

# Finding lines – part 2

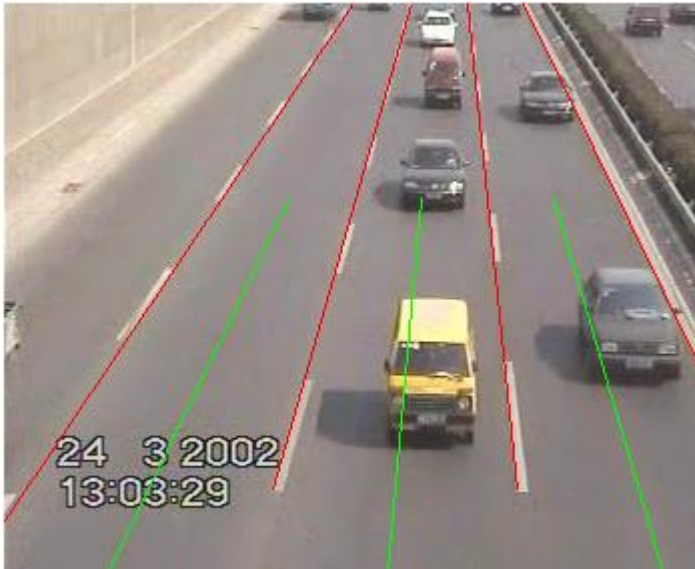
Lihi Zelnik-Manor, Computer Vision

# Today

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- ▶ Edge detection
  - ▶ Canny edge detector
  - ▶ Berkeley edge probability
- ▶ **Line fitting**
  - ▶ Hough transform
  - ▶ (Generalized) Hough transform application
  - ▶ RANSAC

# Fitting a parametric model to data



# parameters
parametric equation
parameters

Image credit Zhaozheng Yin @ wisc.edu

Image credit Yuan-Liang Tang on Mathworks

# Fitting a parametric model to data

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- ▶ **Design questions:**

- ▶ What is a good model to represent our data?
- ▶ Do we plan to fit multiple instances?

- ▶ **Challenges:**

- ▶ Which features belong to the model? To which instance?
- ▶ How many instances are there?
- ▶ Computational complexity (typically we cannot examine all possible models).

# Line fitting applications

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detection of power lines in helicopter navigation systems

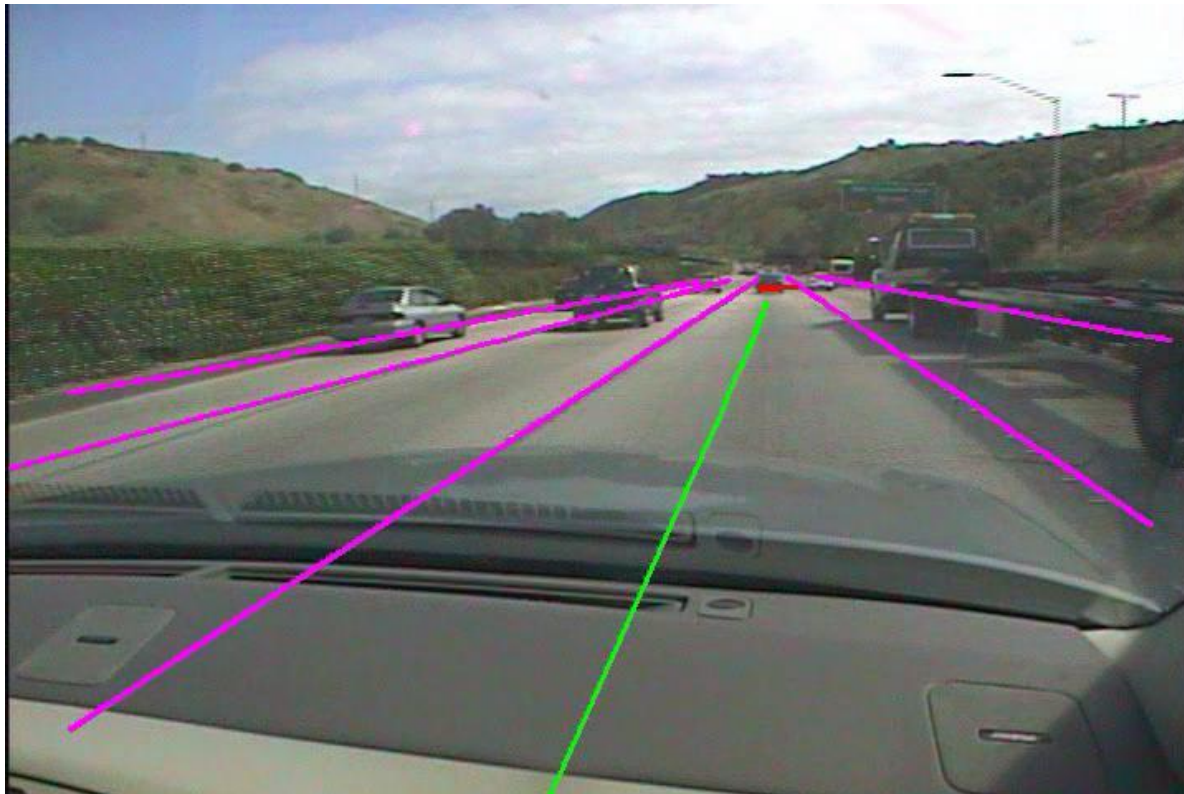


Image credit: Horev et al. SIAM'15

# Line fitting applications

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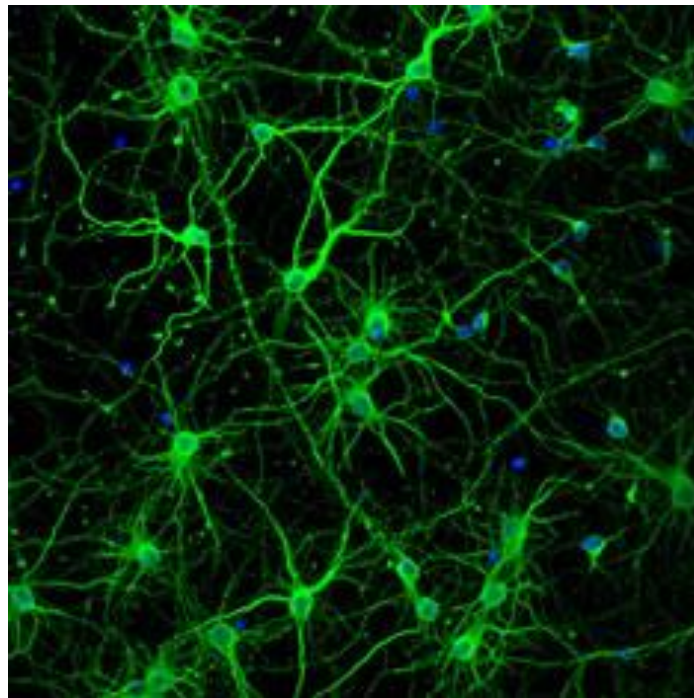
lane detection from car cameras in crashpreventing systems



# Line fitting applications

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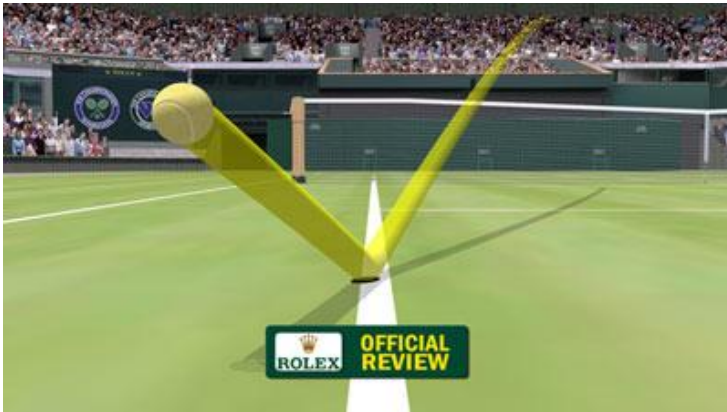
detection of long filaments in high-throughput biological imaging





# Line fitting applications

## Sports

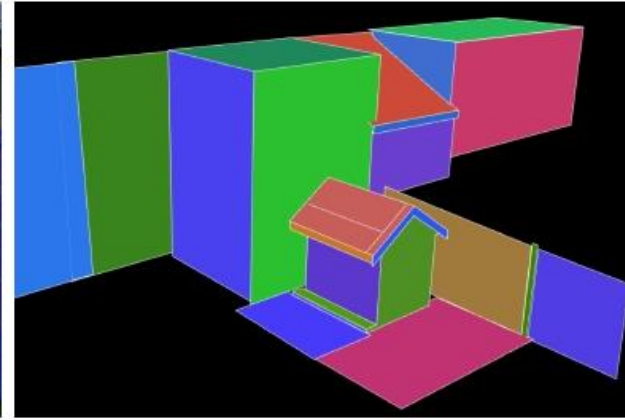




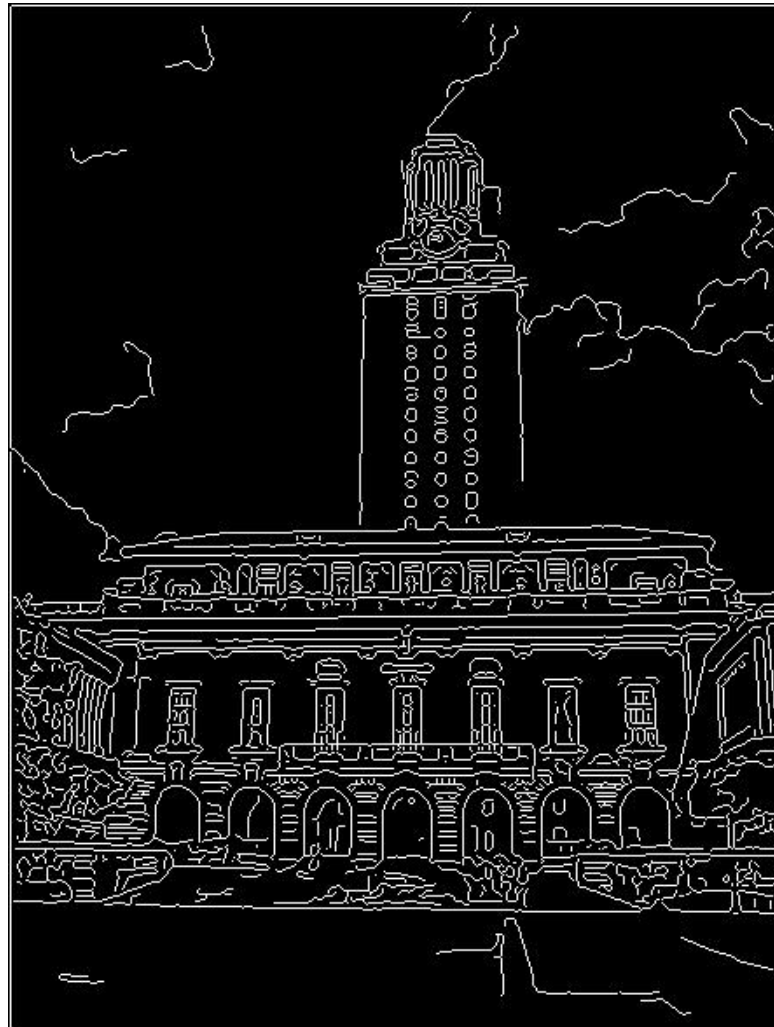
# Line fitting applications

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“Interactive 3D Architectural Modeling from Unordered Photo Collections” Sinha et al. 2008

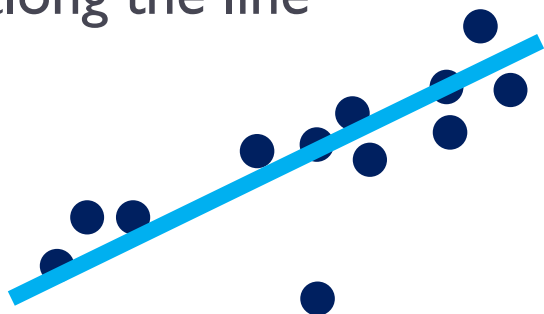


# Challenges of line fitting

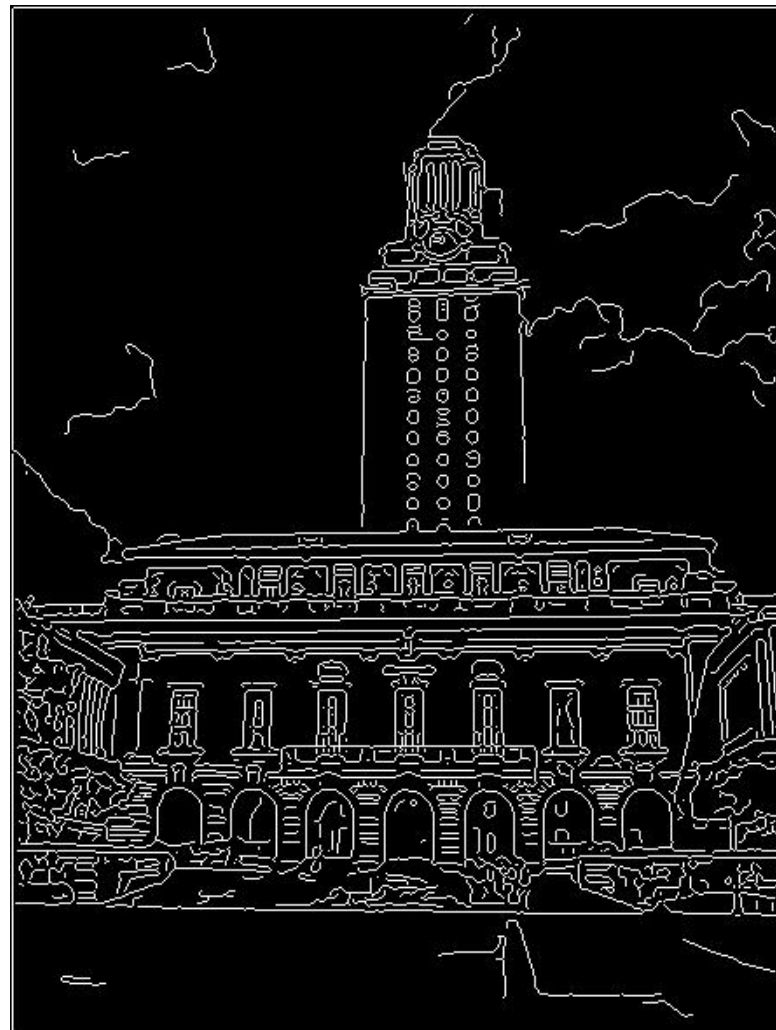


# Challenges of line fitting

- ▶ Which points on which line?
- ▶ Noisy edge detection:
  - ▶ Clutter
  - ▶ Missed parts
  - ▶ Points are only approximately along the line



- ▶ Large search space.
- ▶ How many lines are there?



# Voting

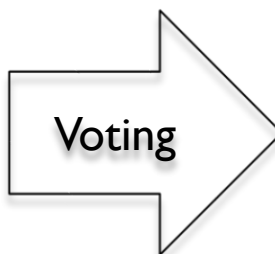
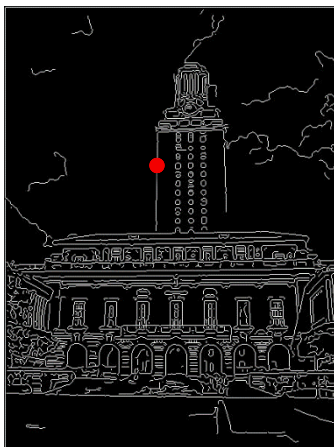
- ▶ **Problem:**

- ▶ We cannot try all possible models

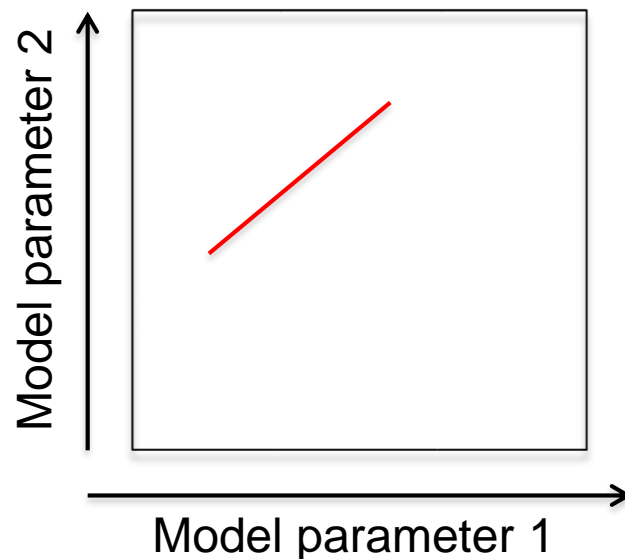
- ▶ **Solution by voting:**

- ▶ Features (points) vote for models they are compatible with
  - ▶ Search for models with lots of votes

feature space



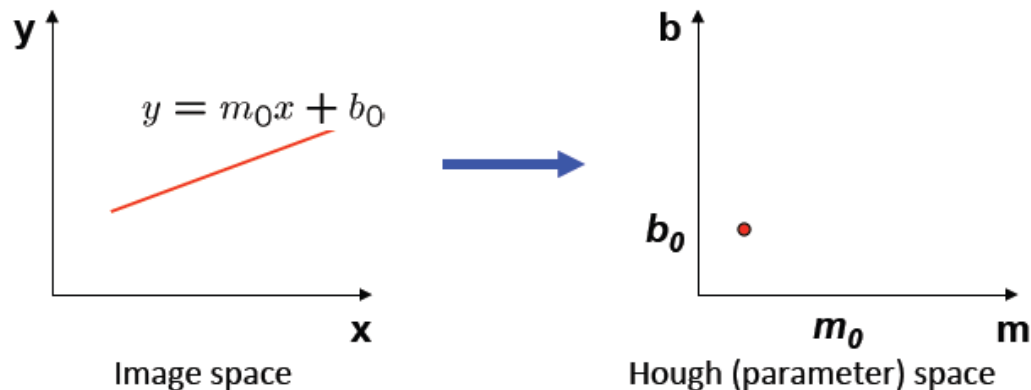
model space



# The Hough transform

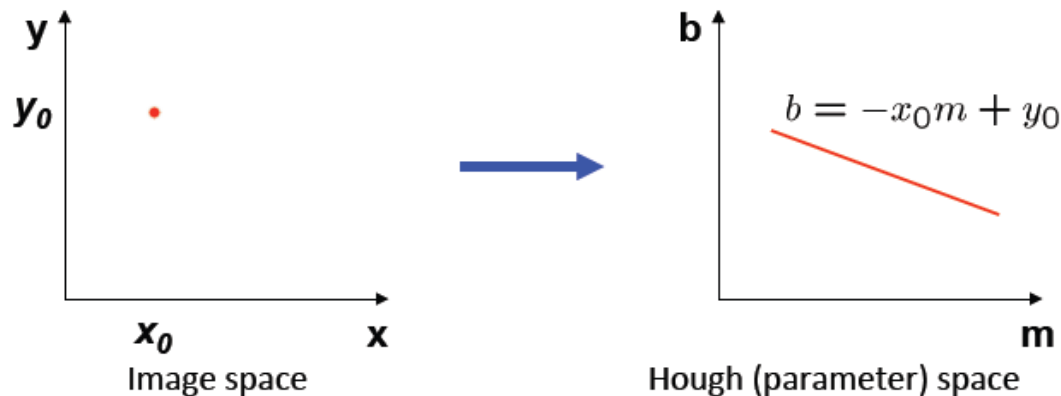
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- ▶ Transformation from image space  $(x, y)$  to Hough space  $(m, b)$
- ▶ A line in the image corresponds to a point in Hough space
  - ▶ Image  $\rightarrow$  Hough:  
Given a set of points  $(x, y)$  find all  $(m, b)$  such that  $y = mx + b$



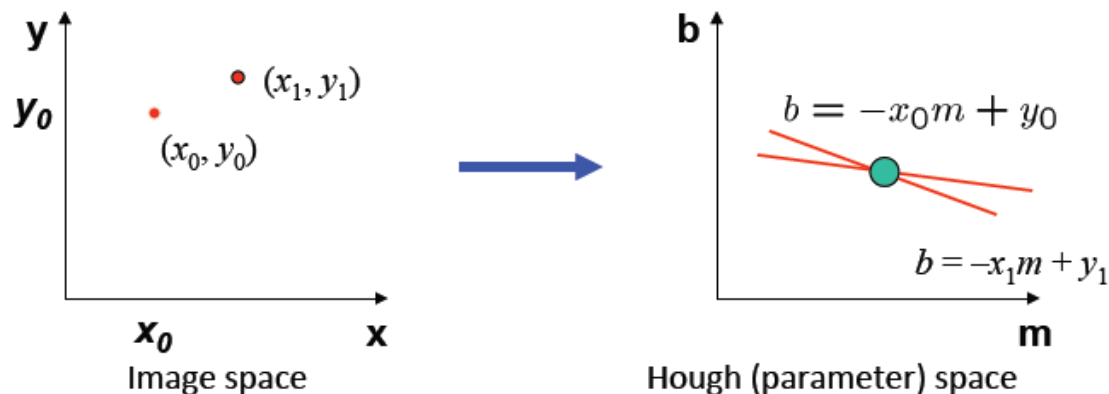
# The Hough transform

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  - ▶ Image  $\rightarrow$  Hough:  
Given a set of points  $(x, y)$  find all  $(m, b)$  such that  $y = mx + b$
  - ▶ Hough  $\rightarrow$  Image:  
A point  $(x_0, y_0)$  in the image is the solution of  $b = -x_0m + y_0$



# The Hough transform

- ▶ Transformation from image space  $(x, y)$  to Hough space  $(m, b)$
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Given a set of points  $(x, y)$  find all  $(m, b)$  such that  $y = mx + b$
  - ▶ Hough  $\rightarrow$  Image:  
A point  $(x_0, y_0)$  in the image is the solution of  $b = -x_0m + y_0$
- ▶ The line that contain both points  $(x_0, y_0)$  and  $(x_1, y_1)$  is the intersection of the lines  $b = -x_0m + y_0$  and  $b = -x_1m + y_1$

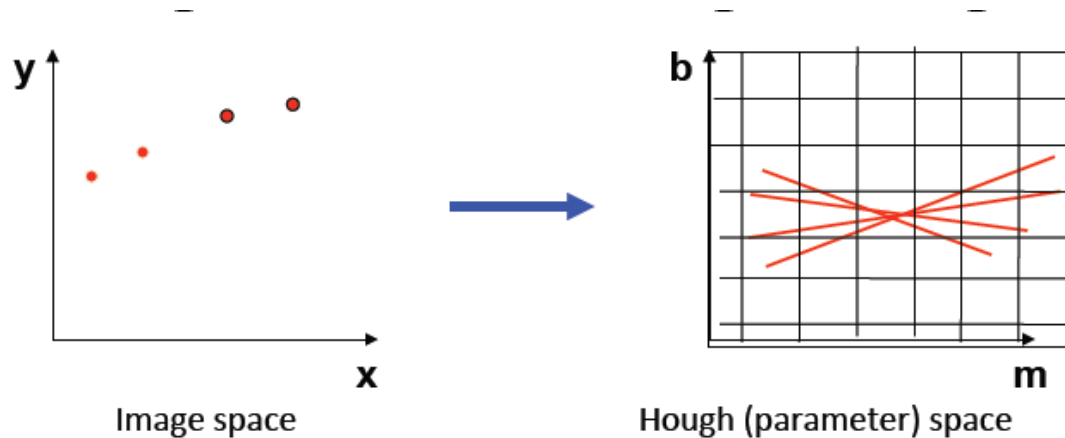




# Finding lines with the Hough transform

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- ▶ Discretize Hough space
- ▶ Each edge point **votes** for all possible parameters in Hough space
- ▶ Parameters with lots of votes indicate lines in image space



# Polar representation for lines

## ► Problem:

The familiar line equation  $y = mx + b$  is problematic:

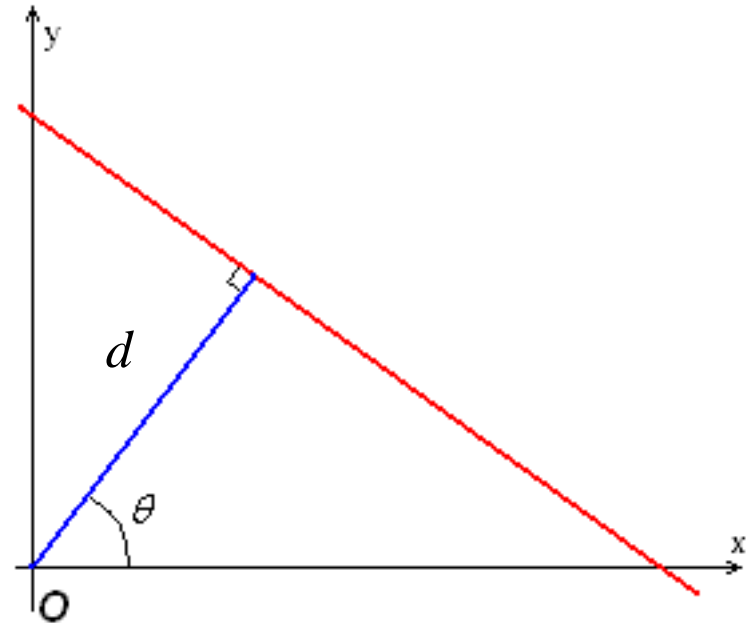
- Can take infinite values
- Undefined for vertical lines

## ► Solution:

Use polar representation

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

$$\theta \in [0, \pi), \quad d \in \mathbb{R}$$



# The Hough-transform algorithm

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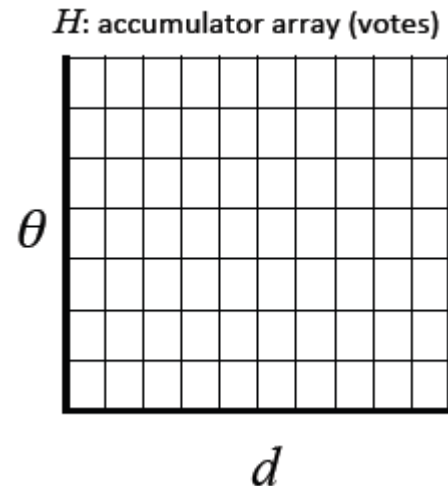
- ▶ Use polar representation

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

- ▶ Quantize Hough space

- ▶ Loop:

1. Initialize  $H[d, \theta] = 0$
2. For each edge point  $(x, y)$  in the image  $H[d, \theta] += 1$  for all lines that go through it
3. Find bins  $H[d, \theta]$  with maximum value

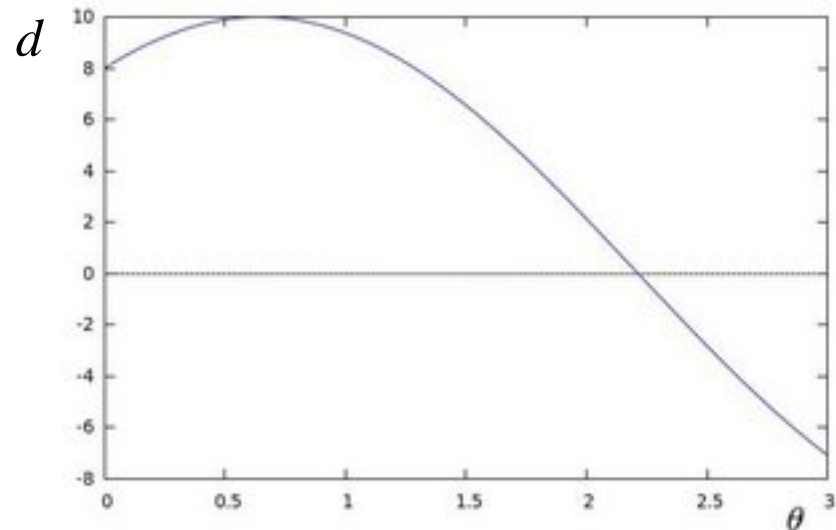
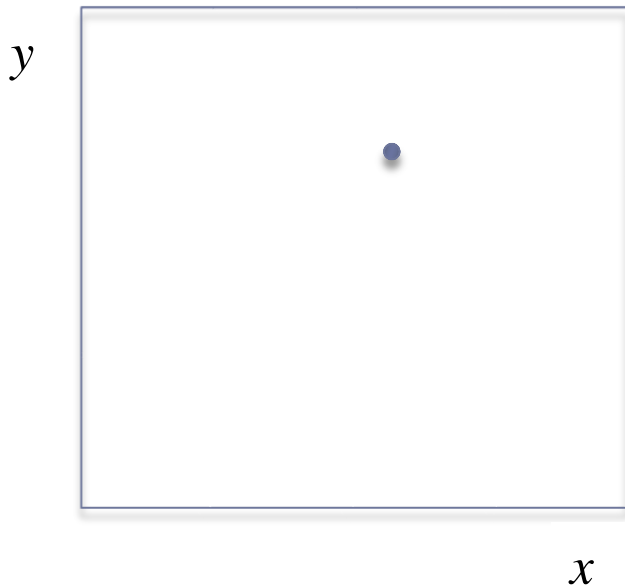


# Example

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For a given point  $(x_0, y_0)$

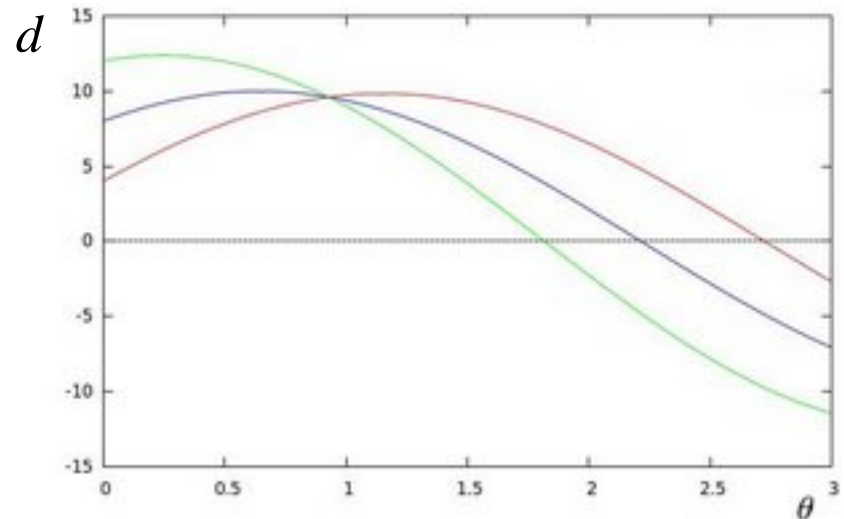
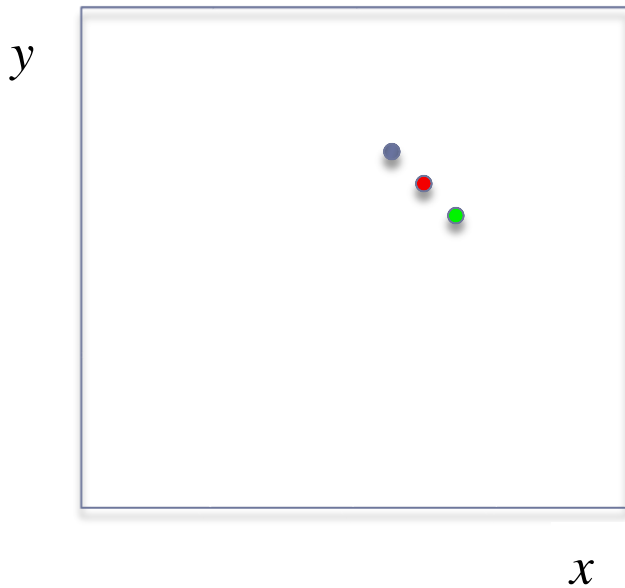
$$d(q) = x_0 \cos q + y_0 \sin q$$



# Example

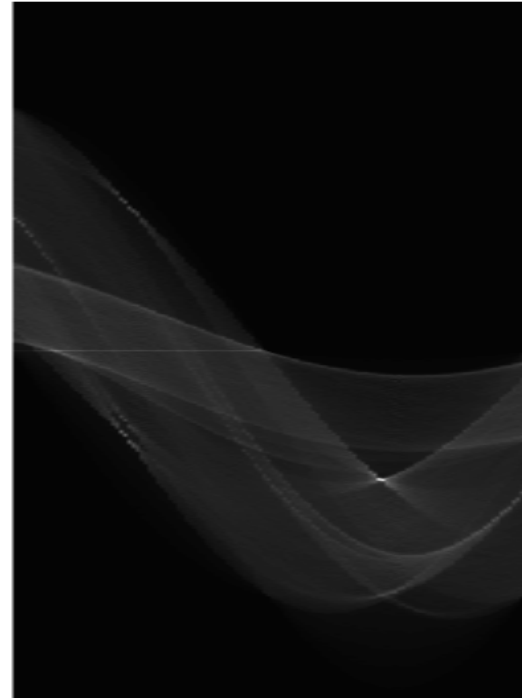
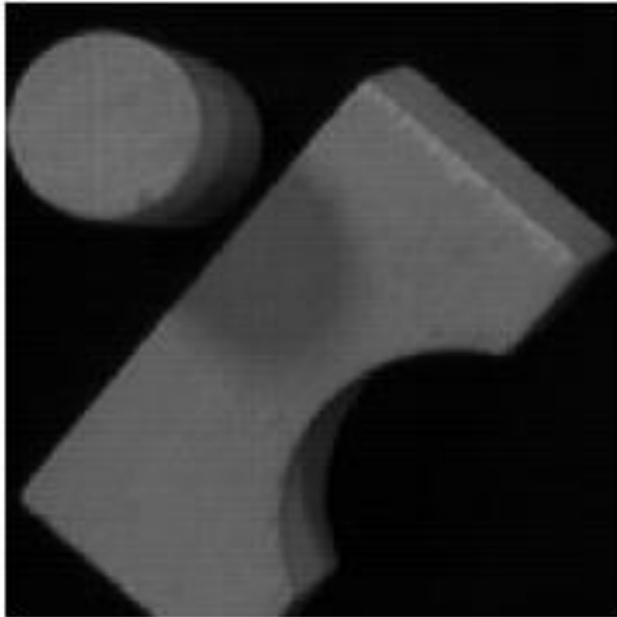
For a given point  $(x_0, y_0)$

$$d(q) = x_0 \cos q + y_0 \sin q$$



# Example: an image with straight lines

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# Properties

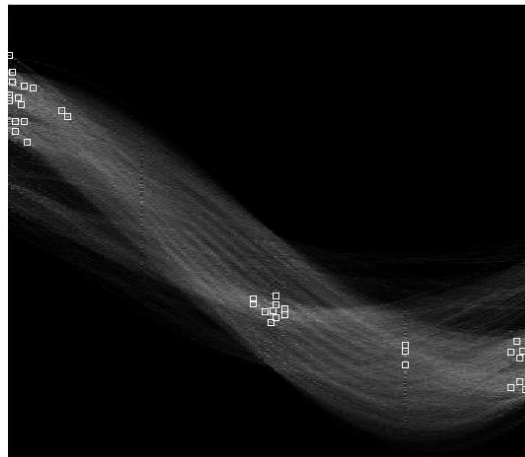
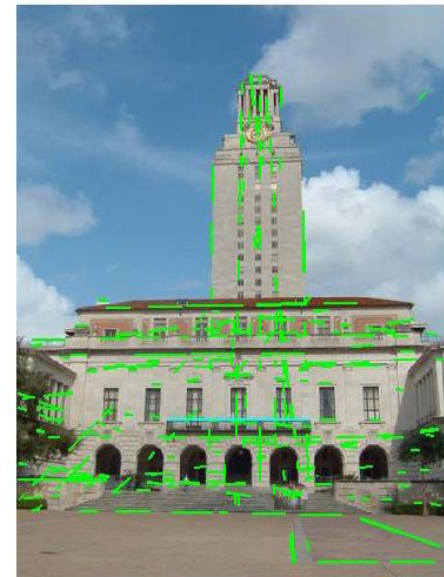
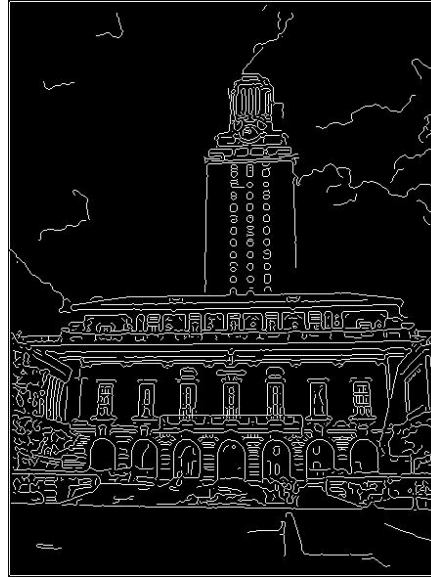
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- ▶ Noise and clutter votes are inconsistent, so will not accumulate.
- ▶ Can handle occlusions if not all points are present as long as model gets enough votes.
- ▶ Efficient.

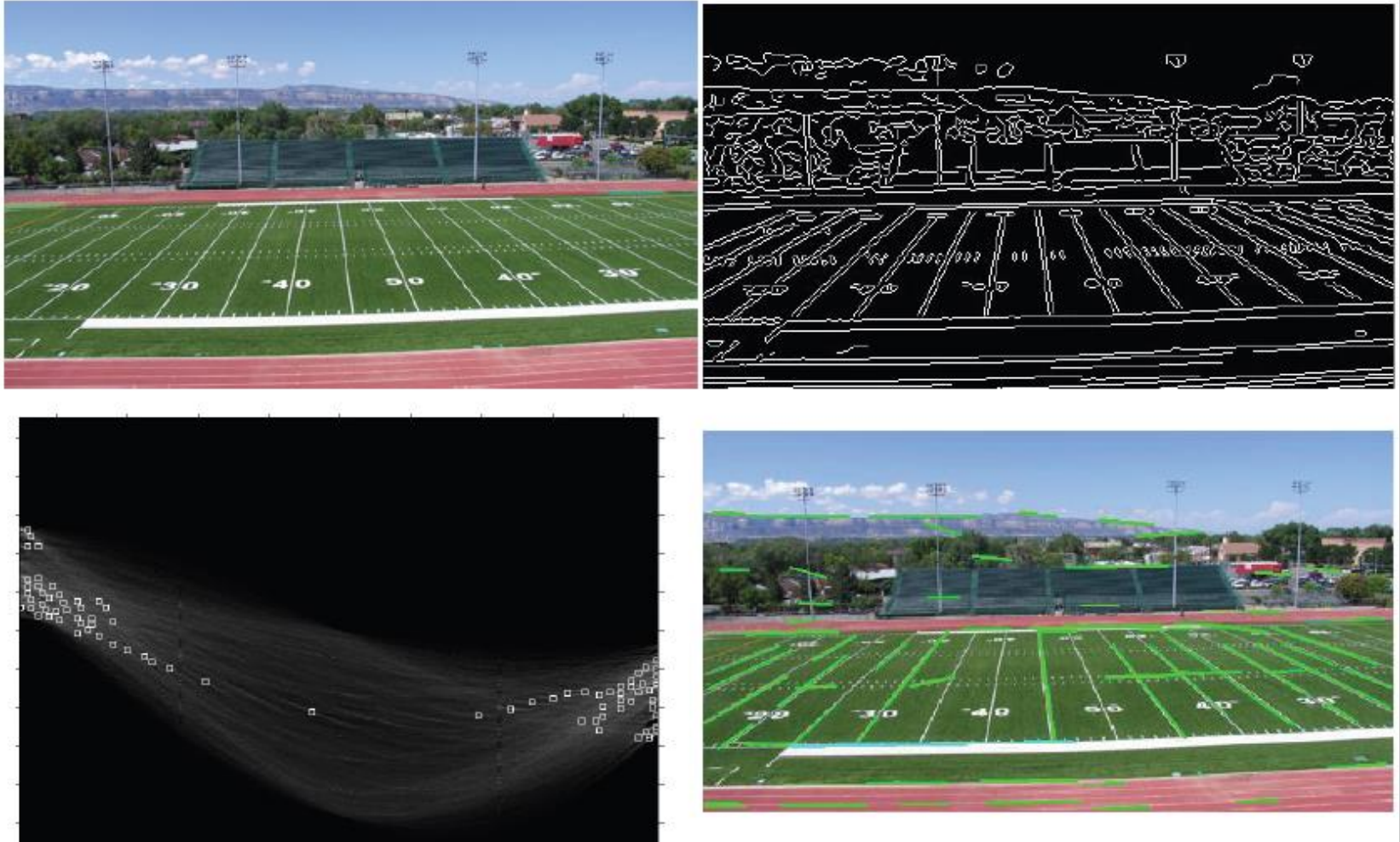


# Example: a real image

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# Example: a real image

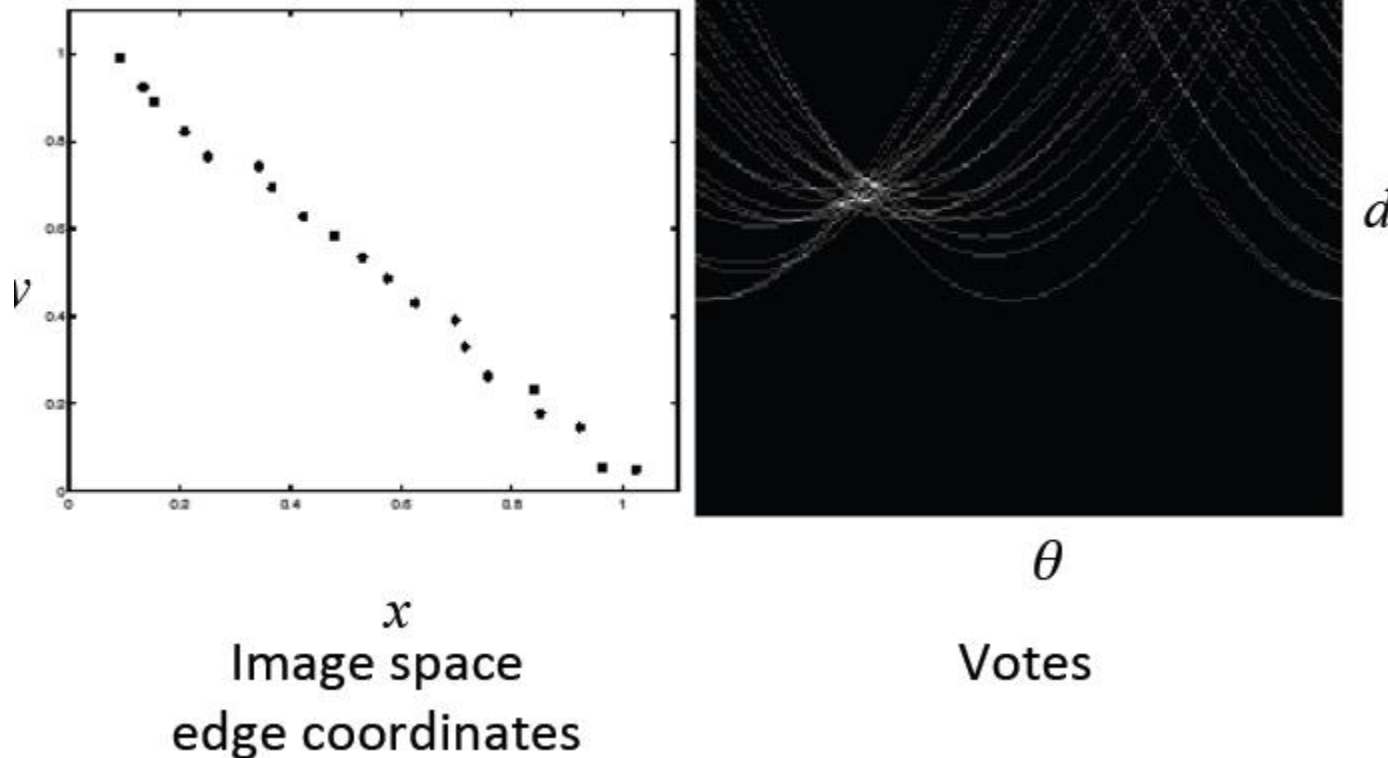


Showing longest segments found

# Impact of noise on Hough transform

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- What difficulties does noise introduce?



# Impact of noise on Hough transform

- ▶ Here everything is “noise” but we still see peaks in the vote space

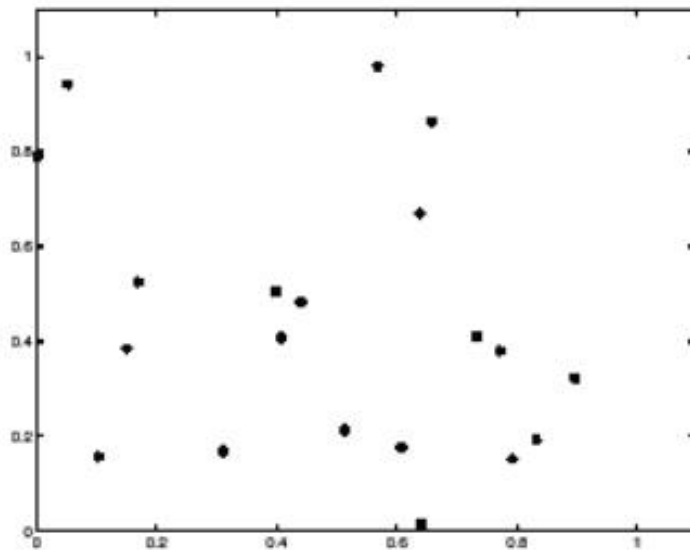
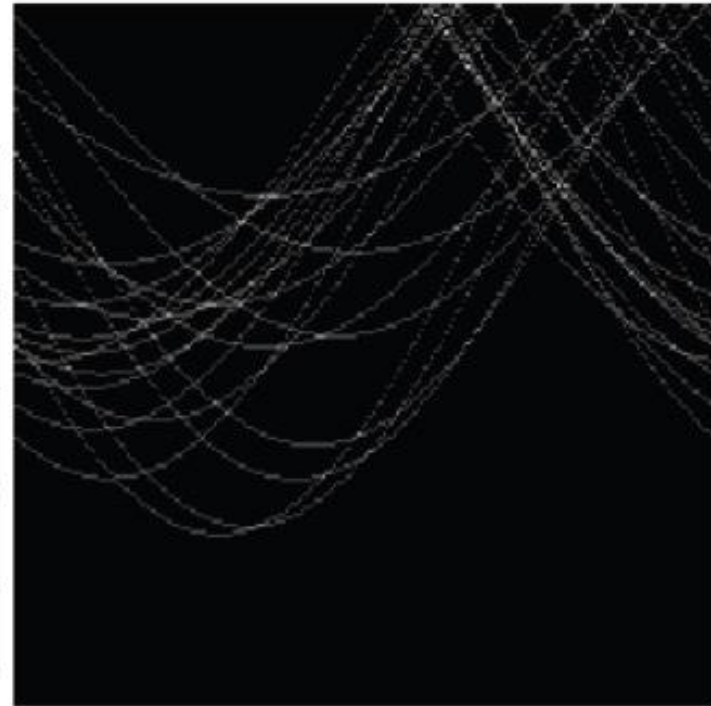


Image space  
edge coordinates



Votes

# Voting: Practical tips

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- ▶ Use only trustworthy points
  - ▶ E.g., edges points with significant gradient magnitude (alternatively weight votes)
  - ▶ Szeliski suggests using edgels instead of points
- ▶ Choose a good quantization grid
  - ▶ Not too coarse – too many lines fall in the same bucket
  - ▶ Not too fine – collinear points vote for different lines
- ▶ Smooth the voting (vote also for neighbors)
- ▶ Non-maxima suppression
- ▶ Refit line using accumulated votes
- ▶ Reduce number of parameters, if possible

# Hough transform summary

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## ▶ Pros

- ▶ Can handle occlusions
- ▶ Some robustness to noise
- ▶ Can detect multiple lines in a single pass over the image

## ▶ Cons

- ▶ Clutter can produce spurious peaks in parameter space
- ▶ Hard to select the right quantization

# Generalized Hough Transform

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- ▶ Can be extended to other parametric models such as: circles, ellipses, rectangles etc.
- ▶ Complexity increases exponentially with the number of parameters.
- ▶ Can be used to detect complex non-parametric models as described in Leibe et al. “Combined object categorization and segmentation with an implicit shape model”.



# Today

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- ▶ Edge detection
  - ▶ Canny edge detector
  - ▶ Berkeley edge probability
- ▶ Line fitting
  - ▶ Hough transform
  - ▶ **RANSAC**



# RANdom SAmples Consensus [Fischler & Bolles 1981]

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- ▶ Key ideas:

- ▶ Look for “inliers” and use only them
- ▶ If we fit a model to “outliers” we will not get a good fitting

# RANSAC algorithm

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Loop:

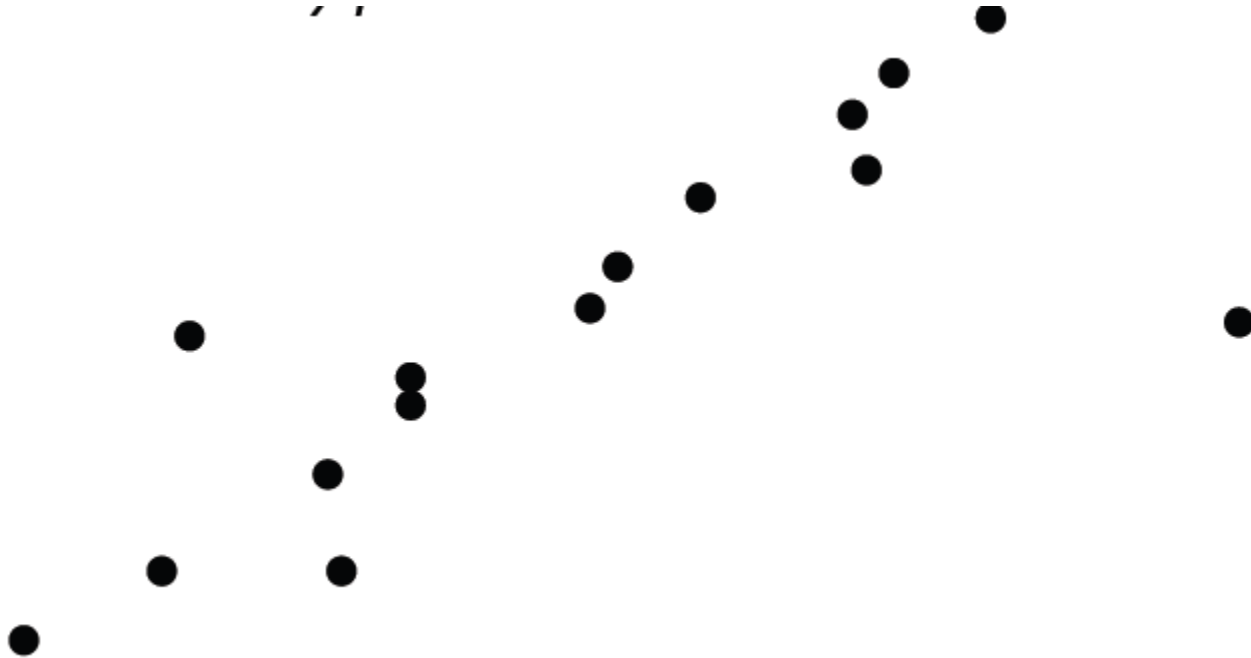
1. Randomly select a group of points
2. Fit a model to the selected group
3. Find the inliers of the computed model
4. If number of inliers is large enough re-compute model using only inliers
5. Compute number of inliers of updated model

The winner: model with the largest number of inlier

# Line fitting with RANSAC

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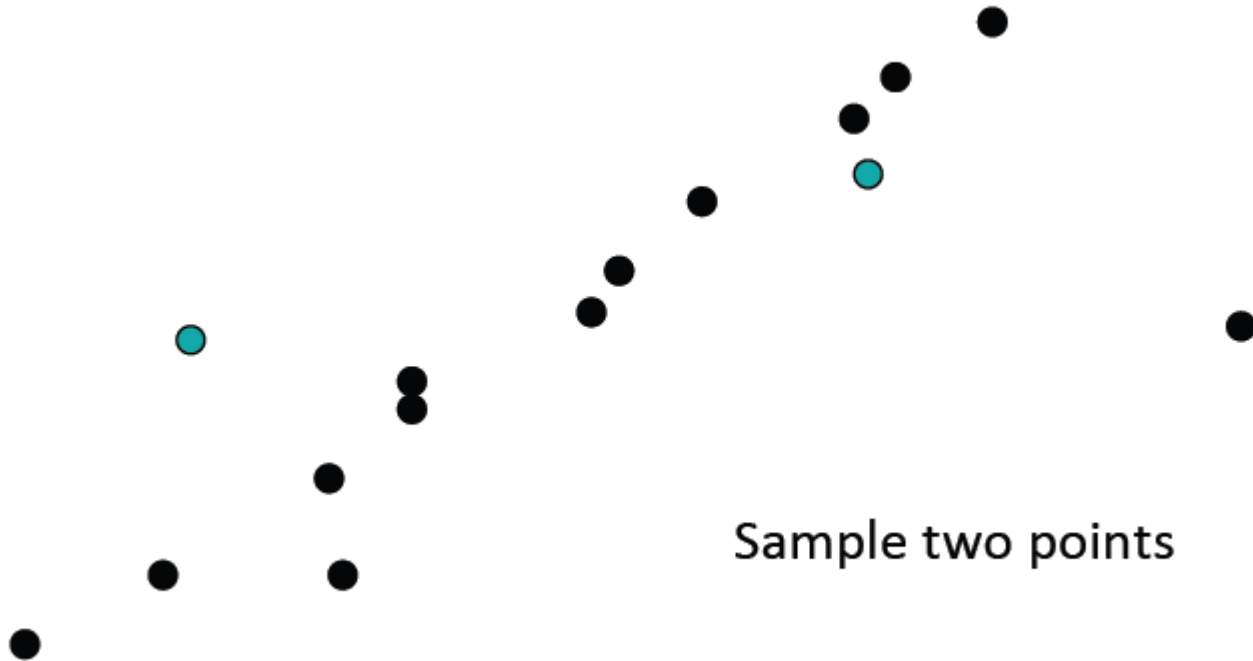
- ▶ Input:  
A set of edge points



# Line fitting with RANSAC

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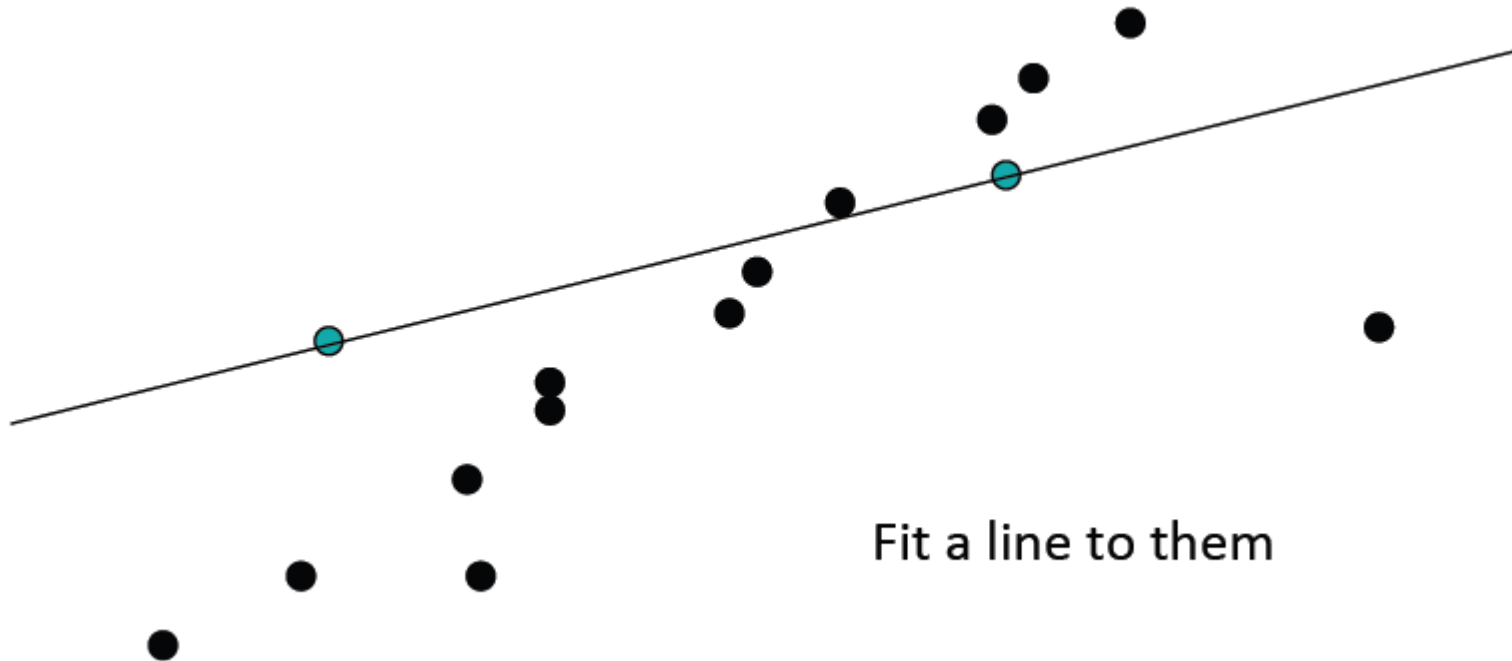
- ▶ Step 1:  
Select two points



# Line fitting with RANSAC

- ▶ Step 2:  
Fit a line to the selected points

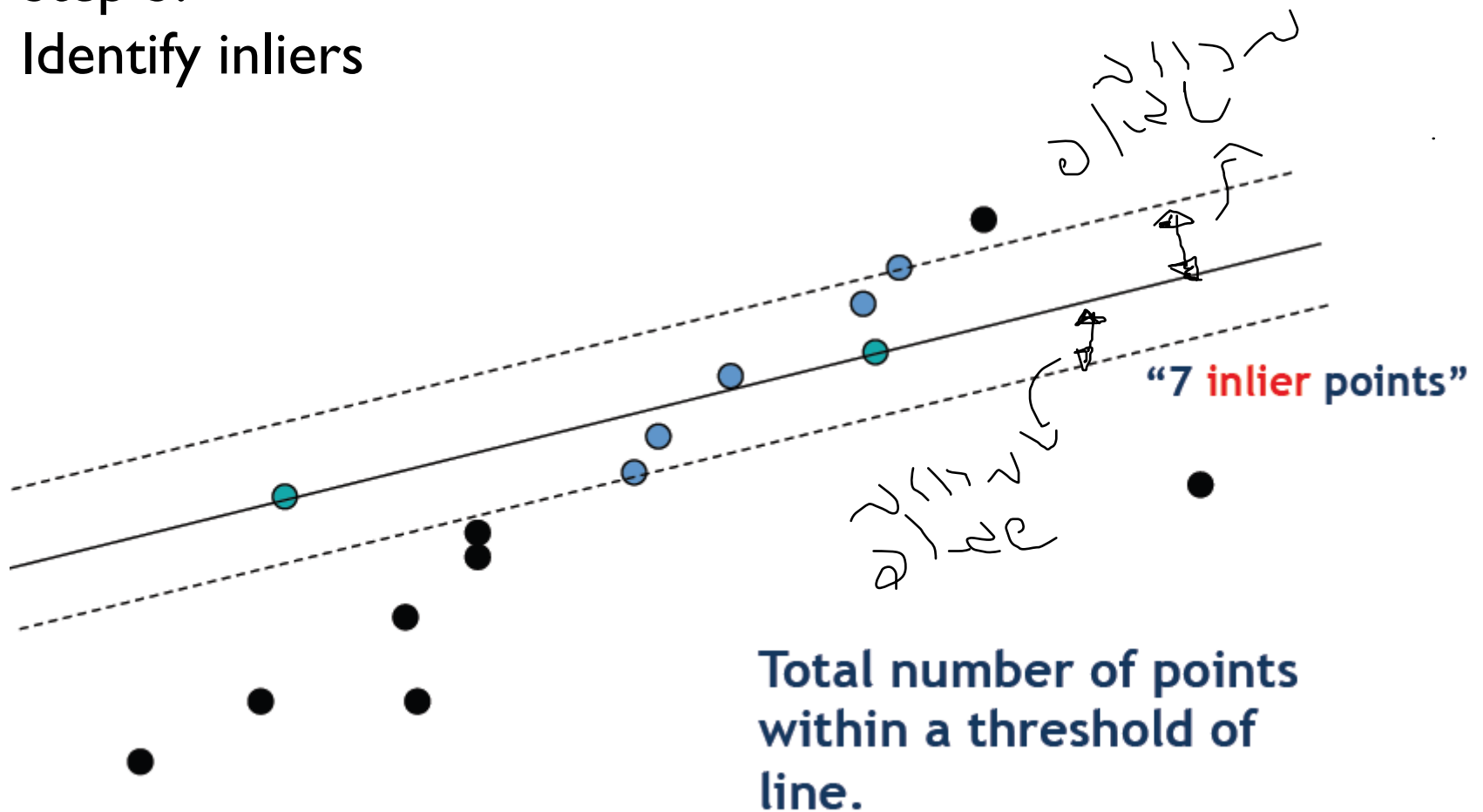
הנקודות  
הבחירה



Fit a line to them

# Line fitting with RANSAC

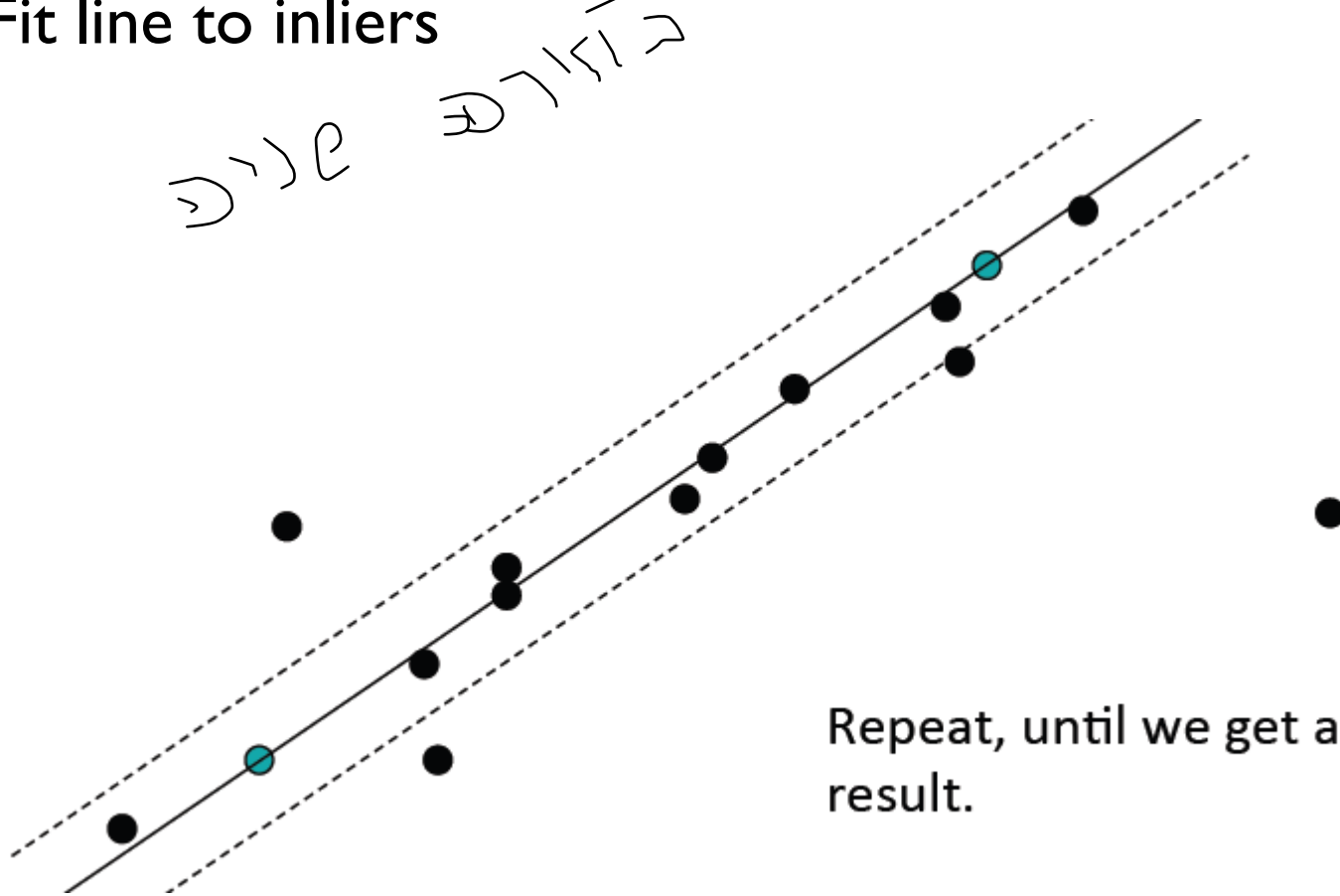
- Step 3:  
Identify inliers





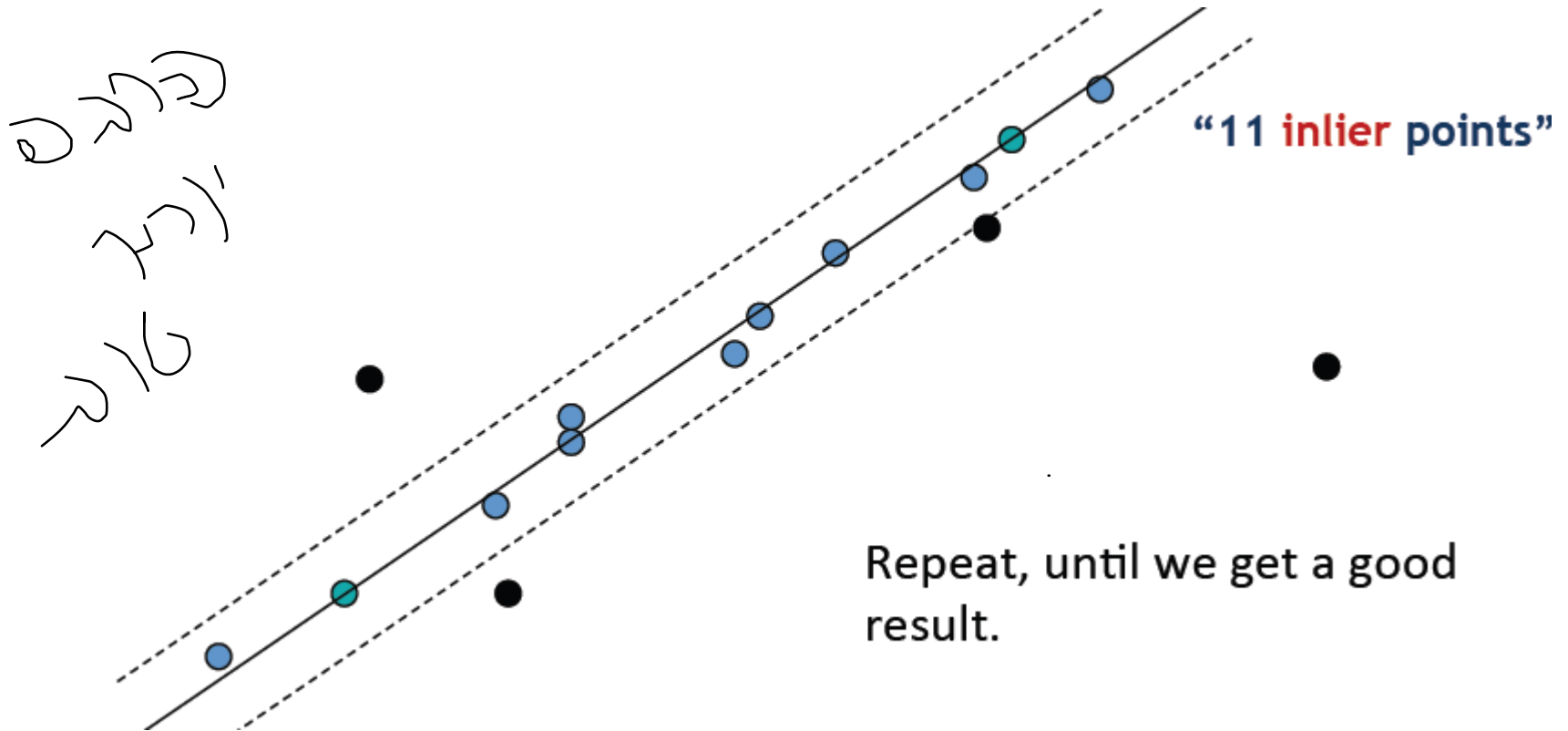
# Line fitting with RANSAC

- ▶ Step 4:  
Fit line to inliers



# Line fitting with RANSAC

- Step 5:  
Count number of new inliers



# RANSAC – stopping criteria

- ▶ Option 1: when the model is good enough:

- ▶ By number of inliers
- ▶ By fitting error

- ▶ Option 2: according to probability

- ▶ Let  $K$  be the number of iterations
- ▶ Let  $n$  be the number of points needed to compute the model
- ▶ Let  $f$  be the fraction of inliers of a model
- ▶ Then the probability that a single sample is correct:  $f^n$
- ▶ The probability that all  $K$  samples fail is  $(1 - f^n)^K$
- ▶ Choose  $K$  high enough to keep the failure rate low enough

מספר הנקודות שצריך כדי לחשב את המודל  
במקרה של קו ישר 2

הסתברות של אנלייזר בתוך המודל הנכון

אפשר לעצור לפי אחוז מסויים של אנלייזרים מתוך ס"כ הנקודות

כאשר  $K=20$ ,  $f=0.5$

$K=20$

# RANSAC – for multiple models?

## ► How can we use RANSAC to compute multiple models?

עובדת די טוב, קל למימוש

חסרון, כאשר אחוז האוטלייר מאד גבוהה וזה  
TIME CONSUMING

איך לחשב מספר מודלים, למשל לא ידע אם המודל שלי הוא קוו ישר או מעגל, לכן אפשר לנסות ... מקוון שאני לא ידע אז אני צריך להגדיר מספר מודלים שאני מאמין שהם נכונים למשל אקספ, קוו ישר או מעגל

לכן בכל פעם שאני מריץ את ה

RANSAC

אני בוחר במספר הנקודות המנימלי שמתאים לכל המודלים

למשל אם אני רוצה לדעת אם זה קוו או עגול אז אני אבחר 3 נקודות  
ואז על 3 נקודות האלה אגדיר מודל עגול ומודל קוו

אחד יהיה המנצח, הנצחון לפי מה שהגדרנו למעלה

הנקודות עם

DATAPOINTS

נשתמש ברנסאק למצוא מודל מתאים בין שתי תמונות שאחת עברה טרנספורמציה לעומת השניה

למשל תמונה שעברה הזזה ביחס לשניה, ואני רוצה לדעת מה הזזה הזאת  
למשל אני בוחר מודל הזזה, למשל הזזה של 20 פיקסלים, ומריצים את האלגוריתם

אם הזזה לא 20, ננסה יותר

זה נקבע לפי האנליירים, וגם לפי מה שהגדרנו למעלה

# RANSAC - summary

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## ▶ Pros

- ▶ General method that works well for lots of model fitting problems
- ▶ Easy to implement

## ▶ Cons

- ▶ When the percentage of outliers is high too many iterations are needed and failure rate increases



# End – finding lines



Now you know how it works