

# Model Fitting: Line and Circle Detection

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# Edges are a local, **low-level** feature



original

Canny with  $\sigma = 1$

Canny with  $\sigma = 2$

Today: how to extract **higher-level** information  
("boundaries")

Boundaries are composed by groups of edge pixels

# Lines are ubiquitous in man-made scenes



# Why is edge detection not enough?

- Usually, more than one line in an image
- Many edge pixels not belonging to any line (clutter)
- Edge pixels belonging to a line might not be perfectly aligned (noise)
- Lines sometimes incomplete

Which pixels go with which line?

# What is model fitting?

- Observations: many low-level features
- Model fitting: find (fit) an high-level explanation (model) that well explains the observations



In our case:

- observations: edges
- model: one or more lines

# Other examples of model fitting

Find edges then identify circles



Find objects with known silhouette



# Voting algorithms (a general technique)

1. Every **feature** casts votes for all **models** that are compatible with it
2. We choose models that accumulated a lot of votes

What about the votes cast by clutter and noise?

- Their votes might be many but will be **inconsistent!**
- Instead, **features belonging to a model will concentrate a lot of votes for that model**

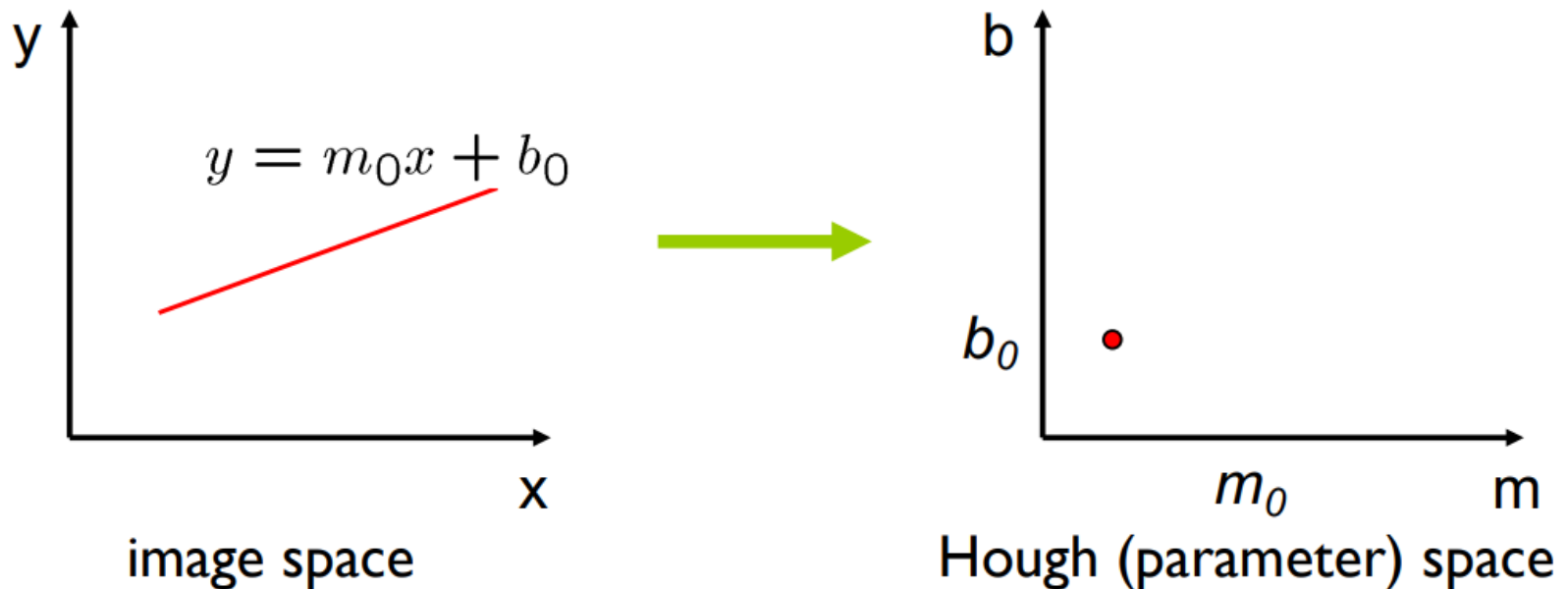
# The Hough Transform: a voting algorithm for finding lines

1. Every **edge point** casts votes for all **lines** that are compatible with it
2. We choose **lines** that accumulated a lot of votes



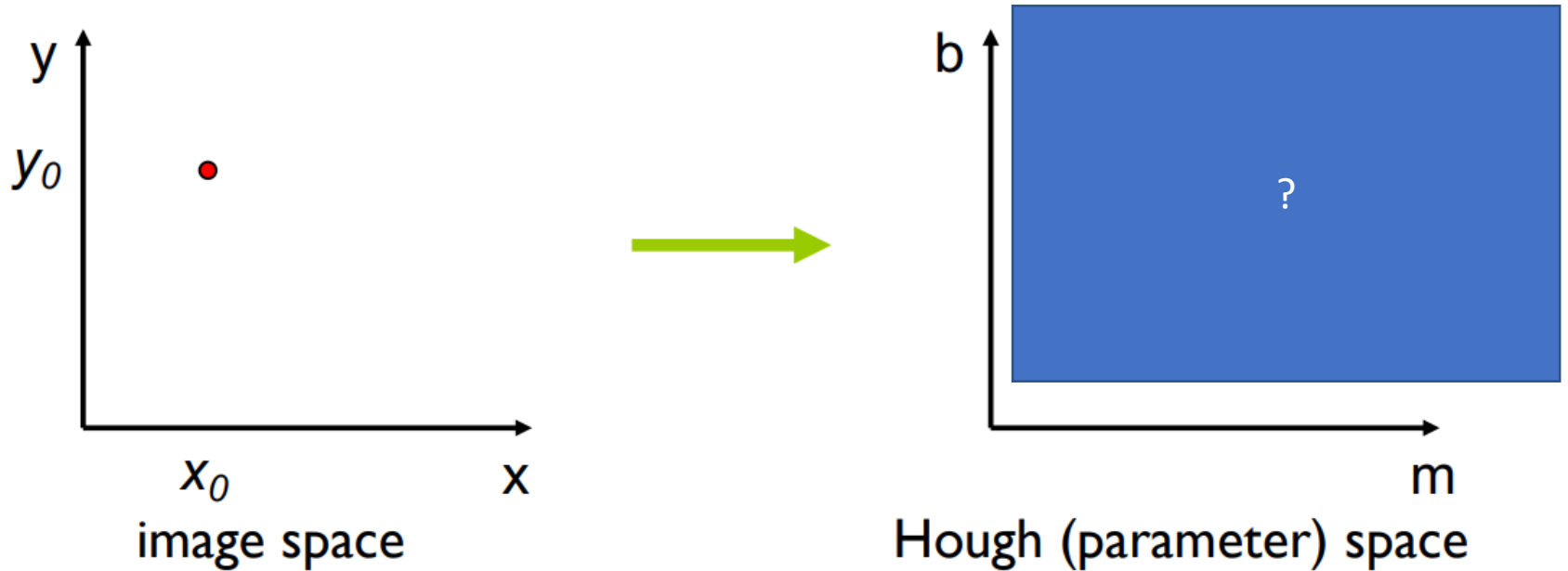
# Part 1: the Hough Algorithm for line fitting

# How to represent a line?



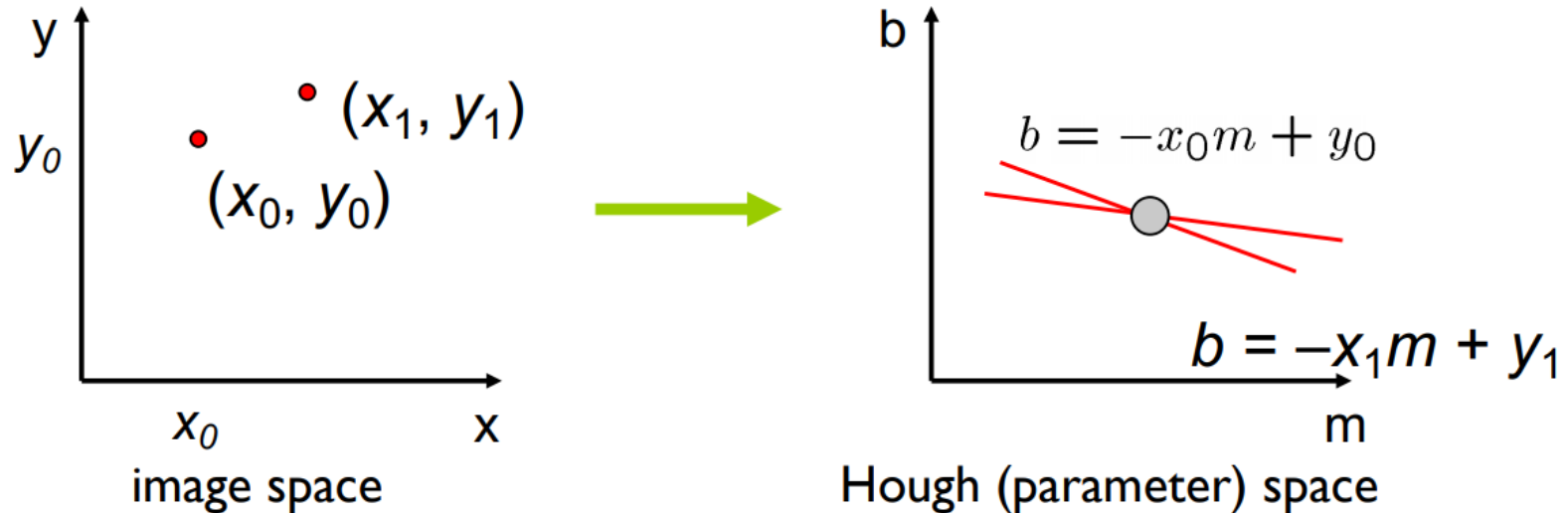
A line in the image corresponds to a point in Hough space

# What does a point correspond to?



A point in the image corresponds to a line in Hough space

# Finding a line through two points



What are the line parameters for the line that contains both  $(x_0, y_0)$  and  $(x_1, y_1)$ ?

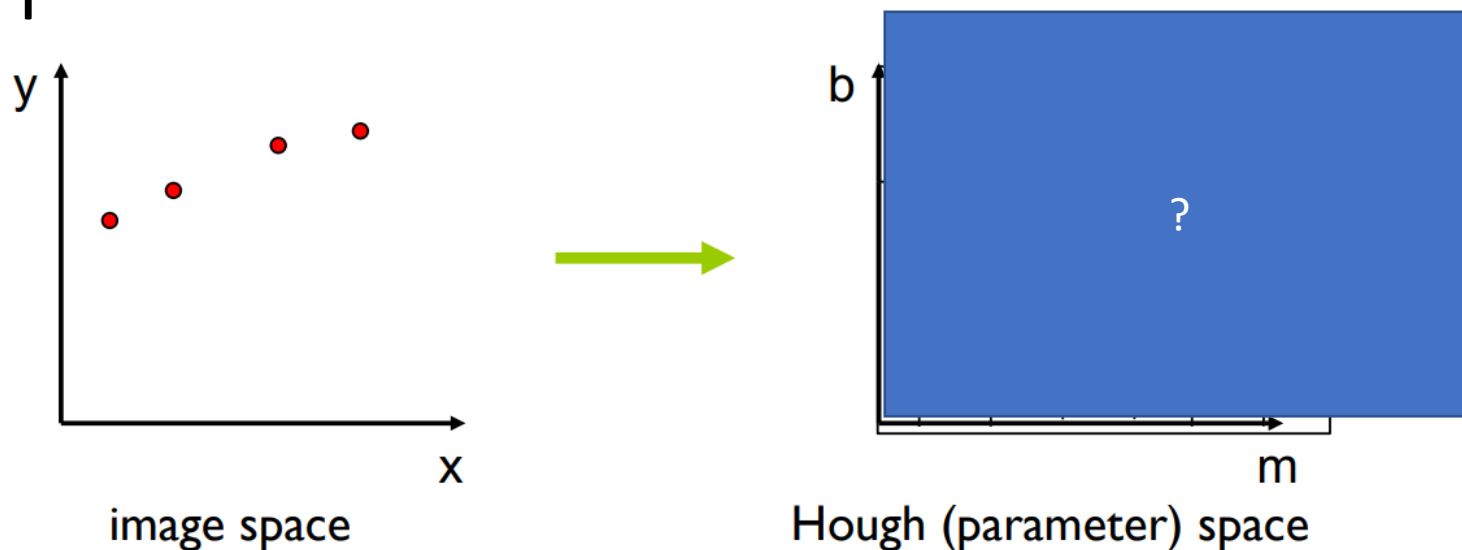
The  $(m, b)$  coordinates of the intersection of the hough-space lines

$$b = -x_0m + y_0$$

and

$$b = -x_1m + y_1$$

# Finding a line through many points



Note that the 4 points are not exactly aligned: in Hough space, the lines corresponding to each point will almost intersect.

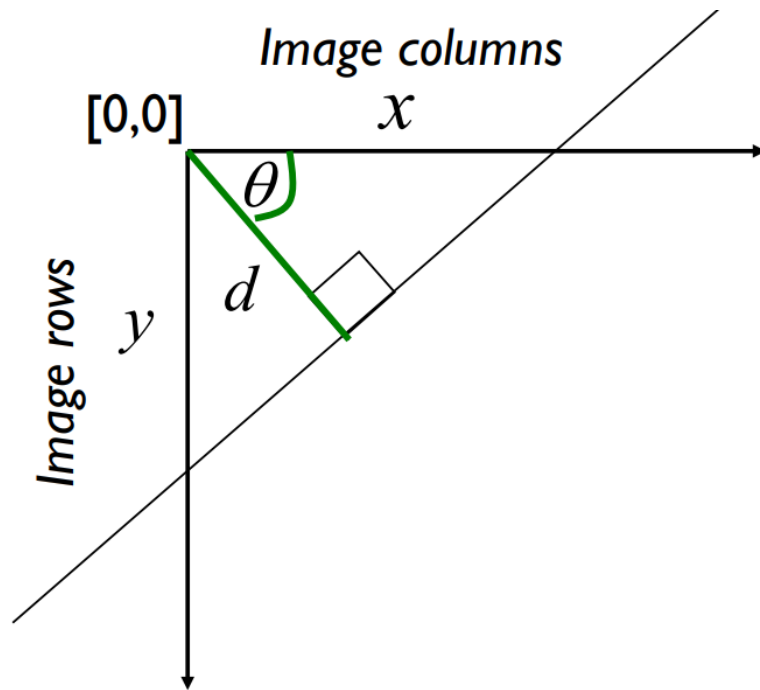
Now, let each edge point in image space vote for a **set of possible parameters** in Hough space.

Accumulate votes in a discrete set of bins; parameters with the most votes indicate a line in image space.

Where is the problem with this approach?



# Solution: represent lines in polar coordinates



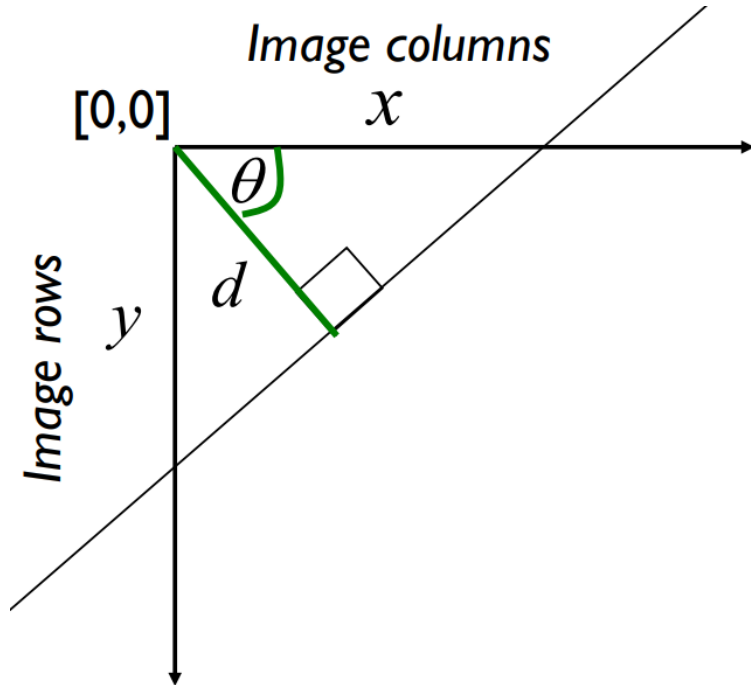
$d$  : perpendicular distance from line to origin

$\theta$  : angle the perpendicular makes with the x-axis

$$x \cos \theta - y \sin \theta = d$$

The hough space is now  $(d, \theta)$  instead of  $(m, b)$   
Same as before: a line in image space is a point in Hough space.

# Pause and ponder

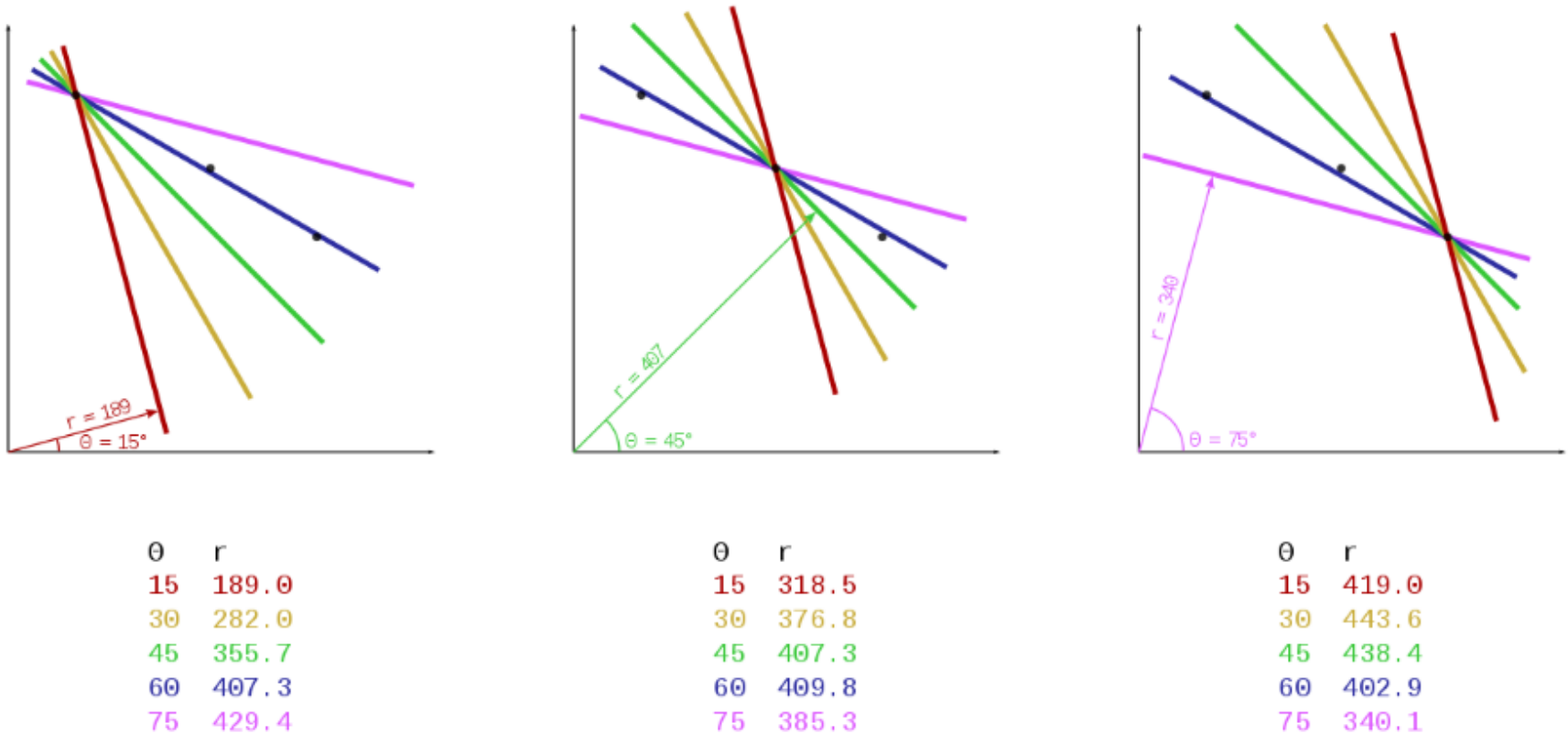


- For an image of size (width, height). What are the boundaries of the Hough space such that we can represent any line overlapping the image?
- Given a point in image space, what is the corresponding shape in Hough space?

(solution: a sinusoid)



# An example



Given 3 points in image space, here are some of the corresponding points in hough space

# Hough Transform: the algorithm

Initialize  $H[d, \theta] = 0$

for each edge point  $(x, y)$  in the image:

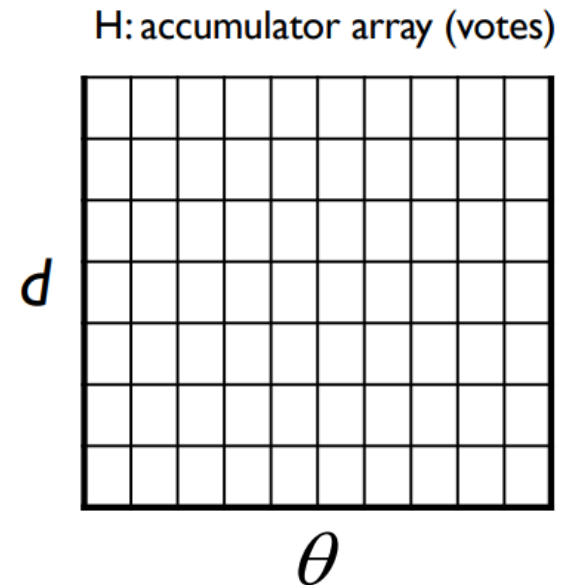
for  $\theta$  in range( $\theta_{\min}, \theta_{\max}$ ):

$$d = x \cos(\theta) - y \sin(\theta)$$

$$H[d, \theta] += 1$$

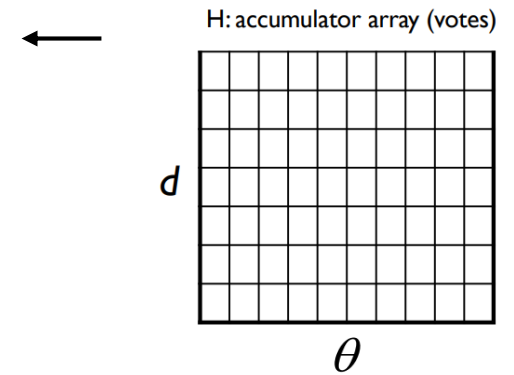
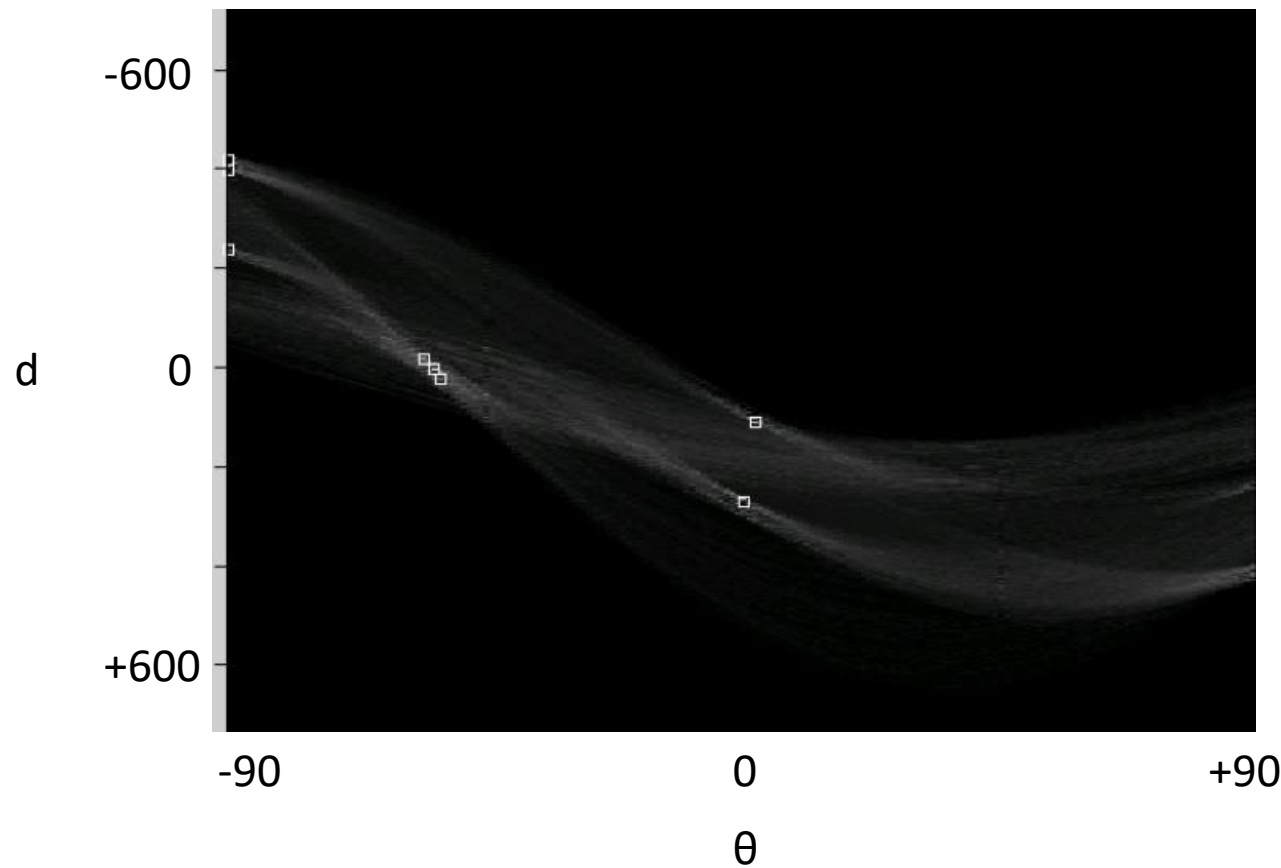
Find the value(s) of  $(d, \theta)$  where  $H[d, \theta]$  is maximum

The detected line in the image is given by  
 $d = x \cos(\theta) - y \sin(\theta)$

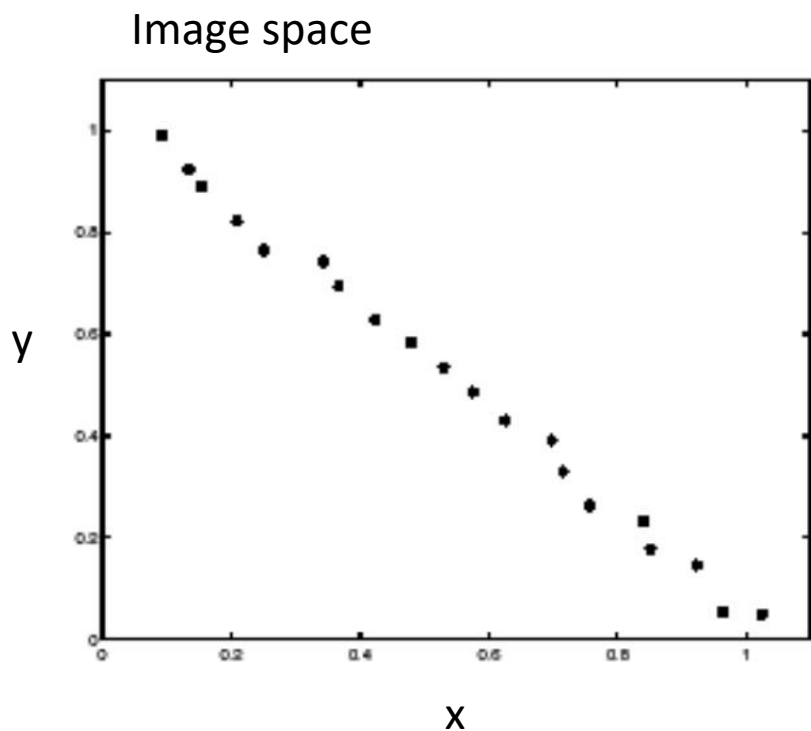




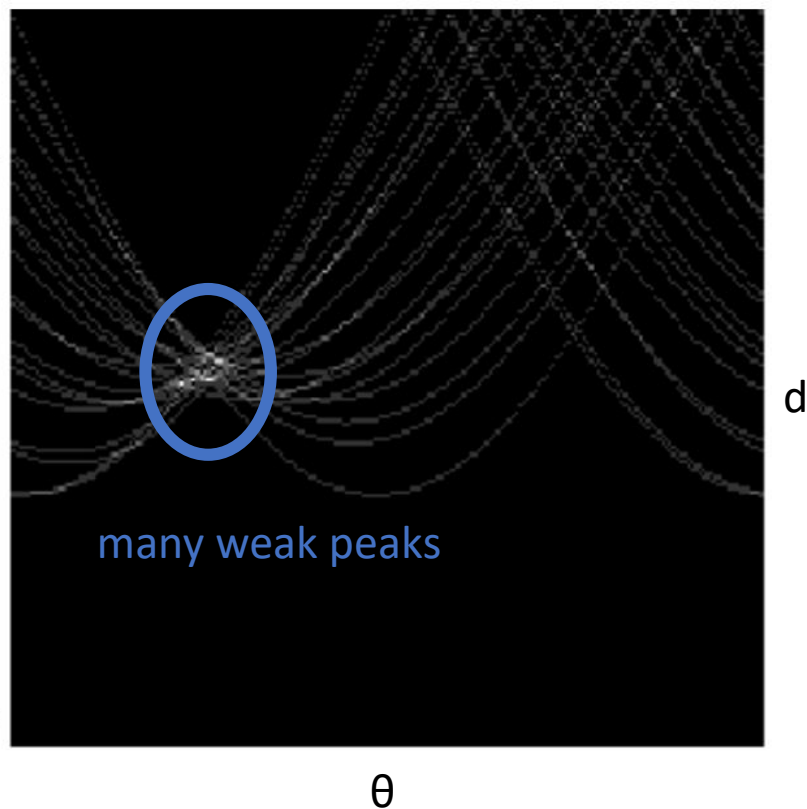
Quiz: identify which maxima represent the four lines of the square object!



# What's the effect of noise?

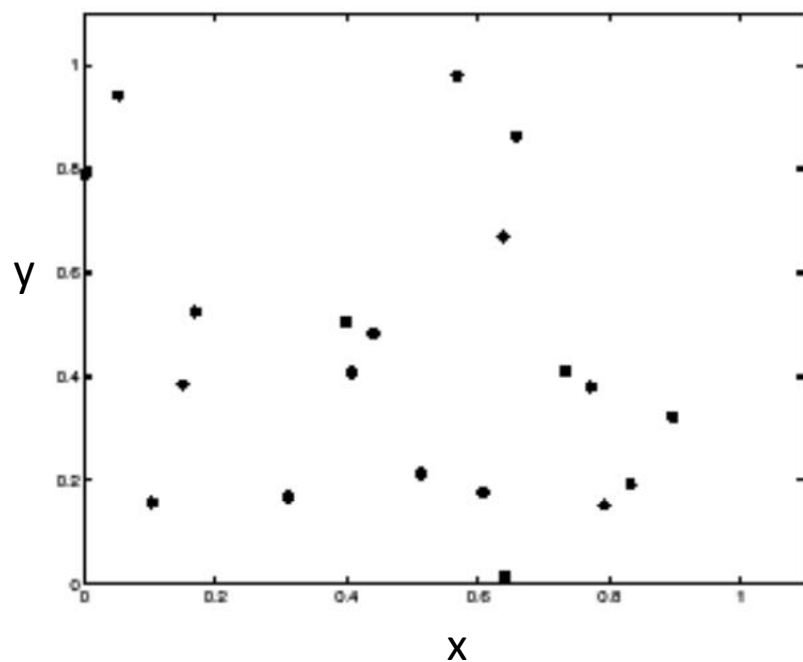


H: accumulator array

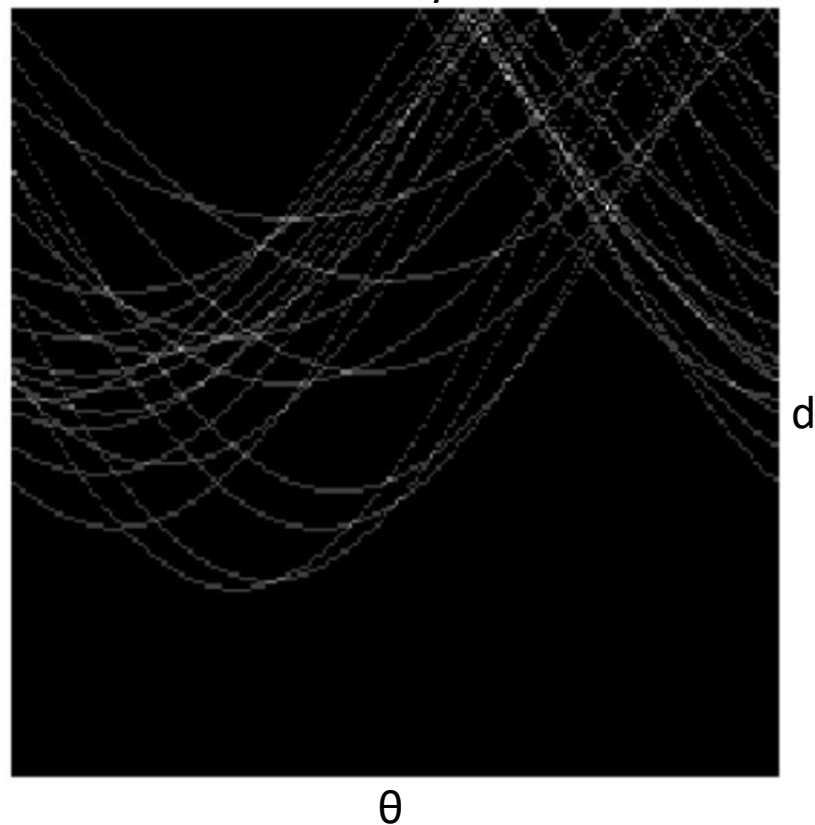


# What's the effect of noise?

Image space



H: accumulator array



# Bin size in the accumulator: an important parameter

How large are the bins in the accumulator?

- Too small:
  - many weak peaks due to noise
- Just right:
  - one strong peak per line, despite noise
- Too large:
  - poor accuracy in locating the line
  - many votes from clutter might end up in the same bin

A solution:

keep bin size small but also vote for neighbors in the accumulator

(this is the same as “smoothing” the accumulator image)

# Extension 1

From the edge detection algorithm, we know the direction of the gradient for each edge pixel

- Remember how that was related to edge direction?  
Edge direction is orthogonal to gradient direction
  - We can make sure an edge pixel only votes for lines that have (almost) the direction of the edge!
- reduces the computation time
- reduces the number of useless votes (better visibility of maxima corresponding to real lines)

## Extension 2

Keep track of edge points that voted for each line.

If a line is chosen, look for groups of edge points that voted for that line → find start point and end point of segment.



# Part 2: the Hough algorithm for circle detection

# The Hough Transform: a voting algorithm...

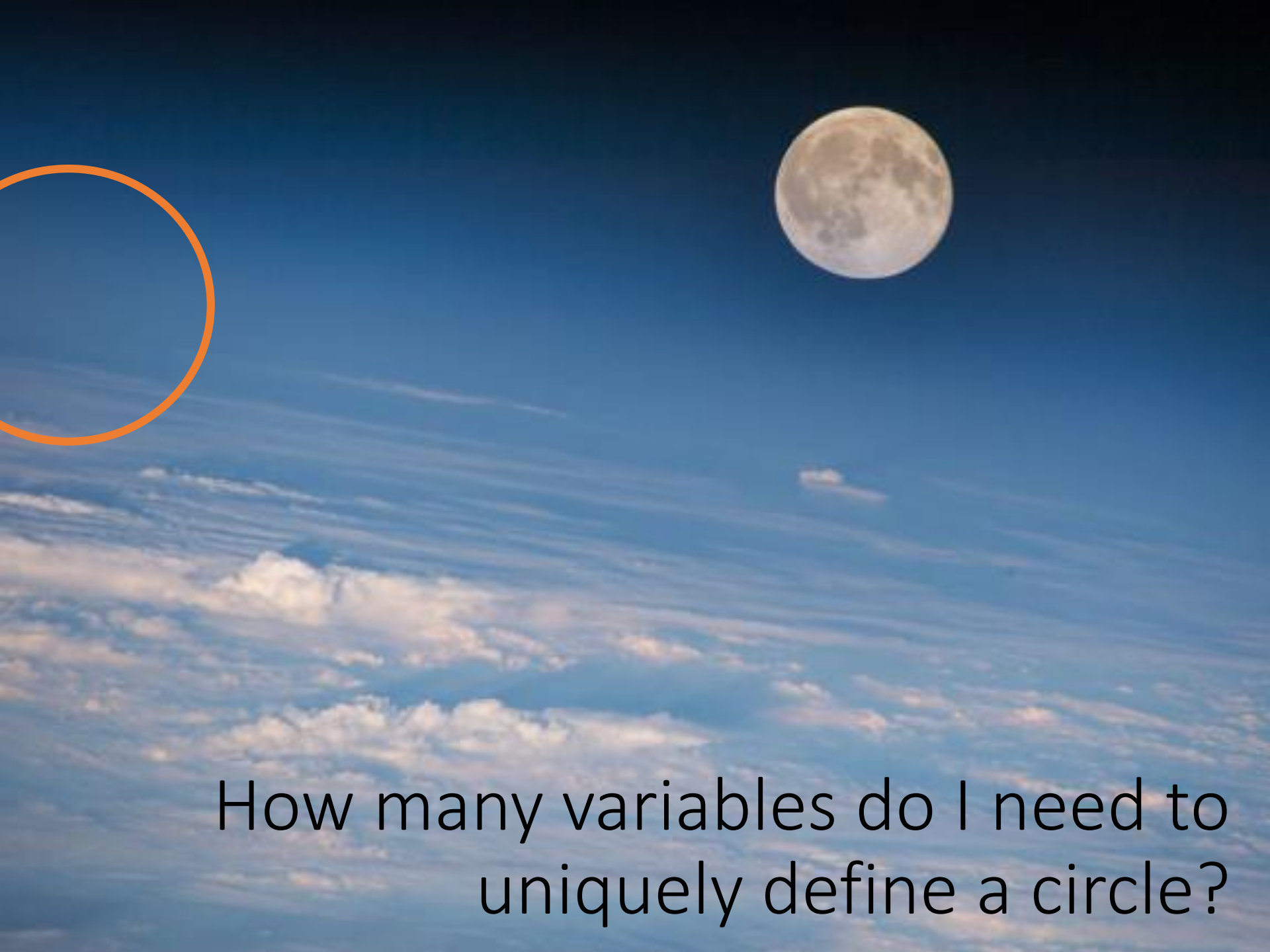
1. Every **feature** casts votes for all **models** that are compatible with it
2. We choose **models** that accumulated a lot of votes

# The Hough Transform: a voting algorithm... for finding **lines**

1. Every **edge point** casts votes for all **lines** that are compatible with it
2. We choose **lines** that accumulated a lot of votes

# The Hough Transform: a voting algorithm... for finding **circles**

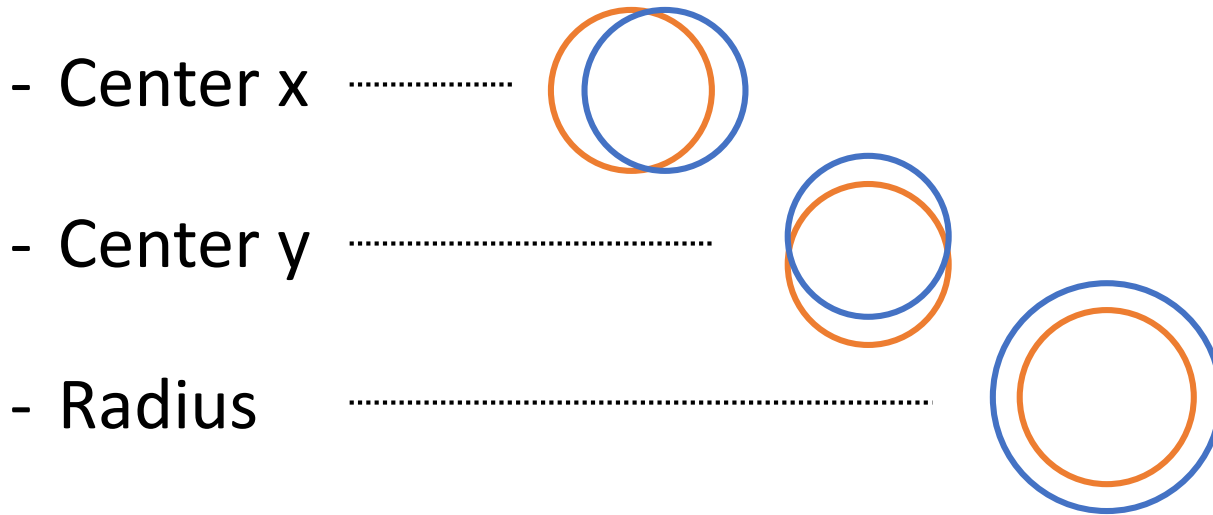
1. Every **edge point** casts votes for all **circles** that are compatible with it
2. We choose **circles** that accumulated a lot of votes



How many variables do I need to uniquely define a circle?

# 3 parameters uniquely define a circle

→ You use a 3-dimensional Hough Space



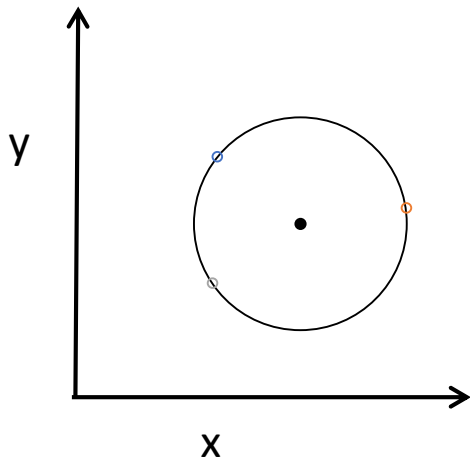
# How do we parametrize circles?

$$(x_i - a)^2 + (y_i - b)^2 = r^2$$

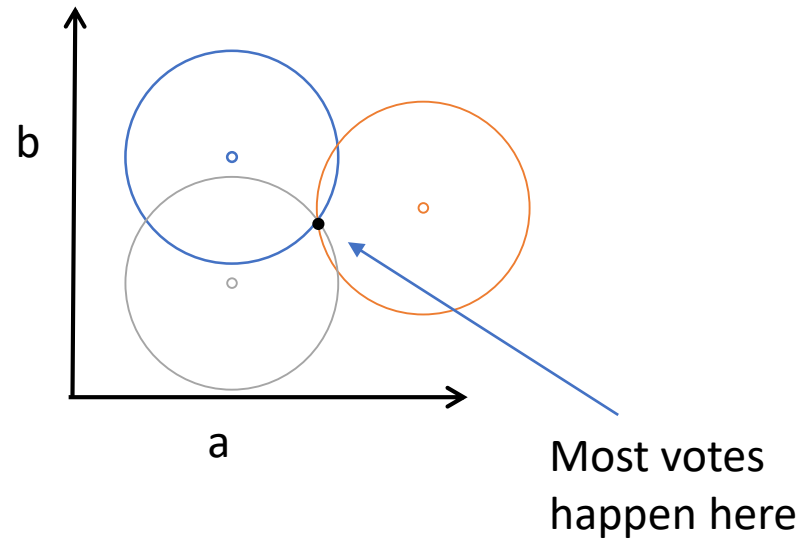
- Center (x=**a**,y=**b**) and radius **r**  
3 degrees of freedom (a, b and r)
- **If we assume known radius (fix r)**
  - Hough space is 2D:
    - a: x coordinate of circle center
    - b: y coordinate of circle center
  - One point in image space maps to...  
a circle in hough space

# Hough space for circles with **known** radius

Image space



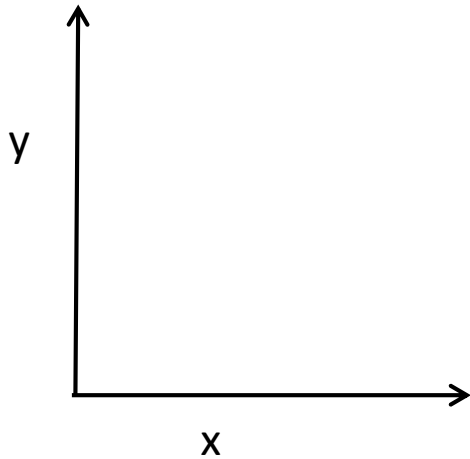
Hough space (2D)



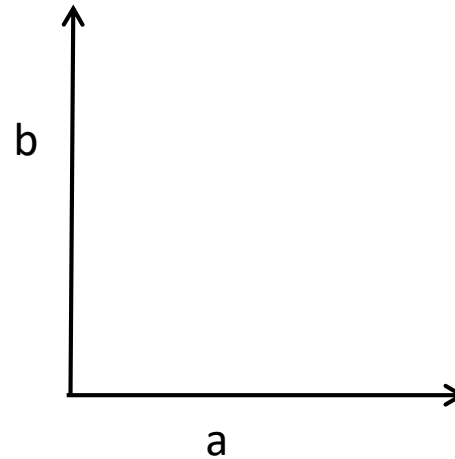


# Hough space for circles with **unknown** radius

Image space

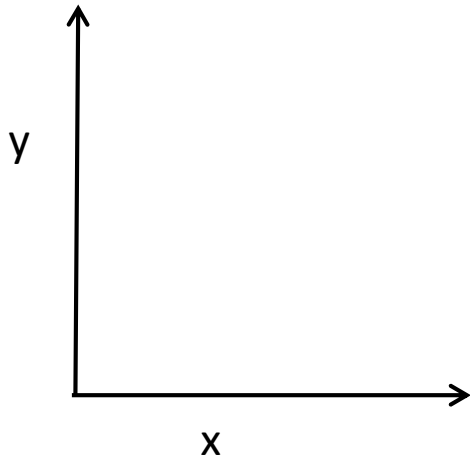


Hough space

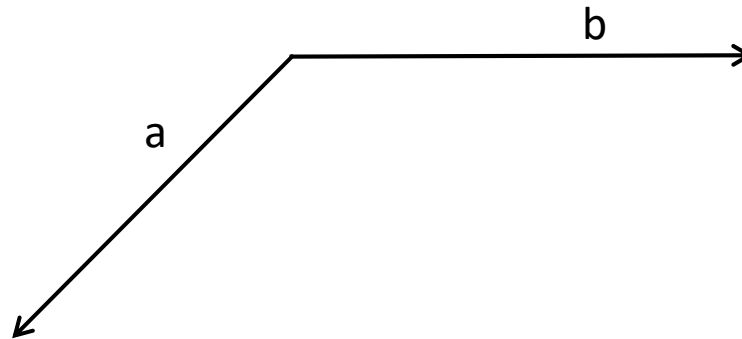


# Hough space for circles with unknown radius

Image space

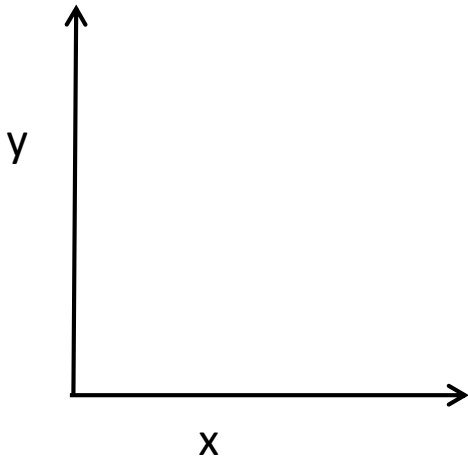


Hough space

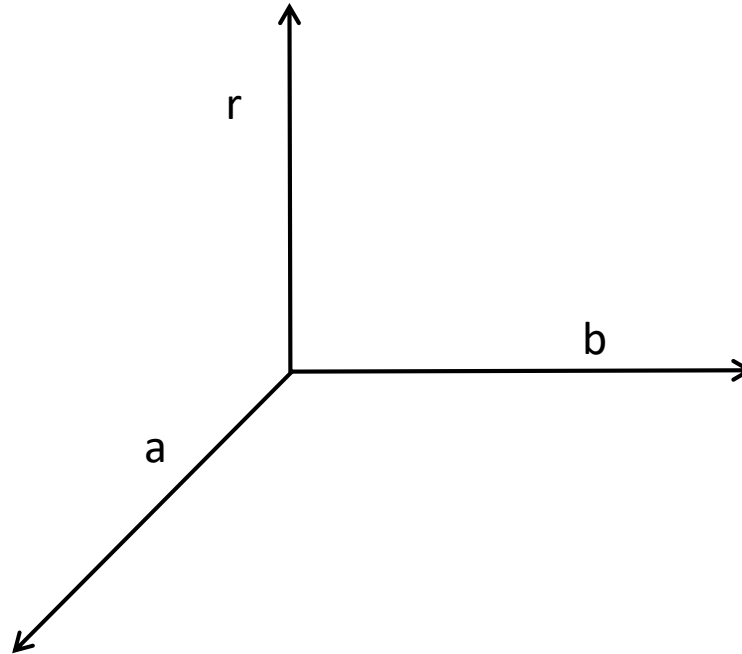


# Hough space for circles with unknown radius

Image space

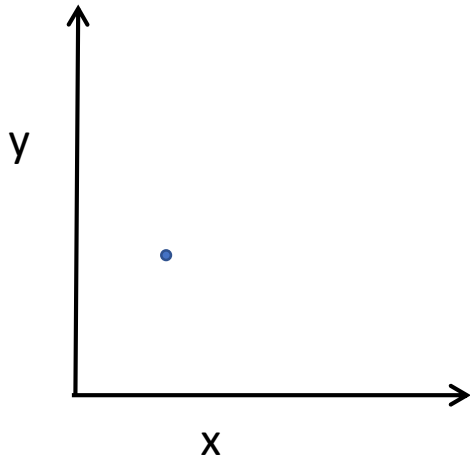


Hough space (3D)

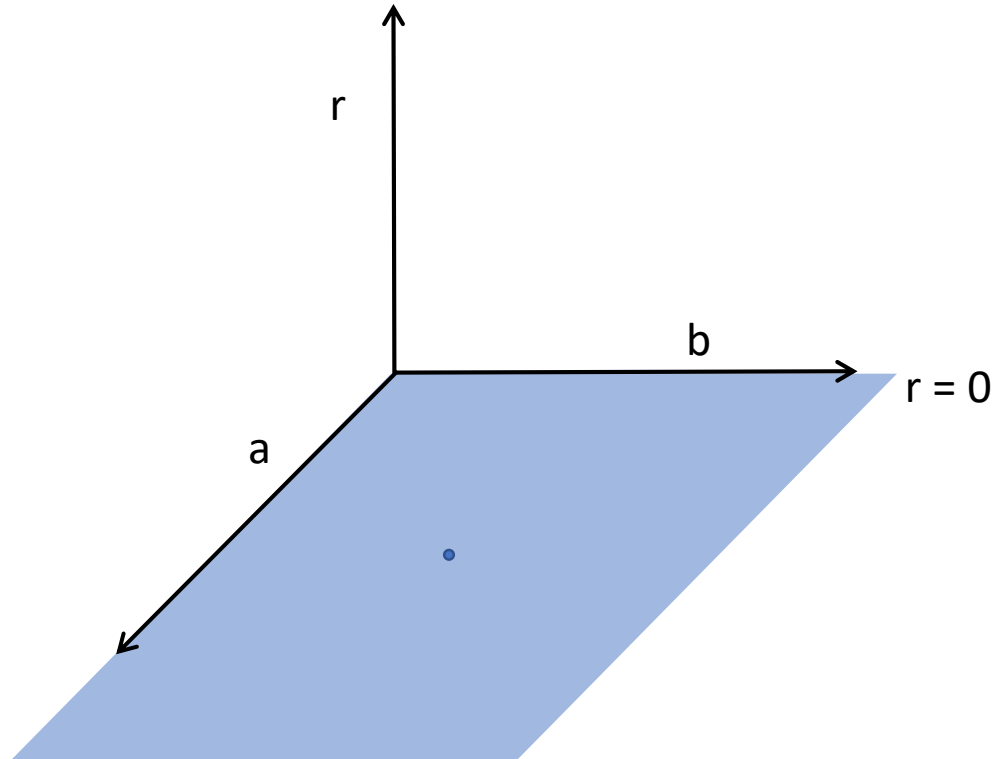


# Hough space for circles with unknown radius

Image space

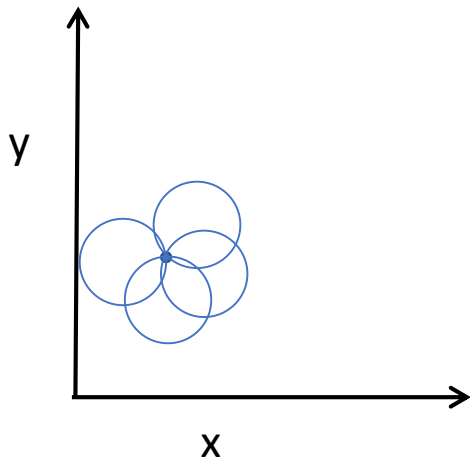


Hough space

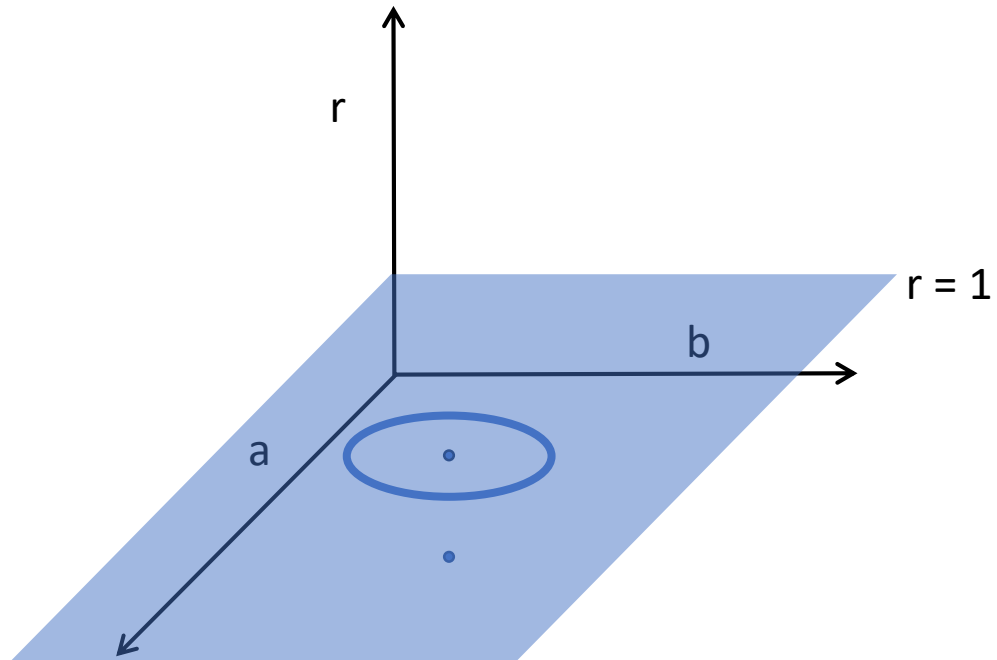


# Hough space for circles with unknown radius

Image space

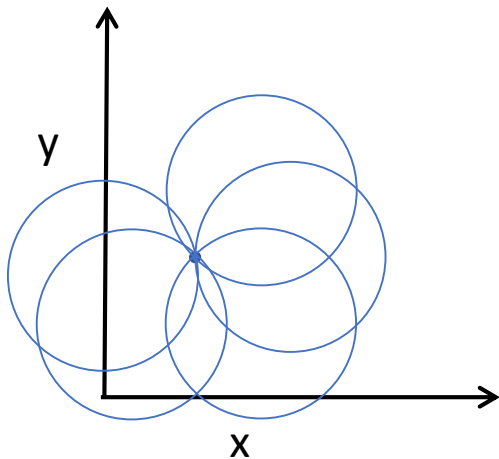


Hough space

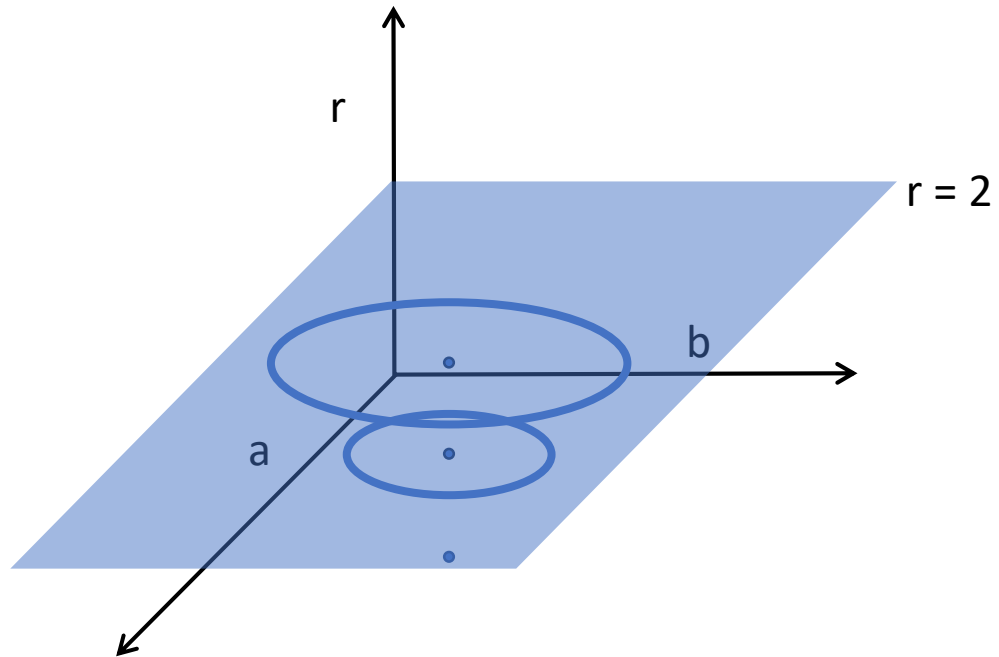


# Hough space for circles with unknown radius

Image space

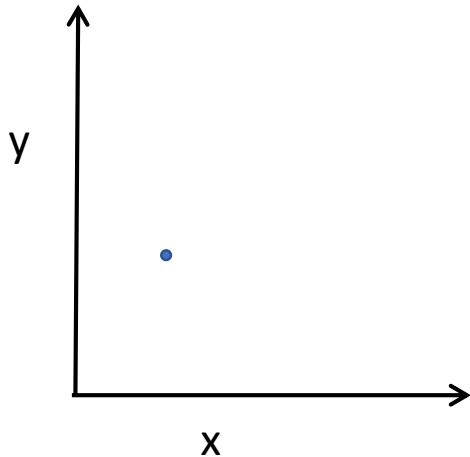


Hough space

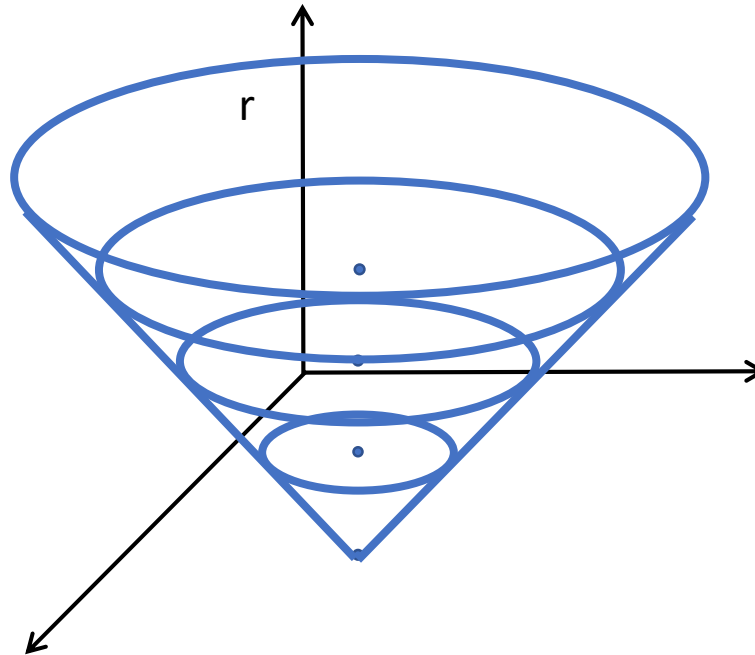


# Hough space for circles with unknown radius

Image space

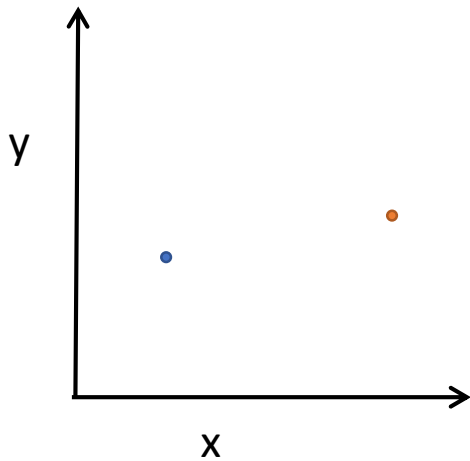


Hough space

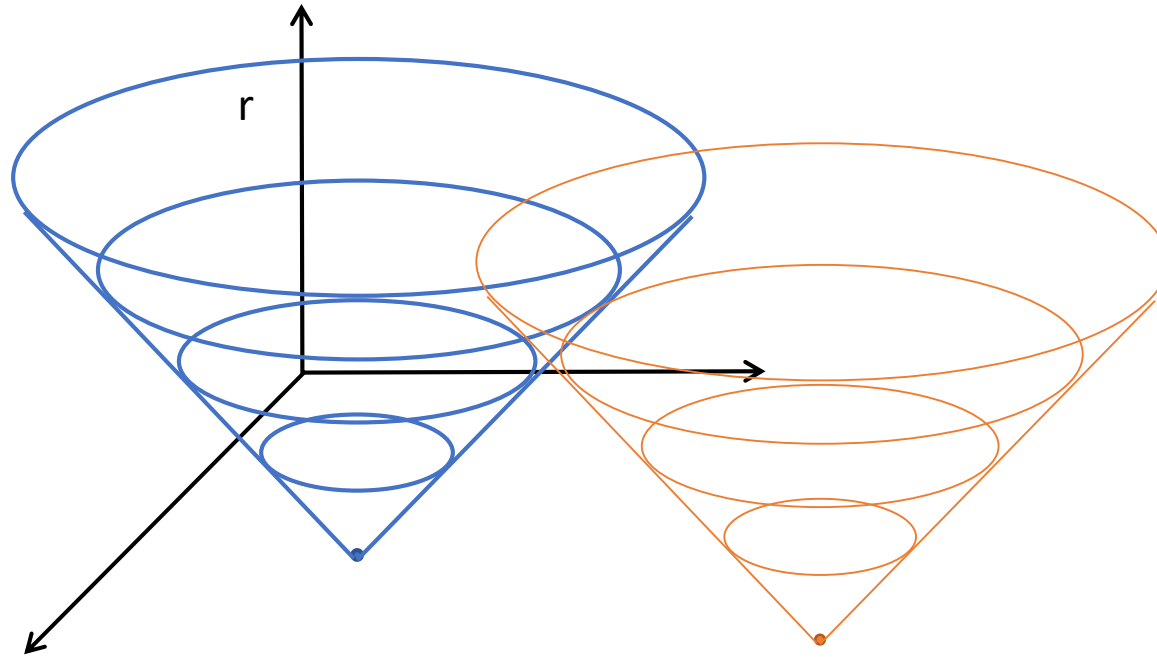


# Hough space for circles with unknown radius

Image space



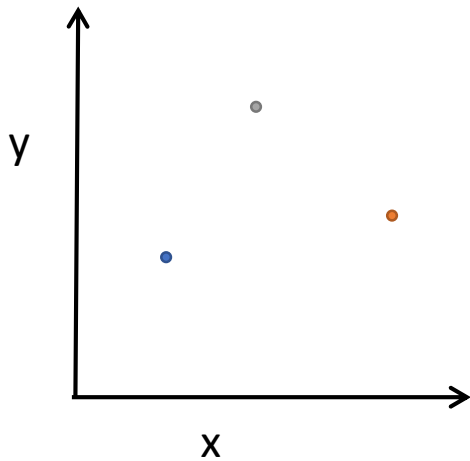
Hough space



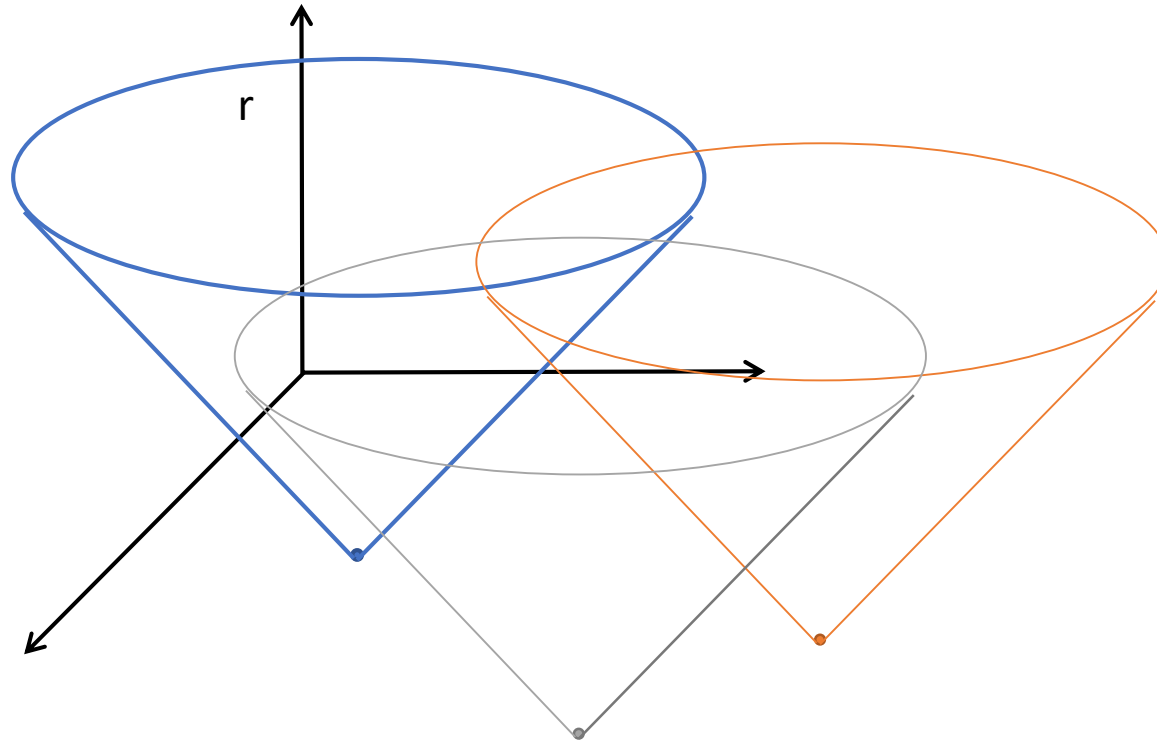


# Hough space for circles with unknown radius

Image space



Hough space



# Algorithm

Initialize H accumulator to zeros

For every edge pixel (x,y):

    For each possible radius value r:

        For each possible direction  $\theta$ :

$a = x - r \cos(\theta)$  // column

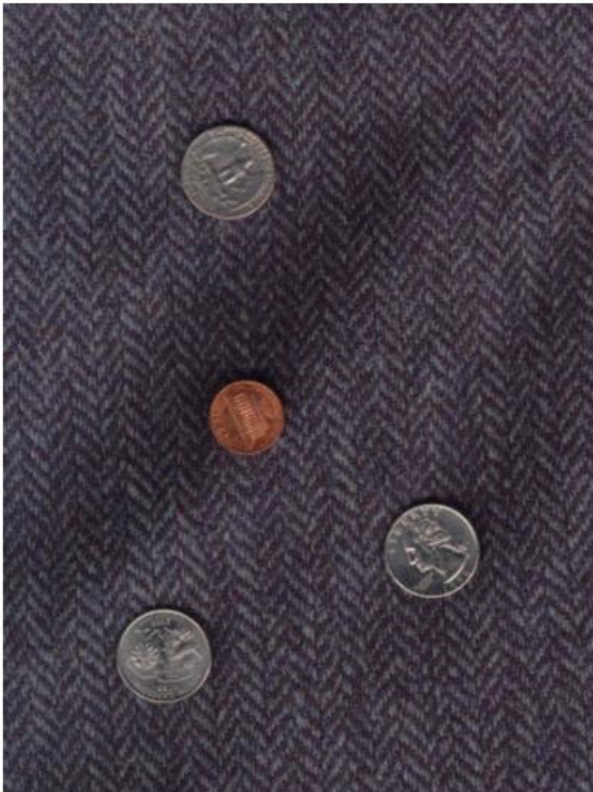
$b = y + r \sin(\theta)$  // row

$H[a,b,r] += 1$

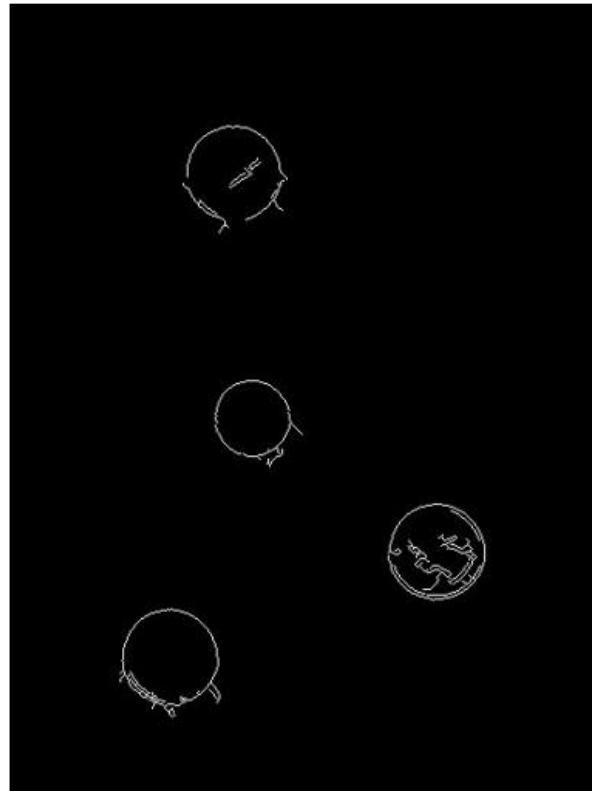
# An example

Accumulator for radius equal to radius of a penny

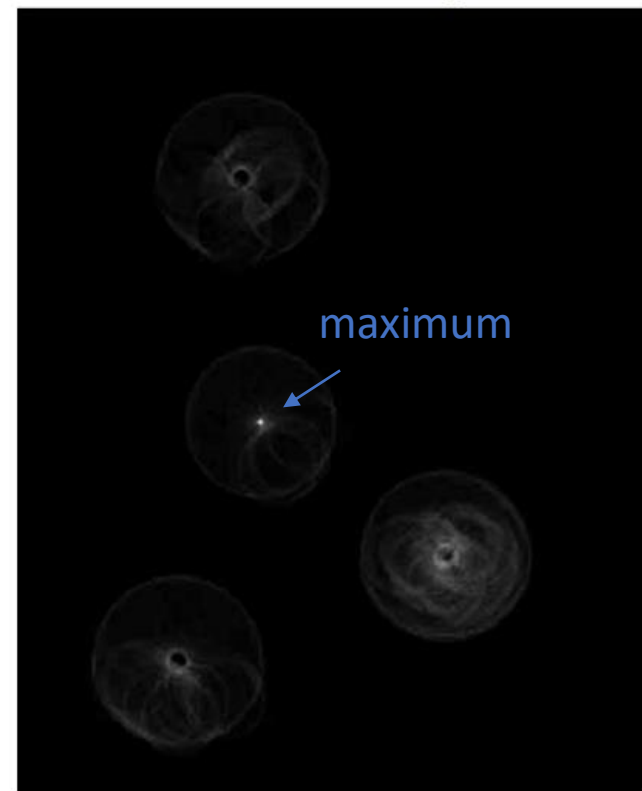
Image



Edges



Accumulator for radius=penny



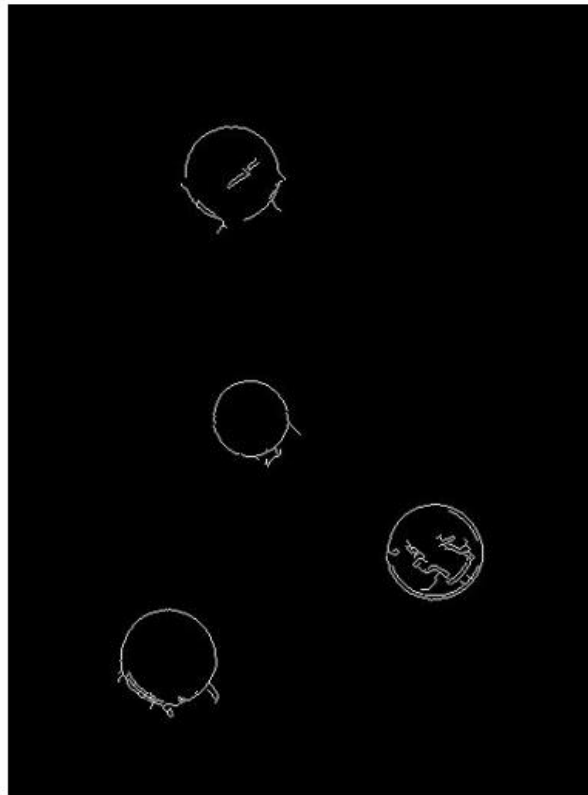
# An example

Accumulator for radius equal to radius of a quarter

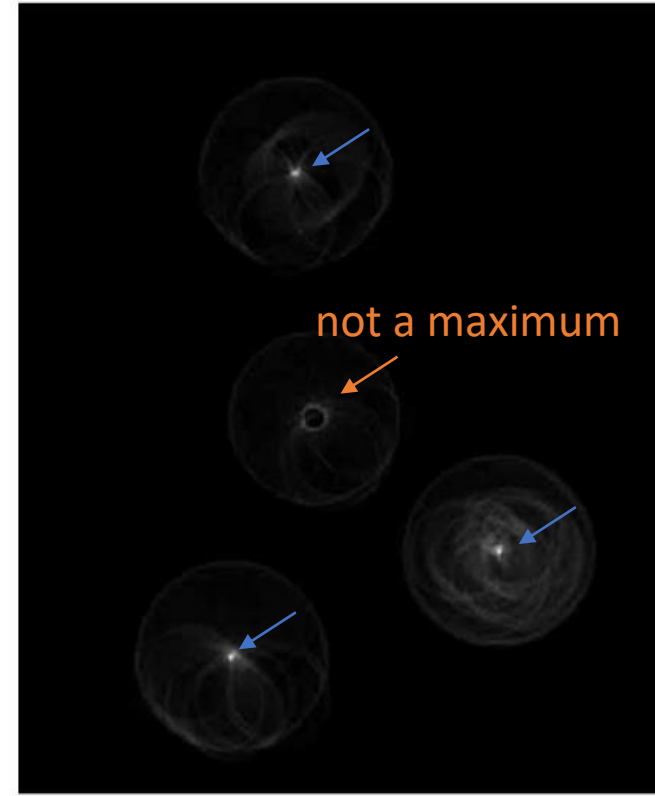
Image



Edges



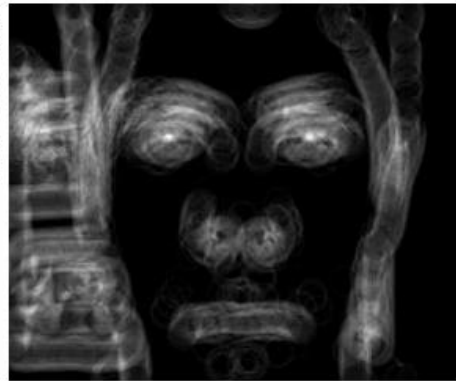
Accumulator for radius=quarter



# Iris detection



Gradient+threshold



Hough space  
(fixed radius)

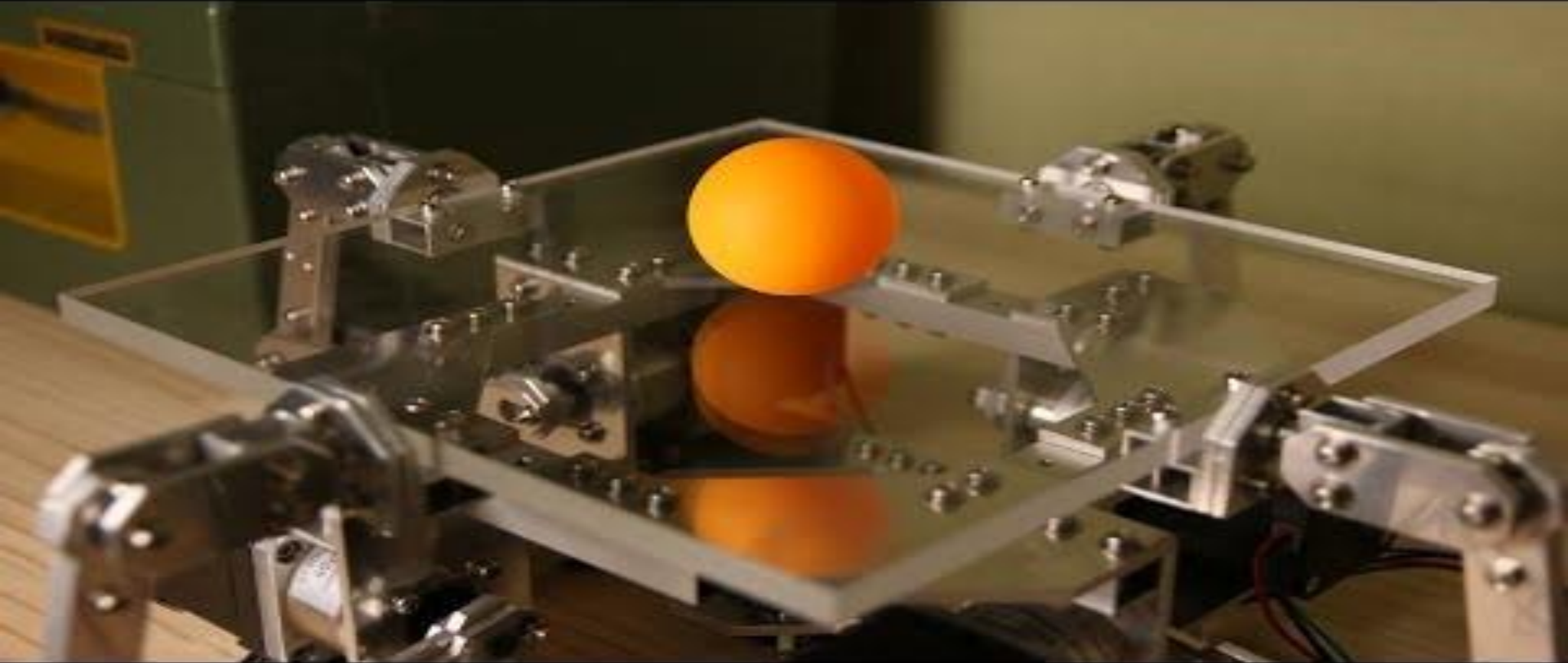


Max detections





# An application to robotics



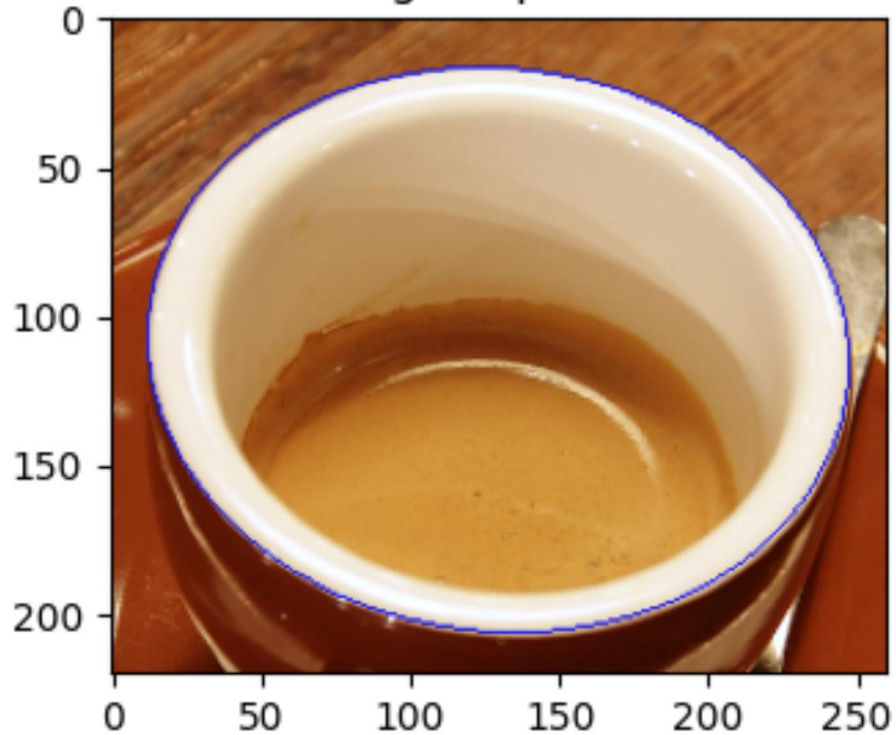
<https://www.youtube.com/watch?v=IYyAMDYzJQM>

# Part 3: Extensions and conclusions

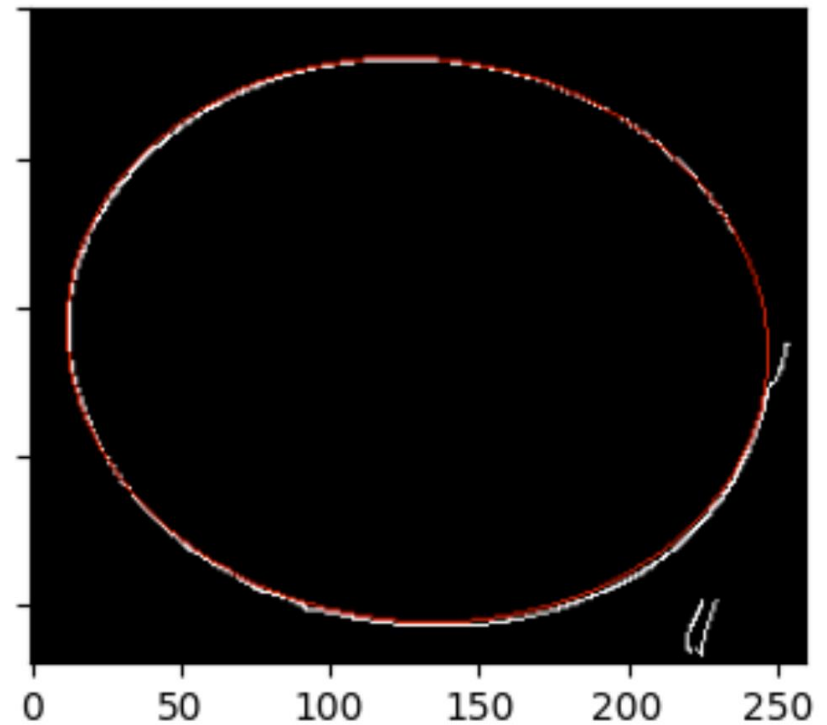


# Detecting ellipses

Original picture



Edge (white) and result (red)



# Quiz

How many parameters are needed to define a generic ellipse in 2D?

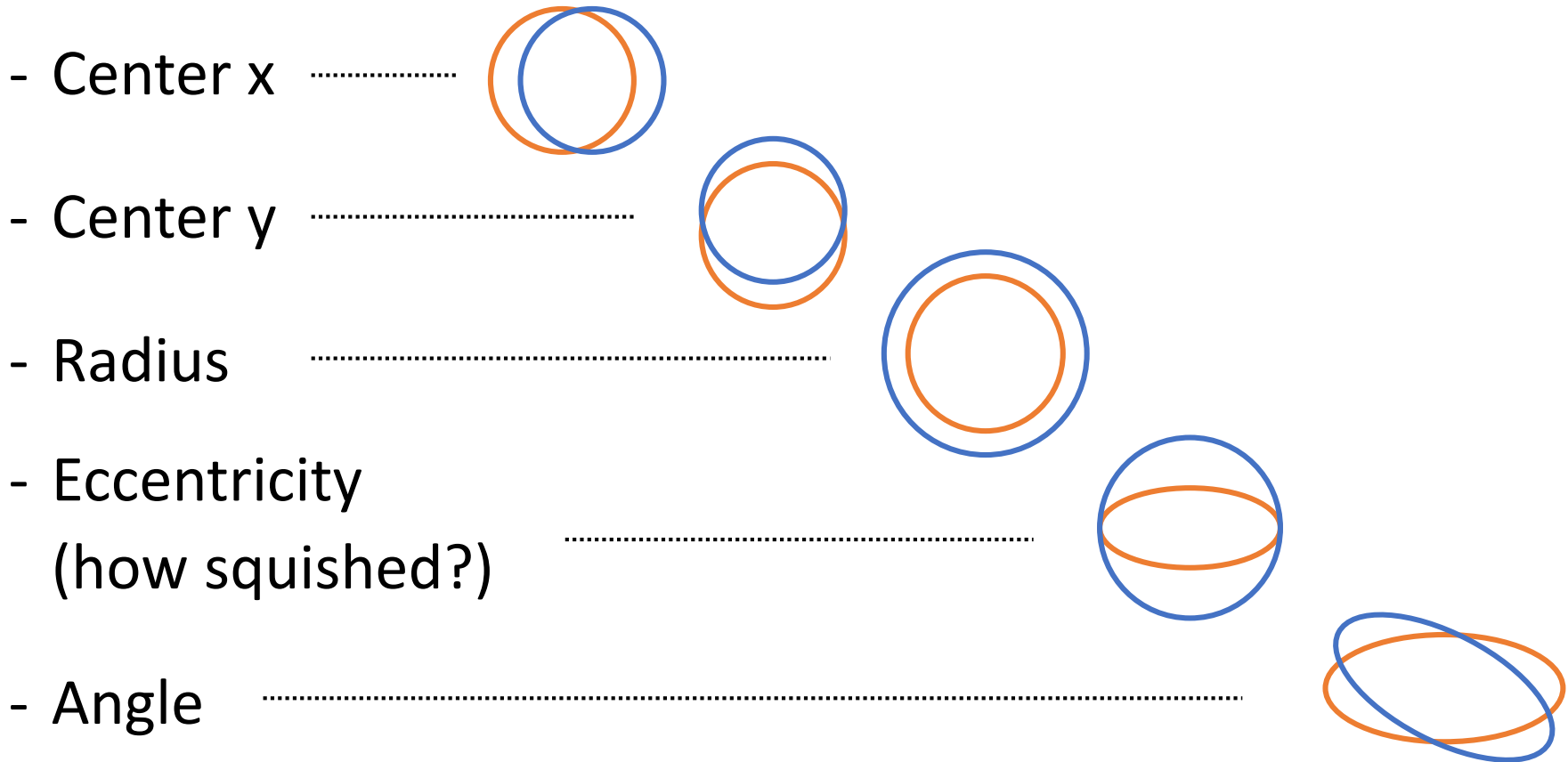


Try to fit an ellipse in powerpoint

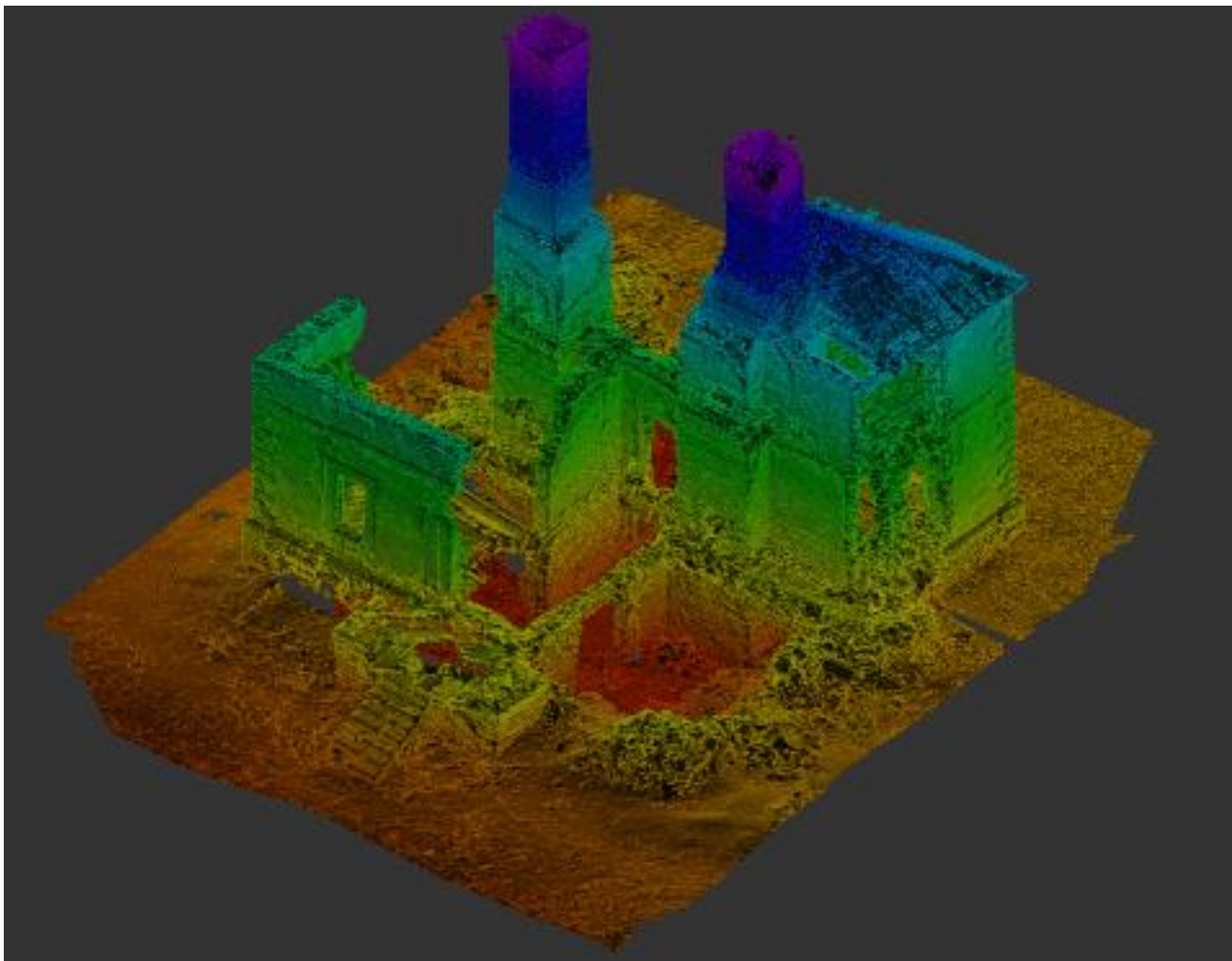


# 5 parameters uniquely define an ellipse

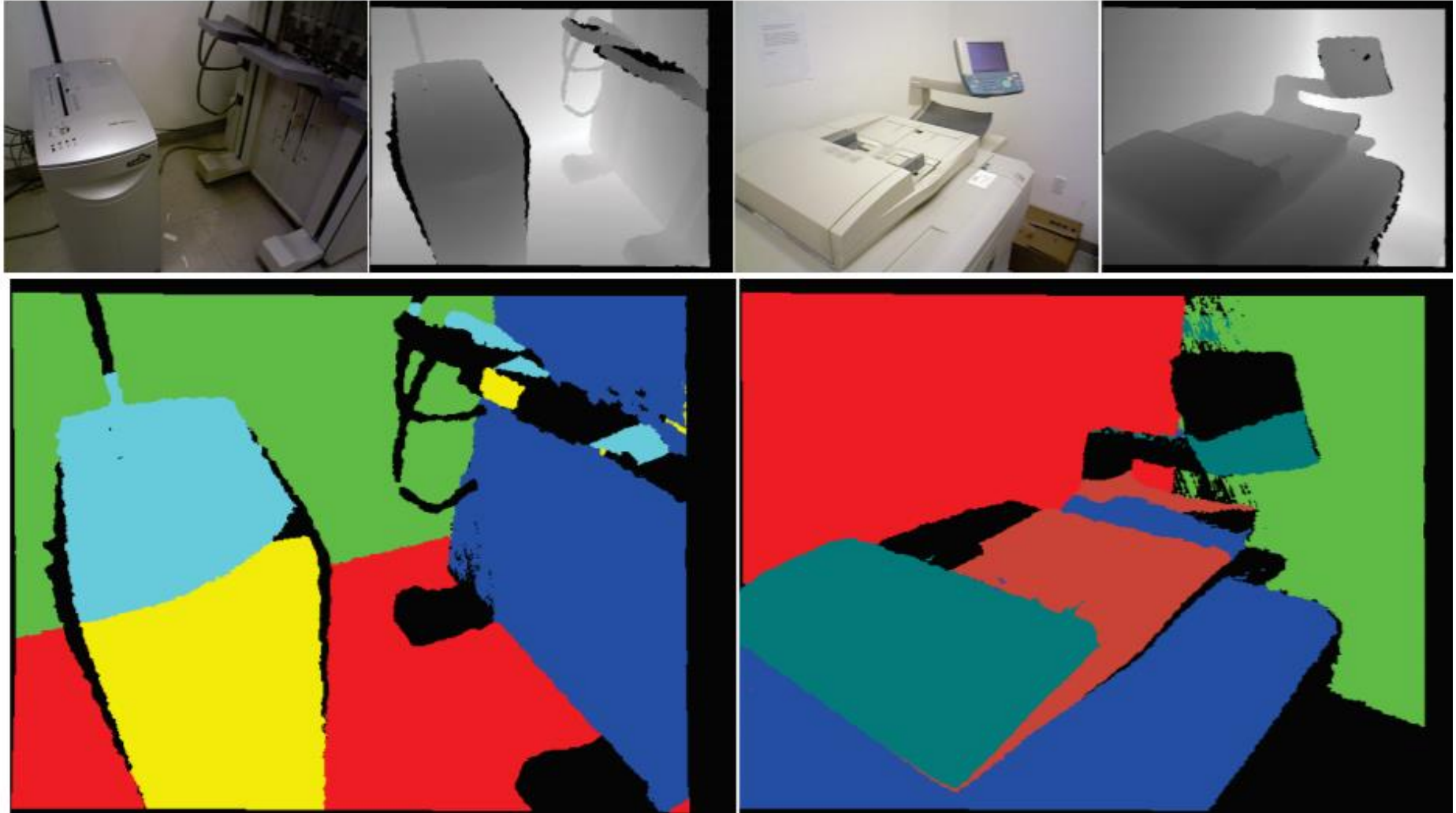
→ You use a 5-dimensional Hough Space



# Finding 3D planes in point clouds



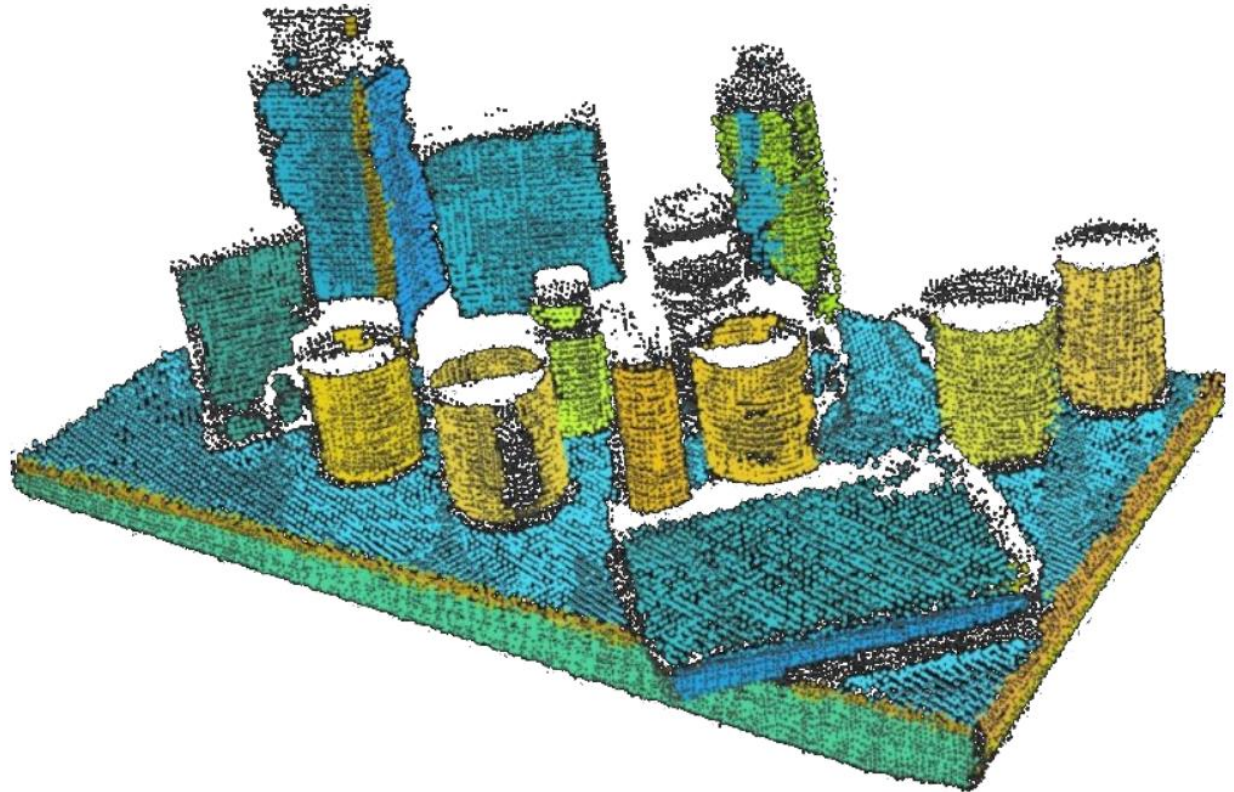
# Finding 3D planes in point clouds





# Finding planes and cylinders in point cloud data

How many parameters are needed to define a plane in 3D?



# Voting Algorithms for Model Fitting - Conclusions

A family of powerful algorithms based on a simple concept

## Advantages

- All points are processed independently, so **the algorithm can cope with occlusions and gaps**
- Voting algorithms are **robust to clutter**, because points not corresponding to any model are unlikely to contribute consistently to any single bin
- Can detect **multiple instances of a model** in a single pass

## Disadvantages

- Only suitable for models with **few parameters**
- Must filter out spurious peaks in hough accumulator
- Quantization of Hough space is tricky