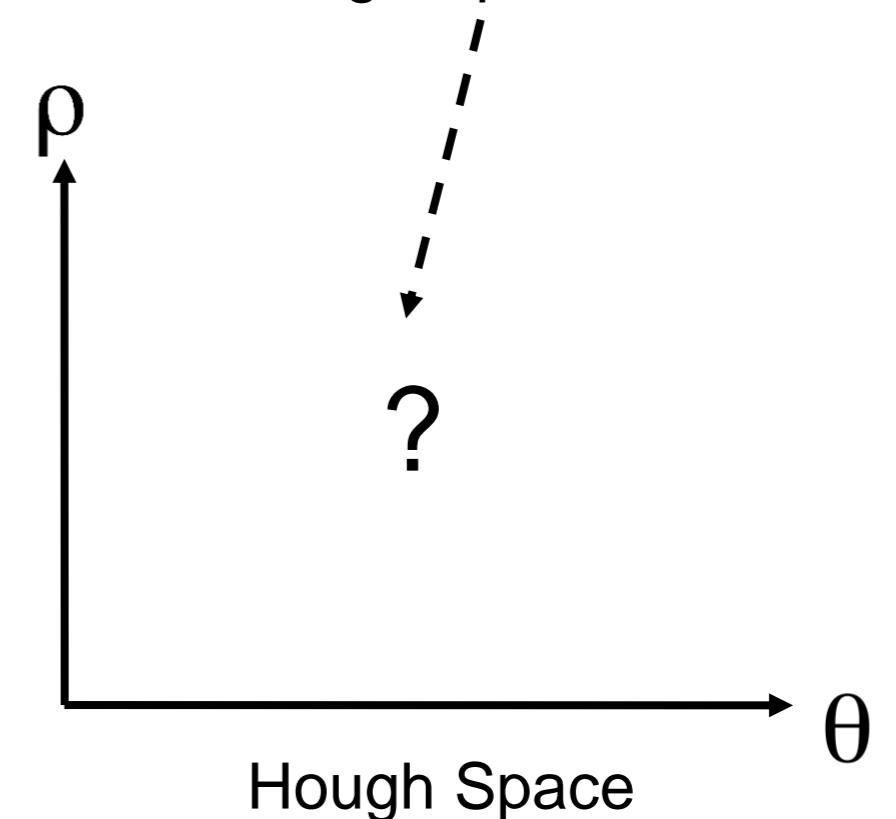
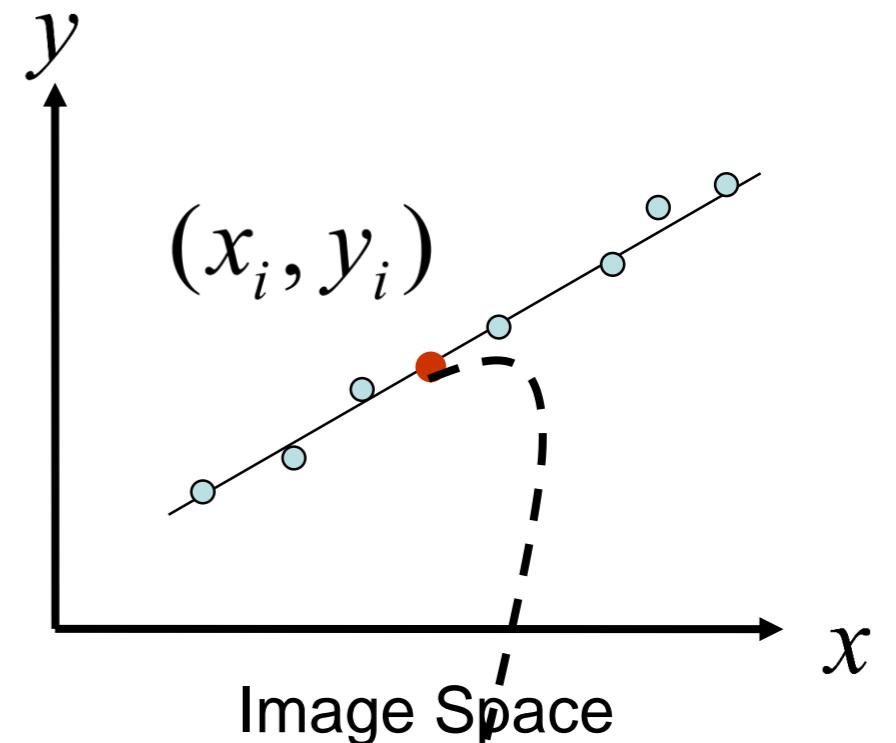
Given points  $(x_i, y_i)$  find  $(\rho, \theta)$

Hough Space Sinusoid

$$0 \leq \theta \leq 2\pi$$

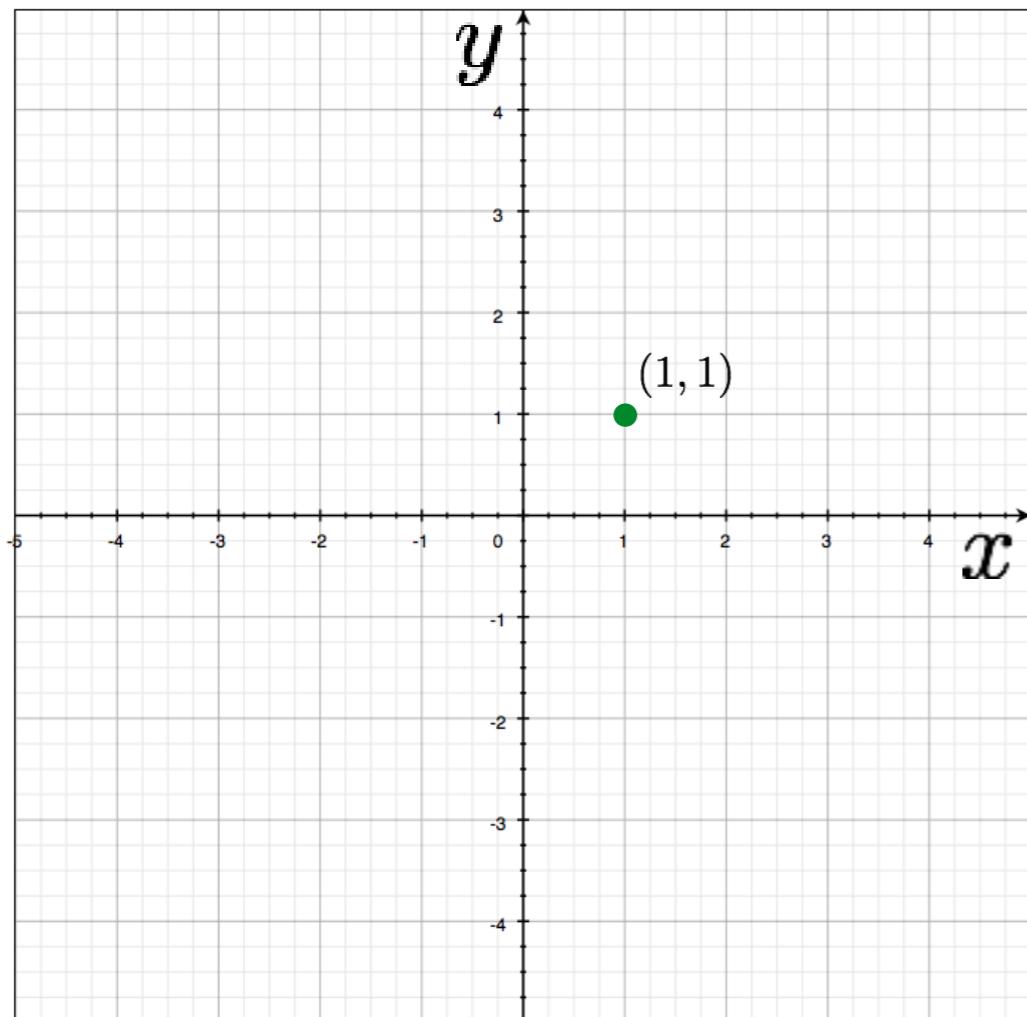
$$0 \leq \rho \leq \rho_{\max}$$

(Finite Accumulator Array Size)



# Image and parameter space

variables  
 $y = mx + b$   
parameters



a point becomes?

parameters  
 $x \cos \theta + y \sin \theta = \rho$   
variables

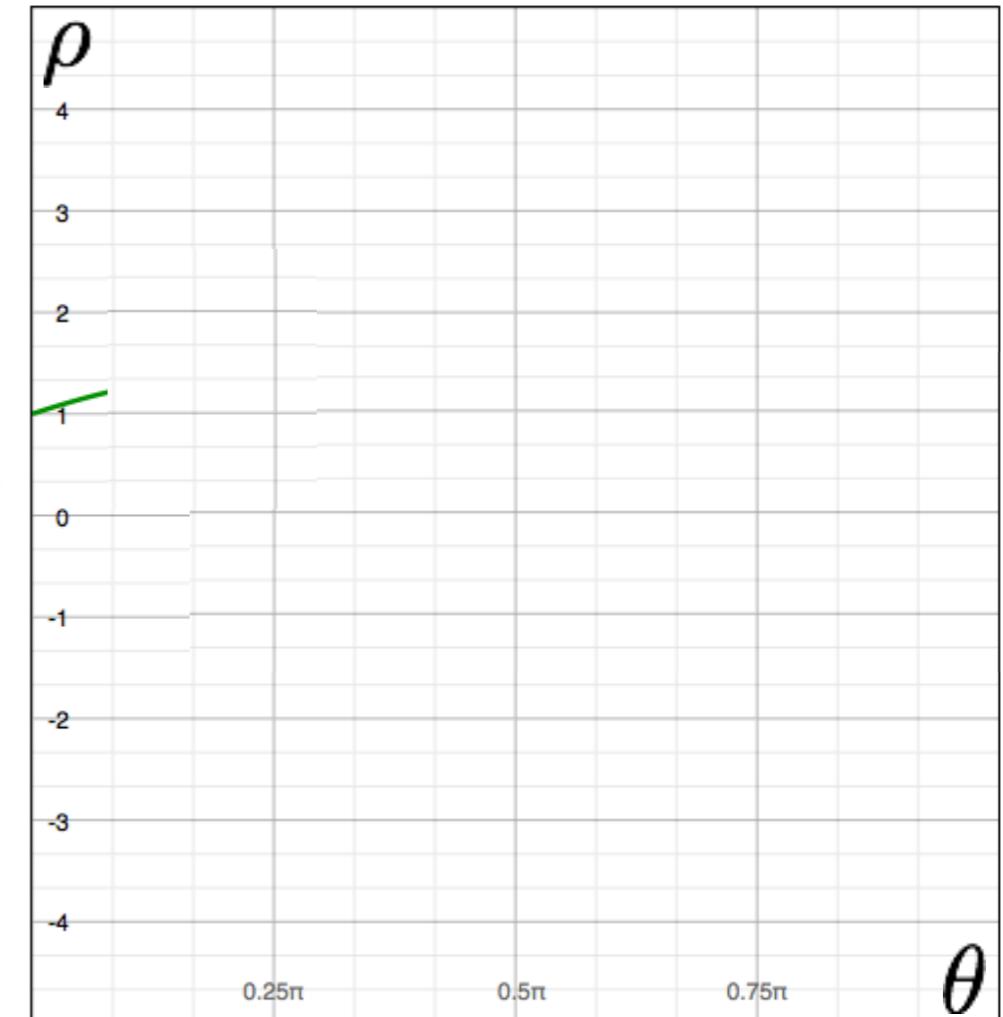
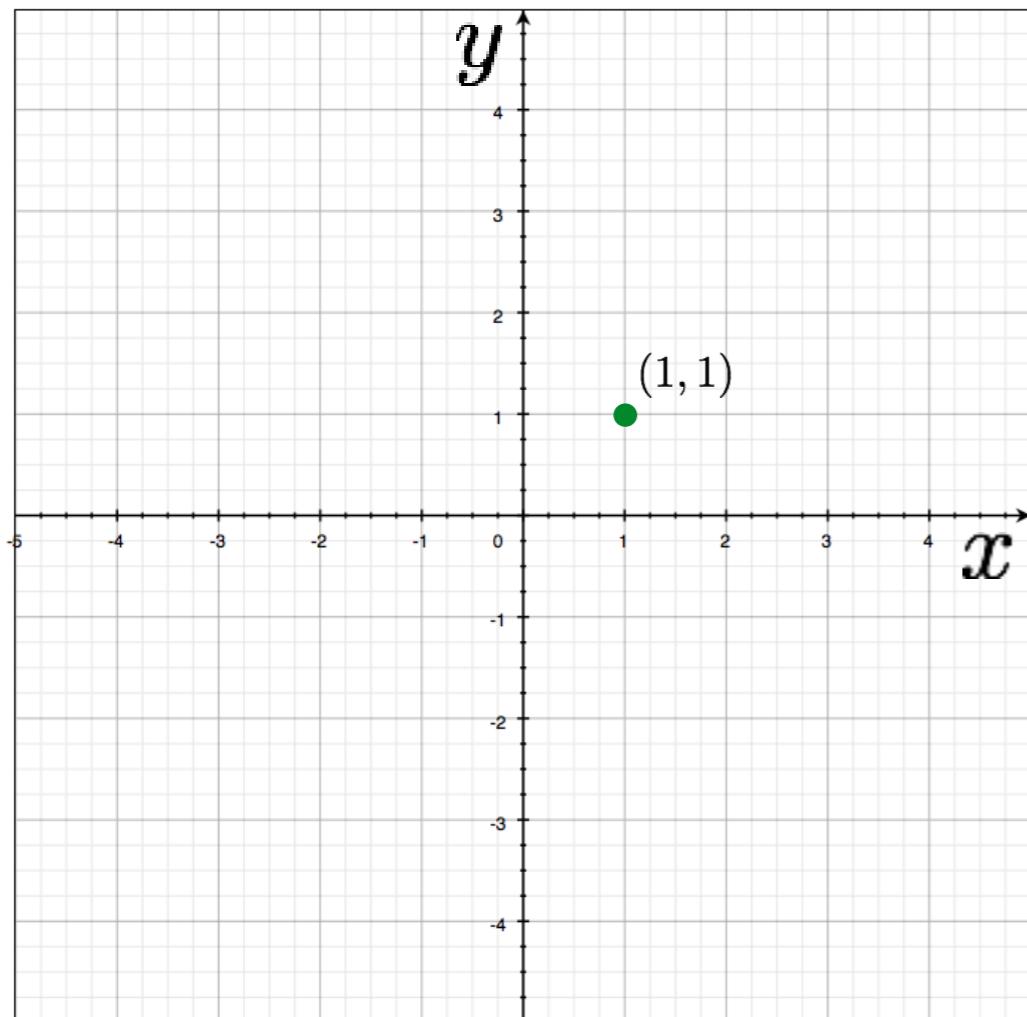


Image space

Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters



a point becomes a wave

parameters  
 $x \cos \theta + y \sin \theta = \rho$   
variables

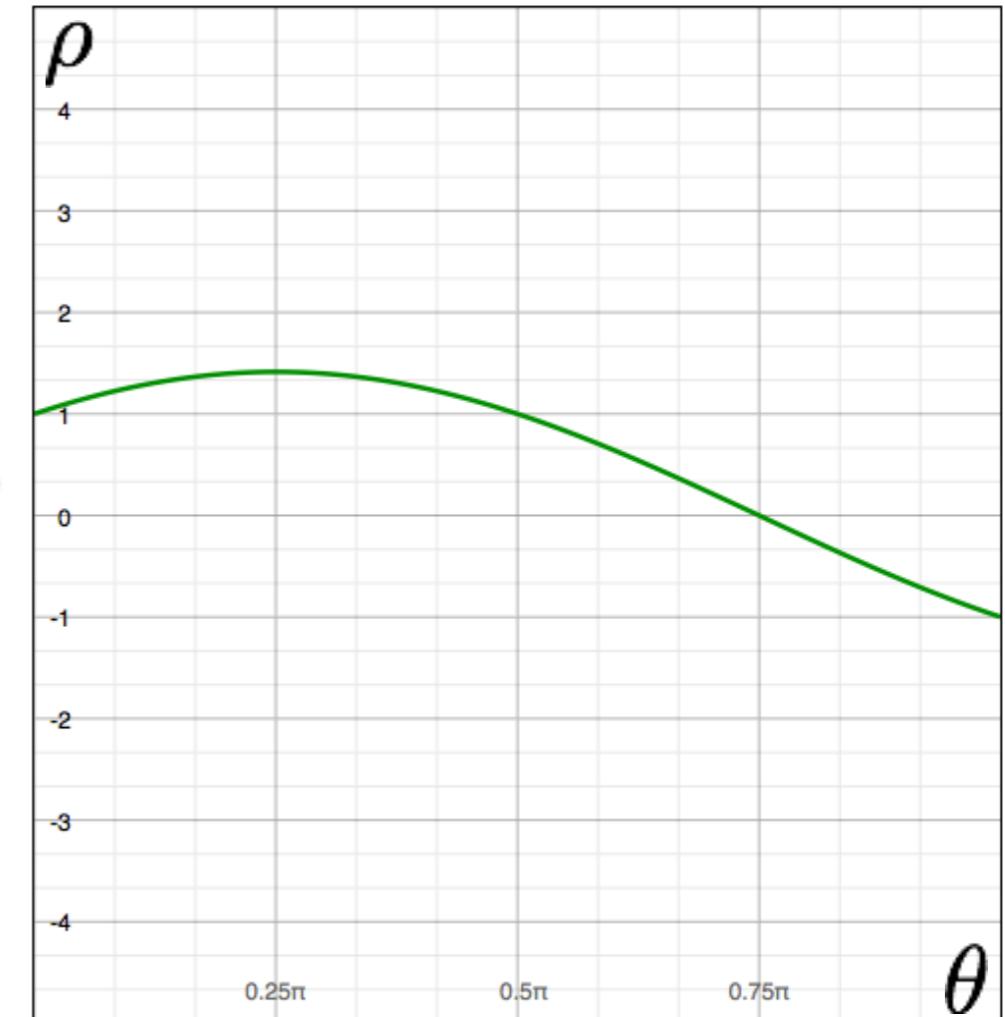
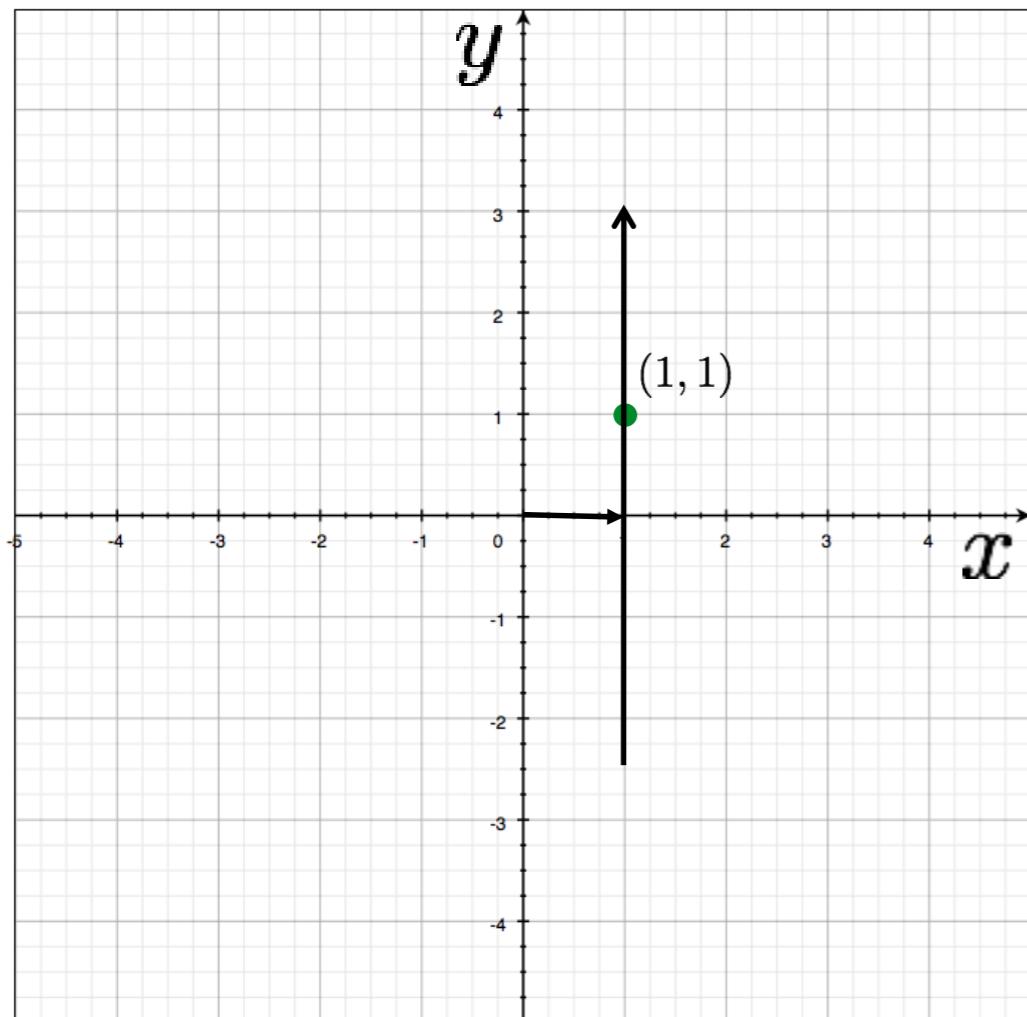


Image space

Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters



a line  
becomes?

$$x \cos \theta + y \sin \theta = \rho$$

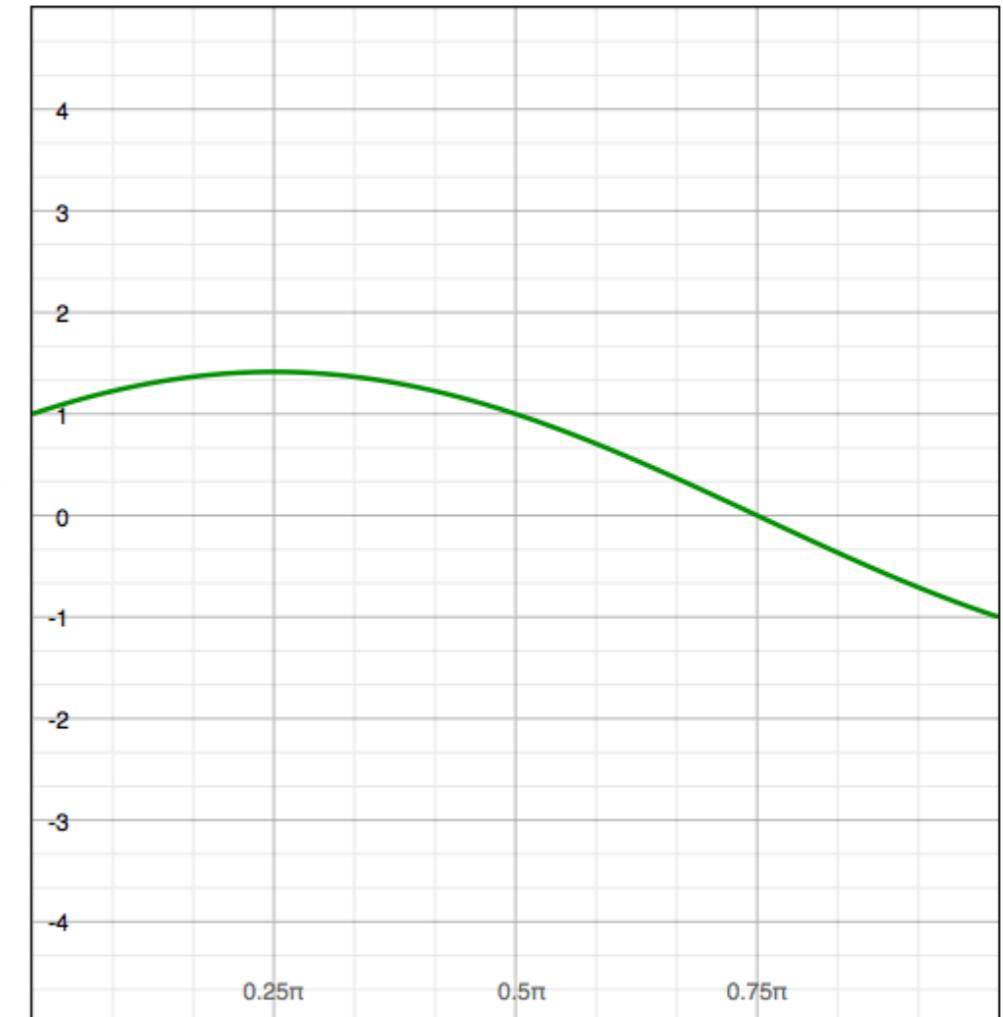


Image space

Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters

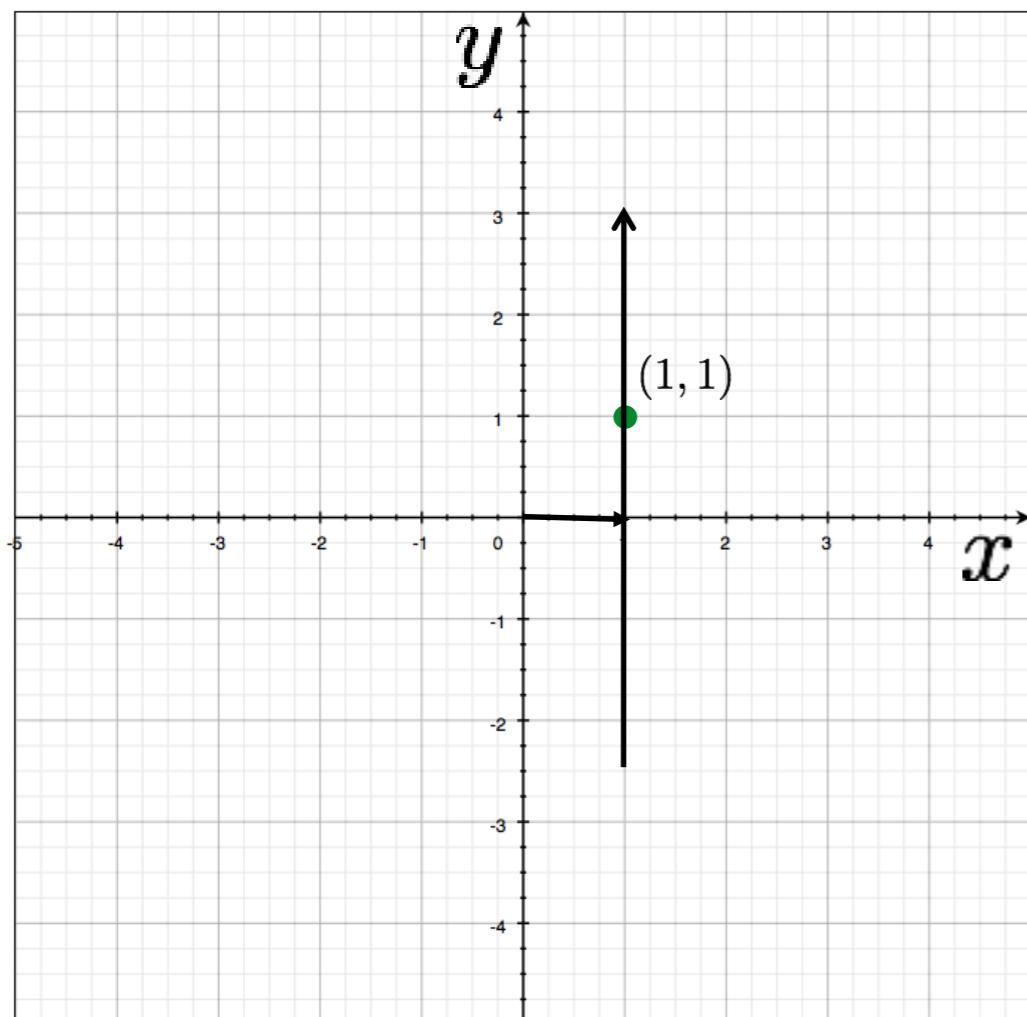
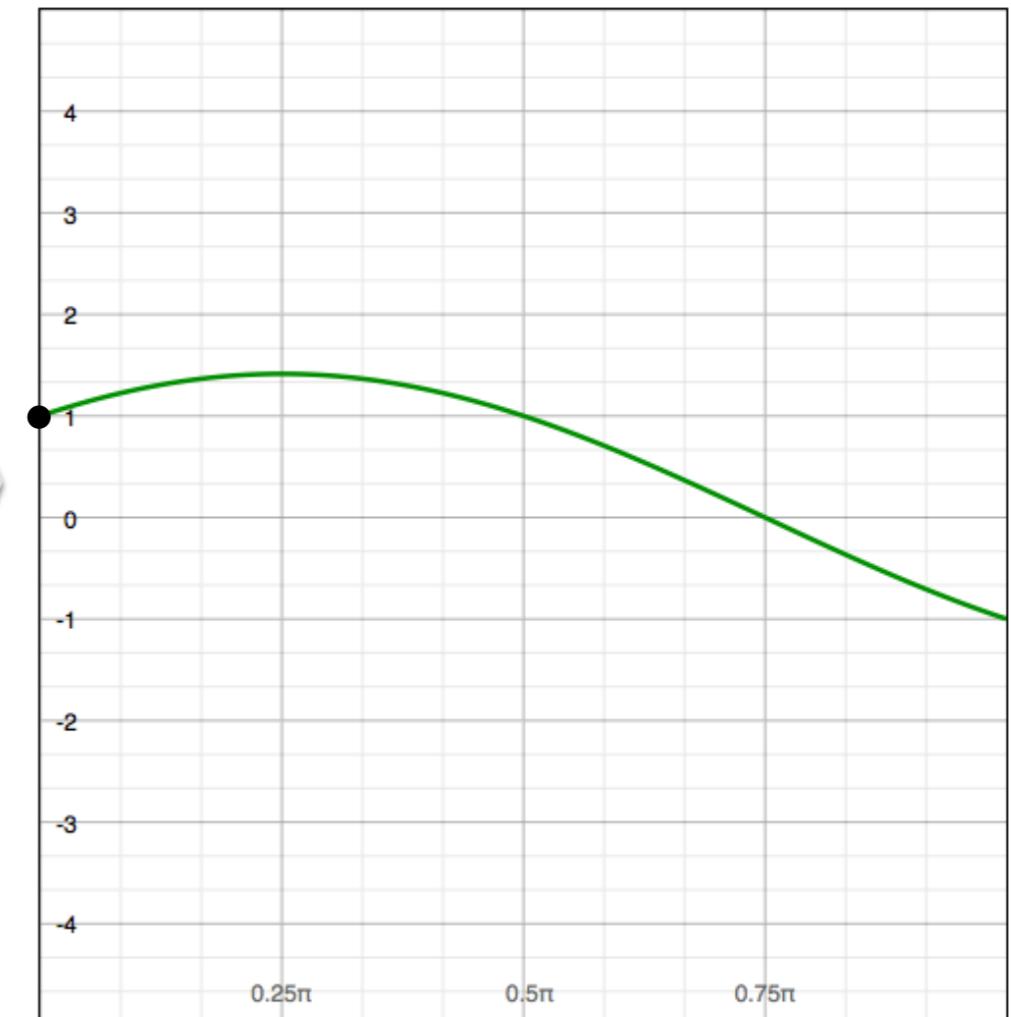


Image space

a line becomes a point

$$x \cos \theta + y \sin \theta = \rho$$



Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters

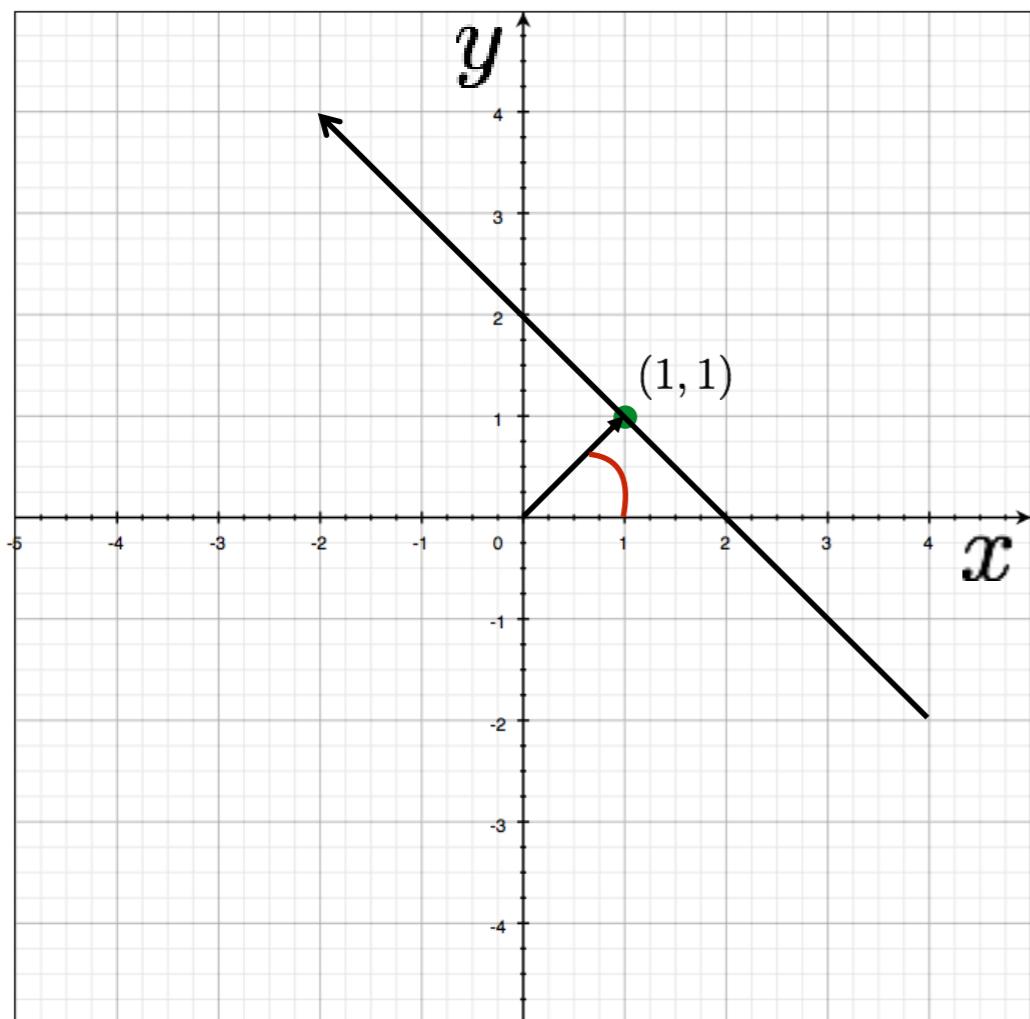
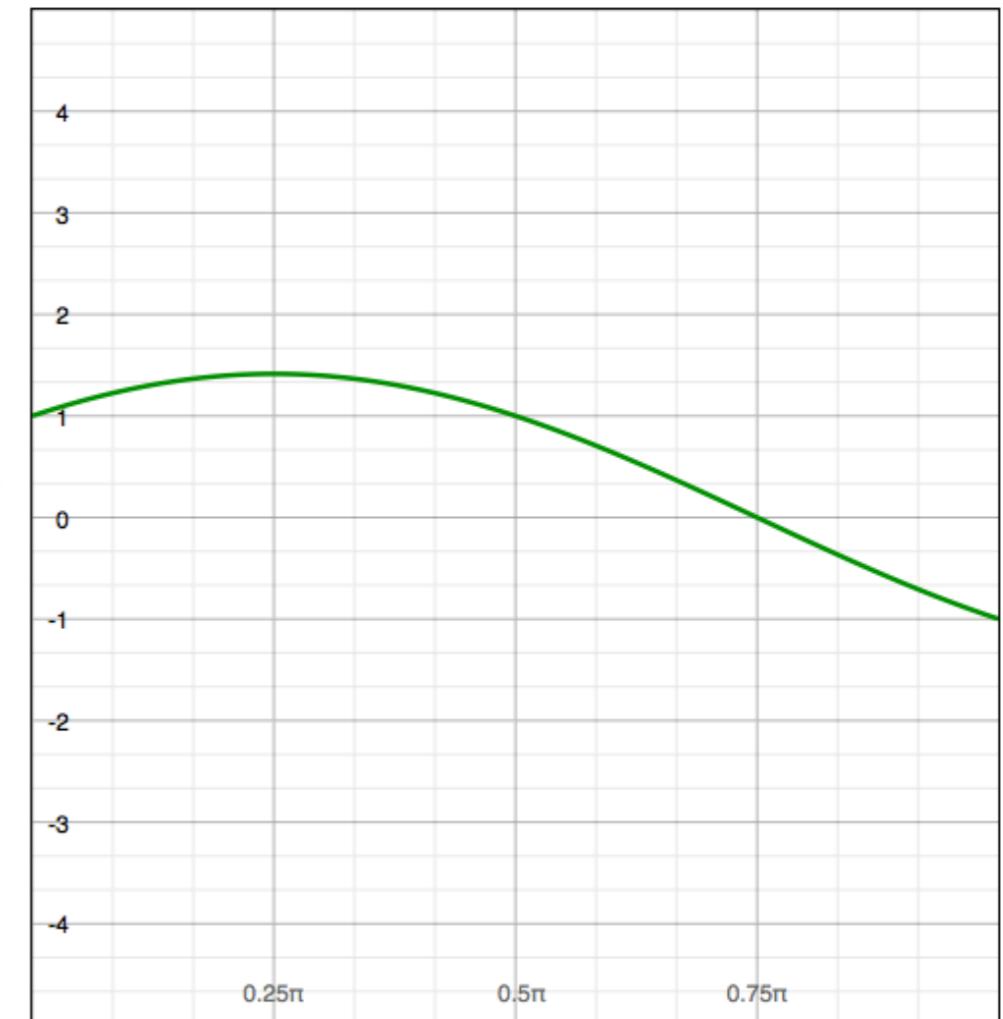


Image space

$$x \cos \theta + y \sin \theta = \rho$$

a line  
becomes?



Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters

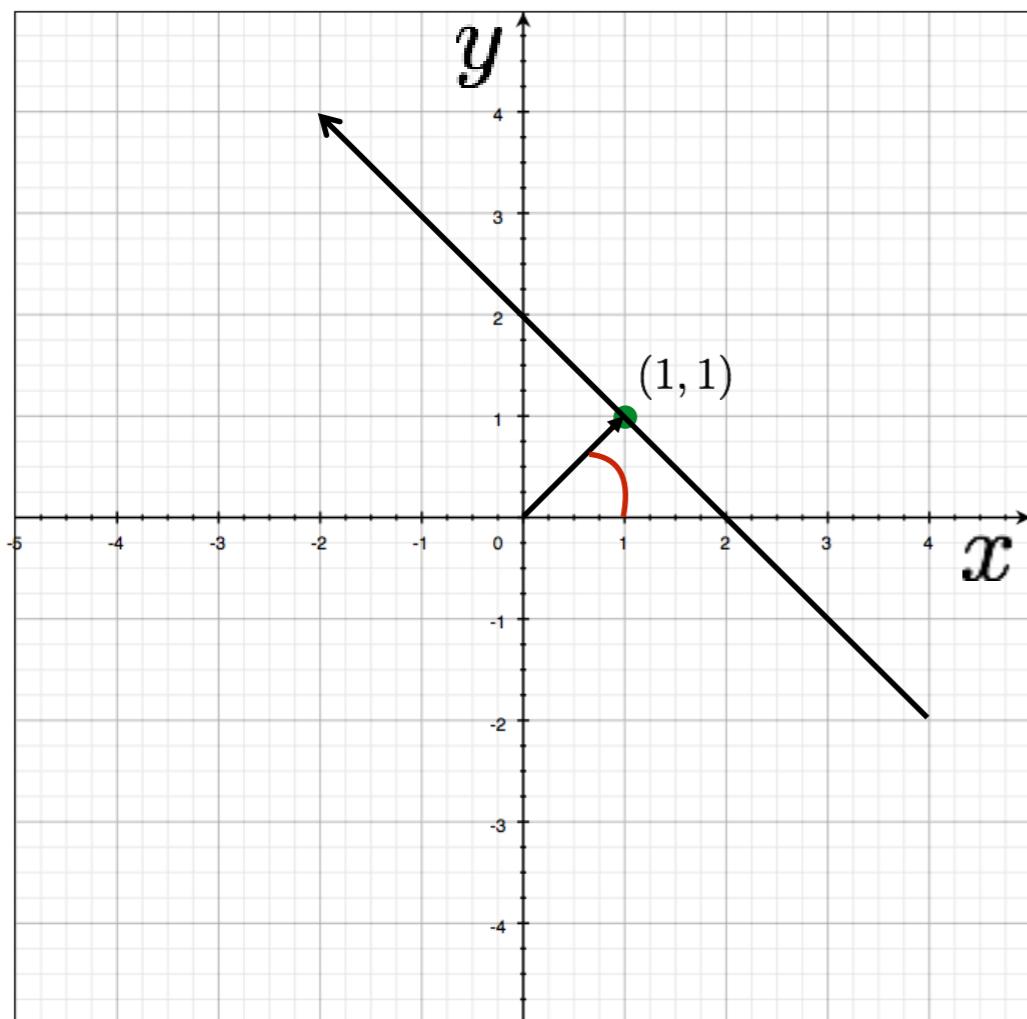
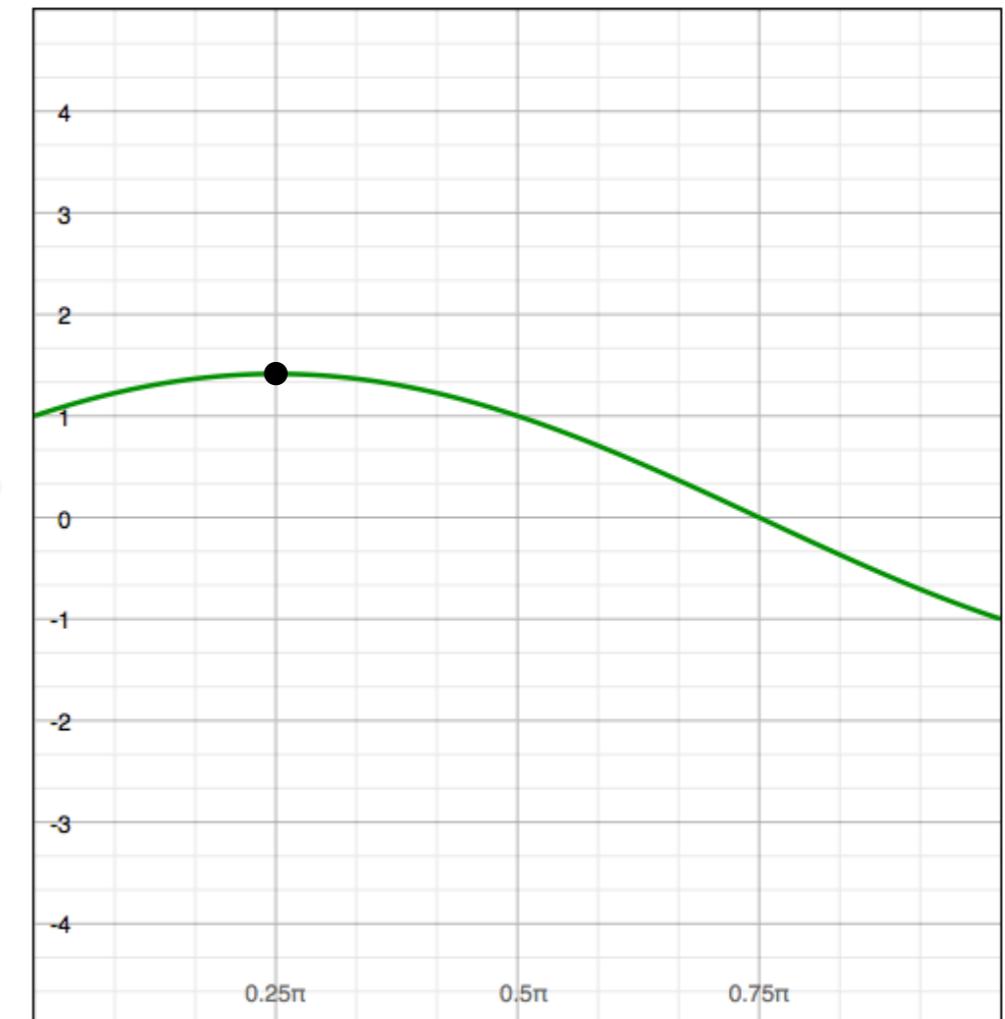


Image space

a line becomes a point

$$x \cos \theta + y \sin \theta = \rho$$



Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters

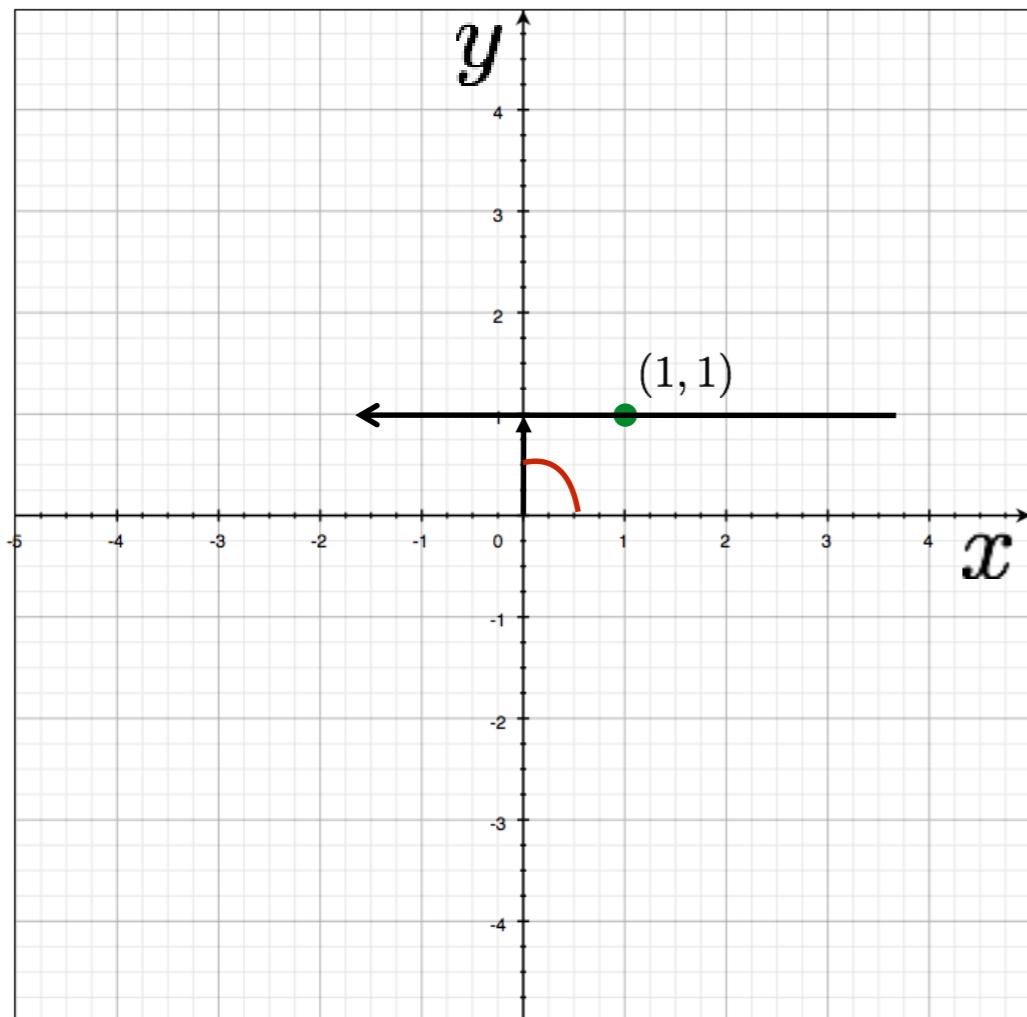
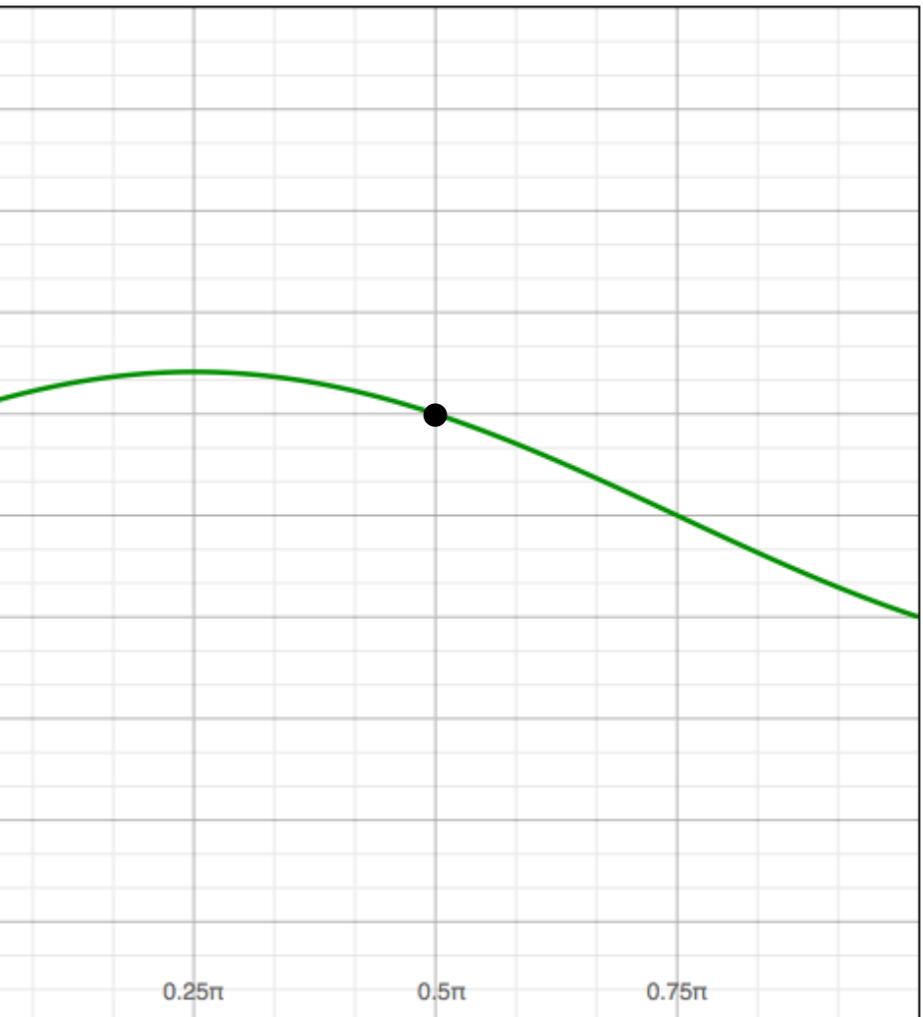


Image space

a line becomes a point



Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters

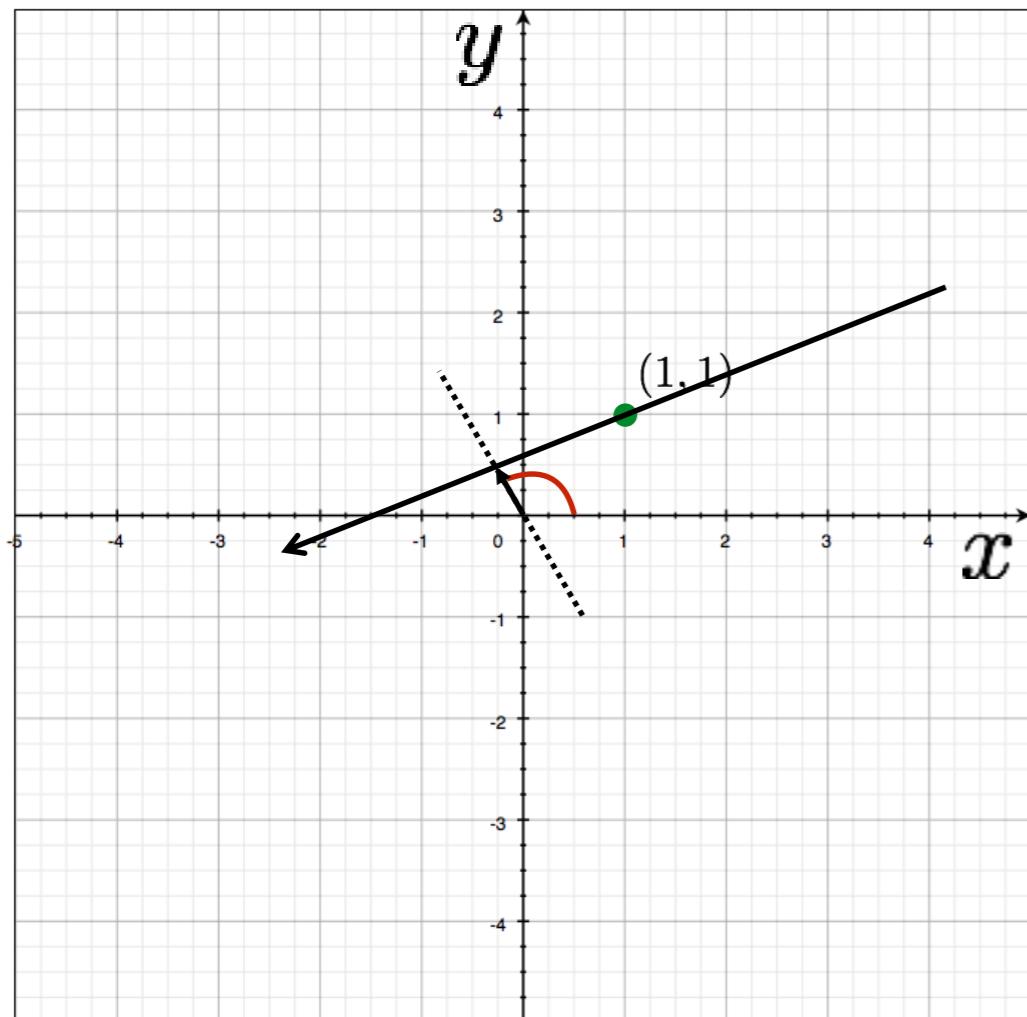
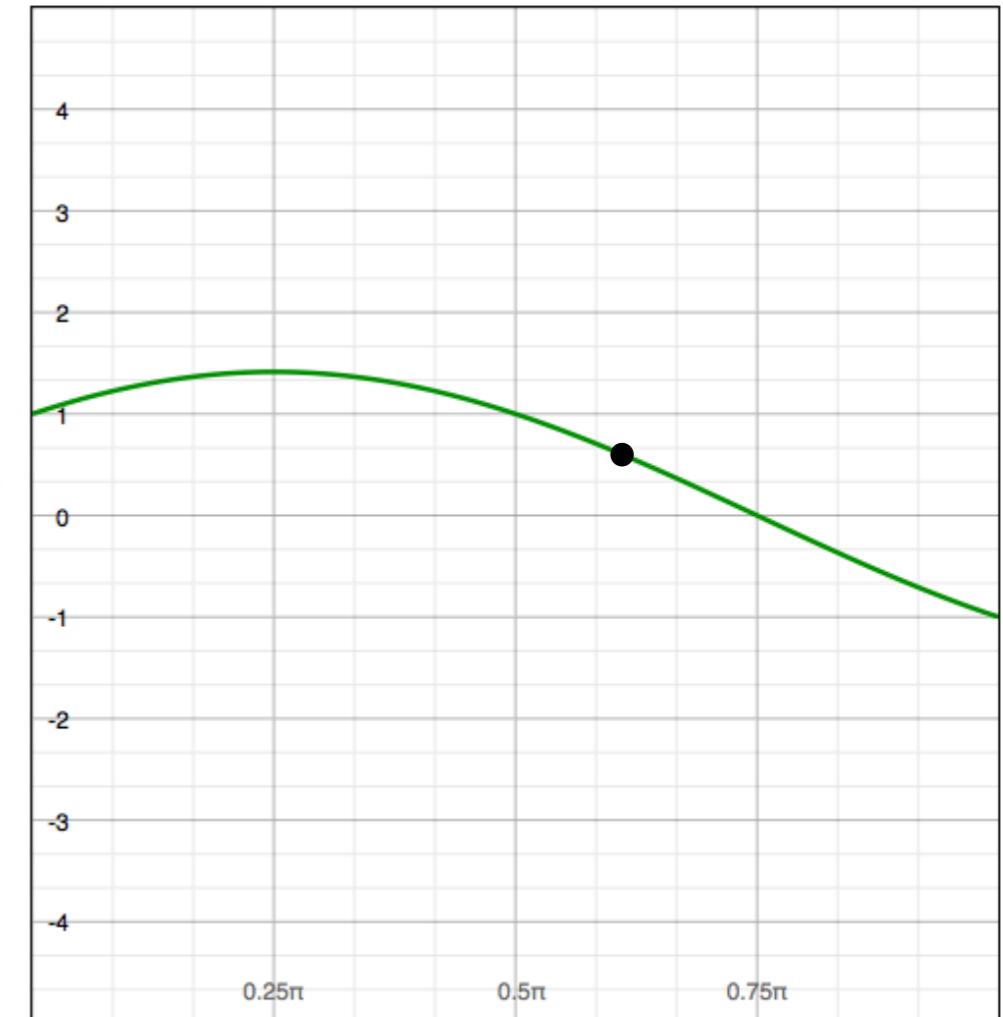


Image space

$$x \cos \theta + y \sin \theta = \rho$$

a line becomes a point



Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters

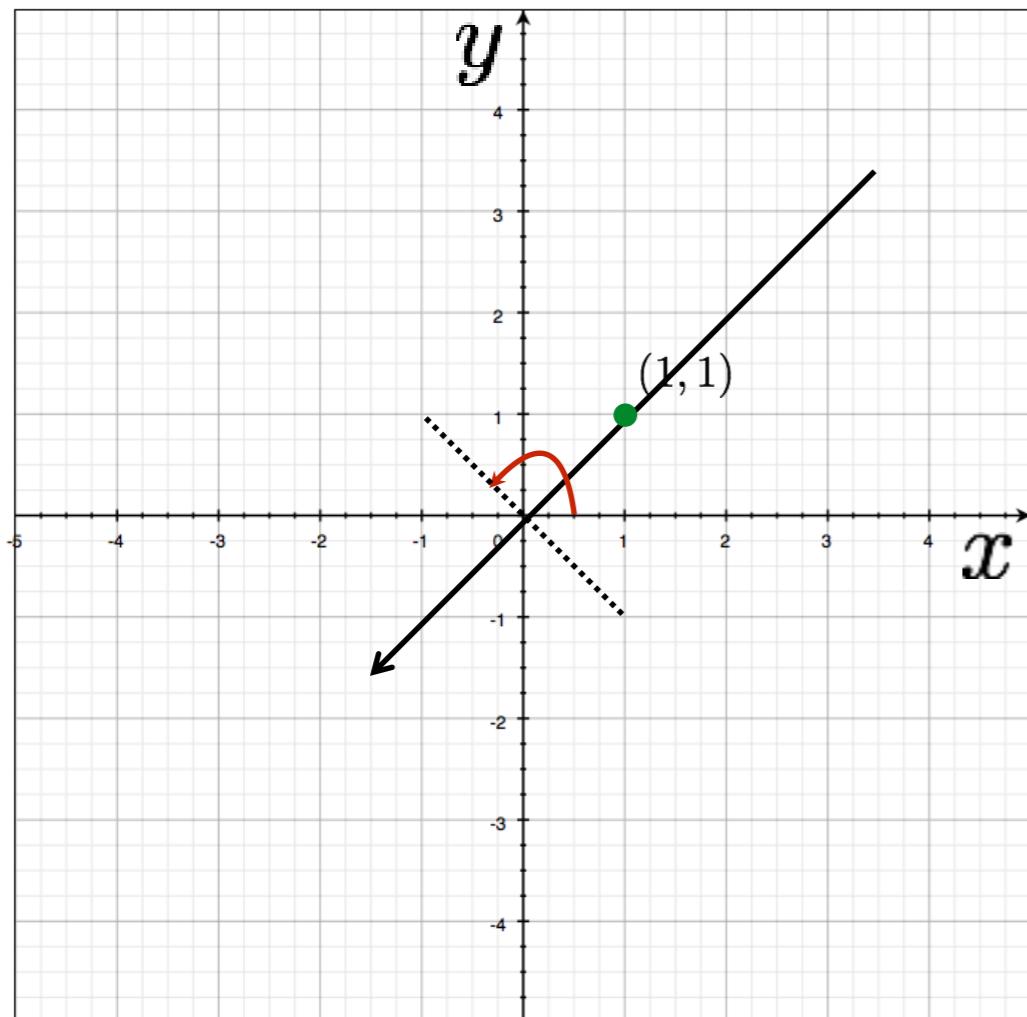
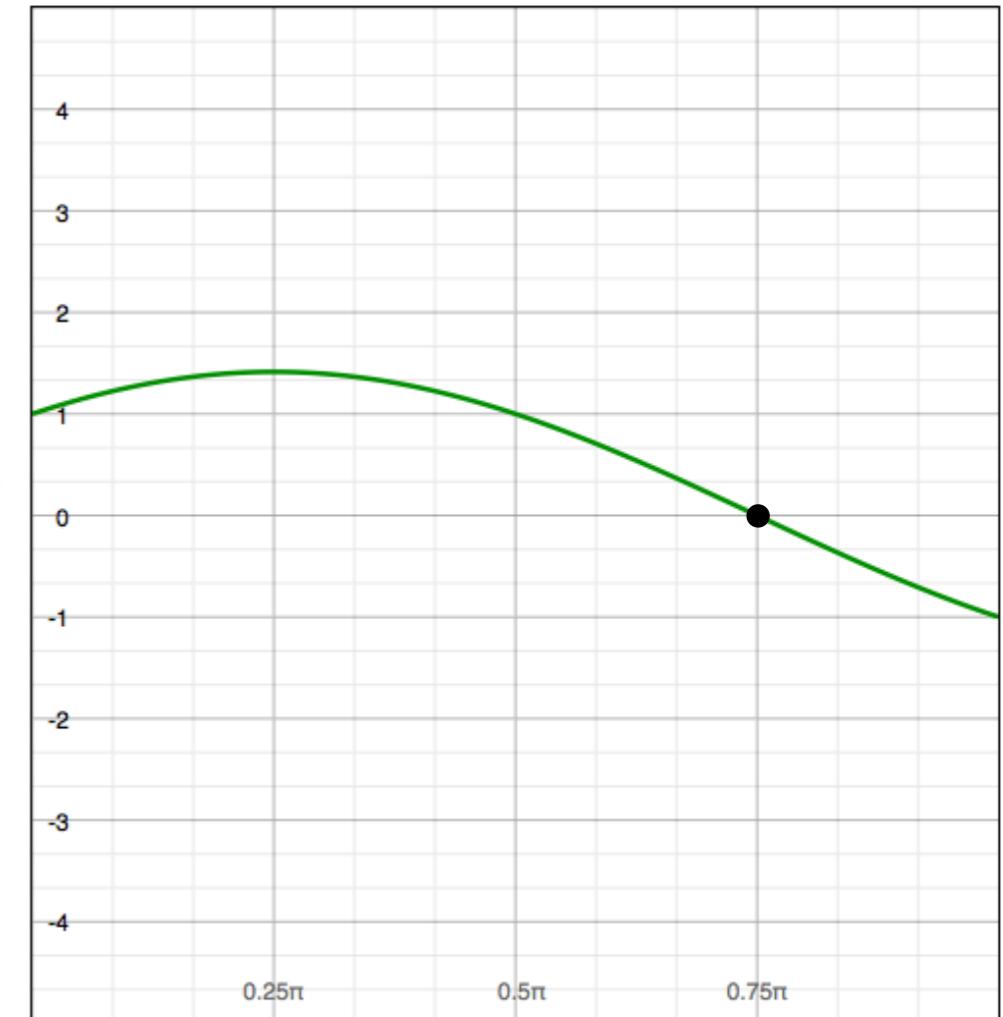


Image space

$$x \cos \theta + y \sin \theta = \rho$$

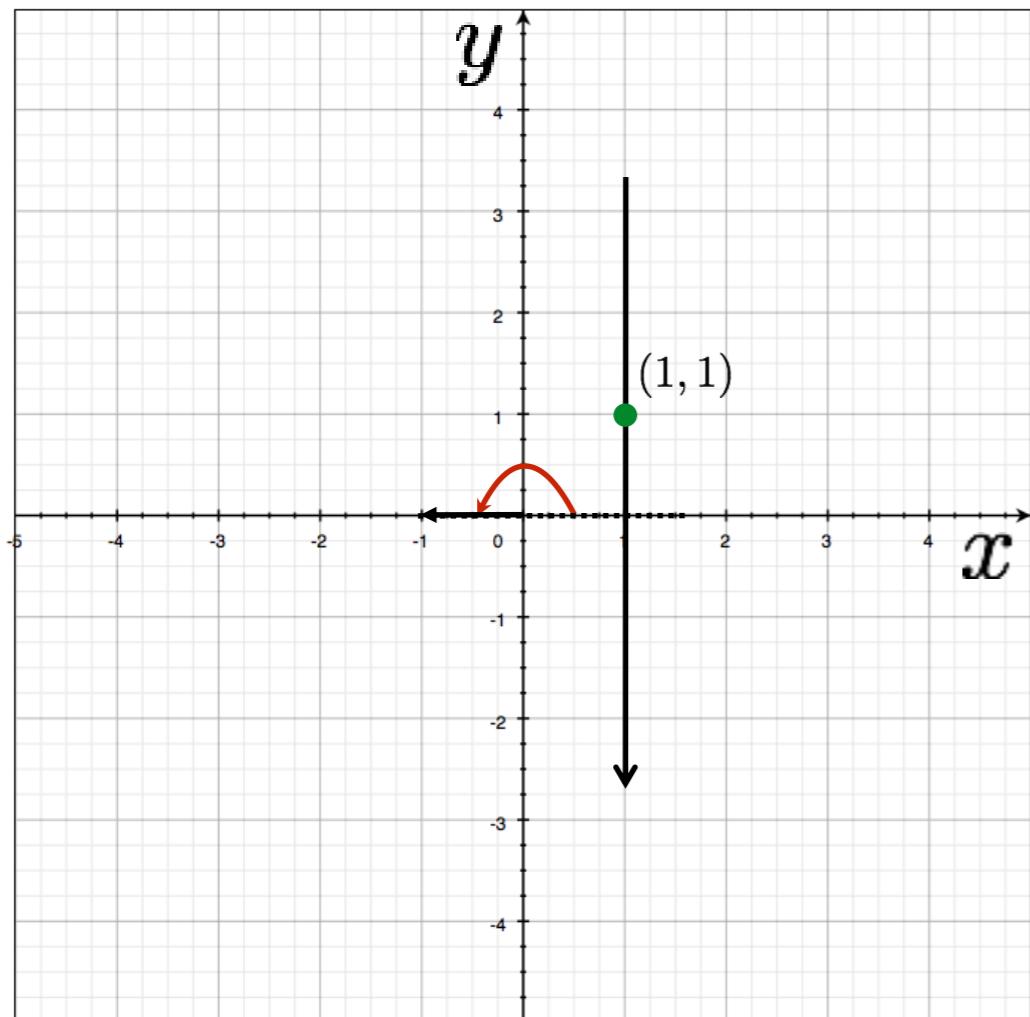
a line becomes a point



Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters



a line  
becomes a  
point

$$x \cos \theta + y \sin \theta = \rho$$

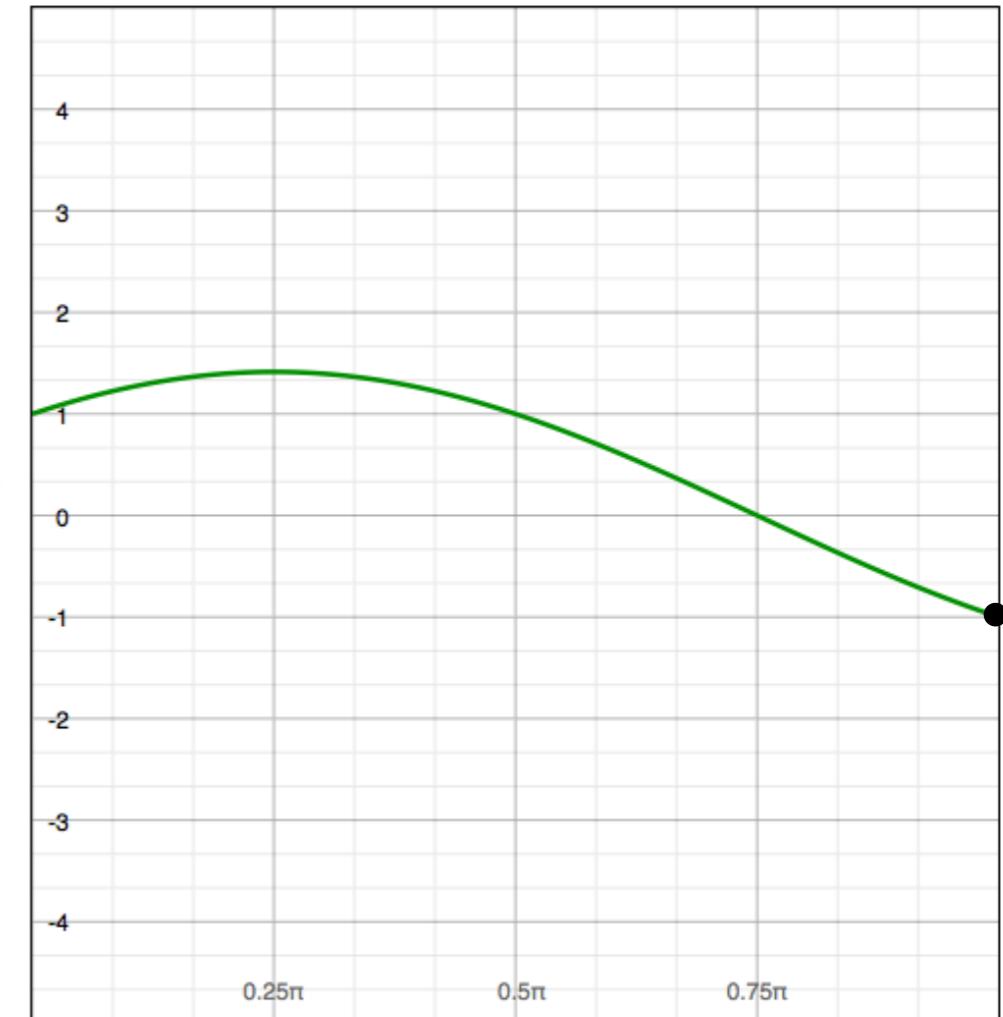
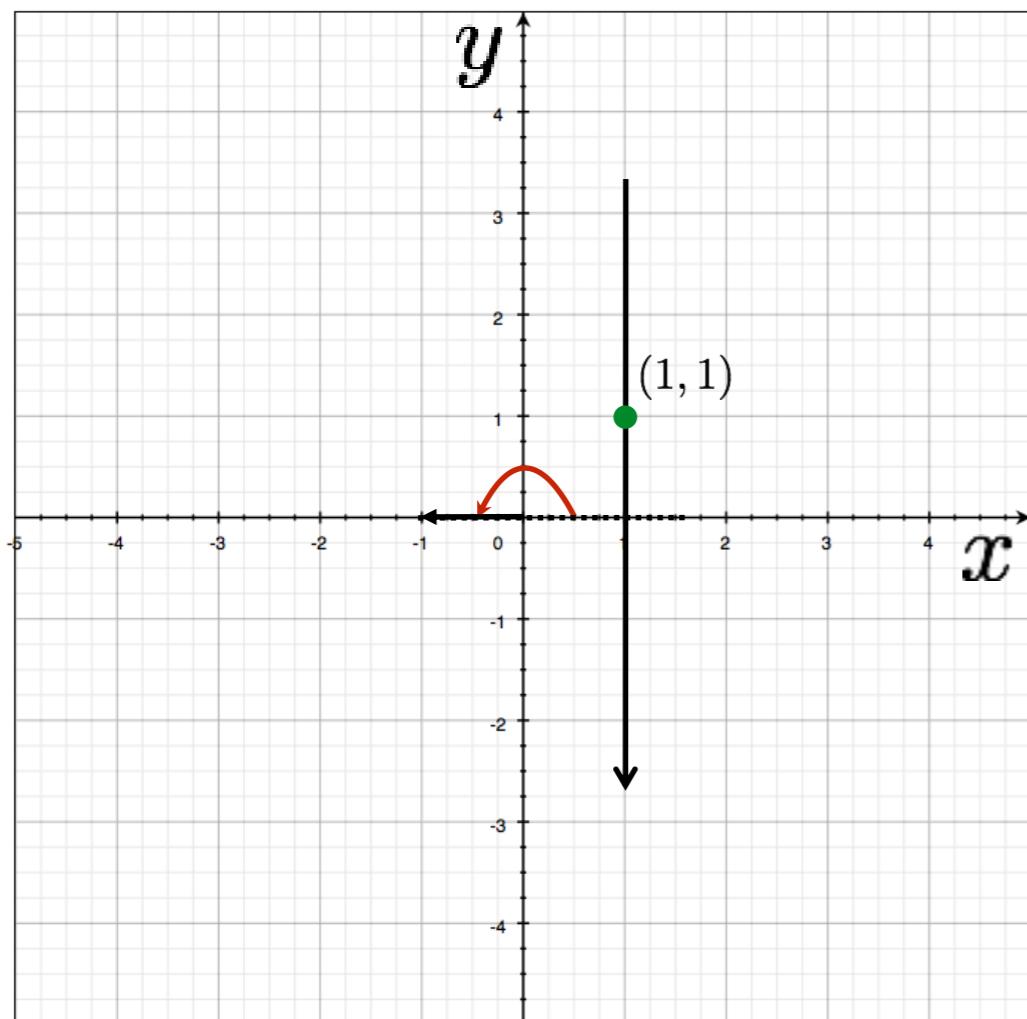


Image space

Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters



a line becomes a point

$$x \cos \theta + y \sin \theta = \rho$$

Wait ... why is rho negative?

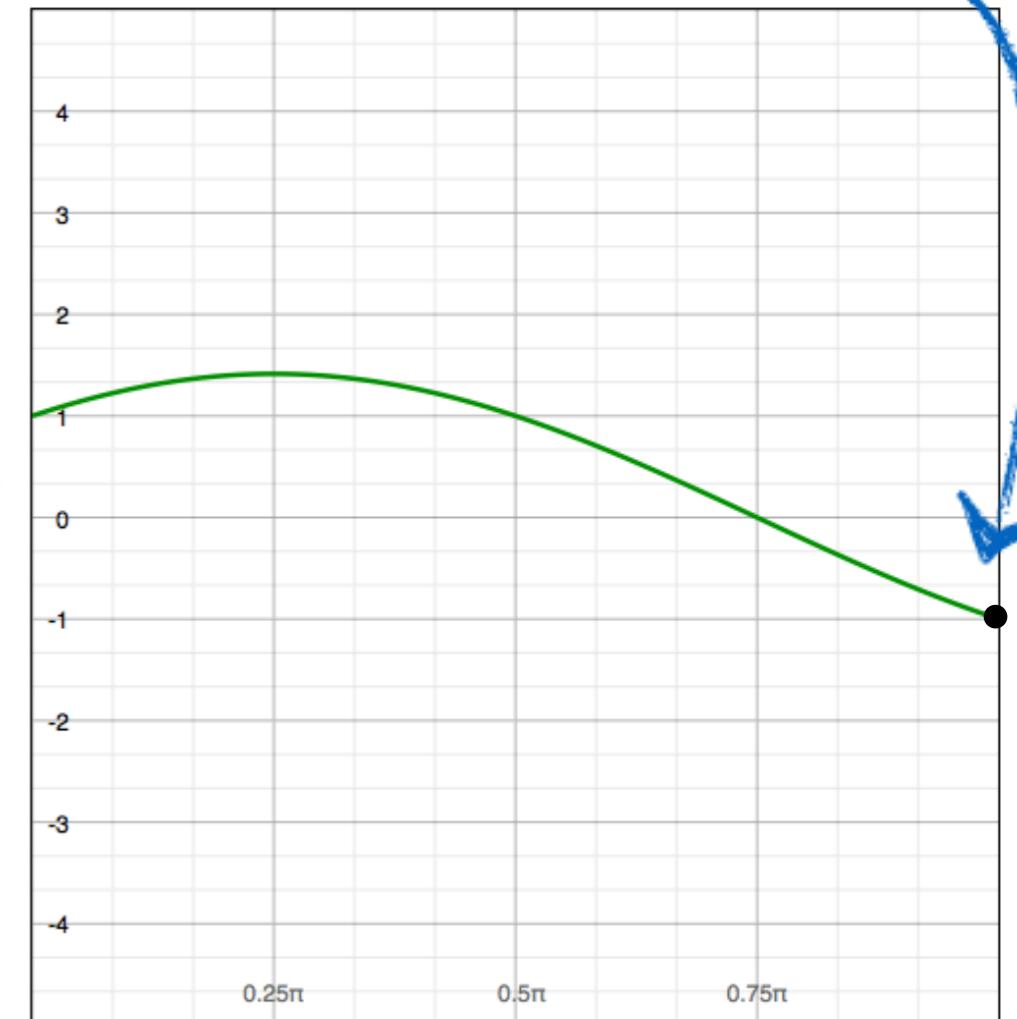
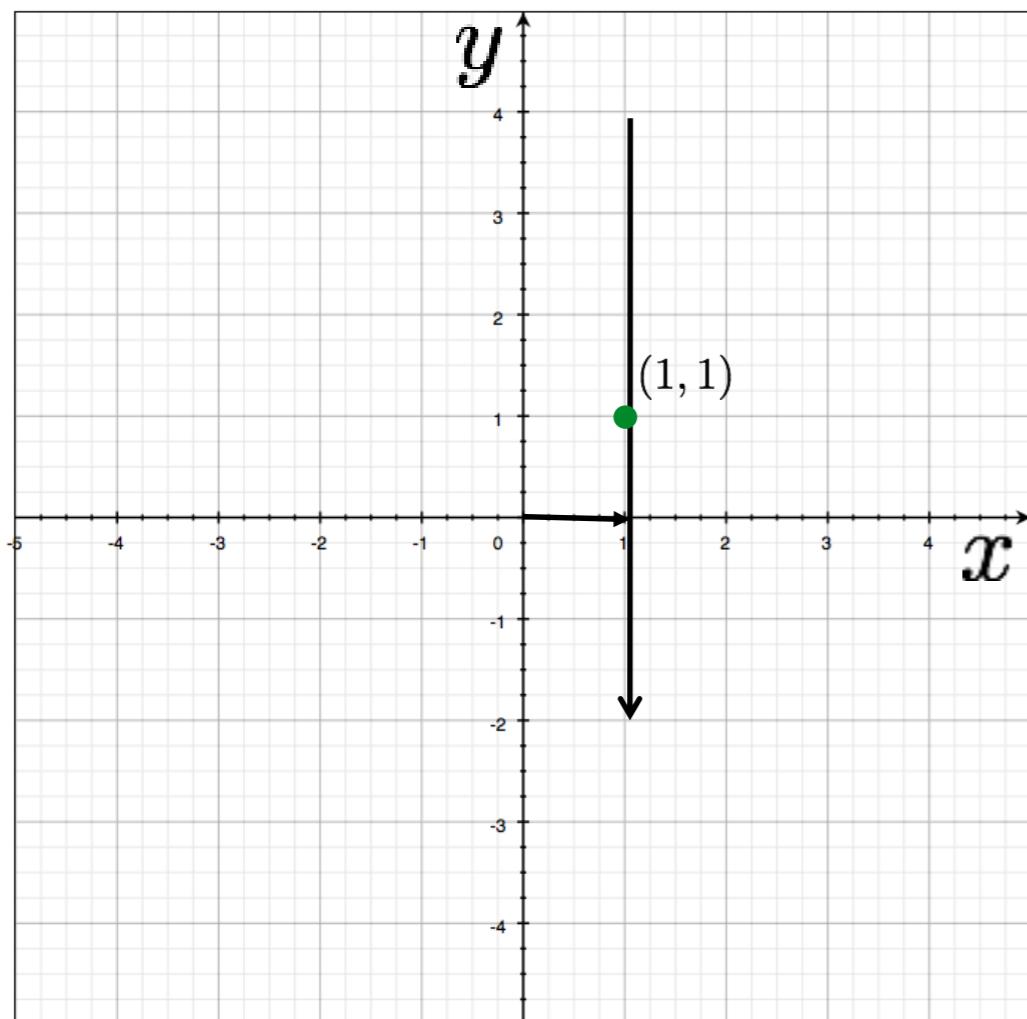


Image space

Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters



a line becomes a point

$$x \cos \theta + y \sin \theta = \rho$$

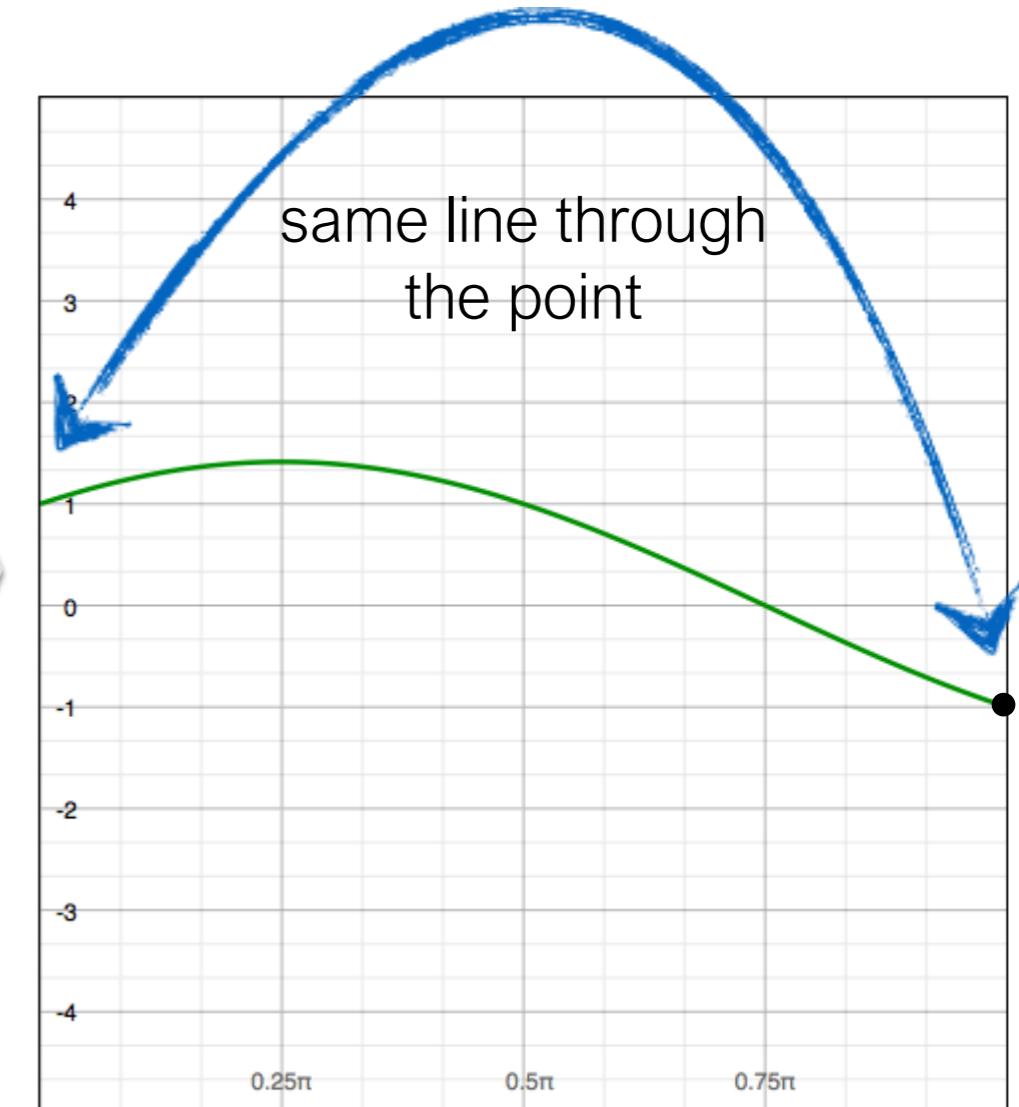


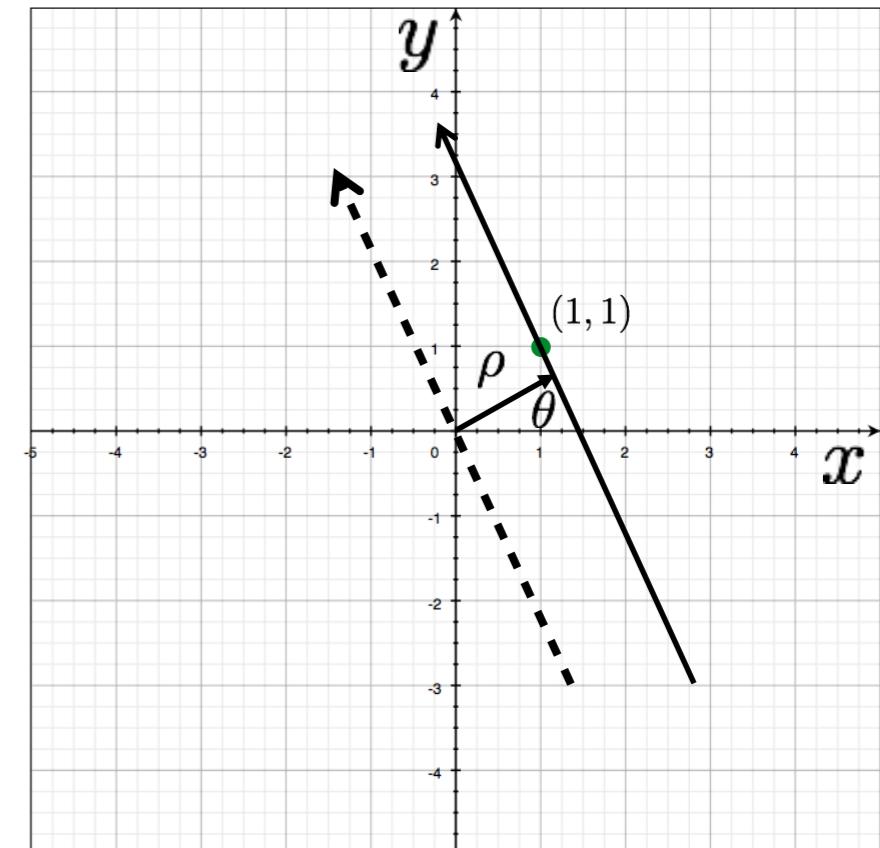
Image space

Parameter space

There are two ways to write the same line:

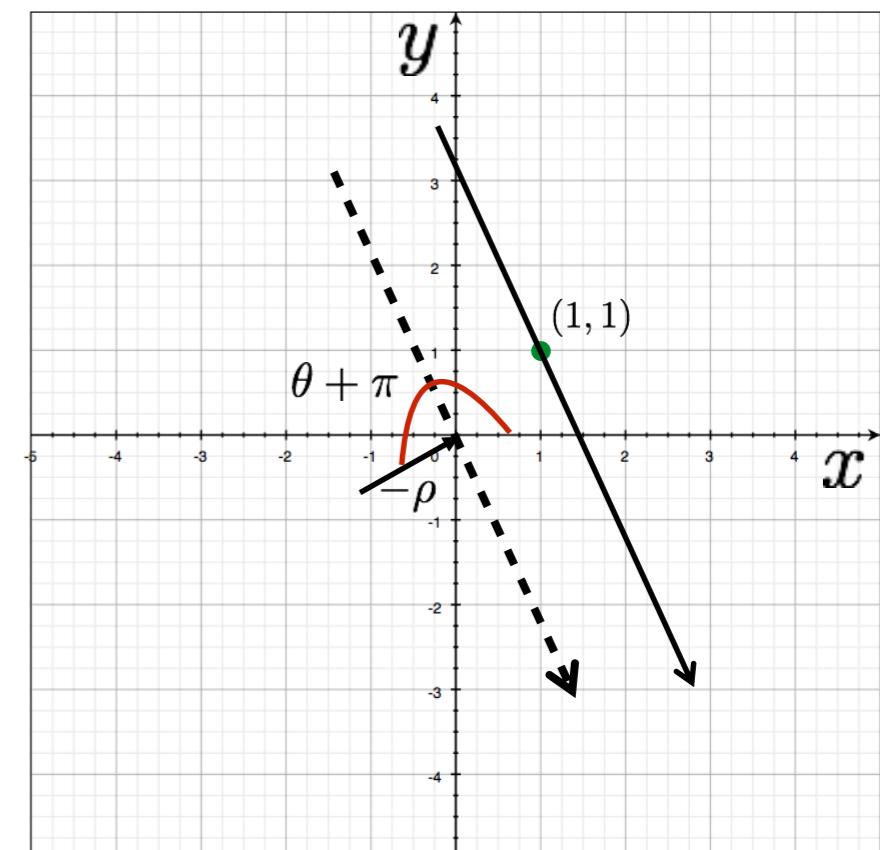
Positive rho version:

$$x \cos \theta + y \sin \theta = \rho$$



Negative rho version:

$$x \cos(\theta + \pi) + y \sin(\theta + \pi) = -\rho$$



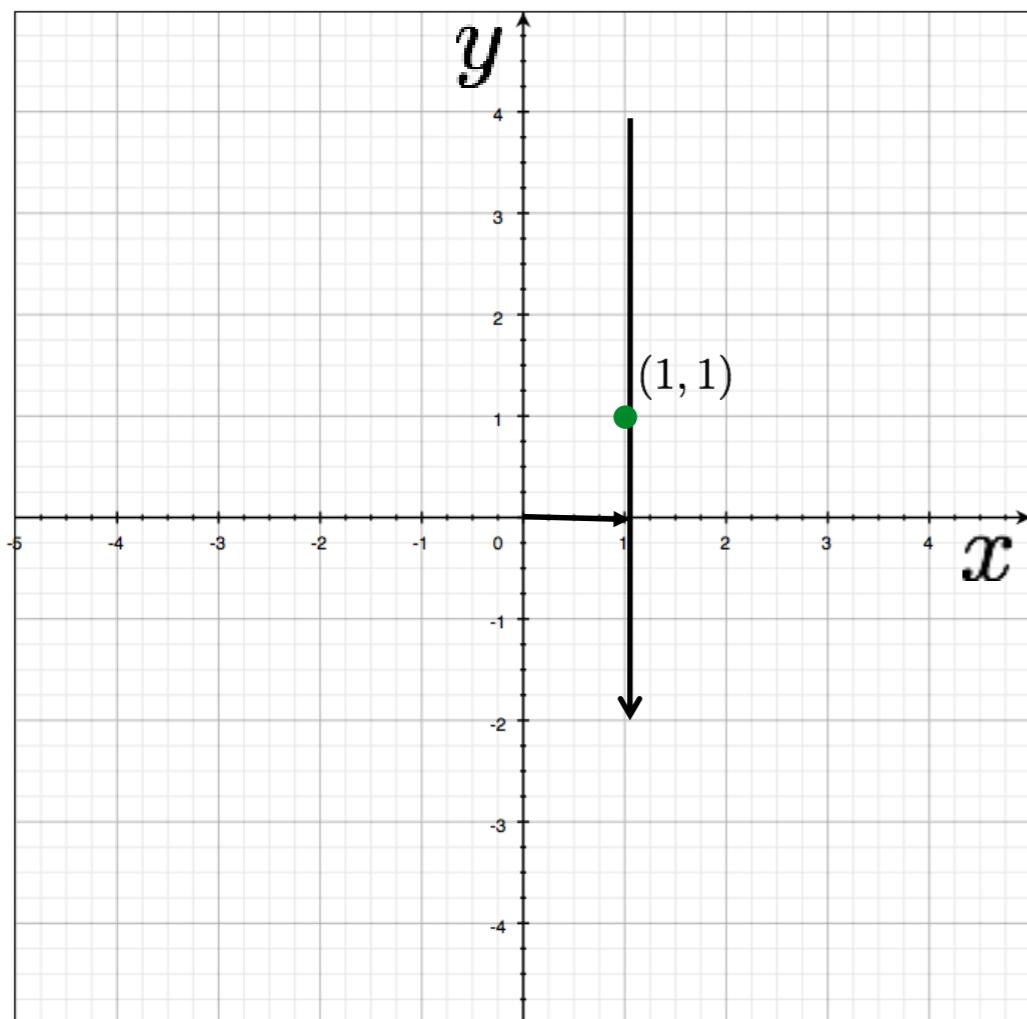
Recall:

$$\sin(\theta) = -\sin(\theta + \pi)$$

$$\cos(\theta) = -\cos(\theta + \pi)$$

# Image and parameter space

variables  
 $y = mx + b$   
parameters



a line becomes a point

$$x \cos \theta + y \sin \theta = \rho$$

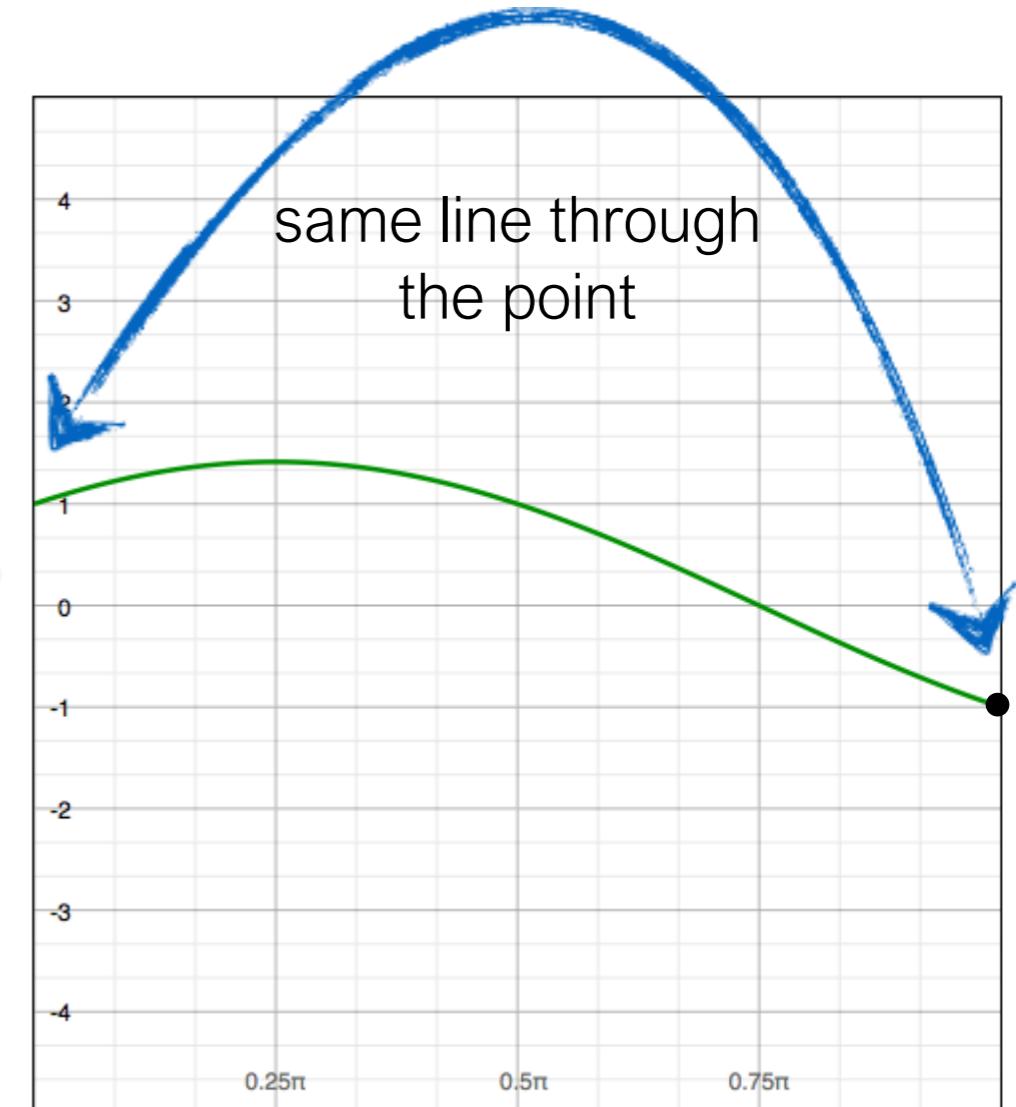
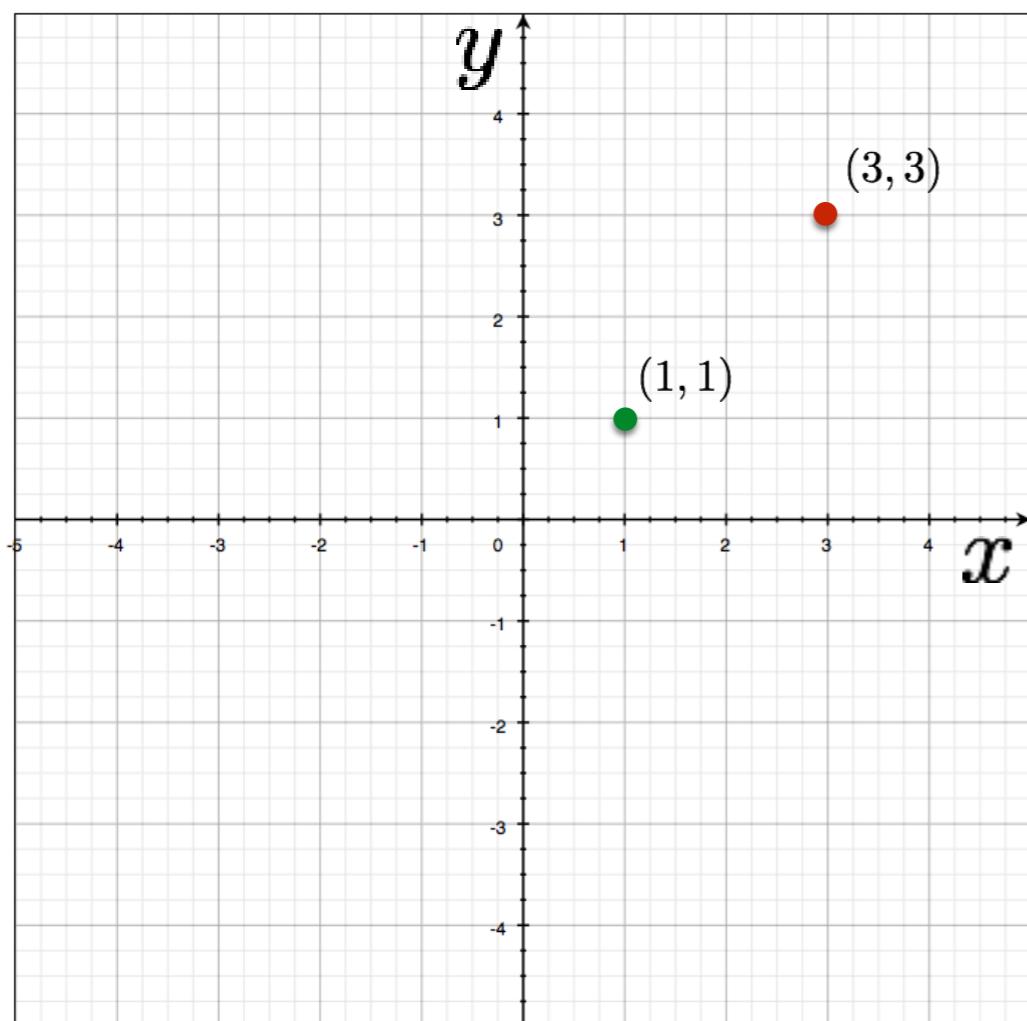


Image space

Parameter space

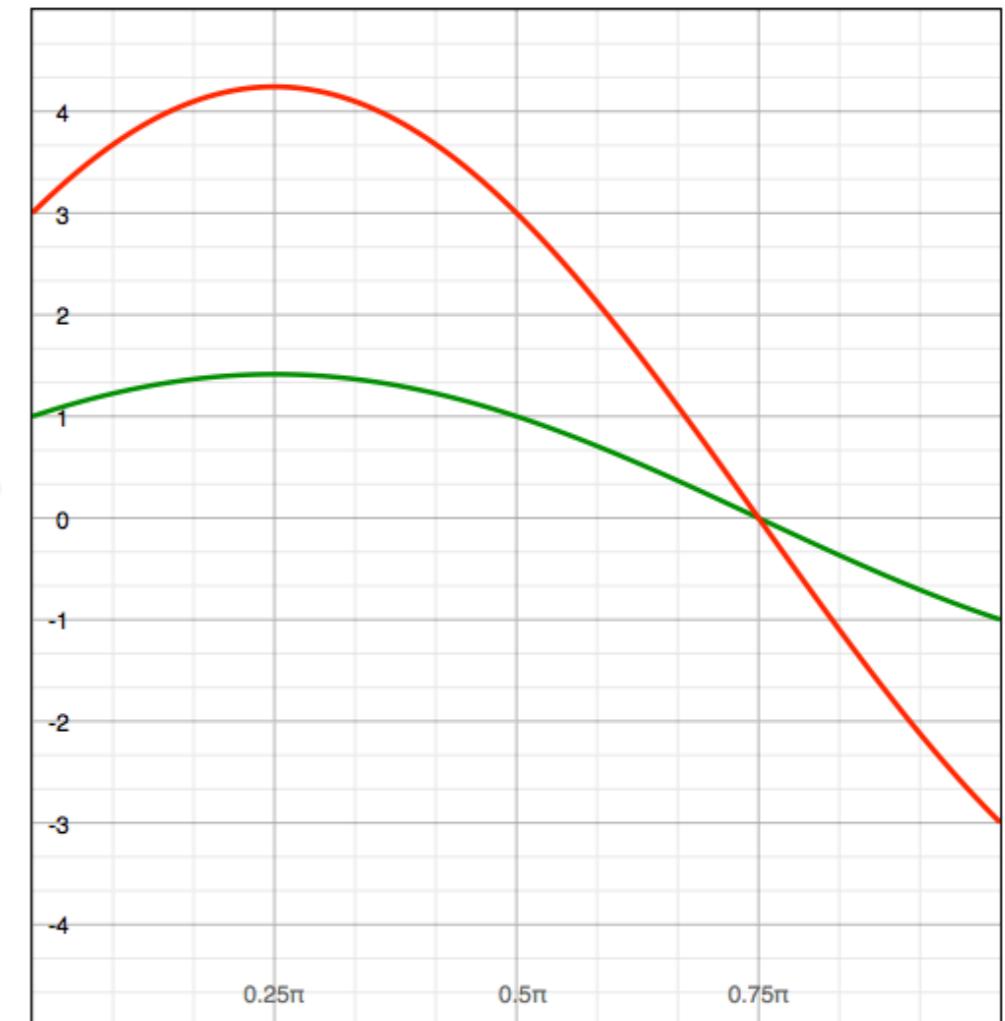
# Image and parameter space

variables  
 $y = mx + b$   
parameters



two points  
become  
?

Image space



Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters

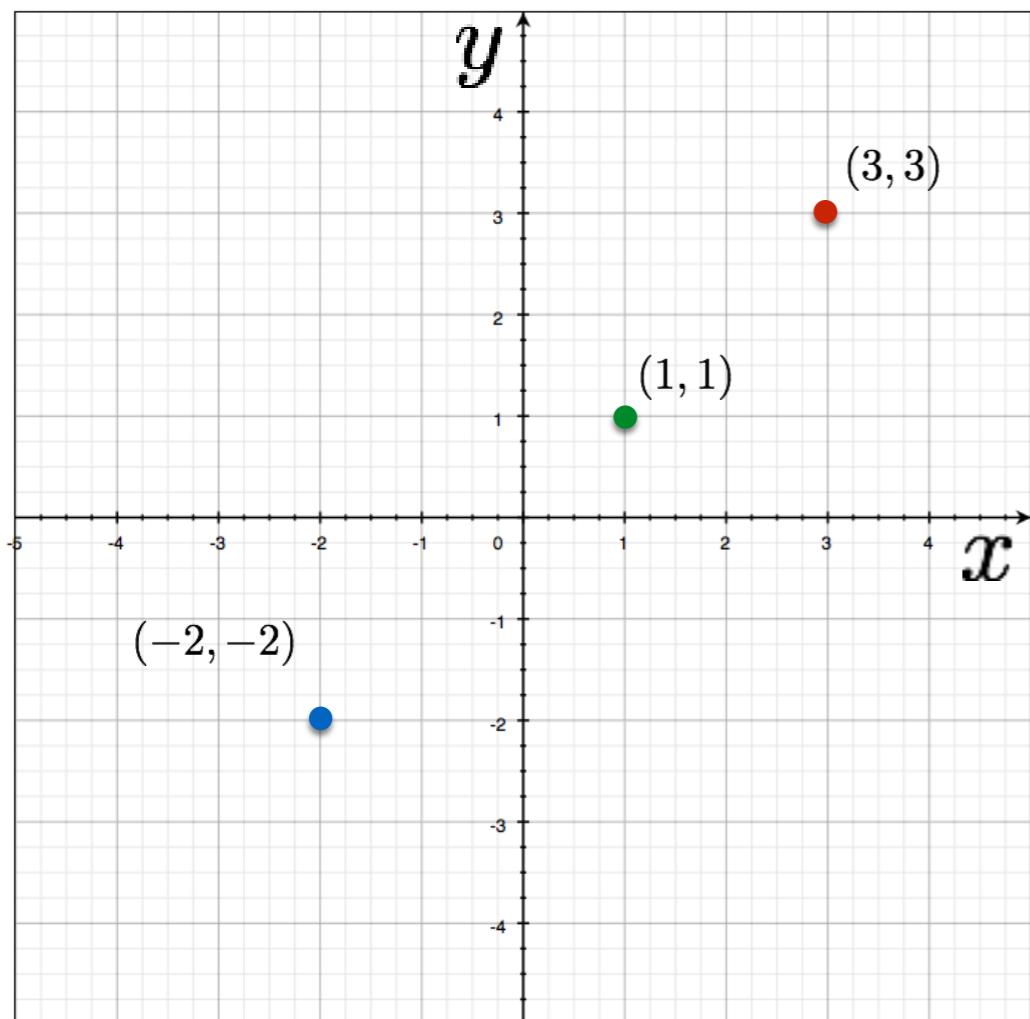
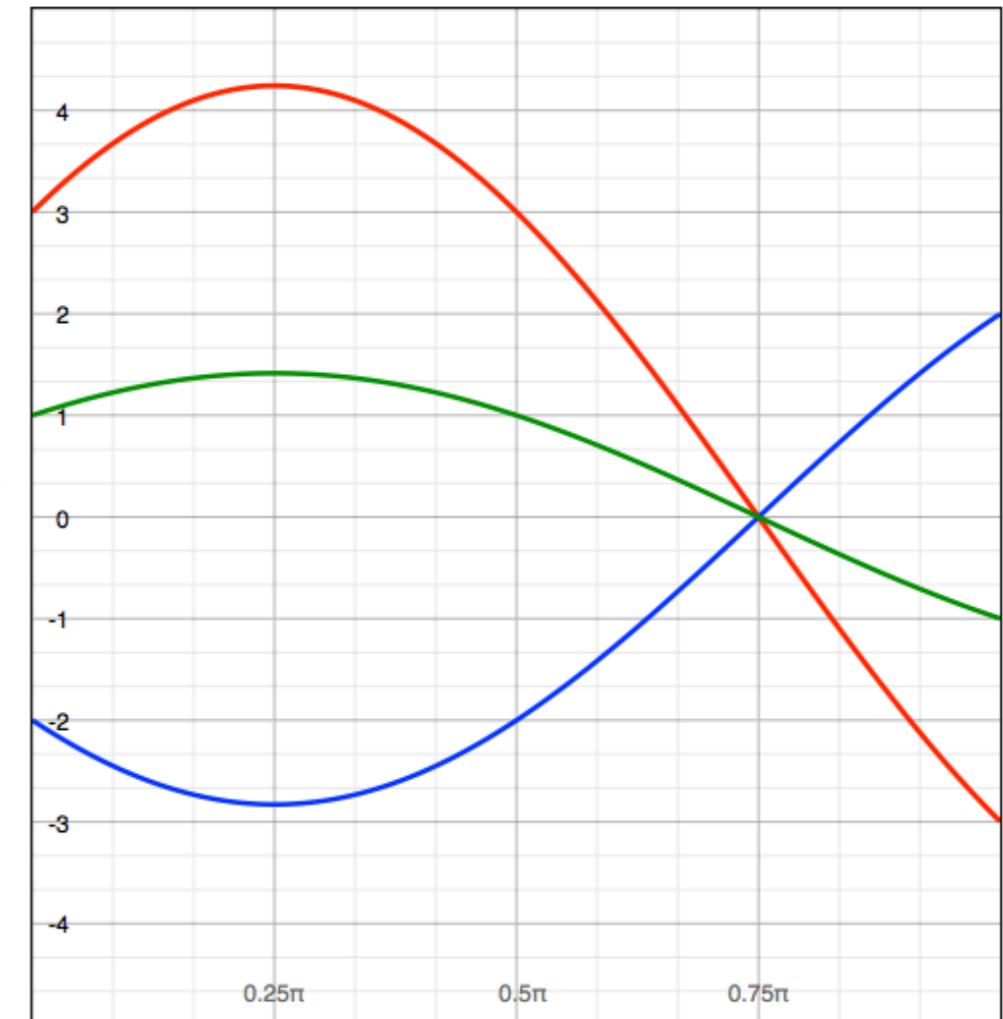


Image space

three points  
become  
?



Parameter space

# Image and parameter space

variables  
 $y = mx + b$   
parameters

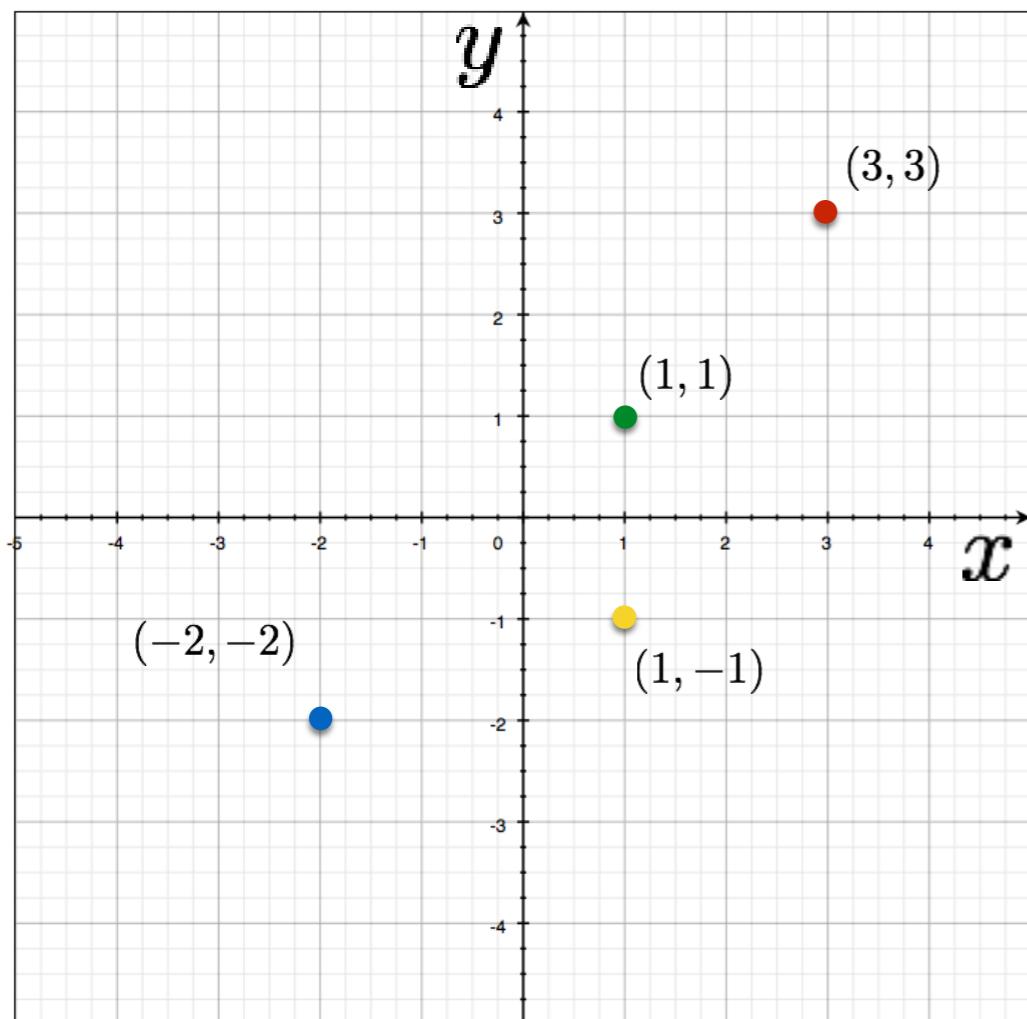
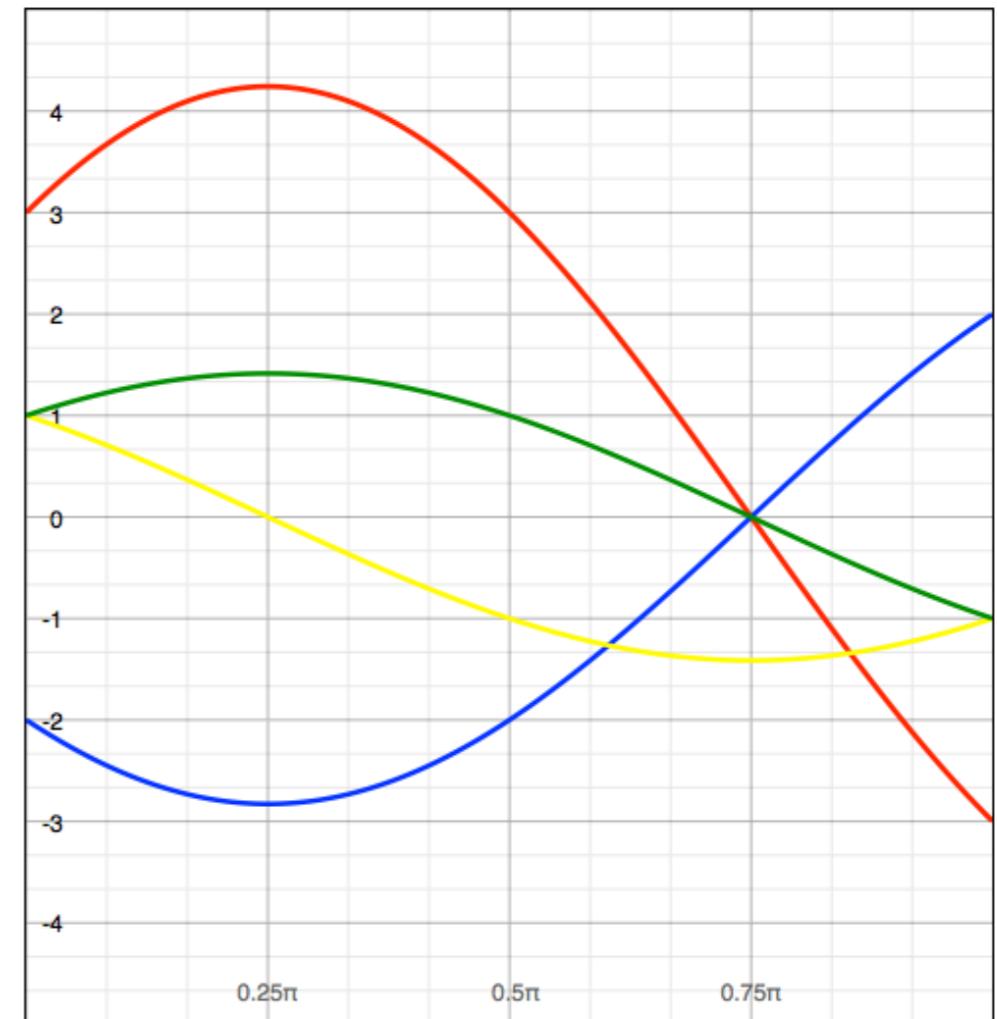


Image space

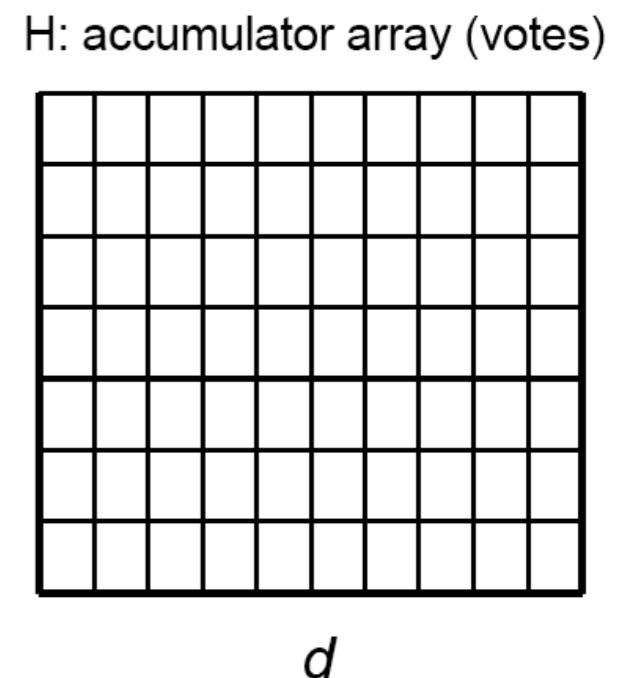
four points  
become  
?



Parameter space

# Implementation

1. Initialize accumulator  $H$  to all zeros
2. For each edge point  $(x, y)$  in the image  
    For  $\theta = 0$  to  $180$   
         $\rho = x \cos \theta + y \sin \theta$   
         $H(\theta, \rho) = H(\theta, \rho) + 1$   
    end  
end
3. Find the value(s) of  $(\theta, \rho)$  where  $H(\theta, \rho)$  is a local maximum
4. The detected line in the image is given by  
$$\rho = x \cos \theta + y \sin \theta$$



NOTE: Watch your coordinates. Image origin is top left!

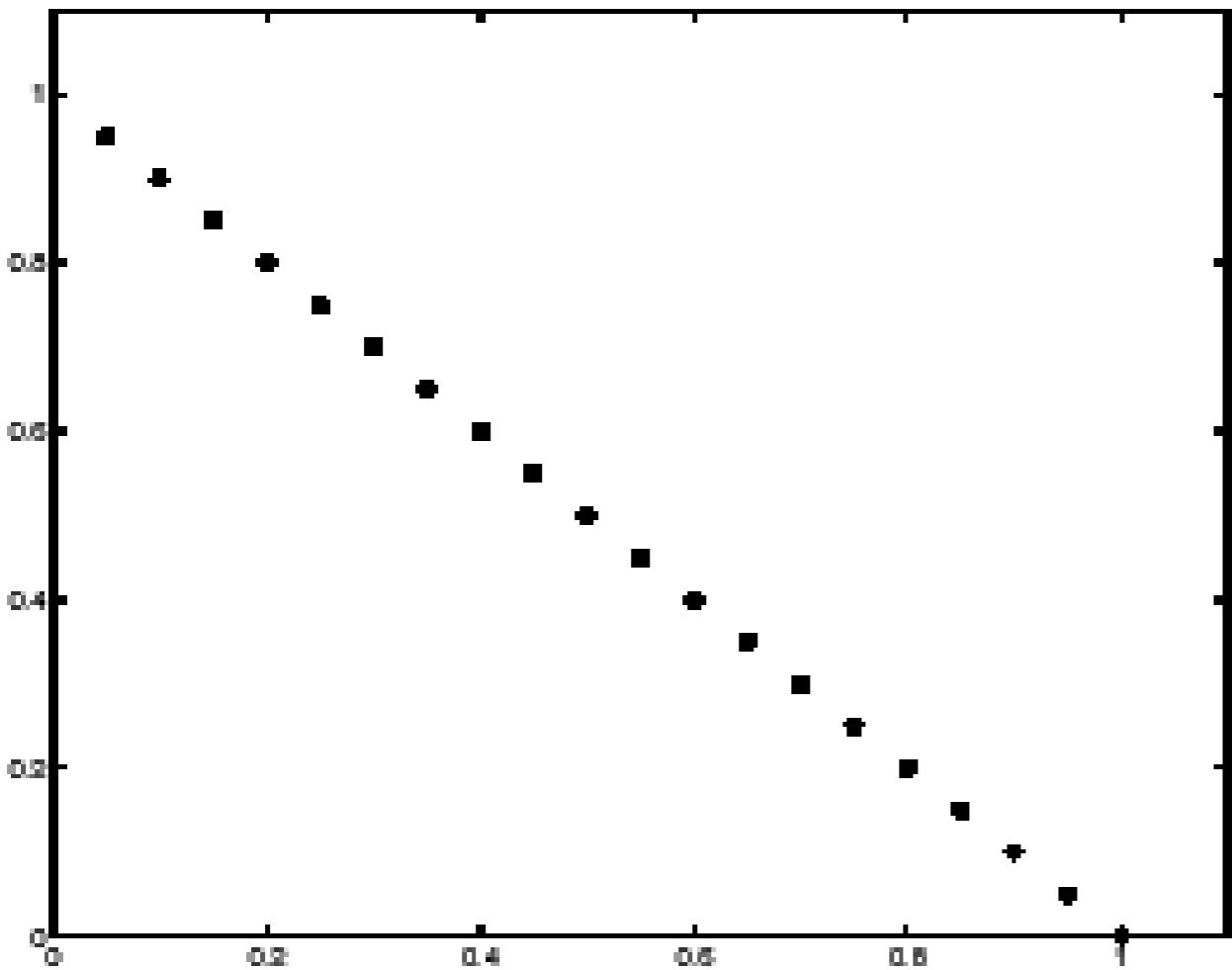
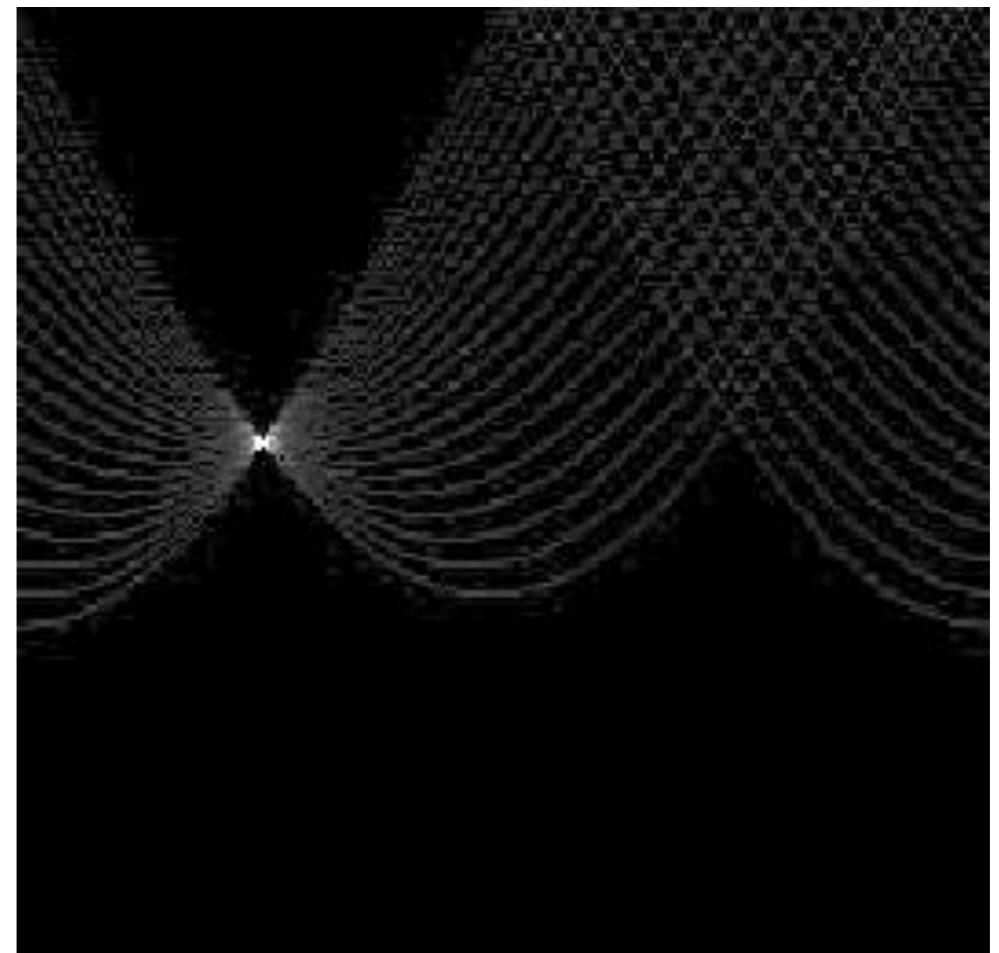


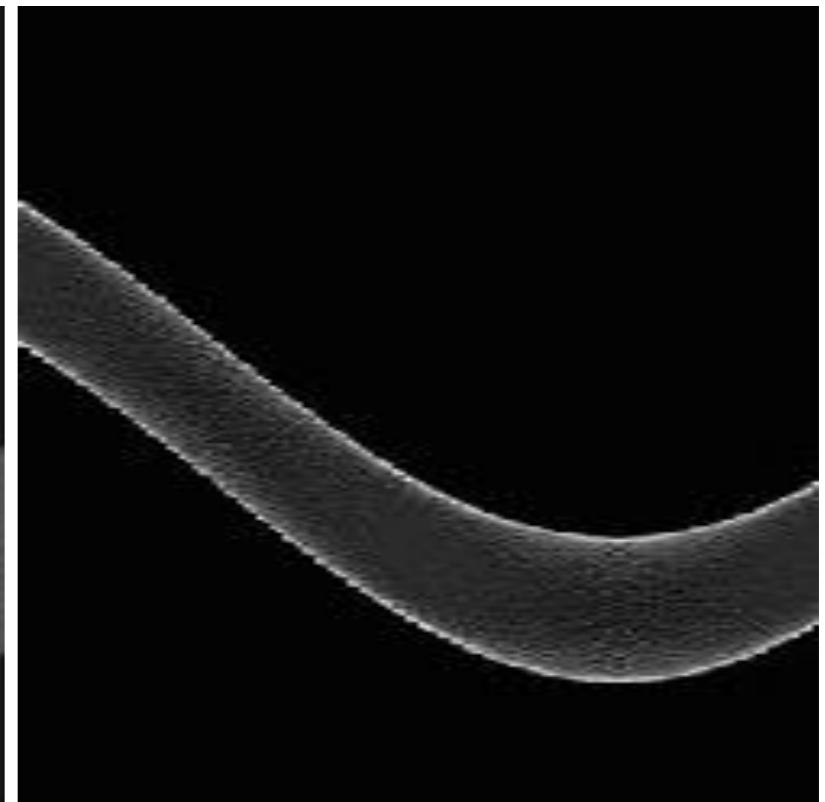
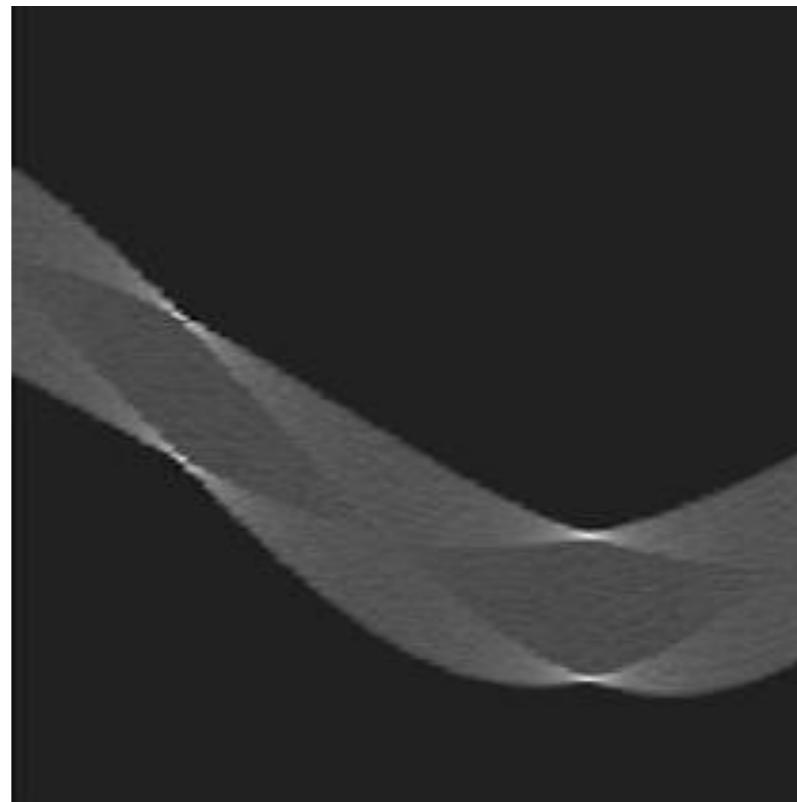
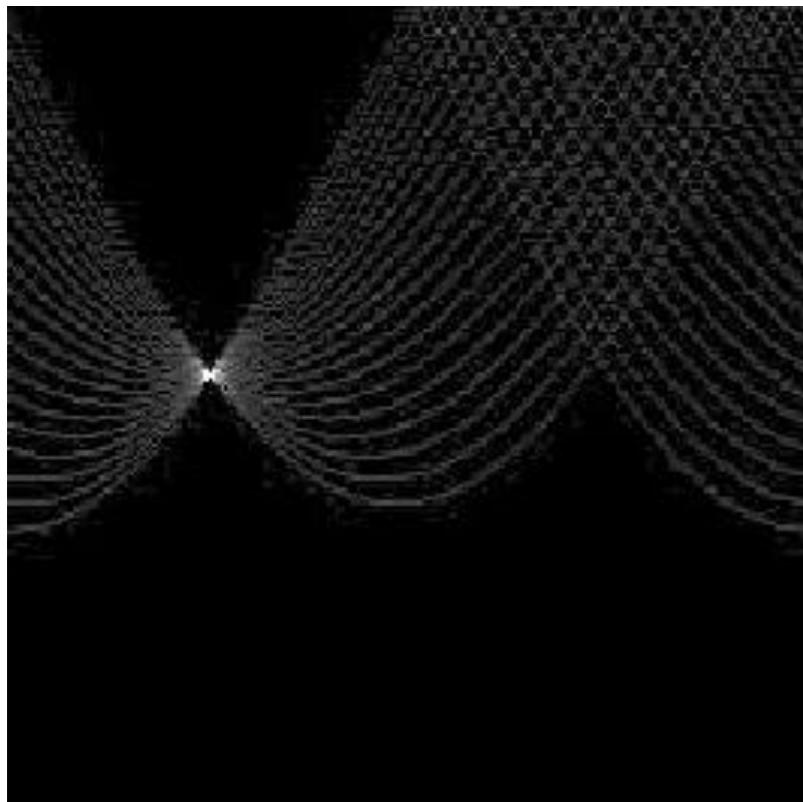
Image space



Votes

# Basic shapes

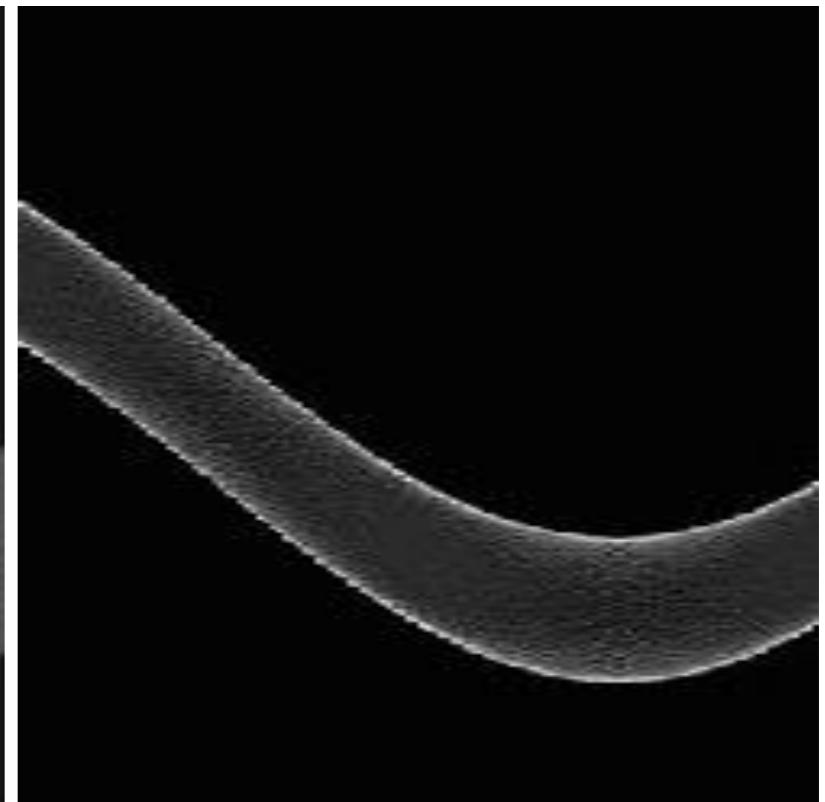
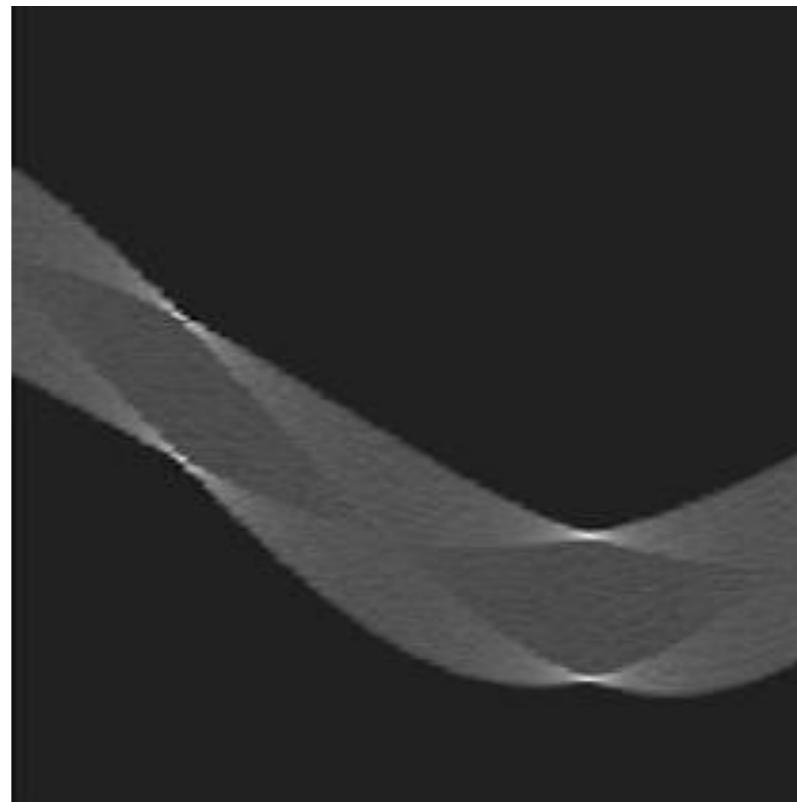
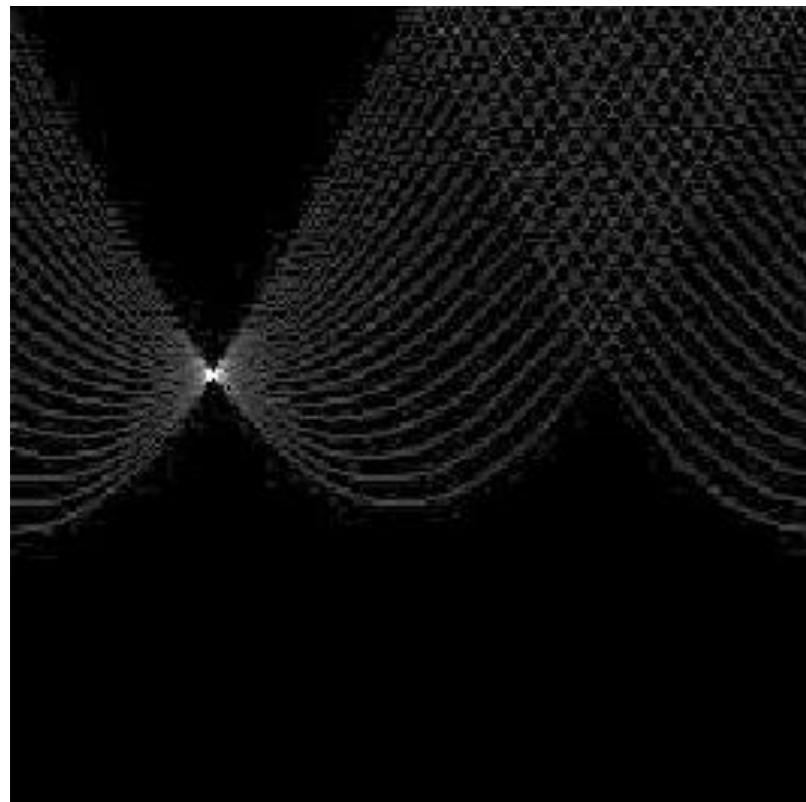
(in parameter space)



*can you guess the shape?*

# Basic shapes

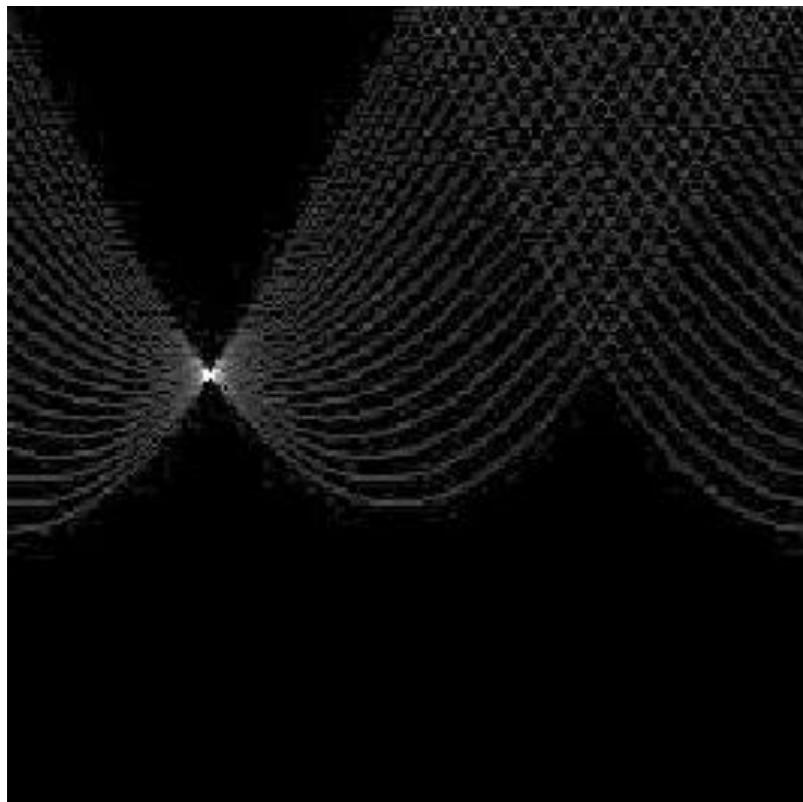
(in parameter space)



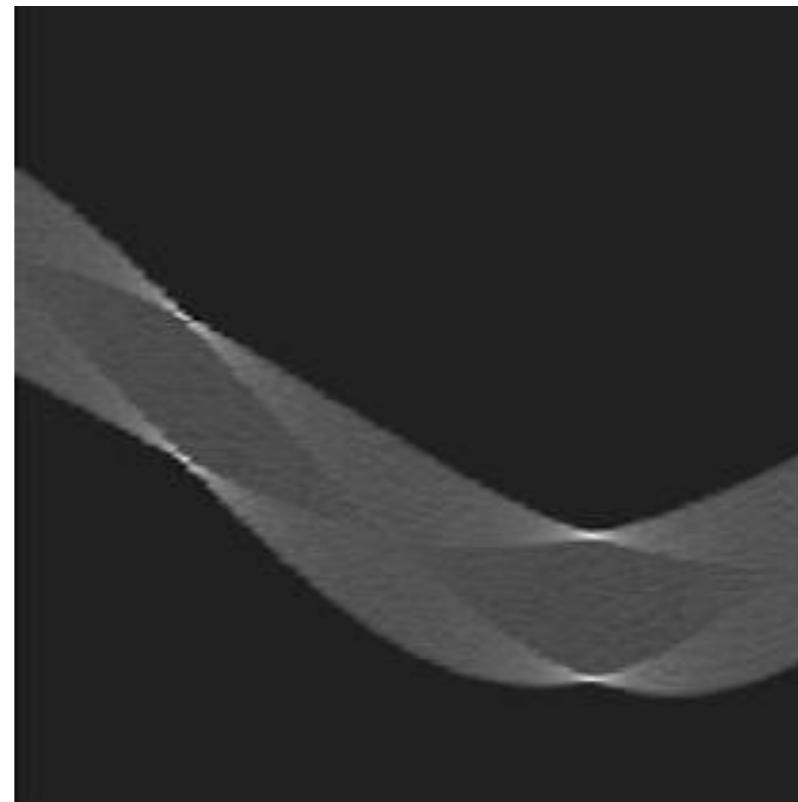
line

# Basic shapes

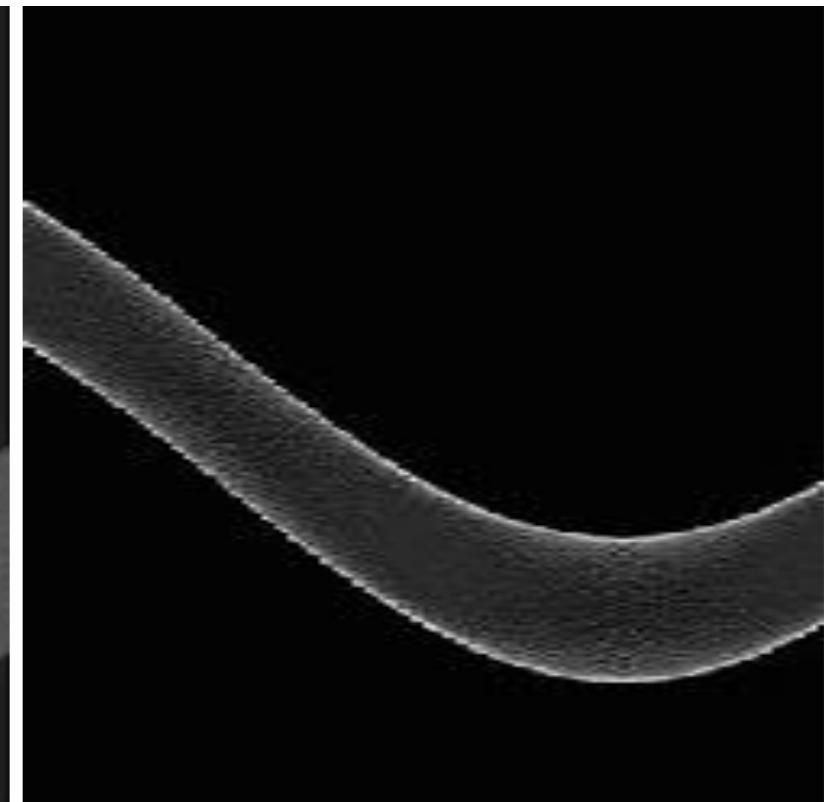
(in parameter space)



line

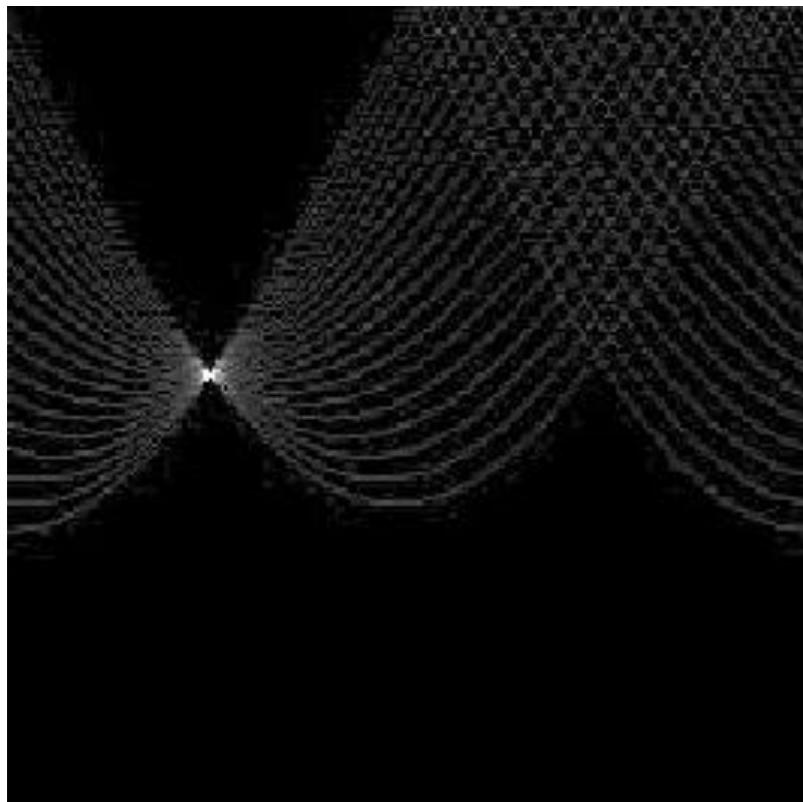


rectangle

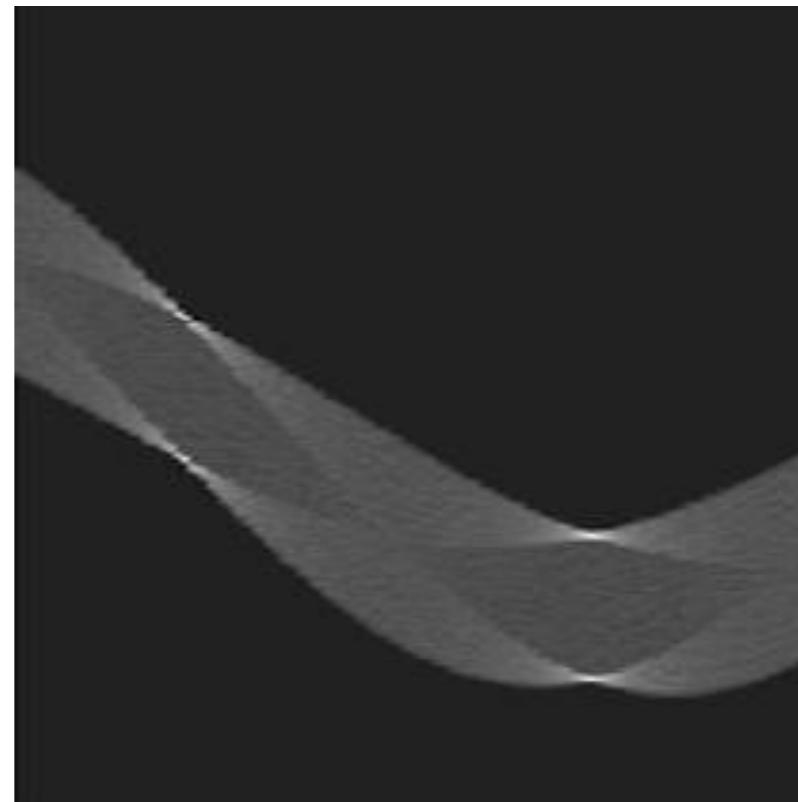


# Basic shapes

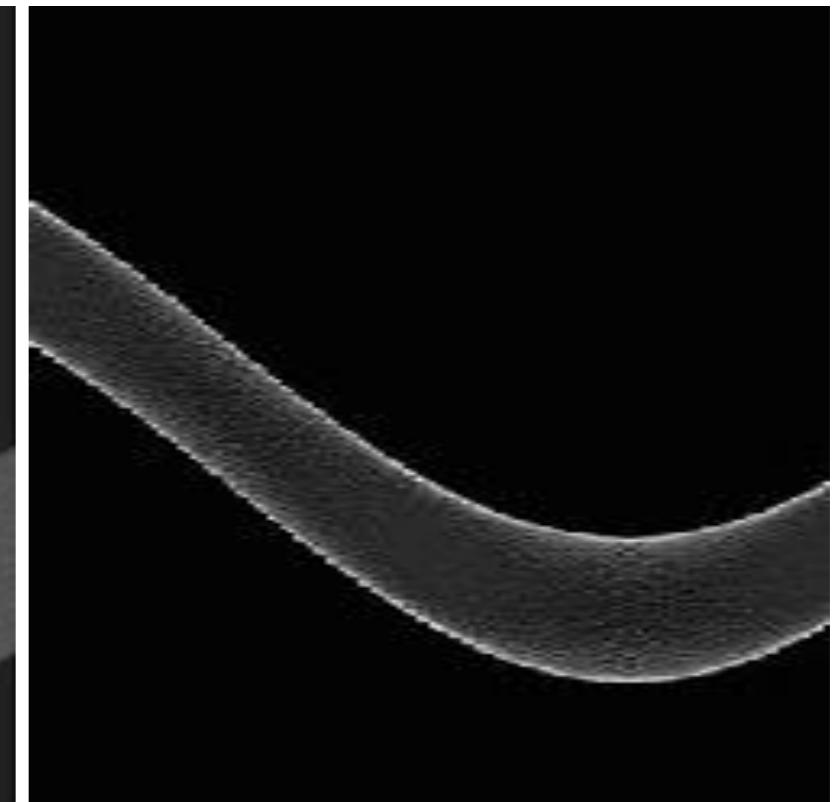
(in parameter space)



line

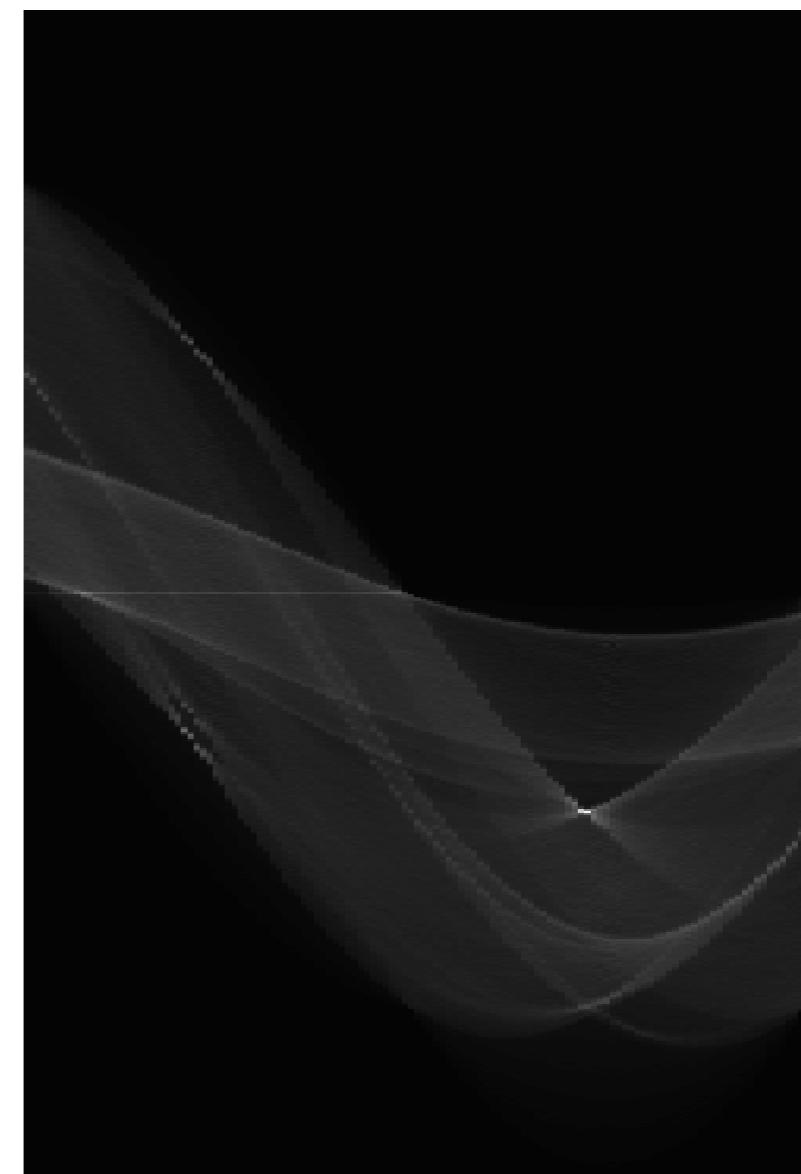
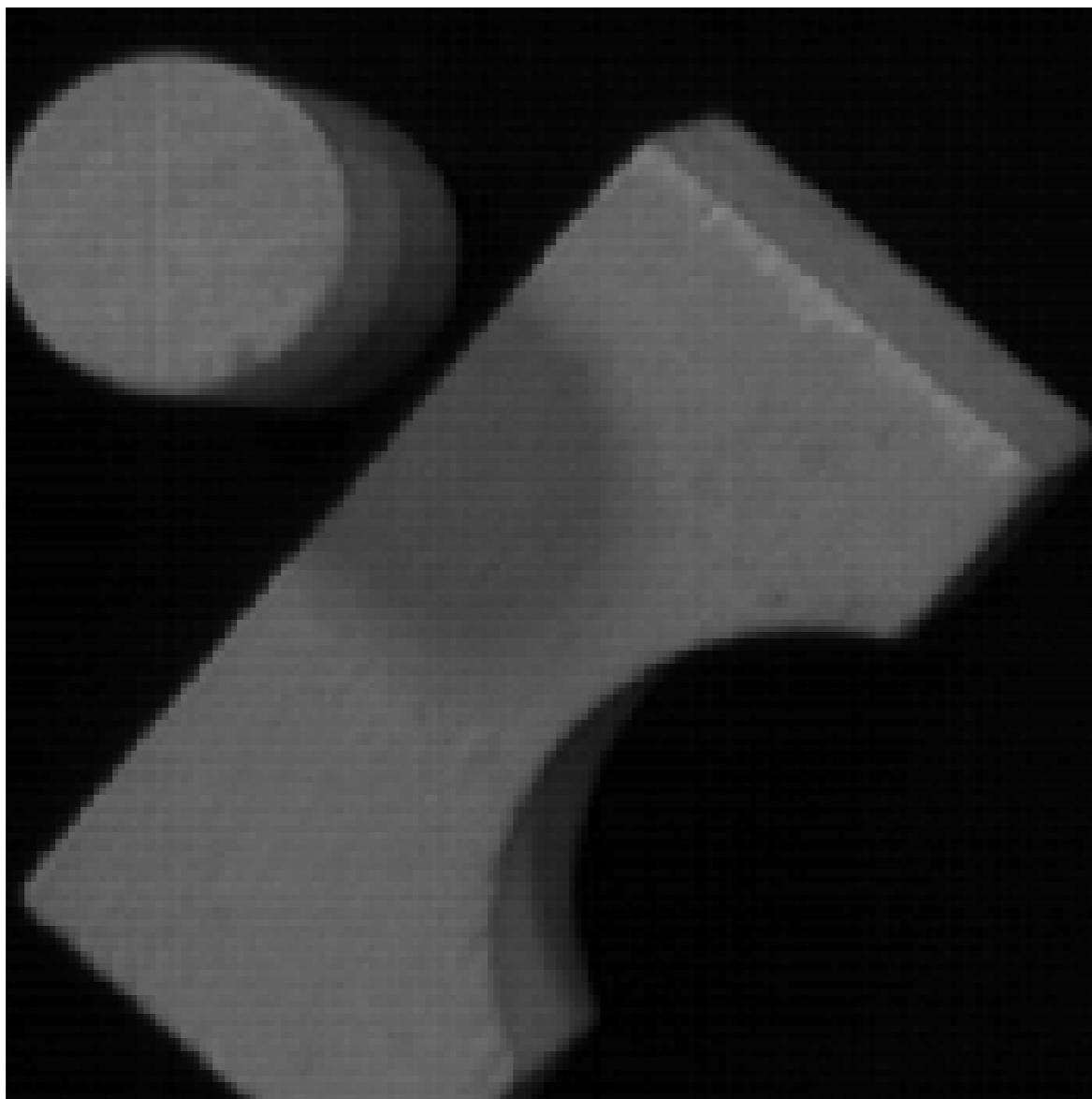


rectangle

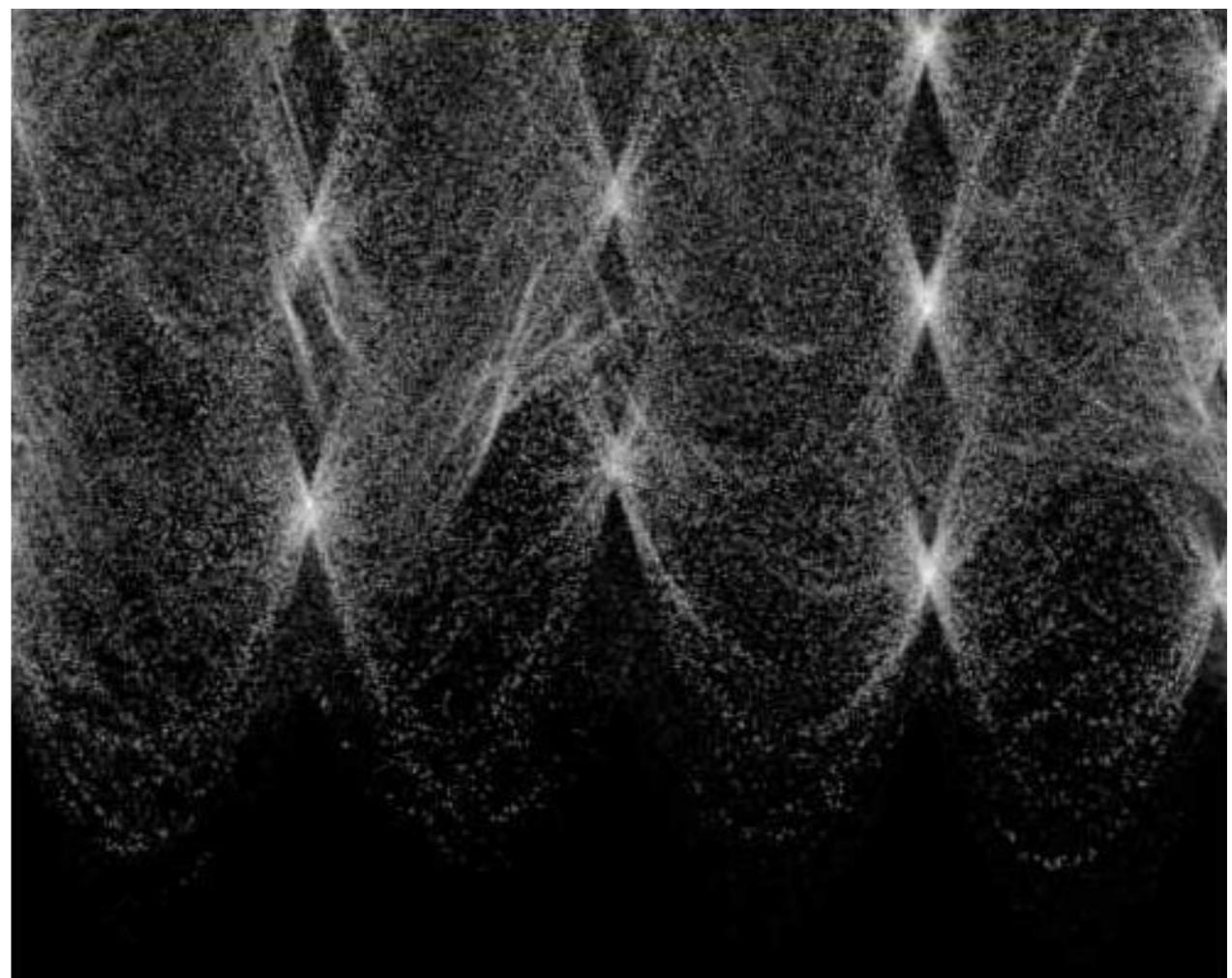


circle

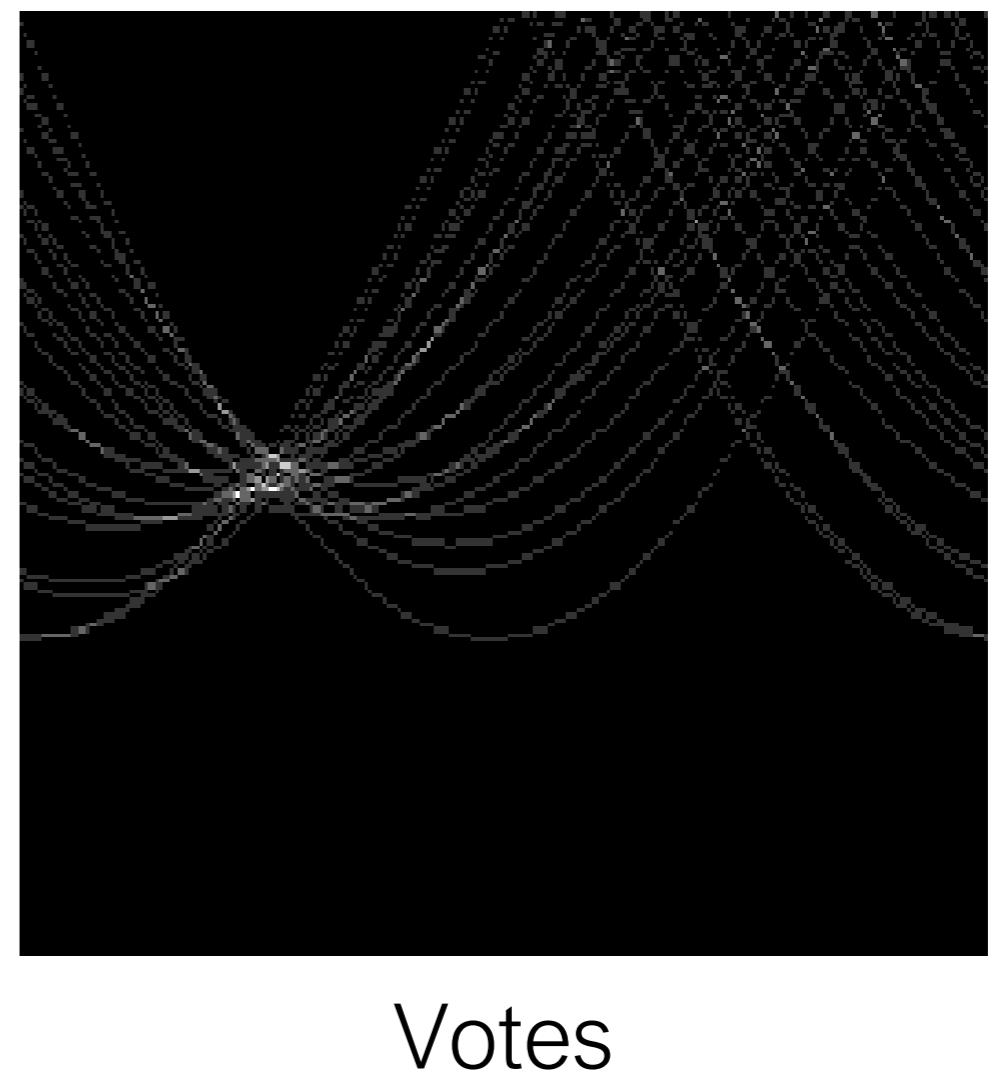
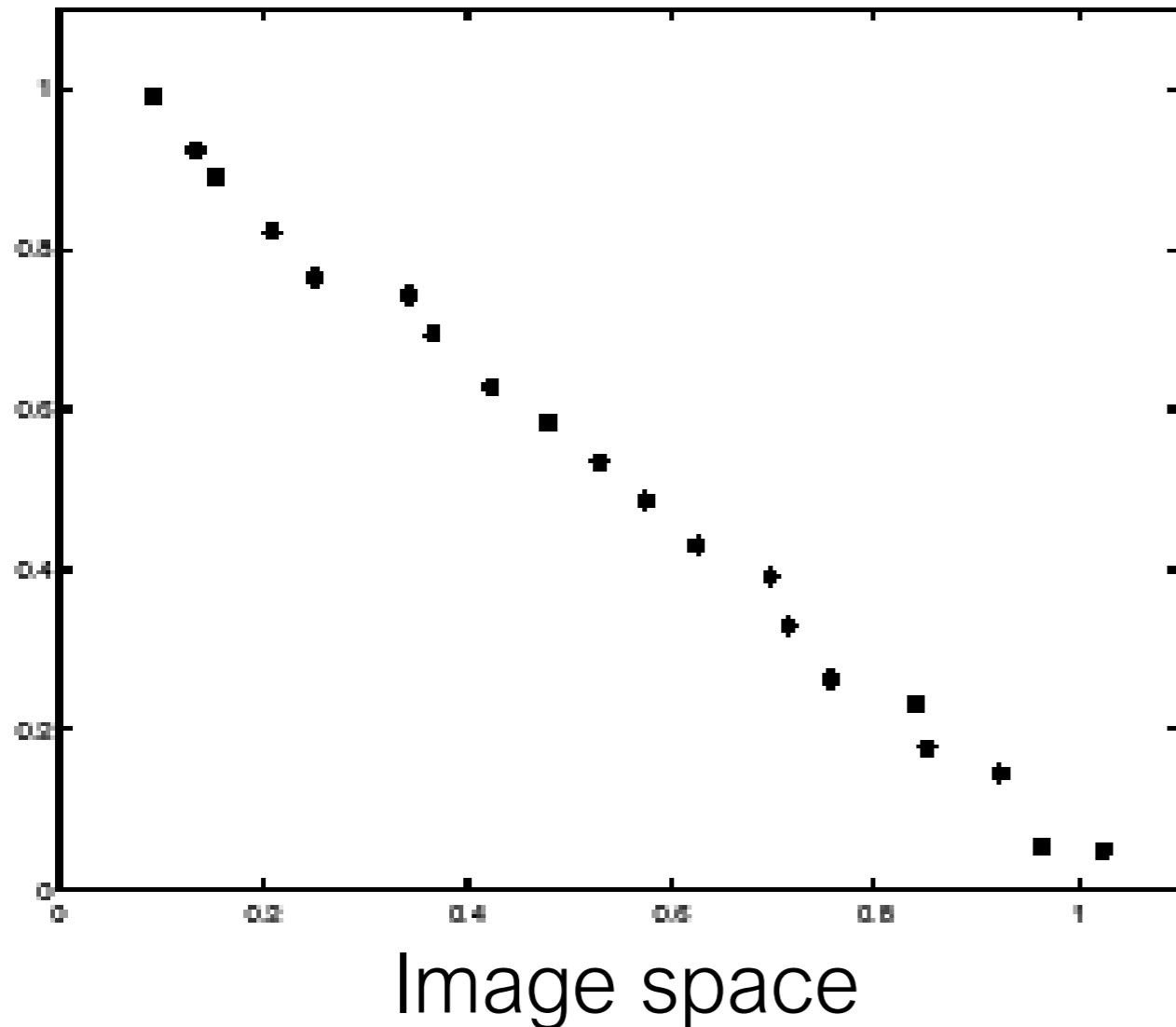
# Basic Shapes



# More complex image



In practice, measurements are noisy...



Too much noise ...

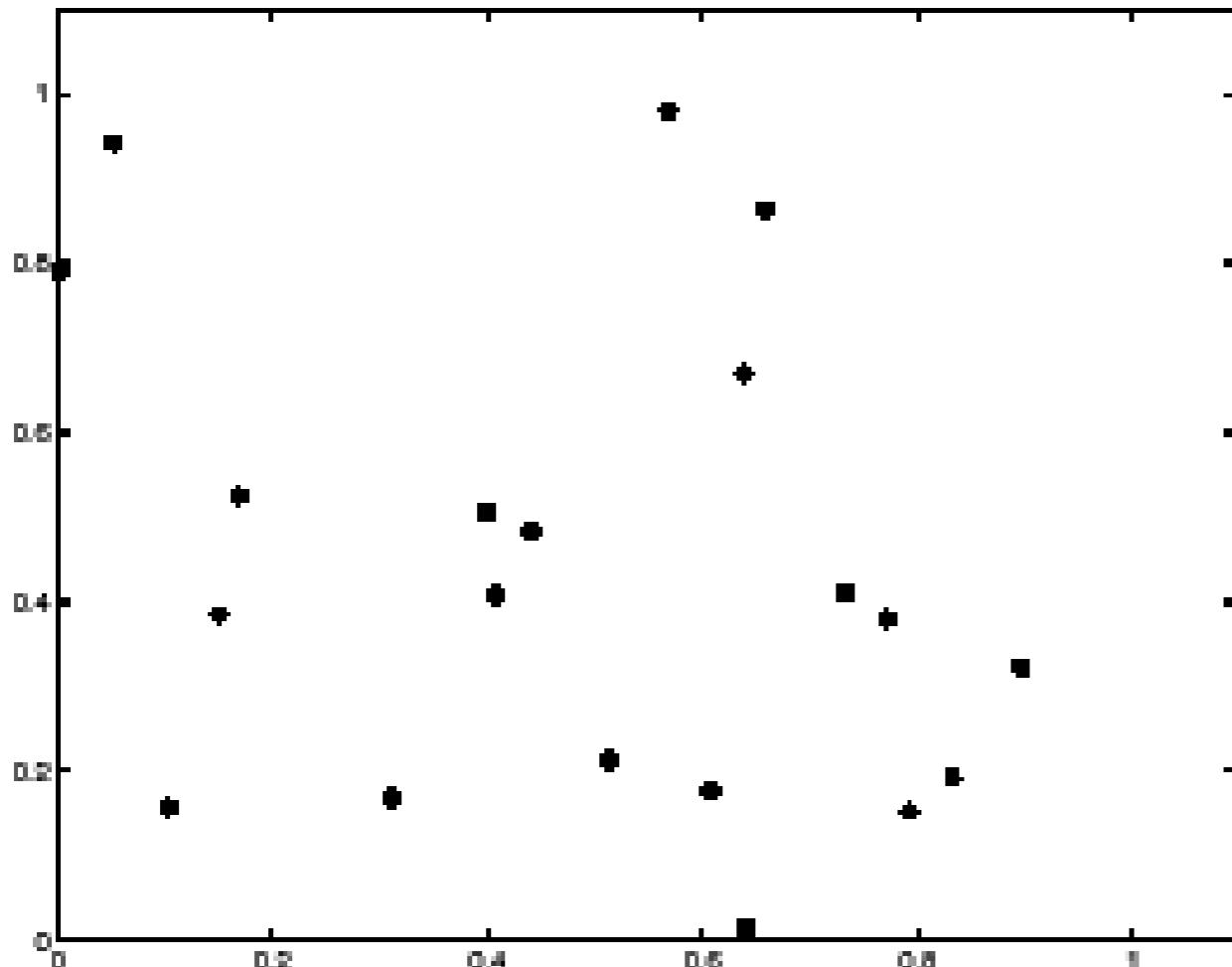
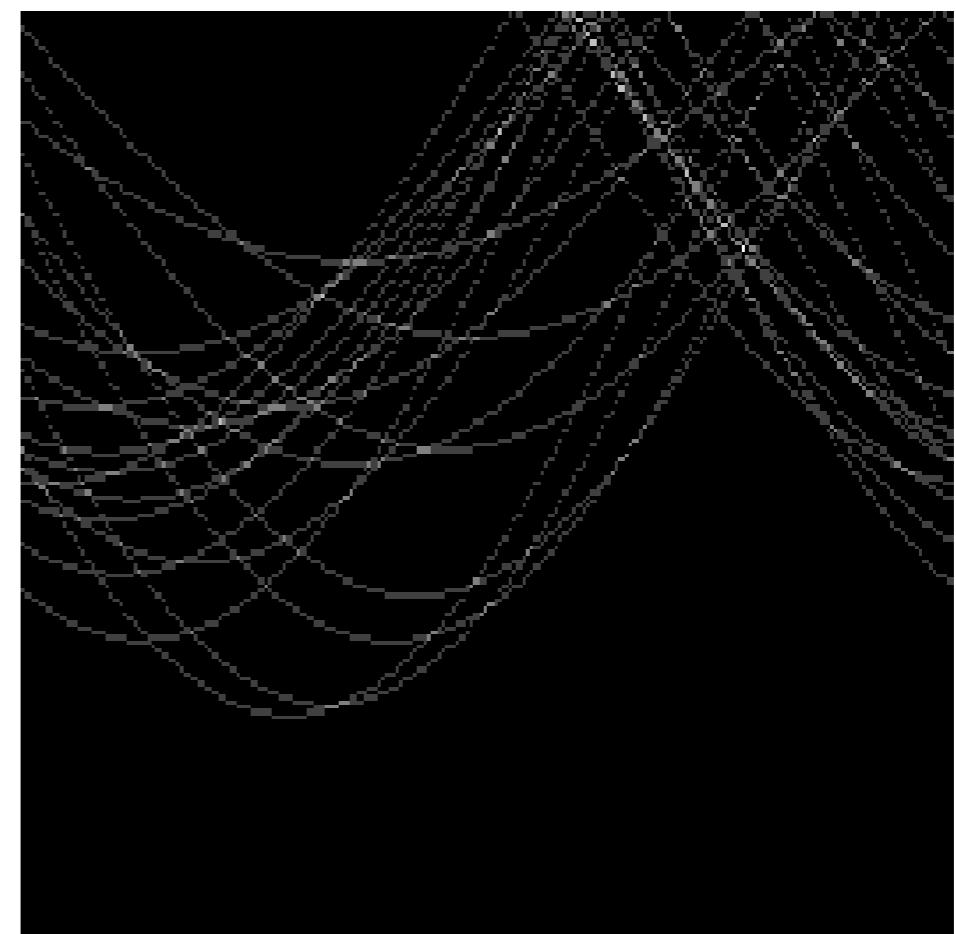


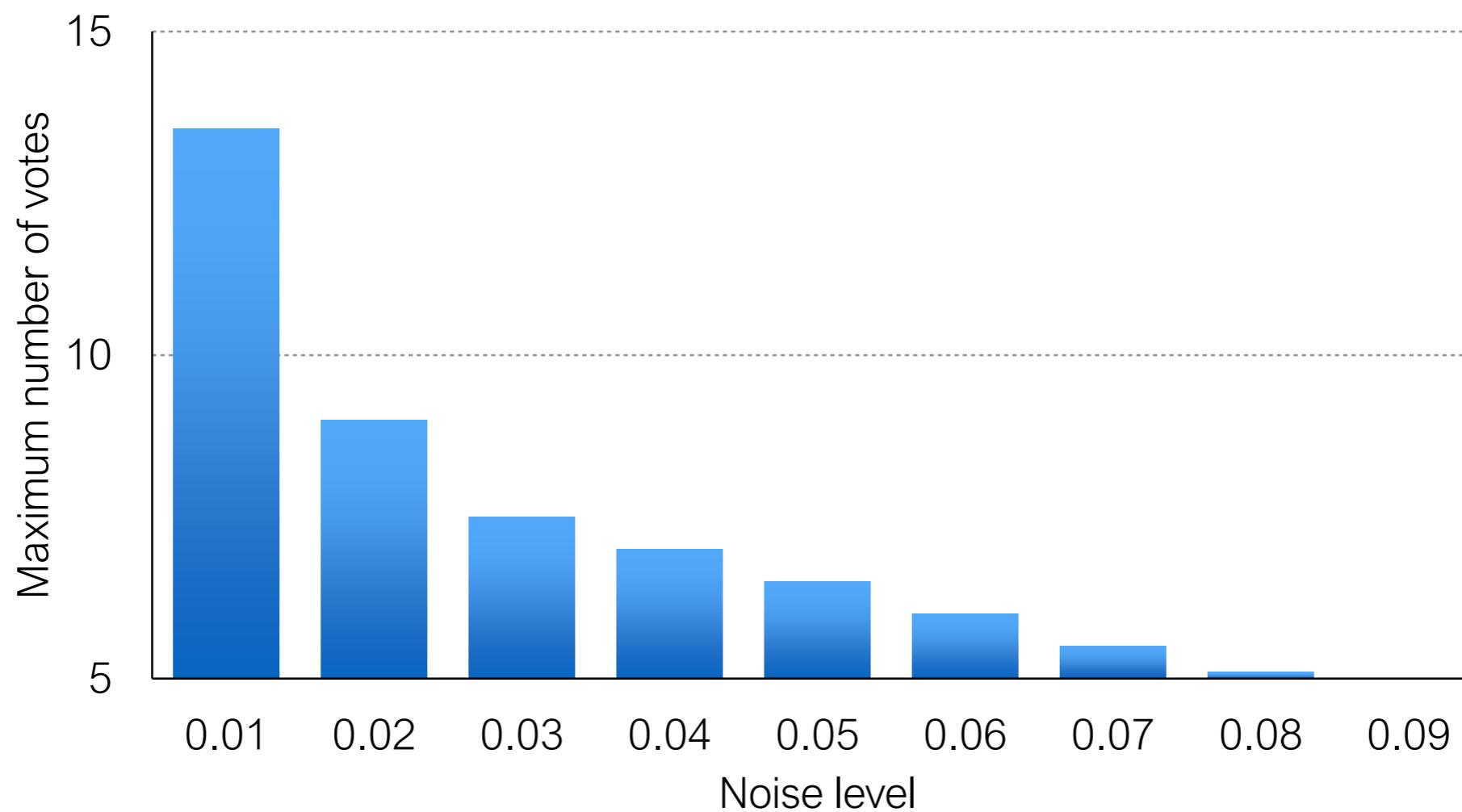
Image space



Votes

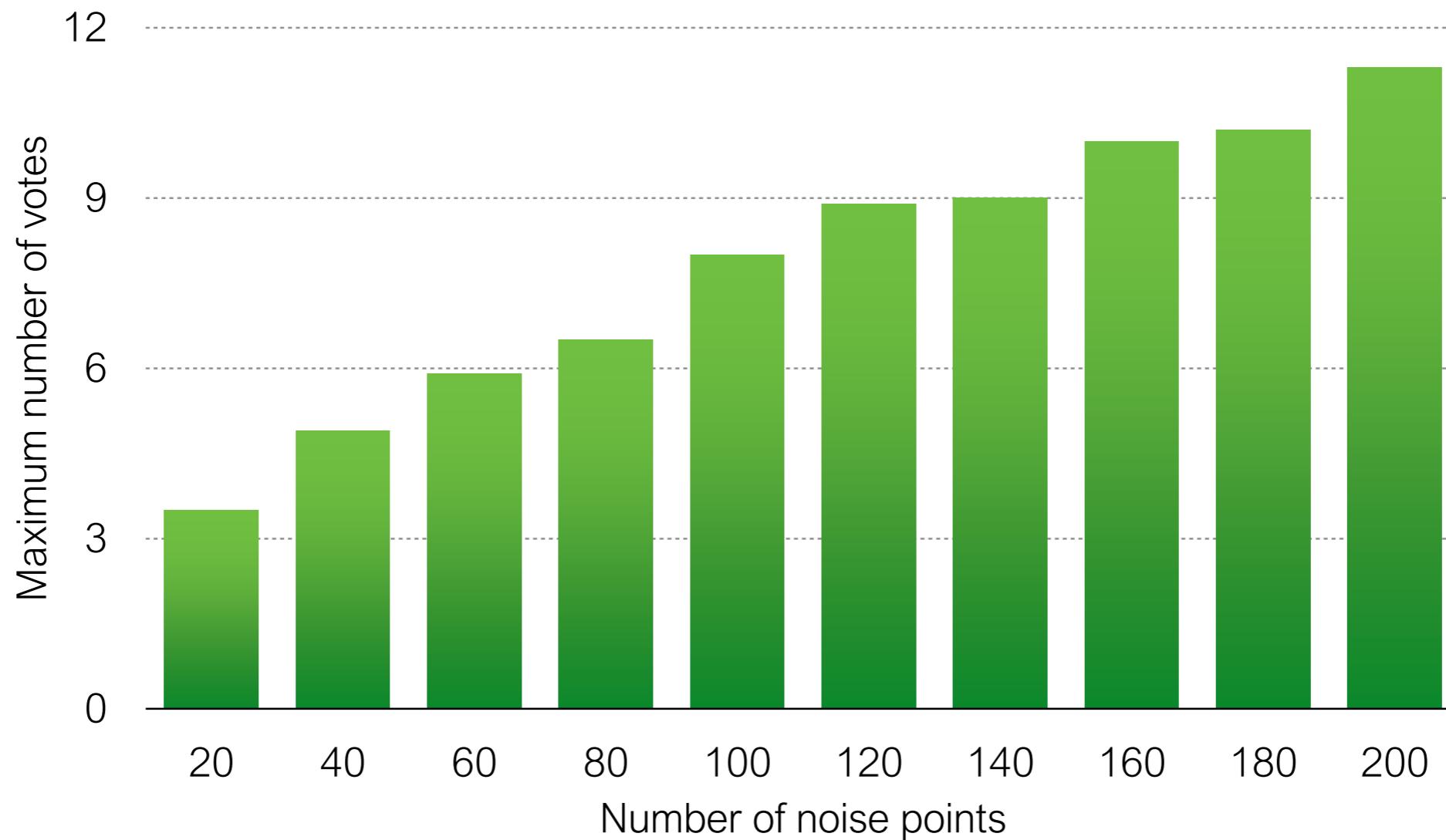
# Effects of noise level

Number of votes for a line of 20 points with increasing noise



More noise, fewer votes (in the right bin)

# Effect of noise points

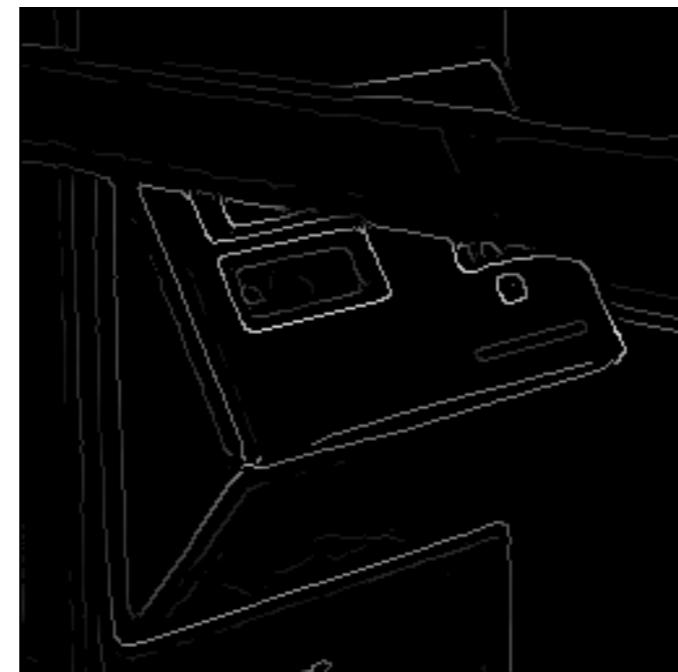


More noise, more votes (in the wrong bin)

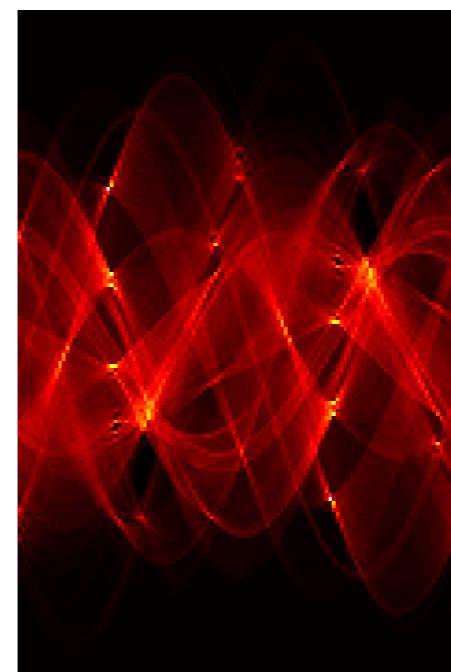
# Real-world example



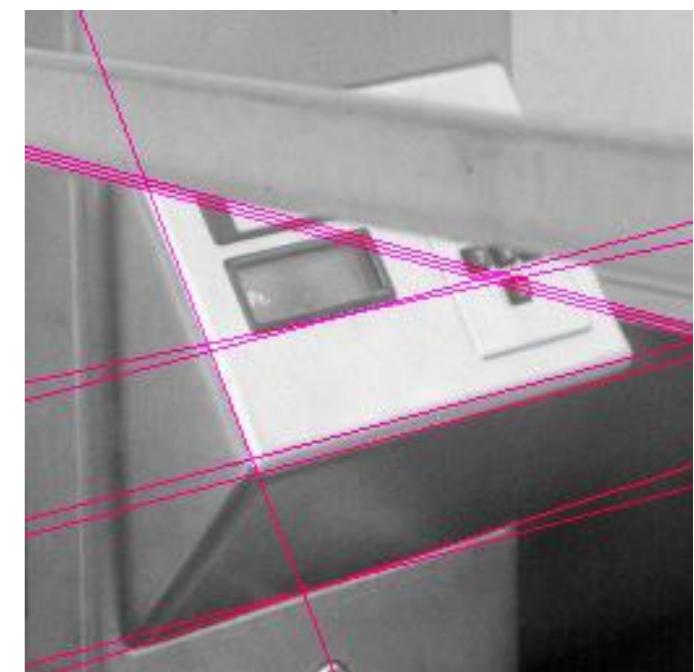
Original



Edges



parameter space



Hough Lines

# Hough Circles

# Let's assume radius known

$$(x - a)^2 + (y - b)^2 = r^2$$

parameters  
variables

$$(x - a)^2 + (y - b)^2 = r^2$$

parameters  
variables

*What is the dimension of the parameter space?*

parameters  
 $(x - a)^2 + (y - b)^2 = r^2$   
variables

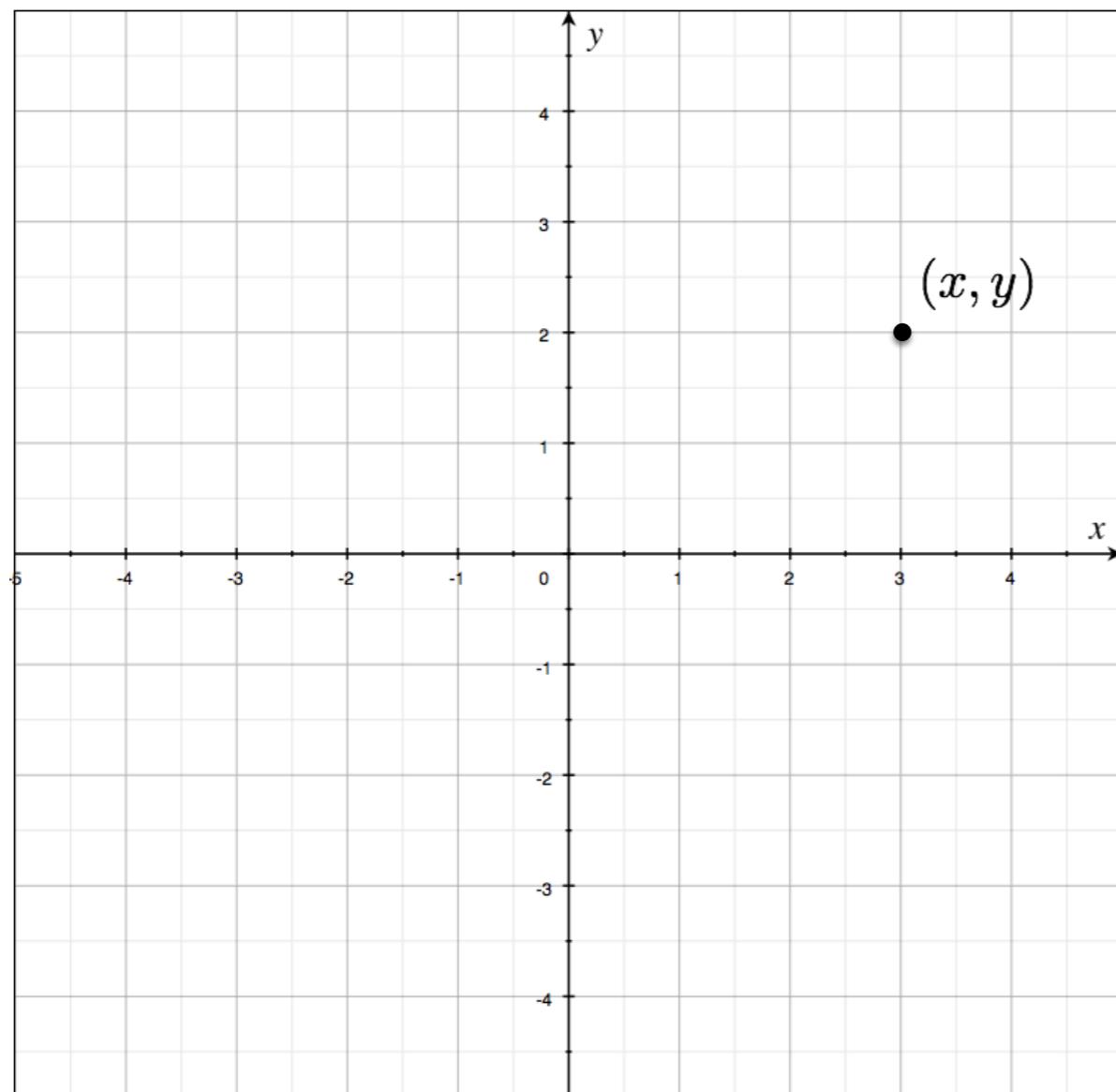
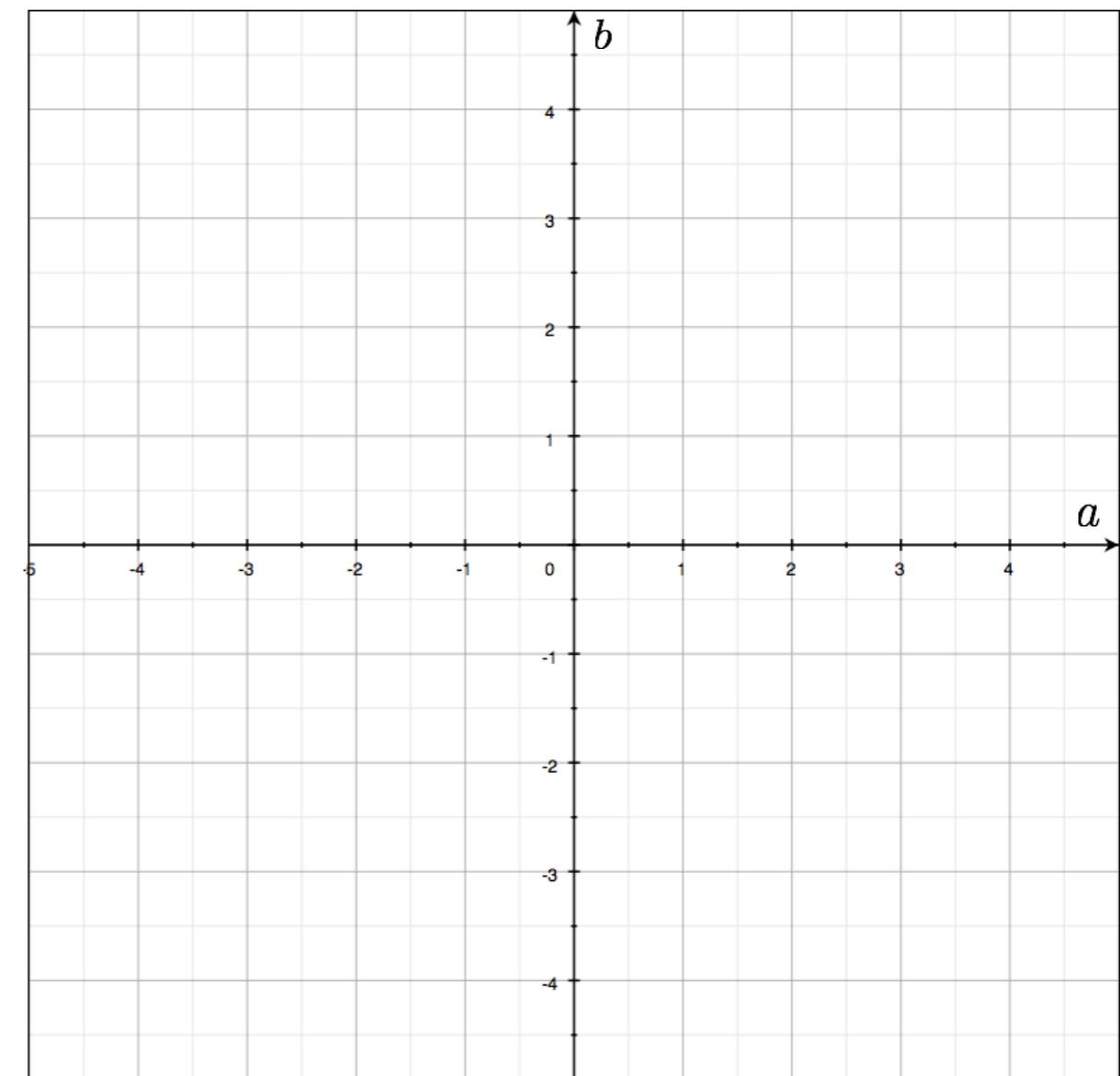


Image space

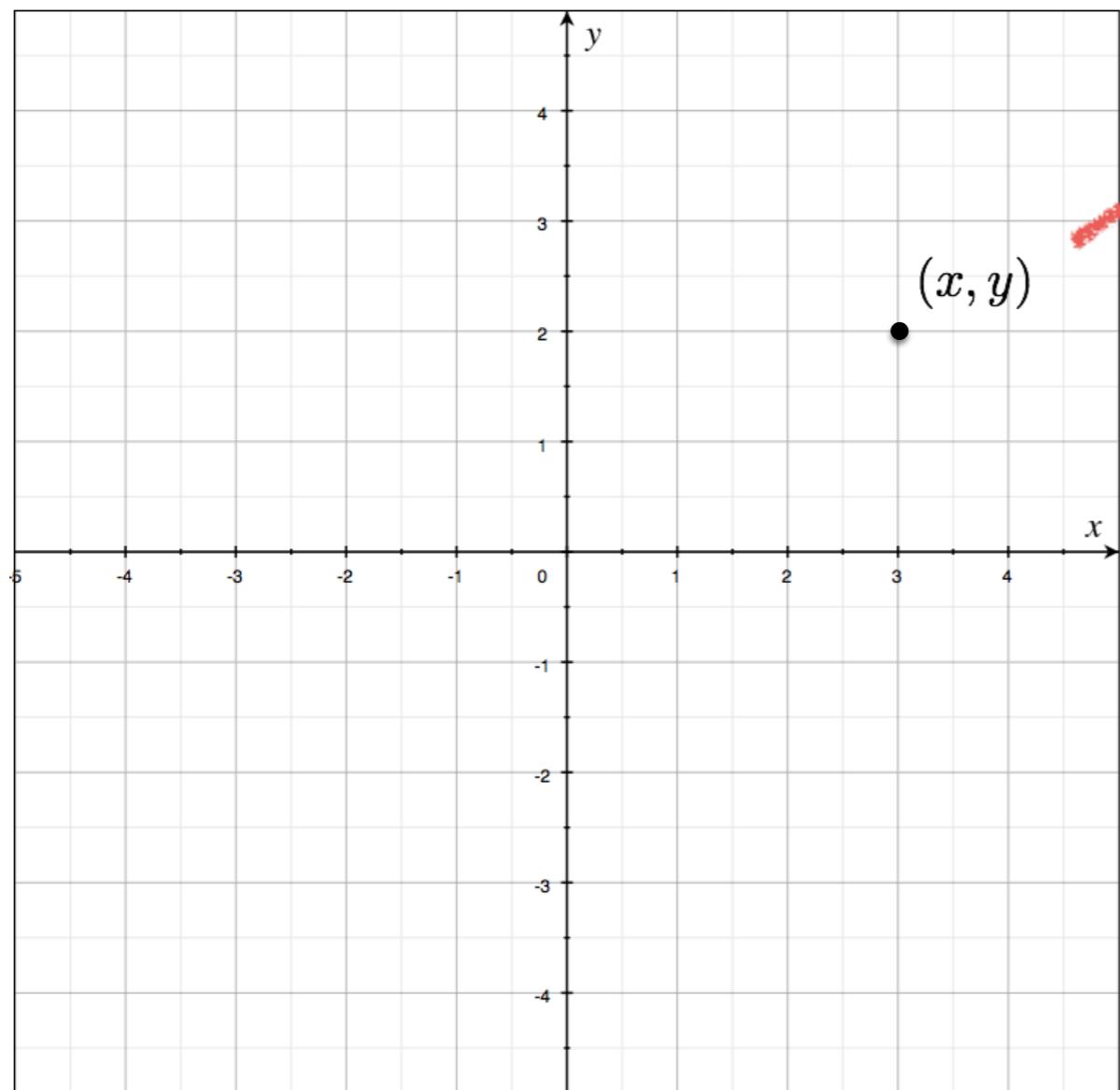
parameters  
 $(x - a)^2 + (y - b)^2 = r^2$   
variables



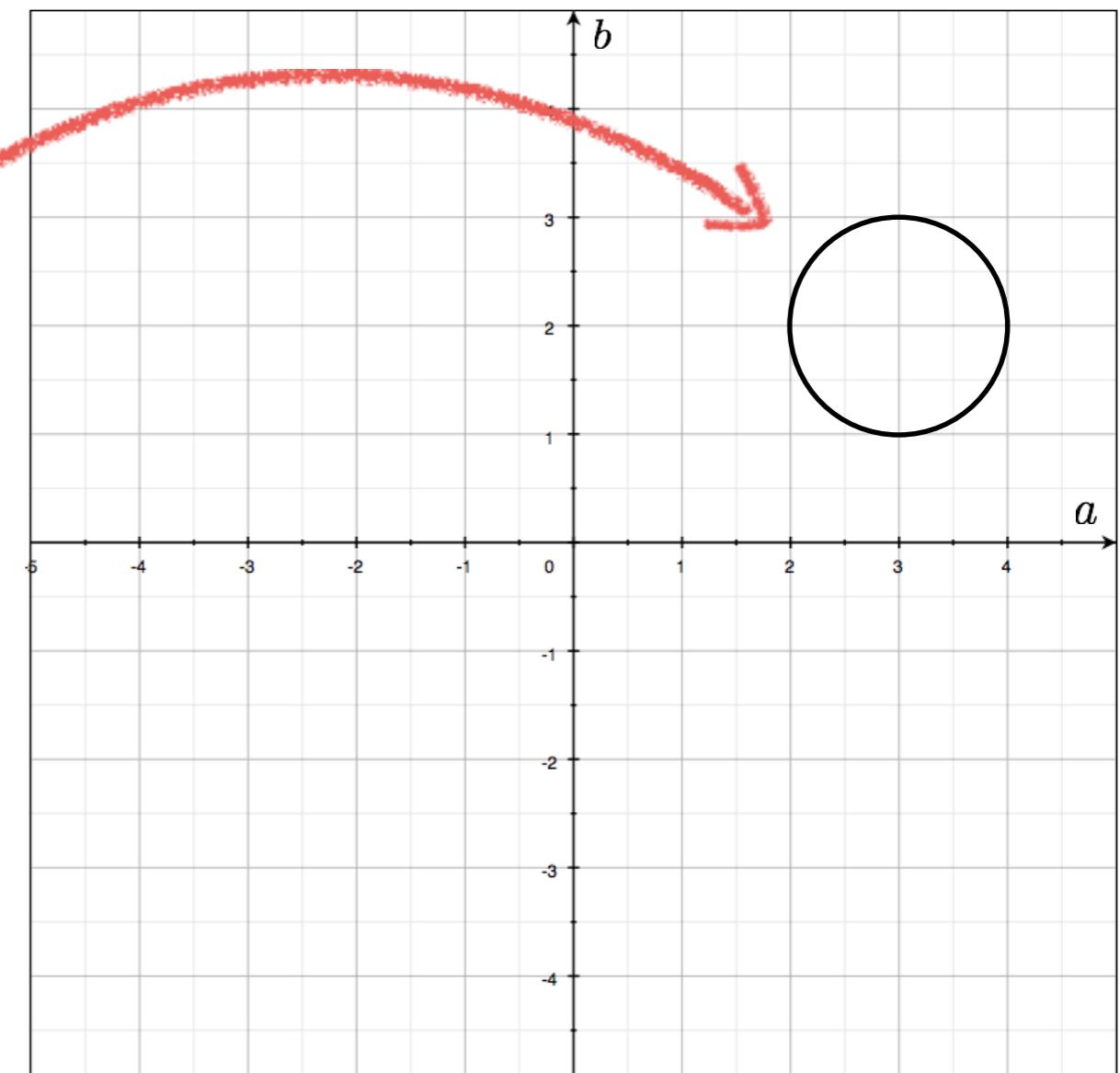
Parameter space

*What does a point in image space correspond to in parameter space?*

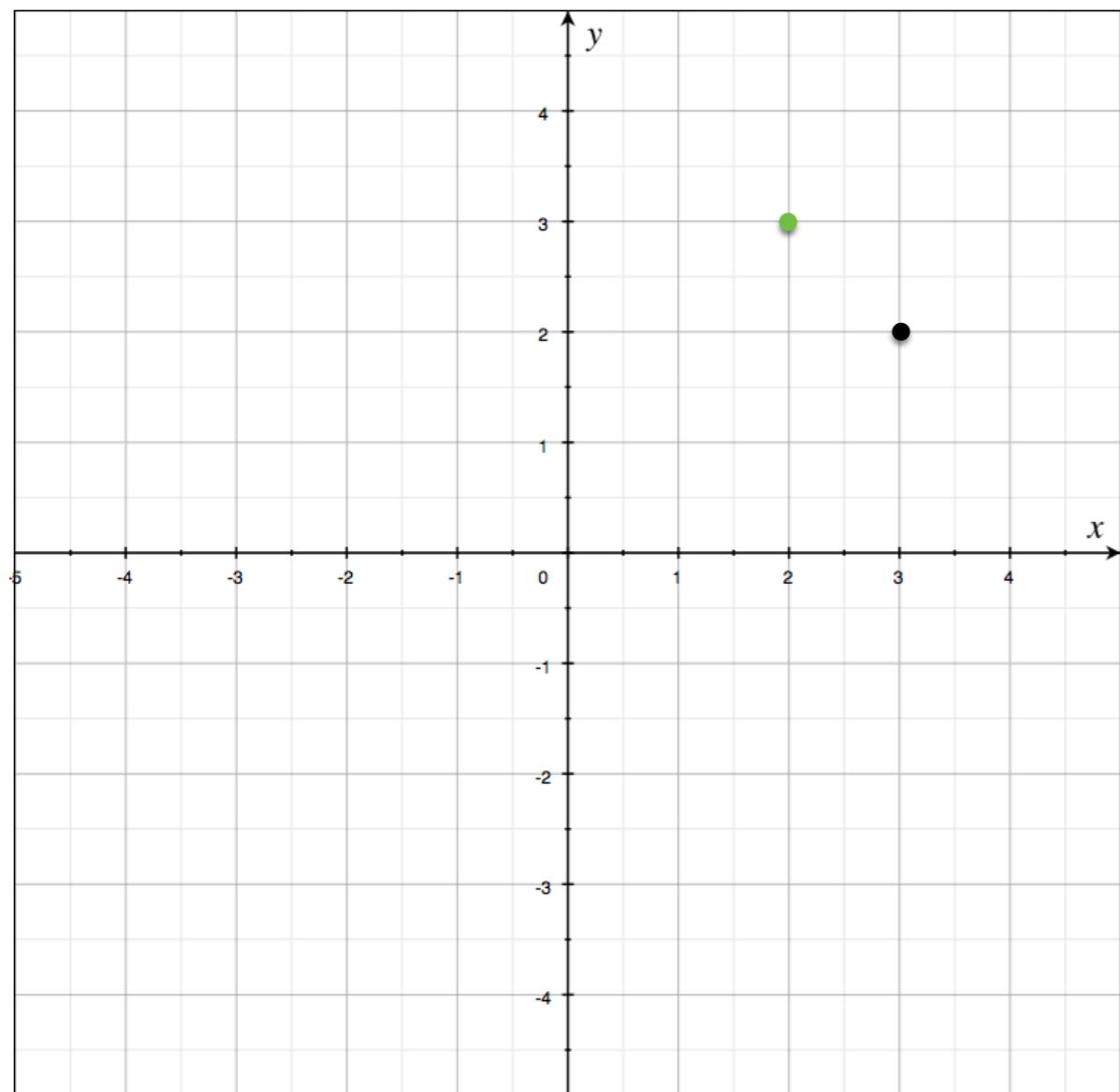
parameters  
 $(x - a)^2 + (y - b)^2 = r^2$   
variables



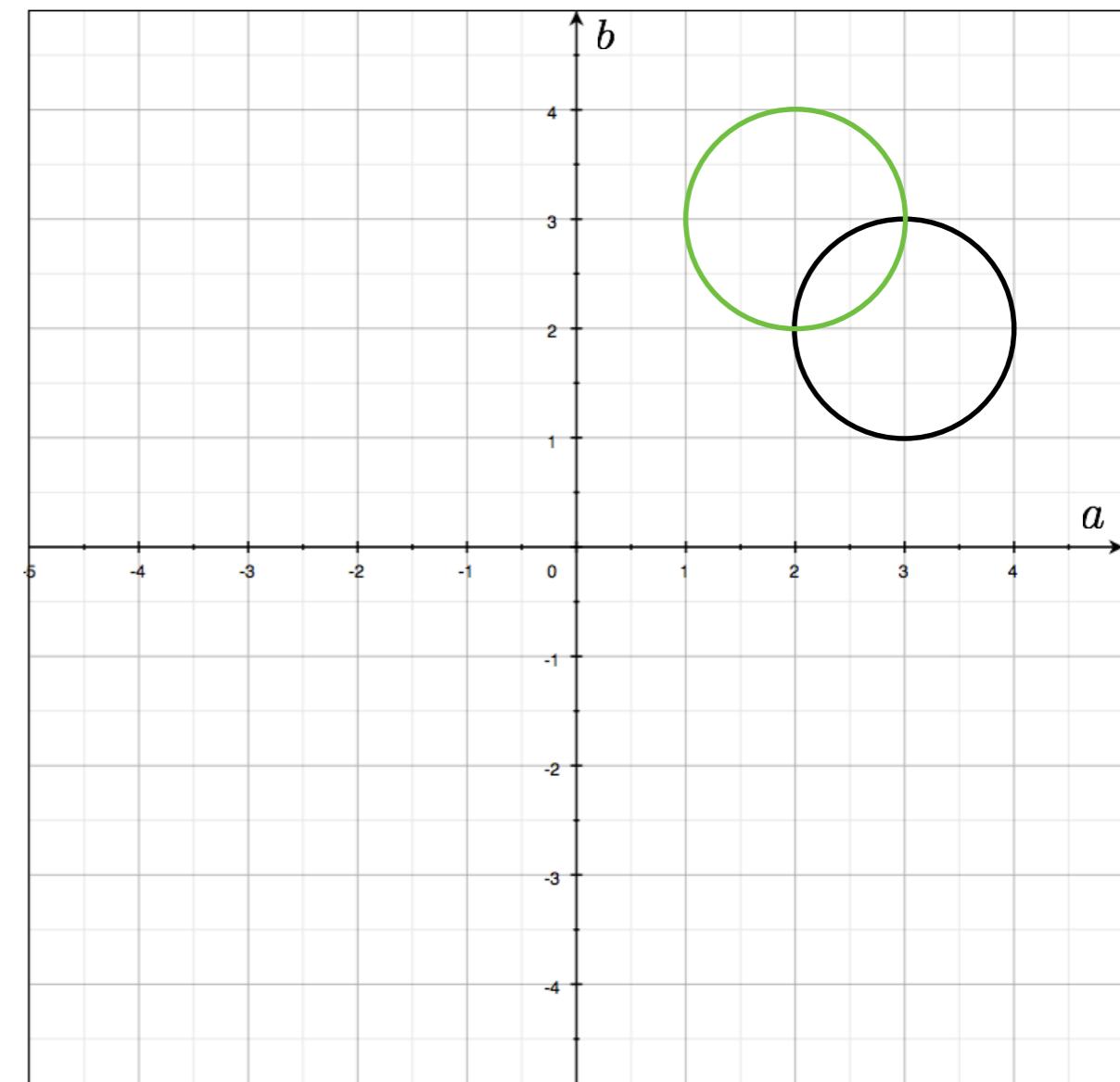
parameters  
 $(x - a)^2 + (y - b)^2 = r^2$   
variables



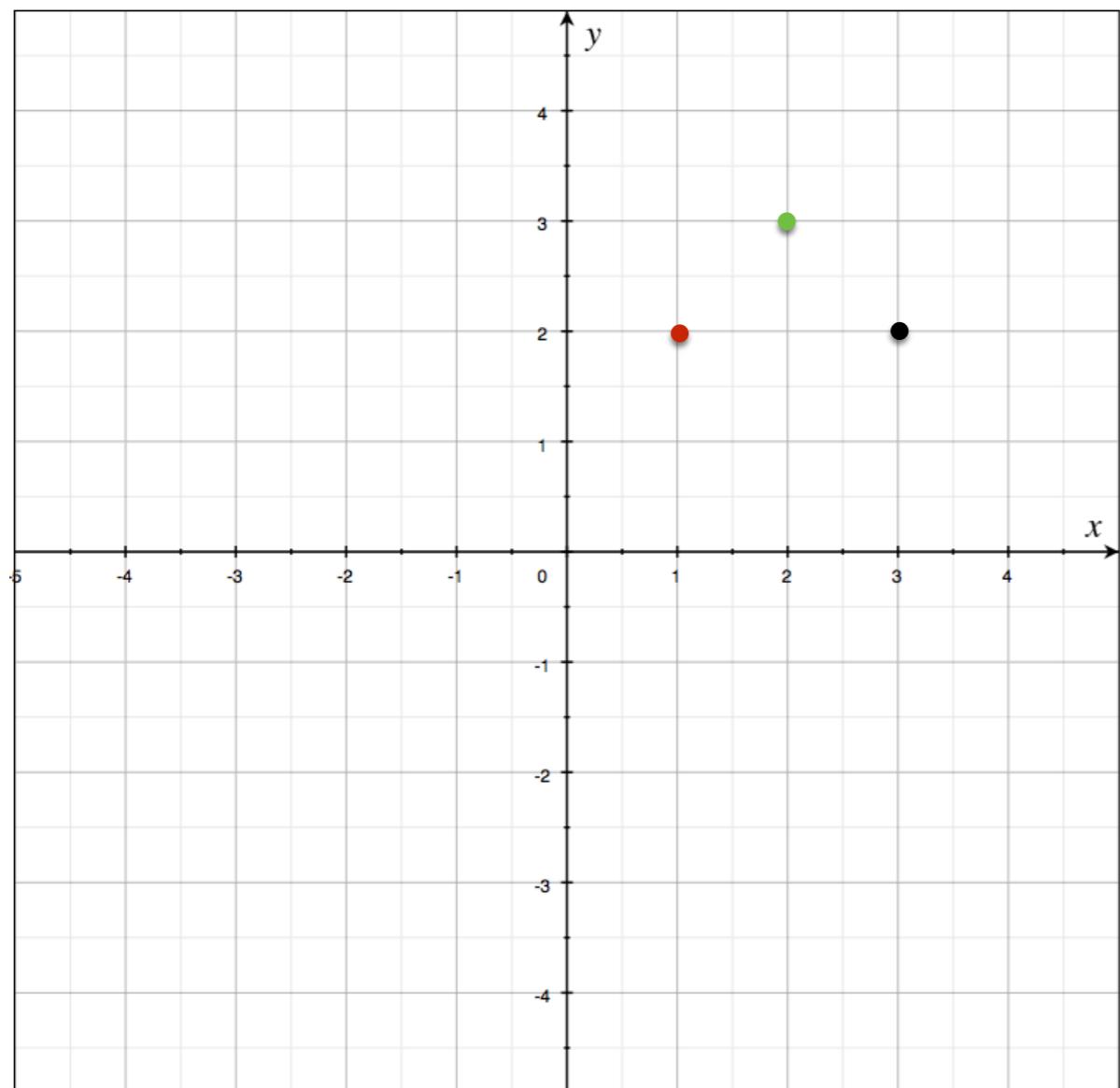
parameters  
 $(x - a)^2 + (y - b)^2 = r^2$   
variables



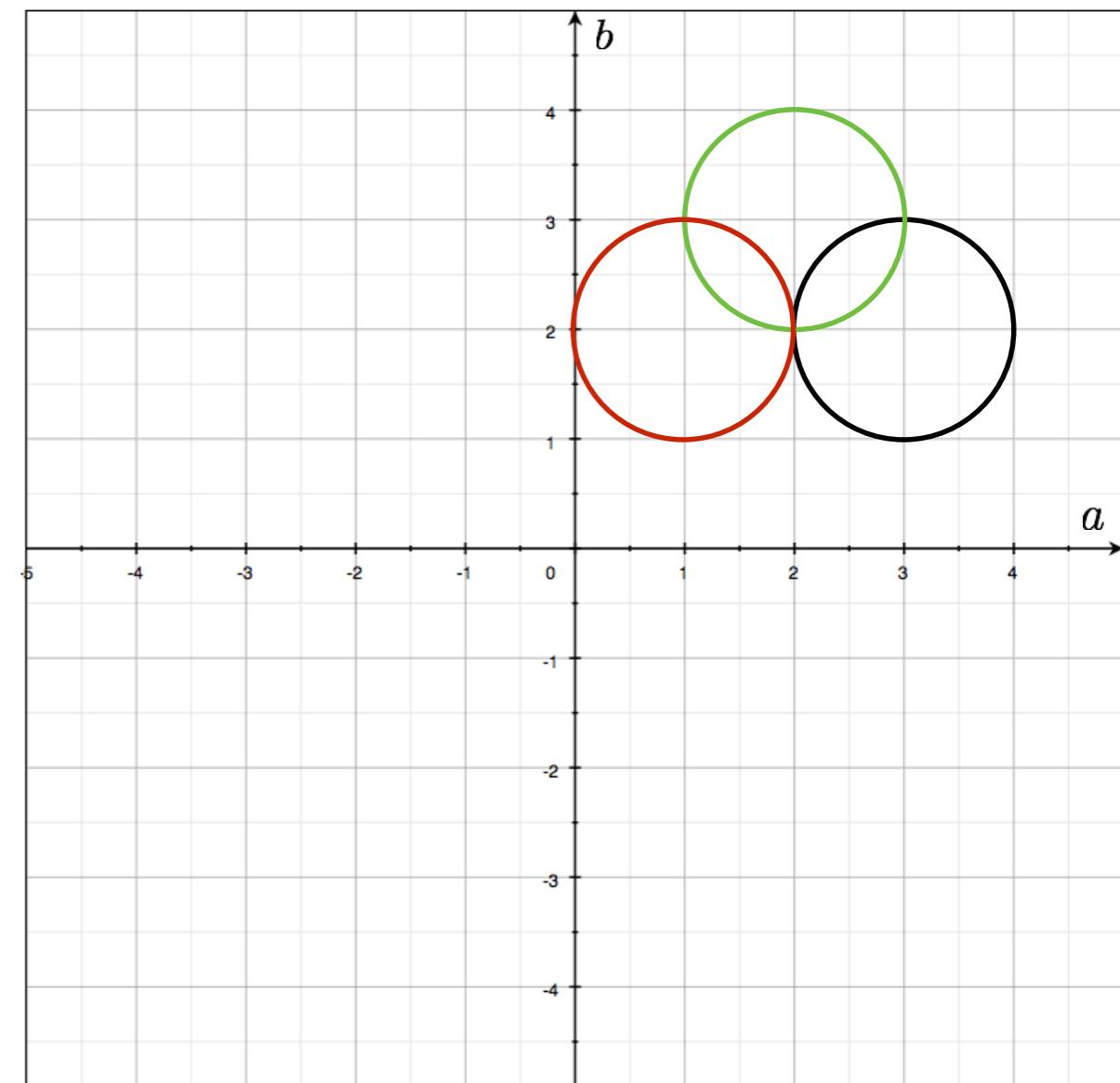
parameters  
 $(x - a)^2 + (y - b)^2 = r^2$   
variables



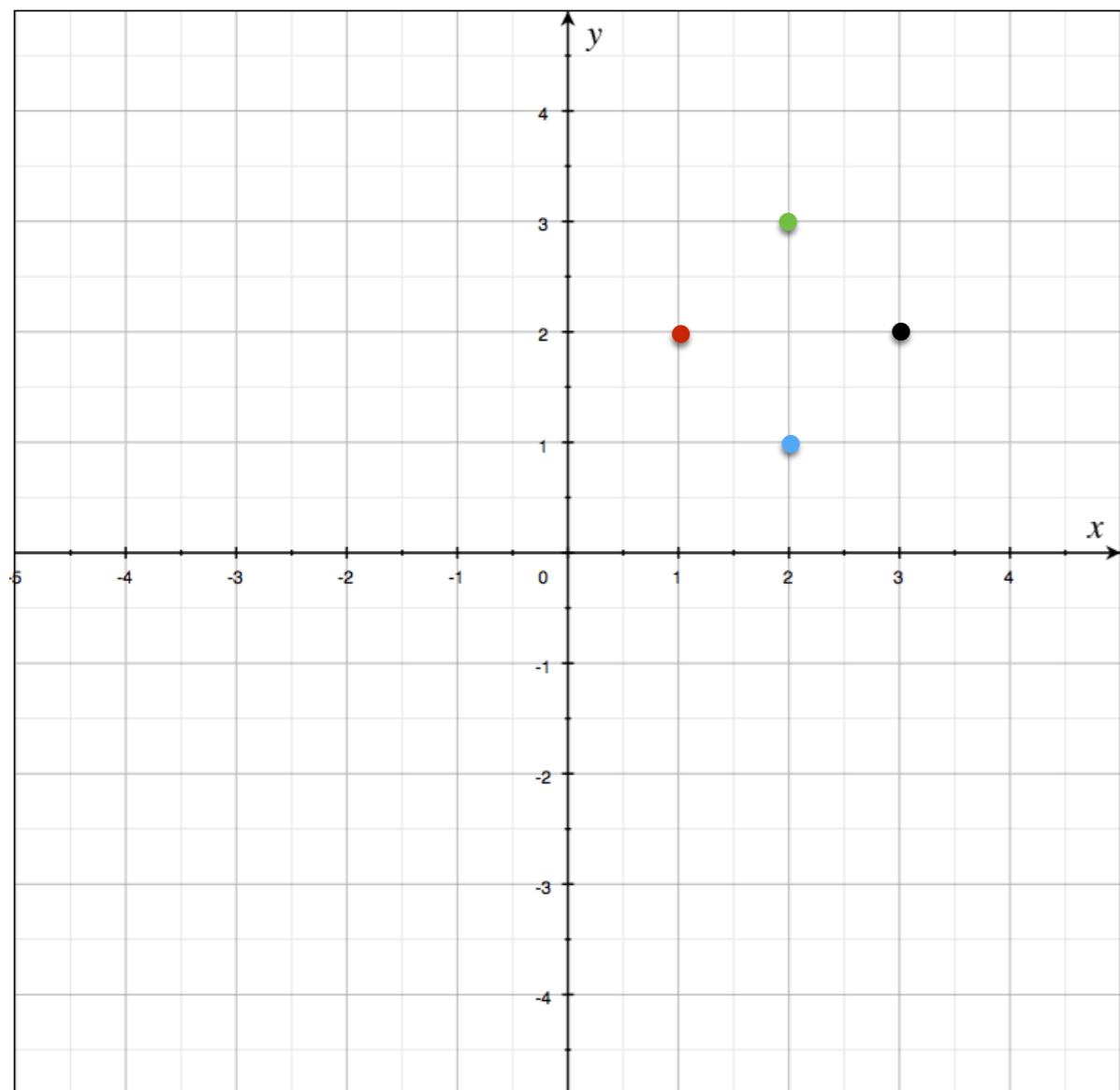
parameters  
 $(x - a)^2 + (y - b)^2 = r^2$   
variables



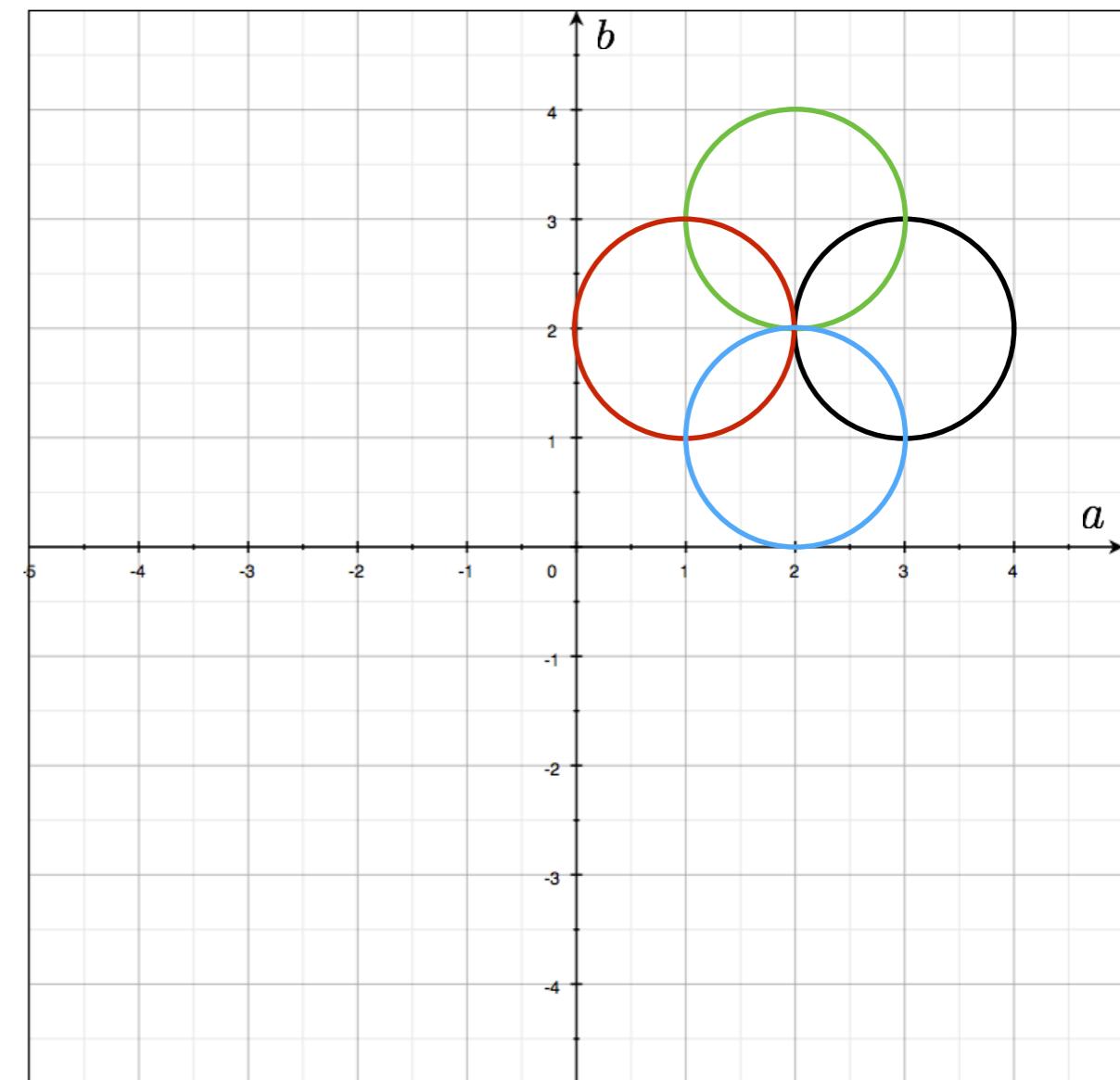
parameters  
 $(x - a)^2 + (y - b)^2 = r^2$   
variables



parameters  
 $(x - a)^2 + (y - b)^2 = r^2$   
variables



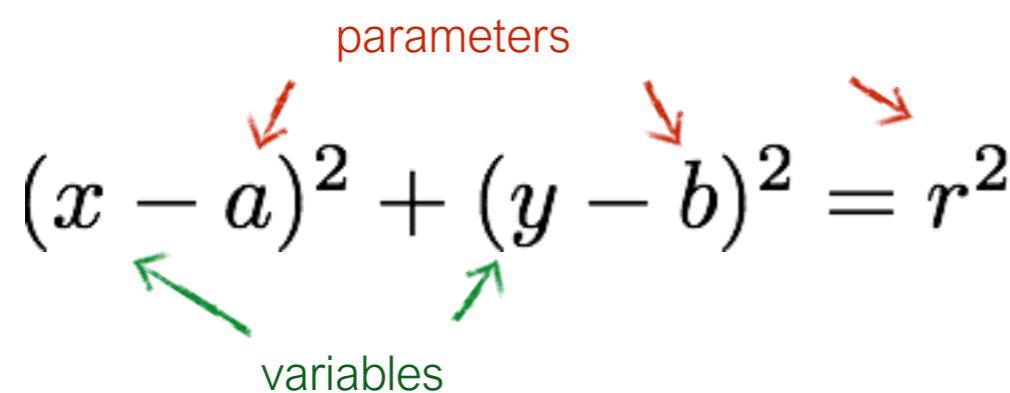
parameters  
 $(x - a)^2 + (y - b)^2 = r^2$   
variables



# What if radius is unknown?

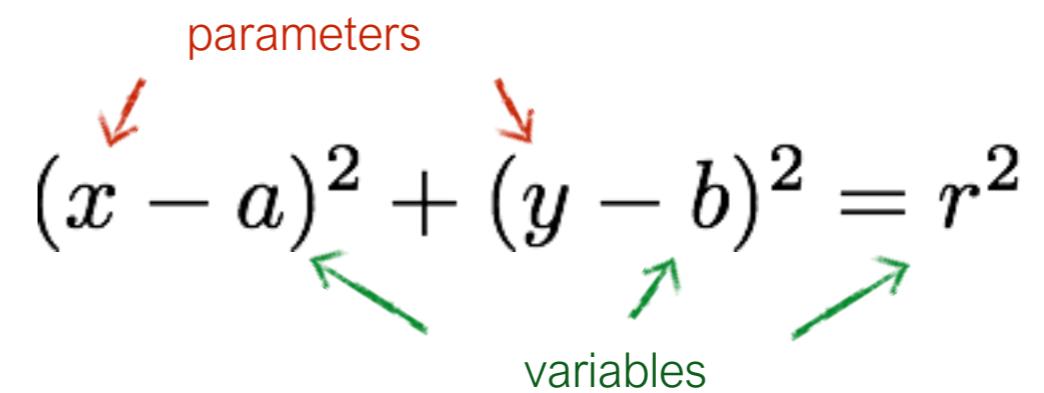
$$(x - a)^2 + (y - b)^2 = r^2$$

parameters  
variables



$$(x - a)^2 + (y - b)^2 = r^2$$

parameters  
variables



# What if radius is unknown?

$$(x - a)^2 + (y - b)^2 = r^2$$

parameters  
variables

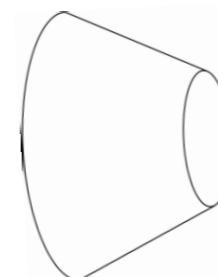
$$(x - a)^2 + (y - b)^2 = r^2$$

parameters  
variables

If radius is not known: 3D Hough Space!

Use Accumulator array  $A(a, b, r)$

Surface shape in Hough space is complicated

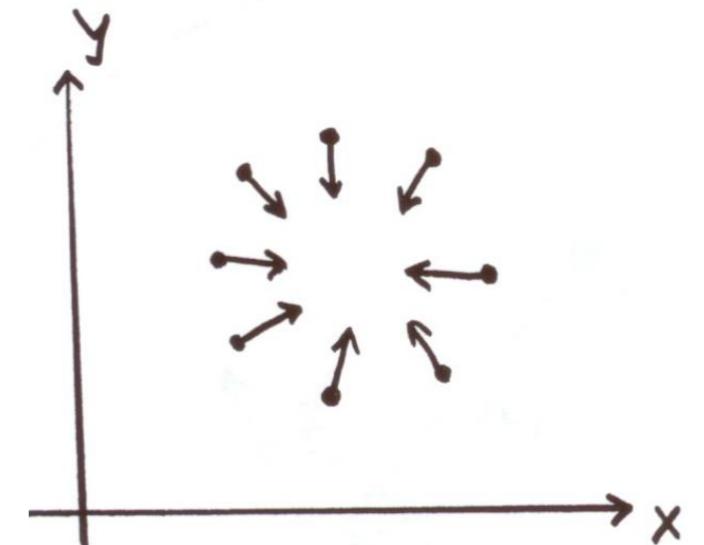


# Using Gradient Information

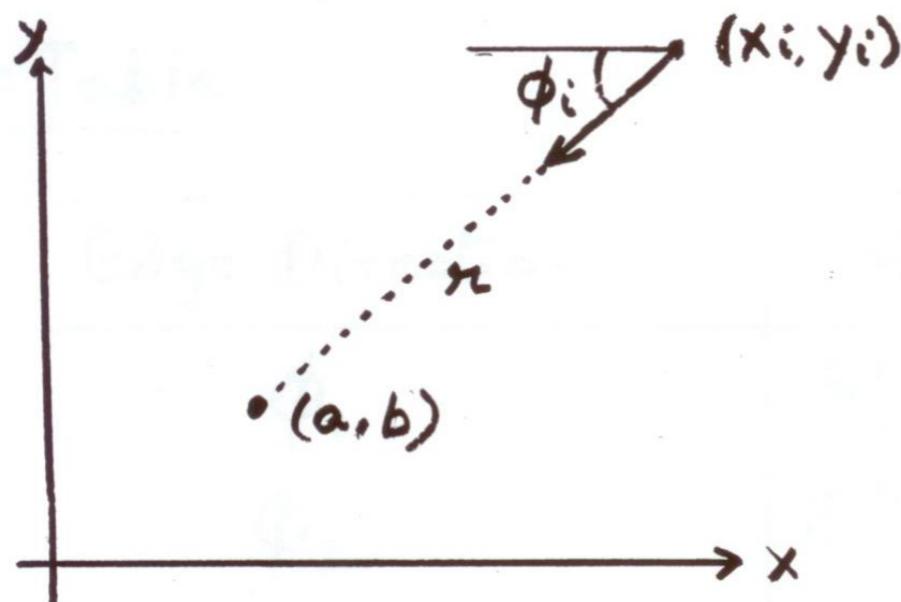
Gradient information can save lot of computation:

Edge Location  $(x_i, y_i)$

Edge Direction  $\phi_i$



Assume radius is known:

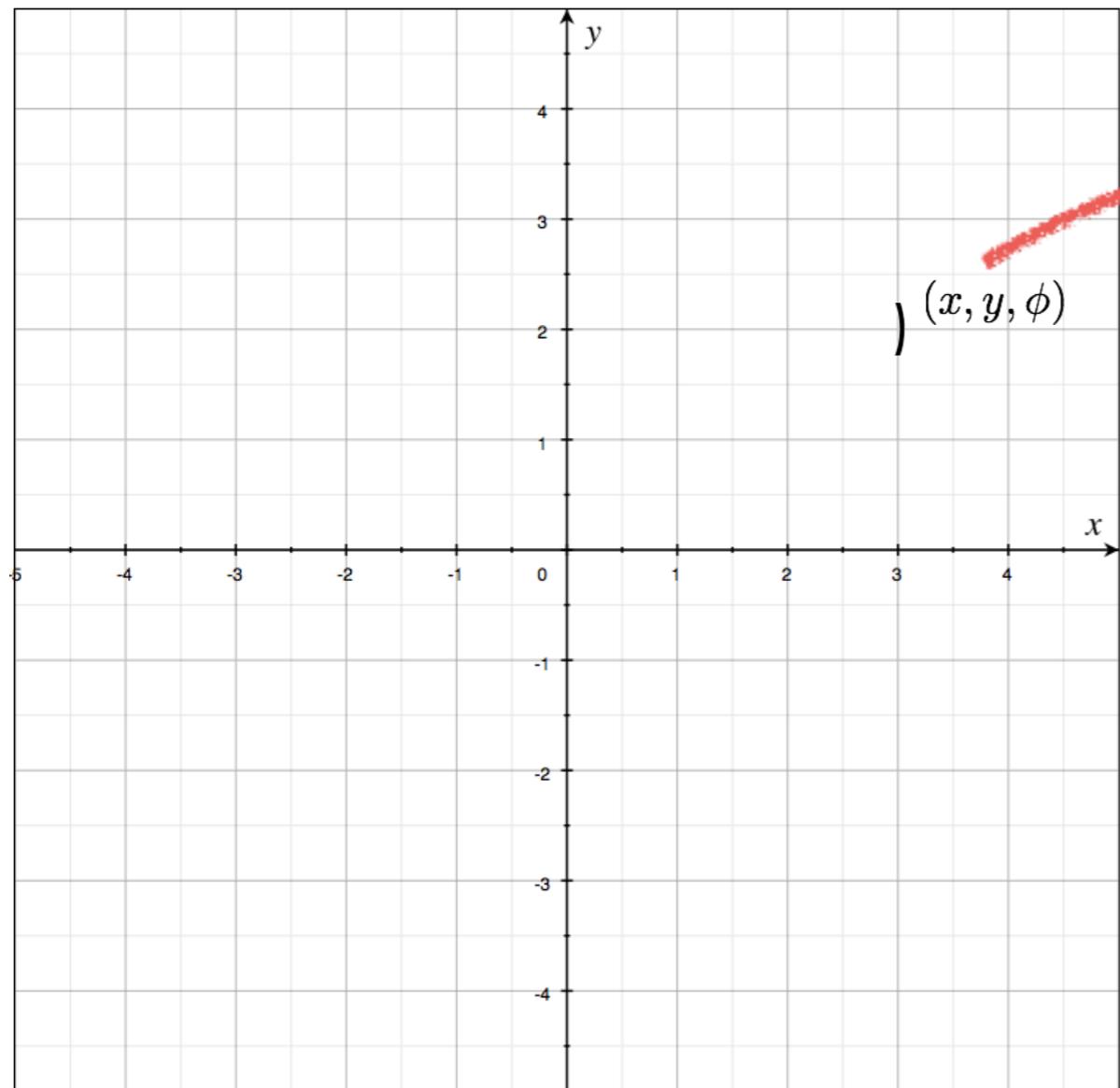


$$a = x - r \cos\phi$$

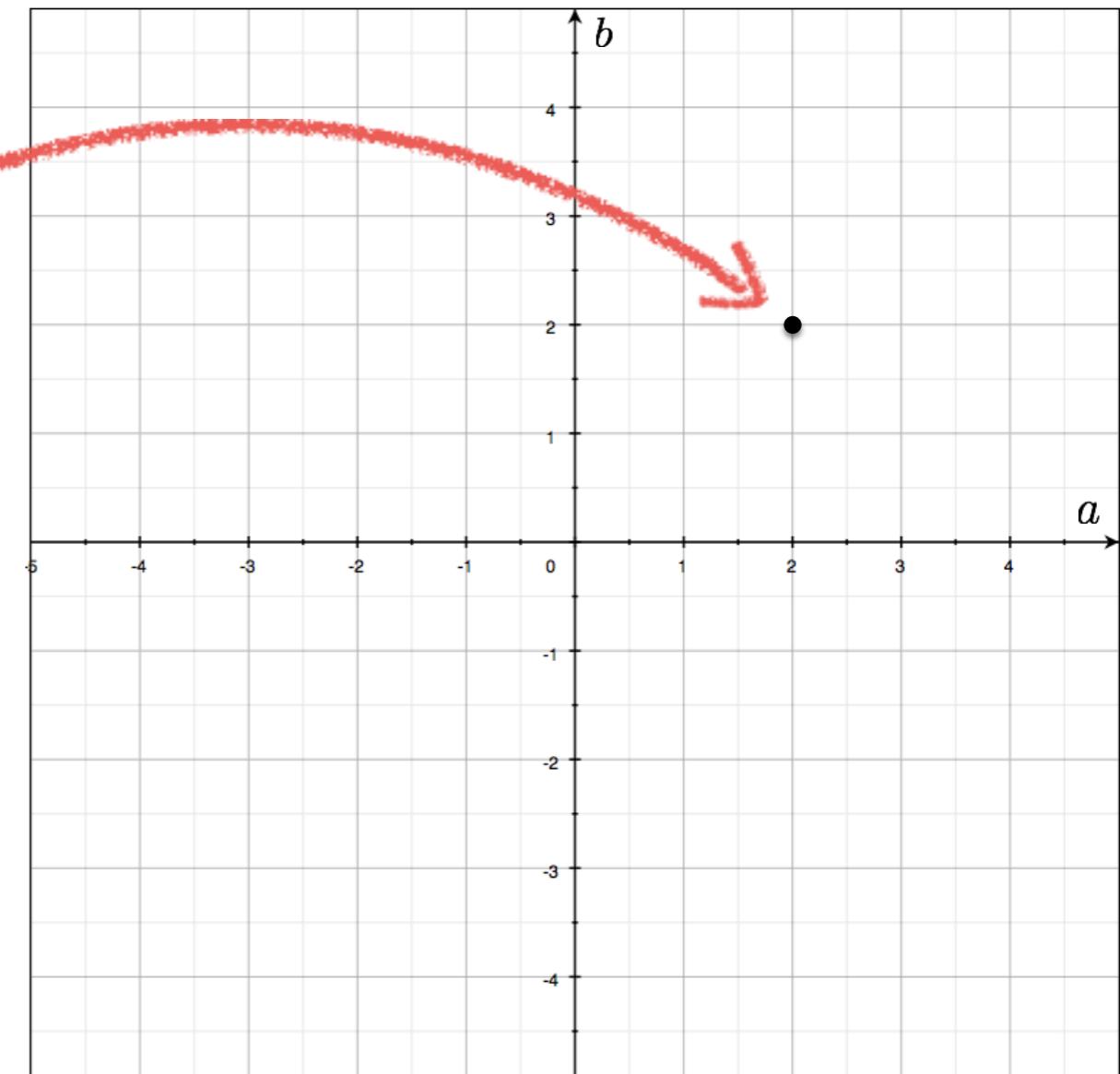
$$b = y - r \sin\phi$$

*Need to increment only one point in accumulator!*

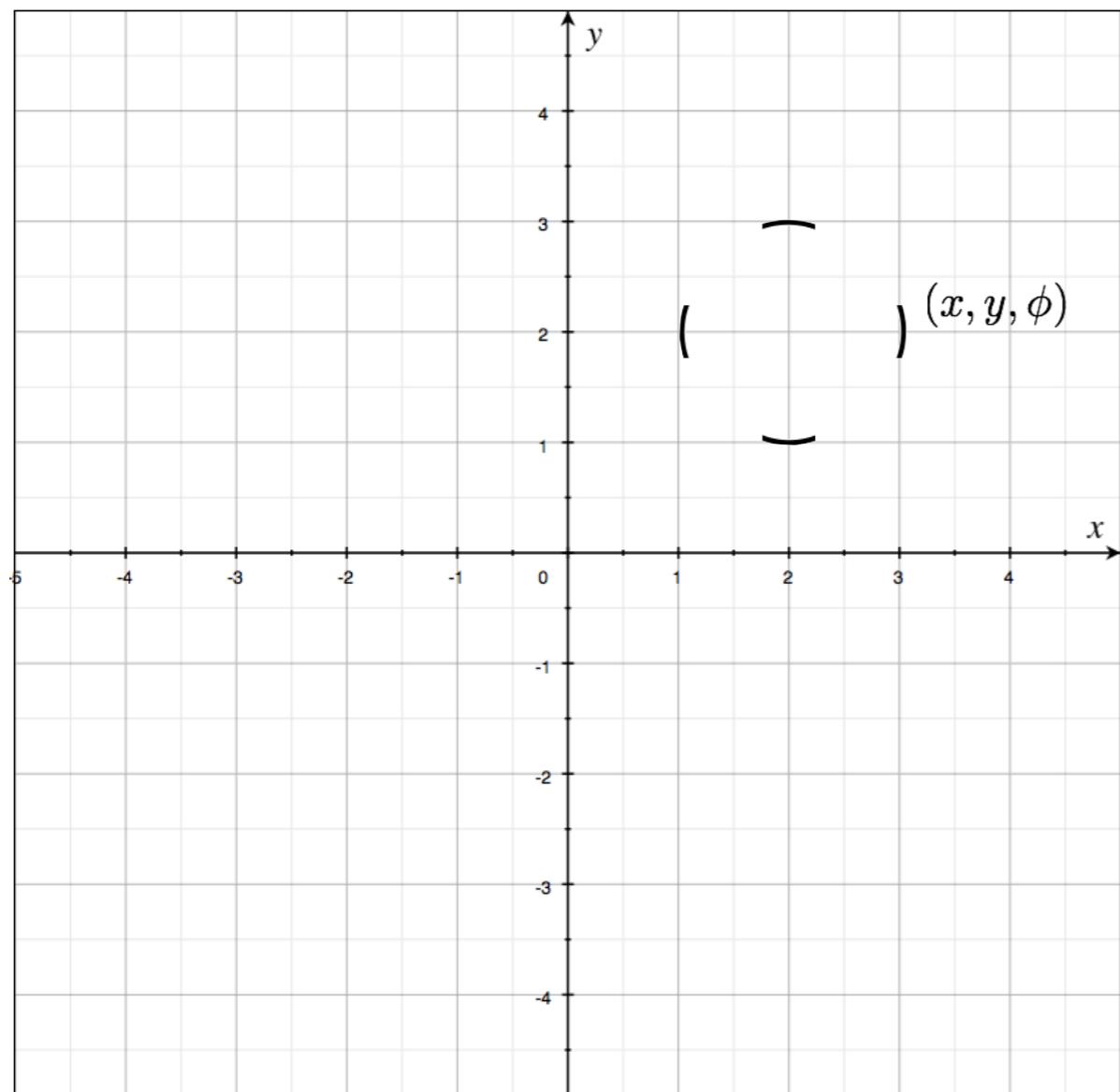
parameters  
 $(x - a)^2 + (y - b)^2 = r^2$   
variables



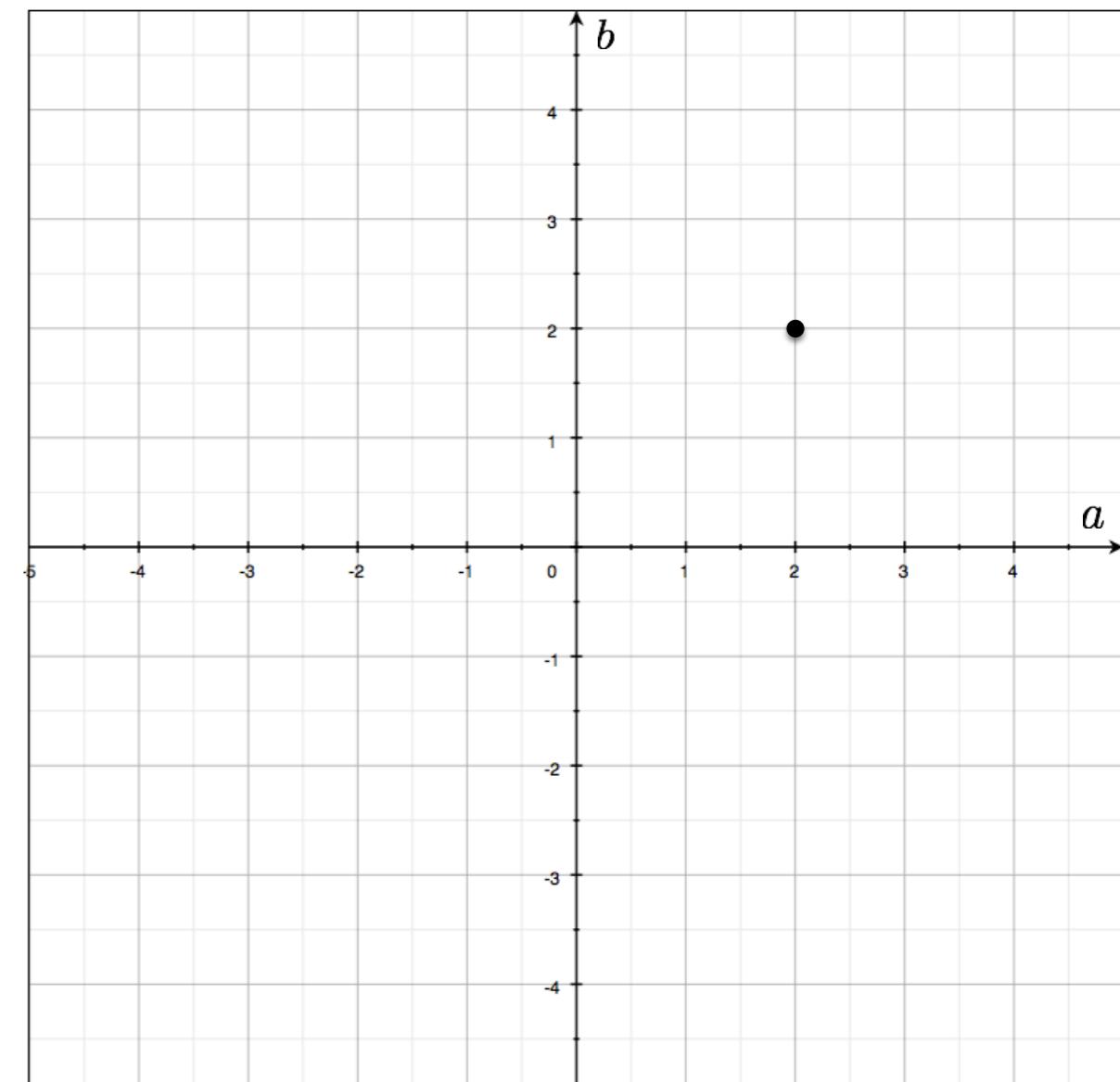
parameters  
 $(x - a)^2 + (y - b)^2 = r^2$   
variables

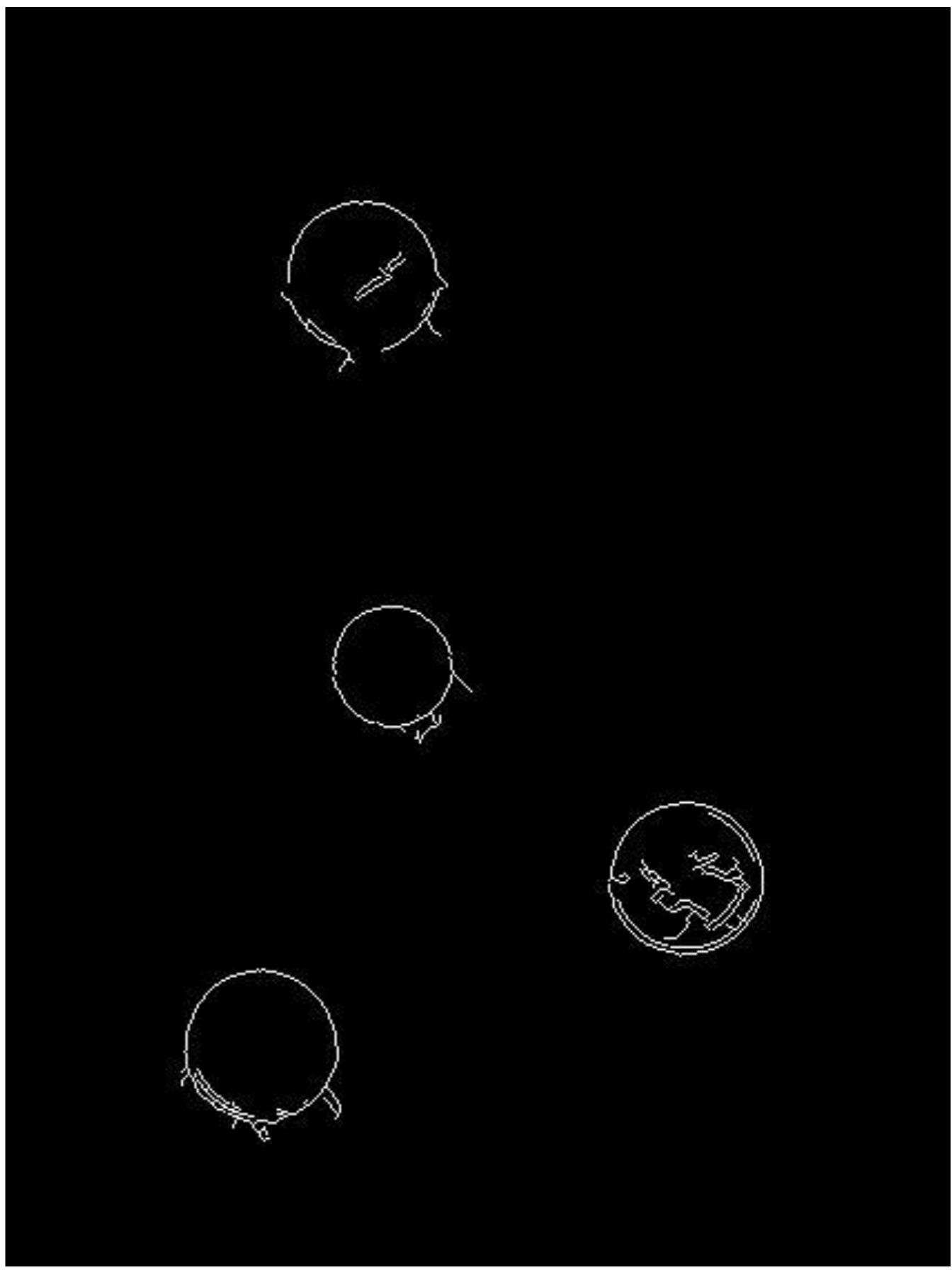
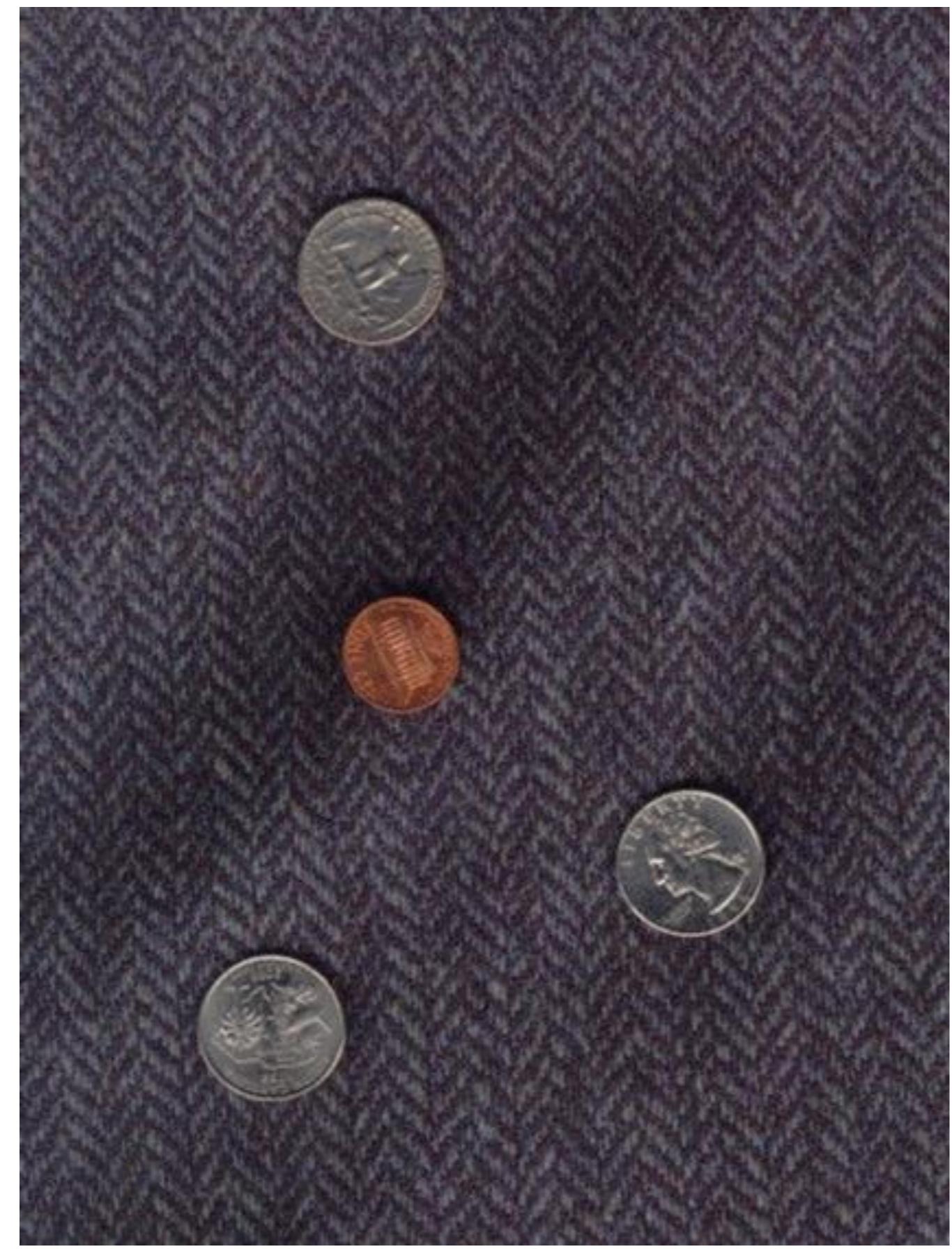


parameters  
 $(x - a)^2 + (y - b)^2 = r^2$   
variables



parameters  
 $(x - a)^2 + (y - b)^2 = r^2$   
variables





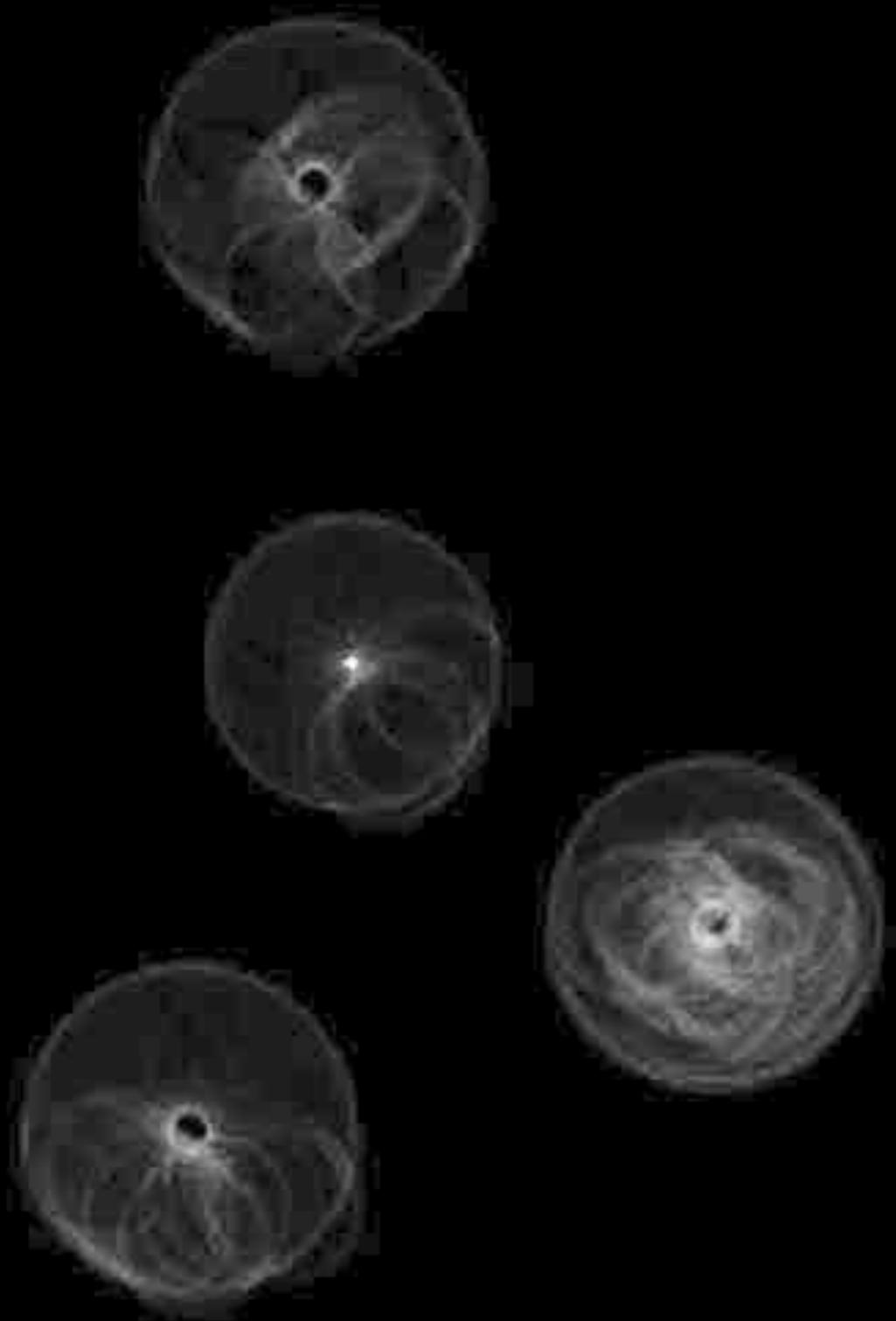
Pennie Hough detector



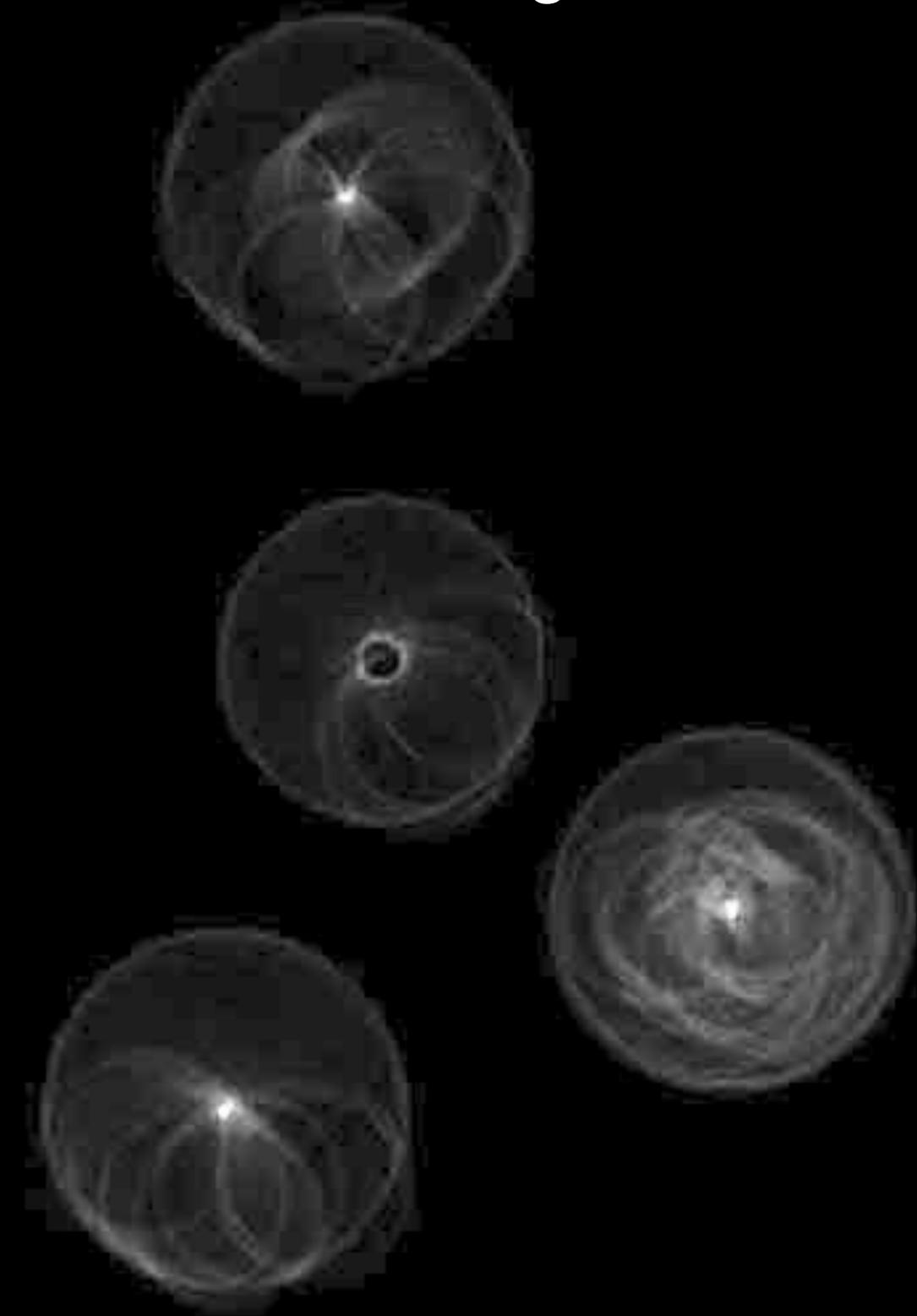
Quarter Hough detector



Pennie Hough detector



Quarter Hough detector



# The Hough transform . . .

Deals with occlusion well?



Detects multiple instances?



Robust to noise?



Good computational complexity?



Easy to set parameters?

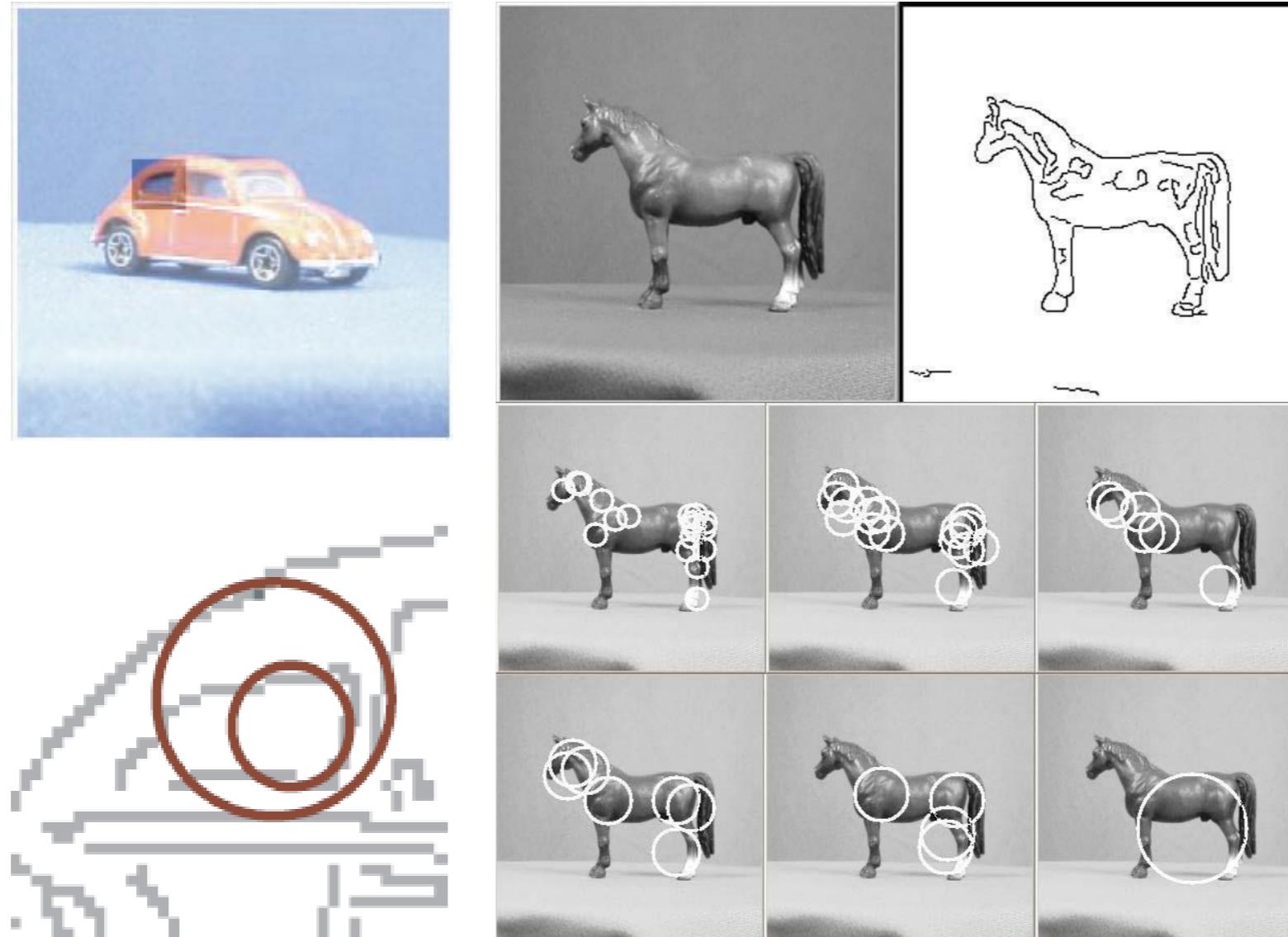


Can you use Hough Transforms for other objects,  
beyond lines and circles?

Do you have to use edge detectors to  
vote in Hough Space?

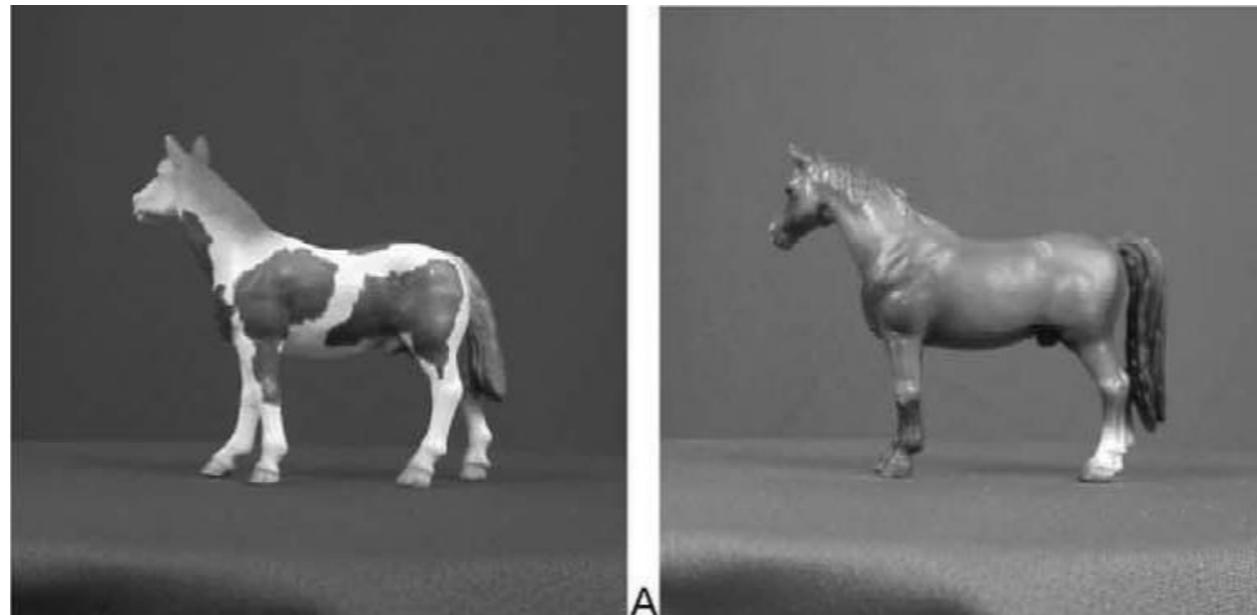
# Application of Hough transforms

# Detecting shape features

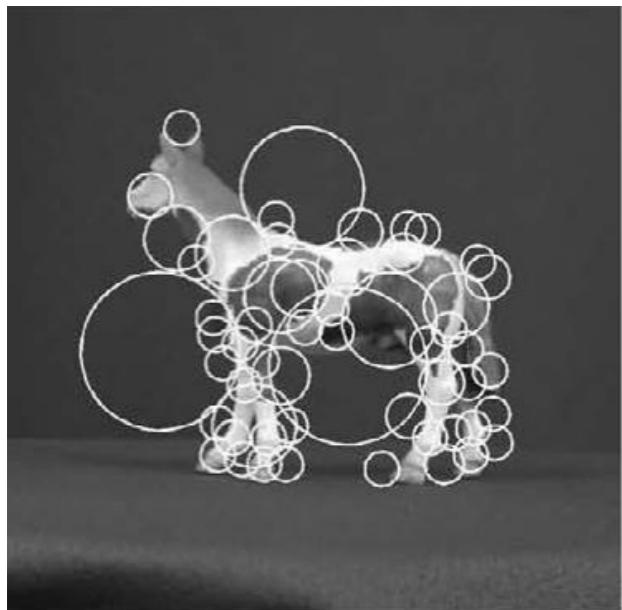


F. Jurie and C. Schmid, Scale-invariant shape features for  
recognition of object categories, CVPR 2004

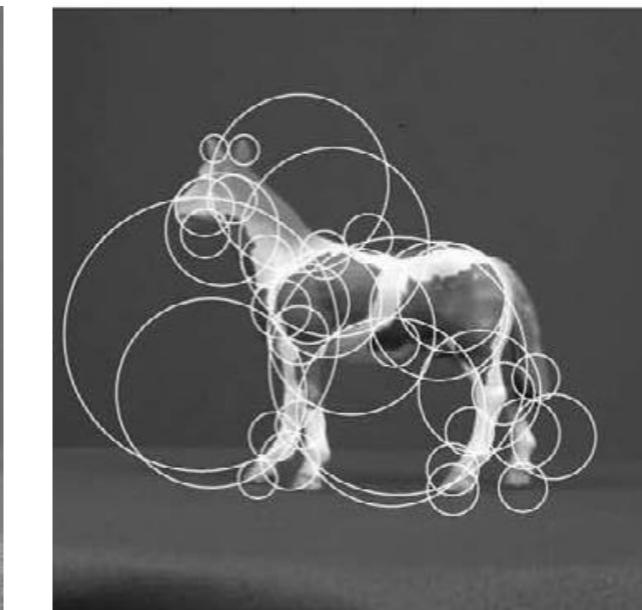
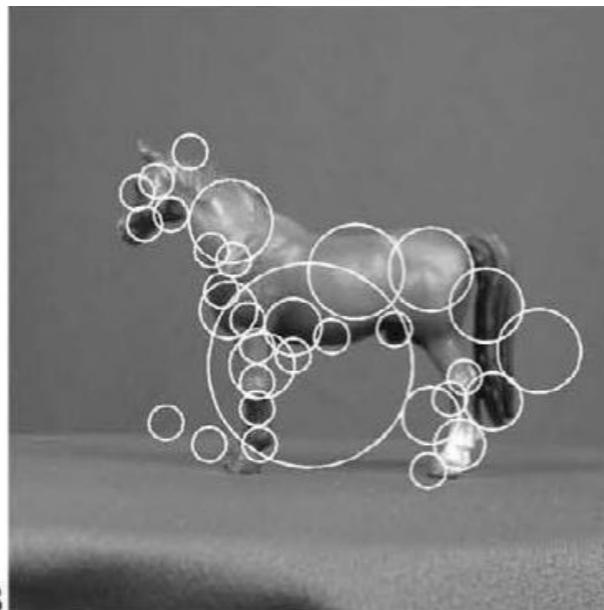
Original  
images



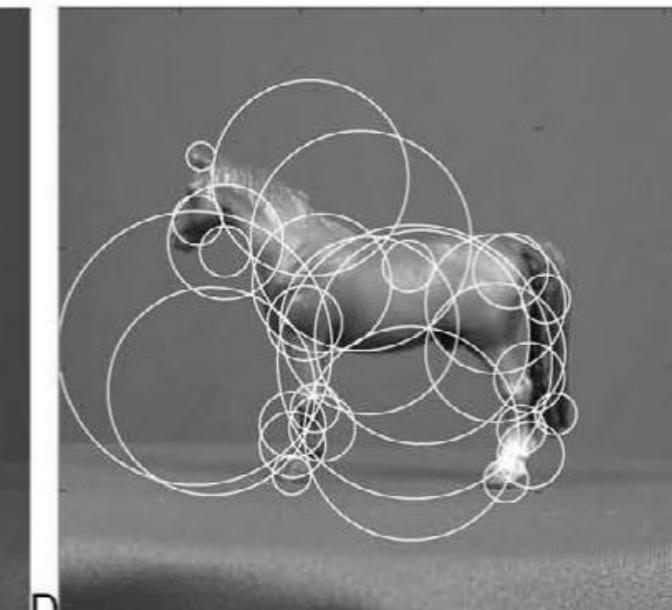
A



B



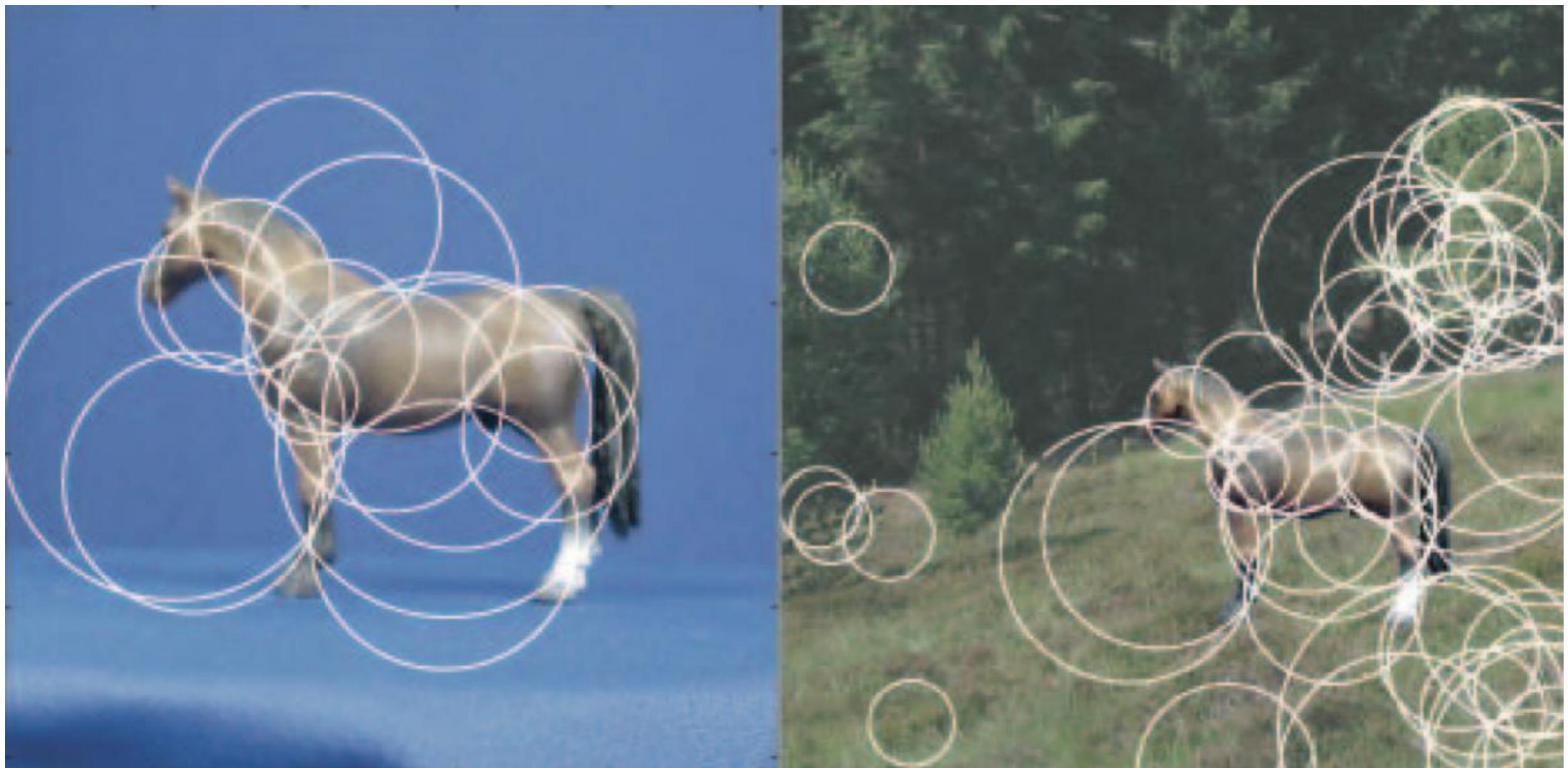
C



Laplacian circles

Hough-like circles

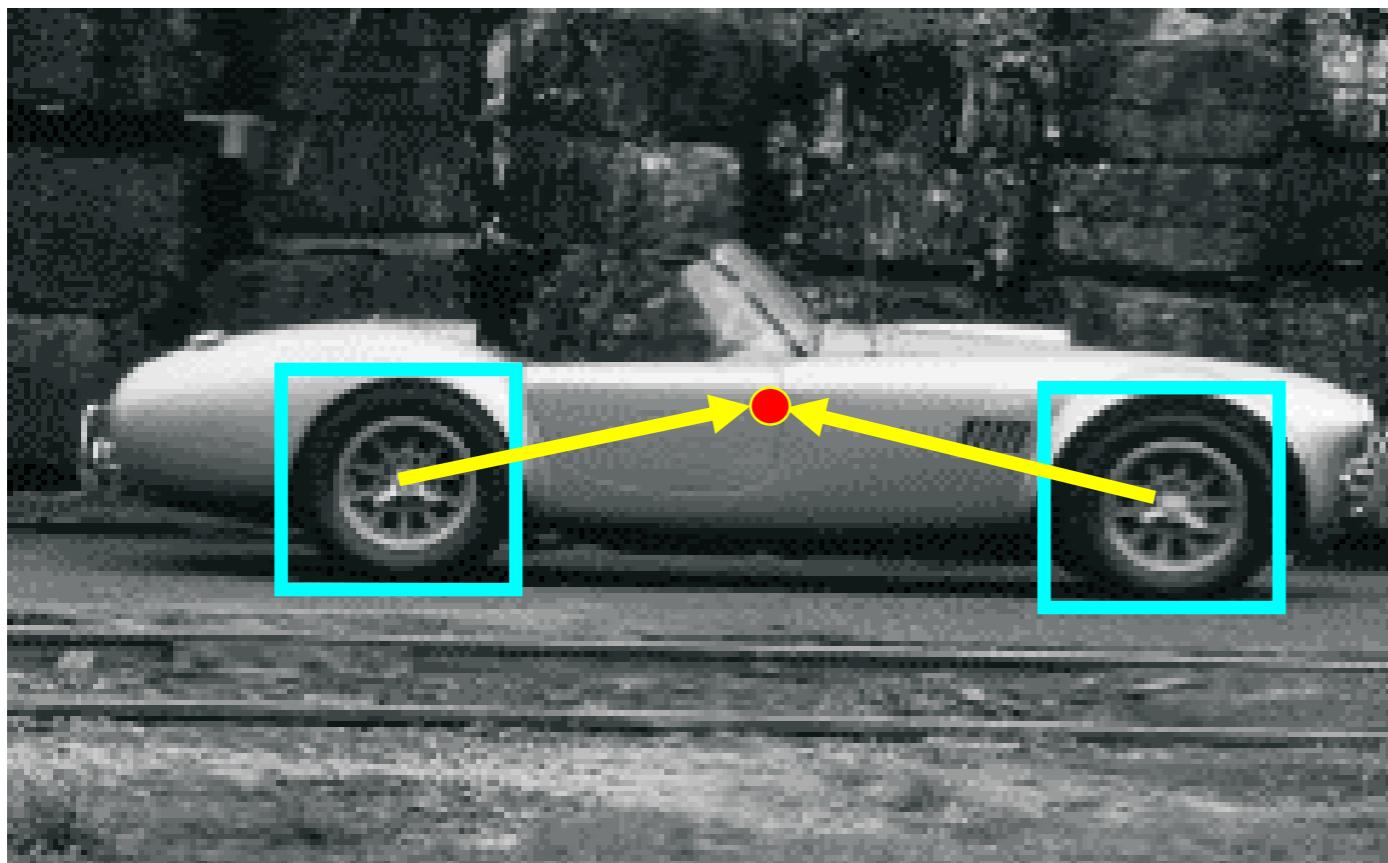
*Which feature detector is more consistent?*



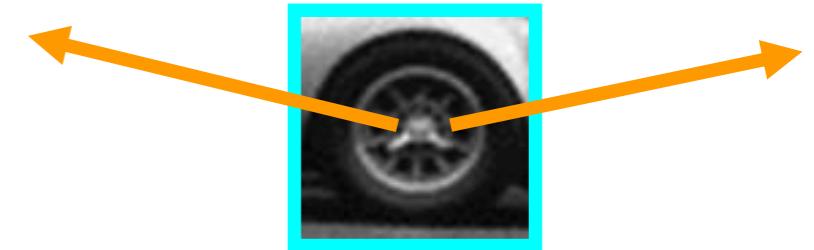
Robustness to scale and clutter

# Object detection

Index displacements by “visual codeword”



training image



visual codeword with  
displacement vectors

B. Leibe, A. Leonardis, and B. Schiele, Combined Object Categorization and Segmentation with an Implicit Shape Model,  
ECCV Workshop on Statistical Learning in Computer Vision 2004



# References

Basic reading:

- Szeliski textbook, Sections 4.2, 4.3.