THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision

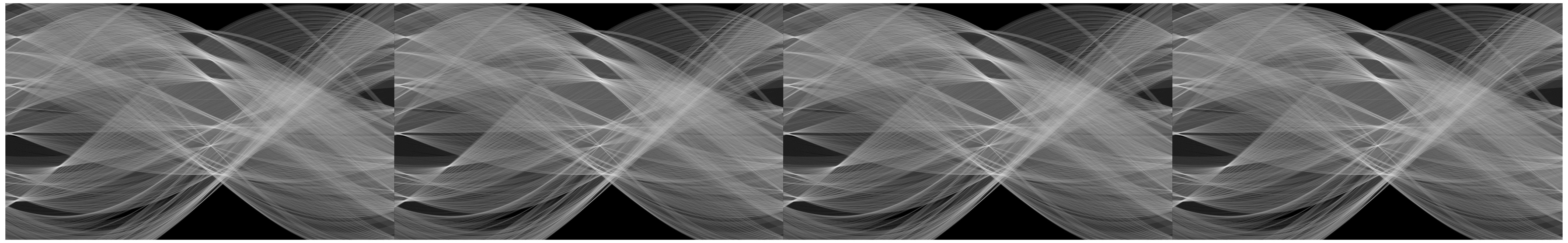


Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

Lecture 15: Hough Transform (cont.)

Menu for Today (**March 5, 2020**)

Topics:

— Hough Transform

— Hough Transform for Object Detection

— Stereo

Redings:

— **Today's** Lecture: Forsyth & Ponce (2nd ed.) 7.1.1, 7.2.1, 7.4, 7.6

— **Next** Lecture: Forsyth & Ponce (2nd ed.) 7.1.1, 7.2.1, 7.4, 7.6

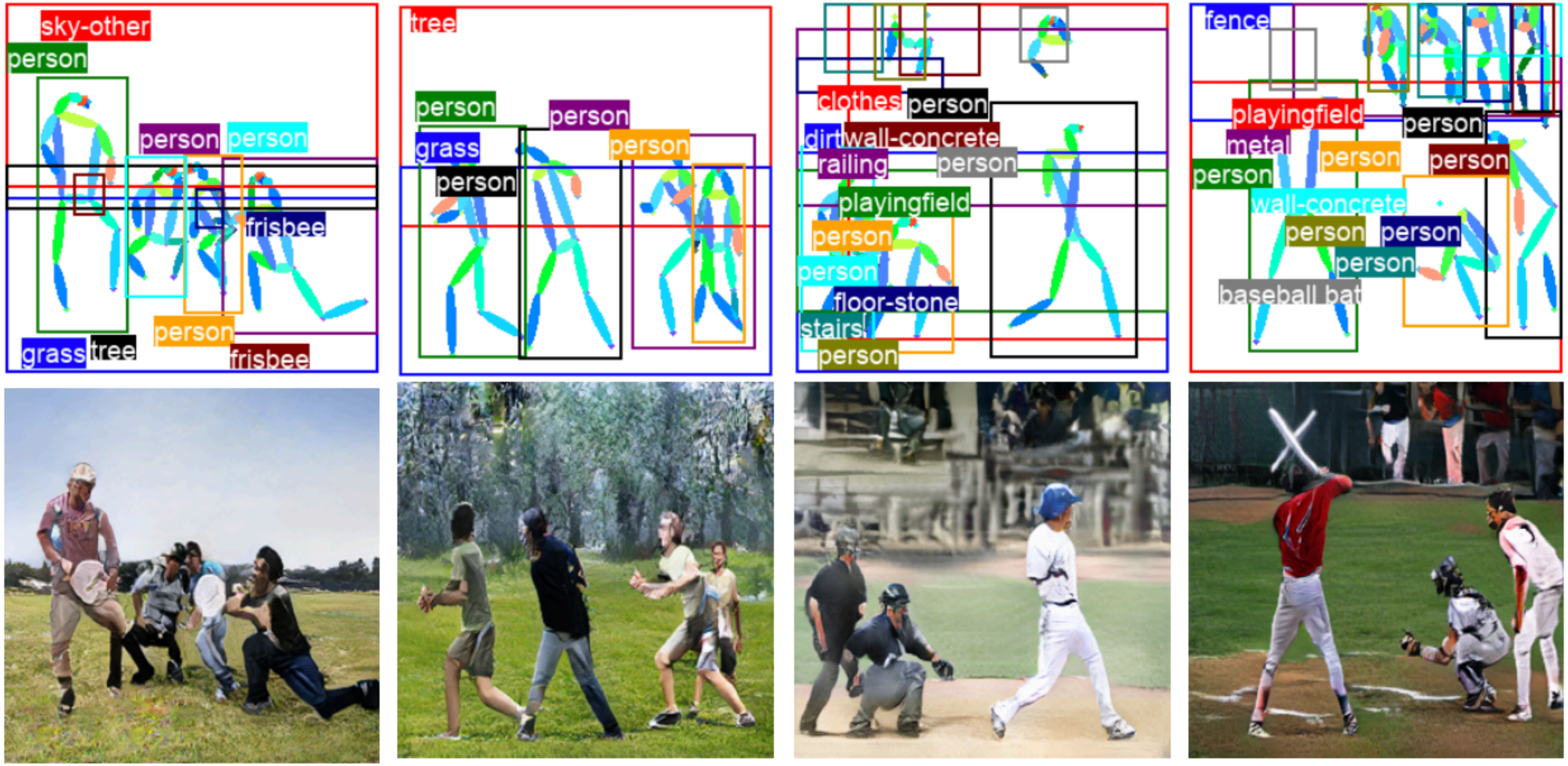
Reminders:

— **Assignment 4**: is out

— Today is **ECCV** deadline (major computer vision conference)

Person-in-Context Synthesis with Compositional Structural Space

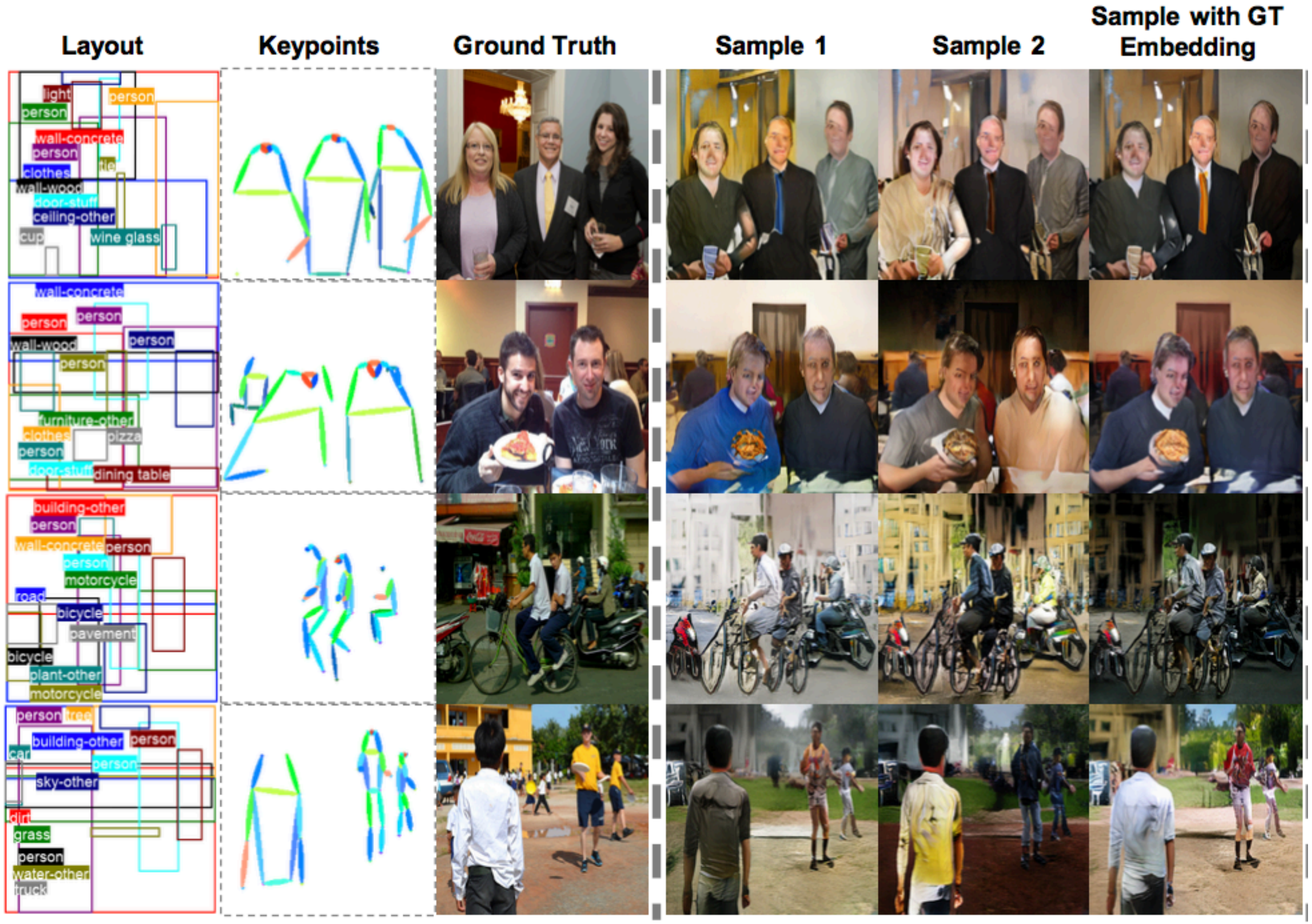
Weidong Yin



Person in Context Synthesis

Person-in-Context Synthesis with Compositional Structural Space

Weidong Yin

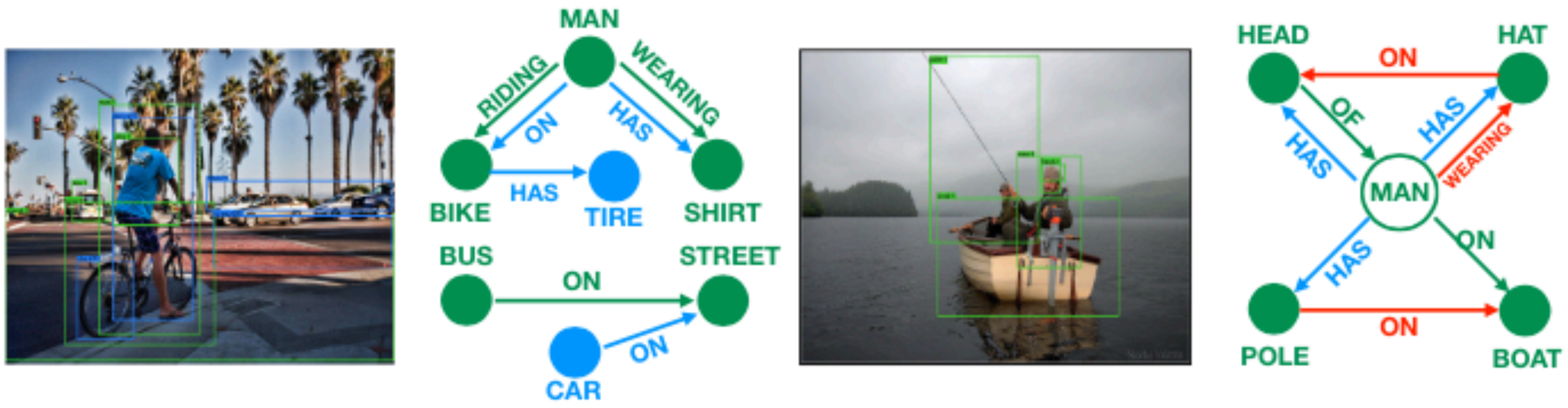


Person-in-Context Synthesis with Compositional Structural Space

Weidong Yin

Living on the Edge: Scene Graph Generation Using Edged Graph Neural Networks

by Suhail Mohammed



Living on the Edge: Scene Graph Generation Using Edged Graph Neural Networks

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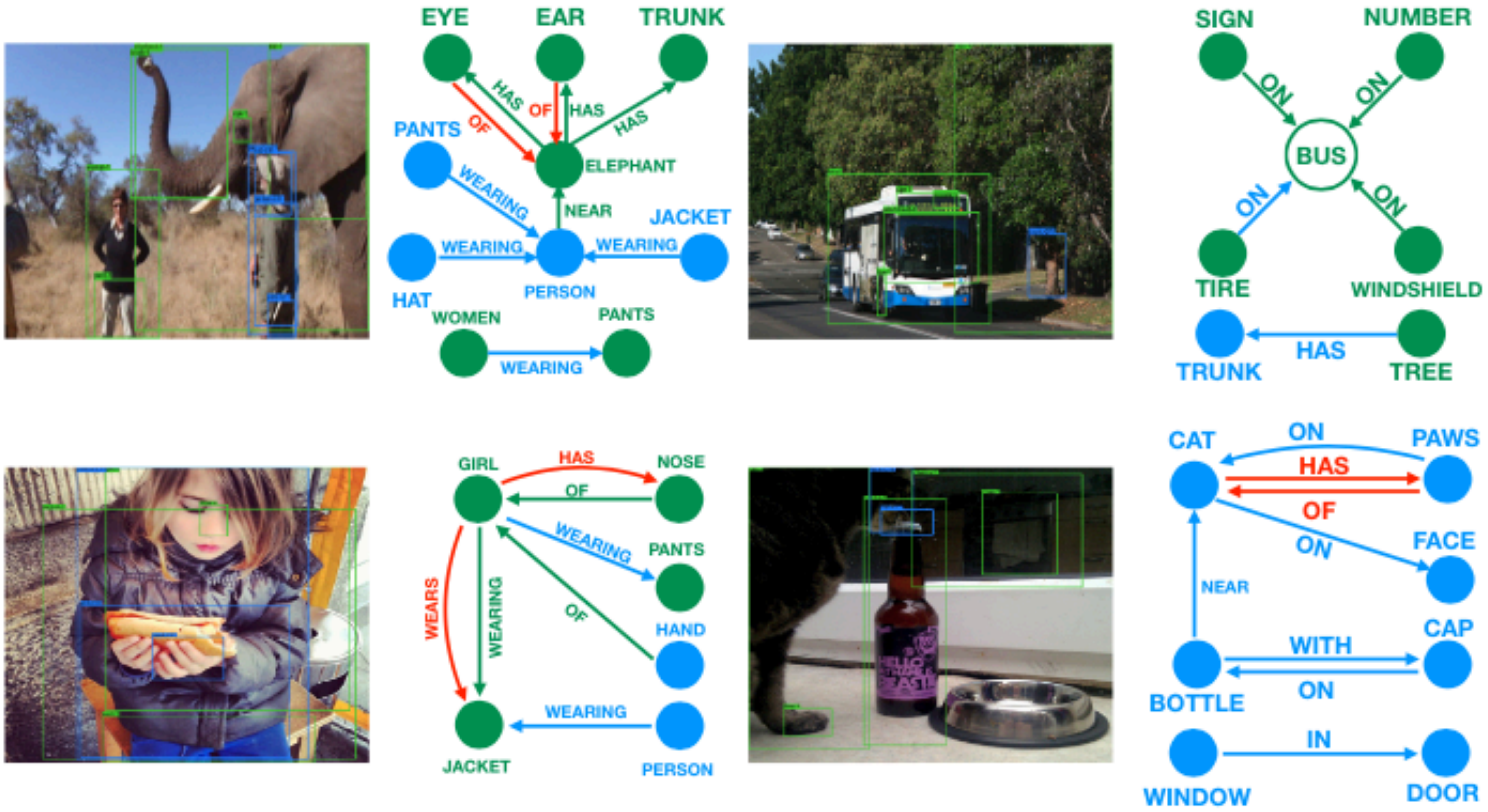


Lecture 14: Re-cap RANSAC

RANSAC is a technique to fit data to a model

— divide data into inliers and outliers

— estimate model from minimal set of inliers

— improve model estimate using all inliers

— alternate fitting with re-classification as inlier/outlier

RANSAC is a general method suited for a wide range of model fitting problems

— easy to implement

— easy to estimate/control failure rate

RANSAC only handles a moderate percentage of outliers without cost blowing up

RANSAC: *k* Samples Chosen (p = 0.99)

Sample size	Proportion of outliers						
n	**5%**	**10%**	**20%**	**25%**	**30%**	**40%**	**50%**
2	2	3	5	6	7	11	17
3	3	4	7	9	11	19	35
4	3	5	9	13	17	34	72
5	4	6	12	17	26	57	146
6	4	7	16	24	37	97	293
7	4	8	20	33	54	163	588
8	5	9	26	44	78	272	1177

Figure Credit: Hartley & Zisserman

Lecture 14: Re-cap Hough Transform

Idea of **Hough transform**:

— For each token vote for all models to which the token could belong

— Return models that get many votes

Example: For each point, vote for all lines that could pass through it; the true lines will pass through many points and so receive many votes

Hough Transform: Lines

variables

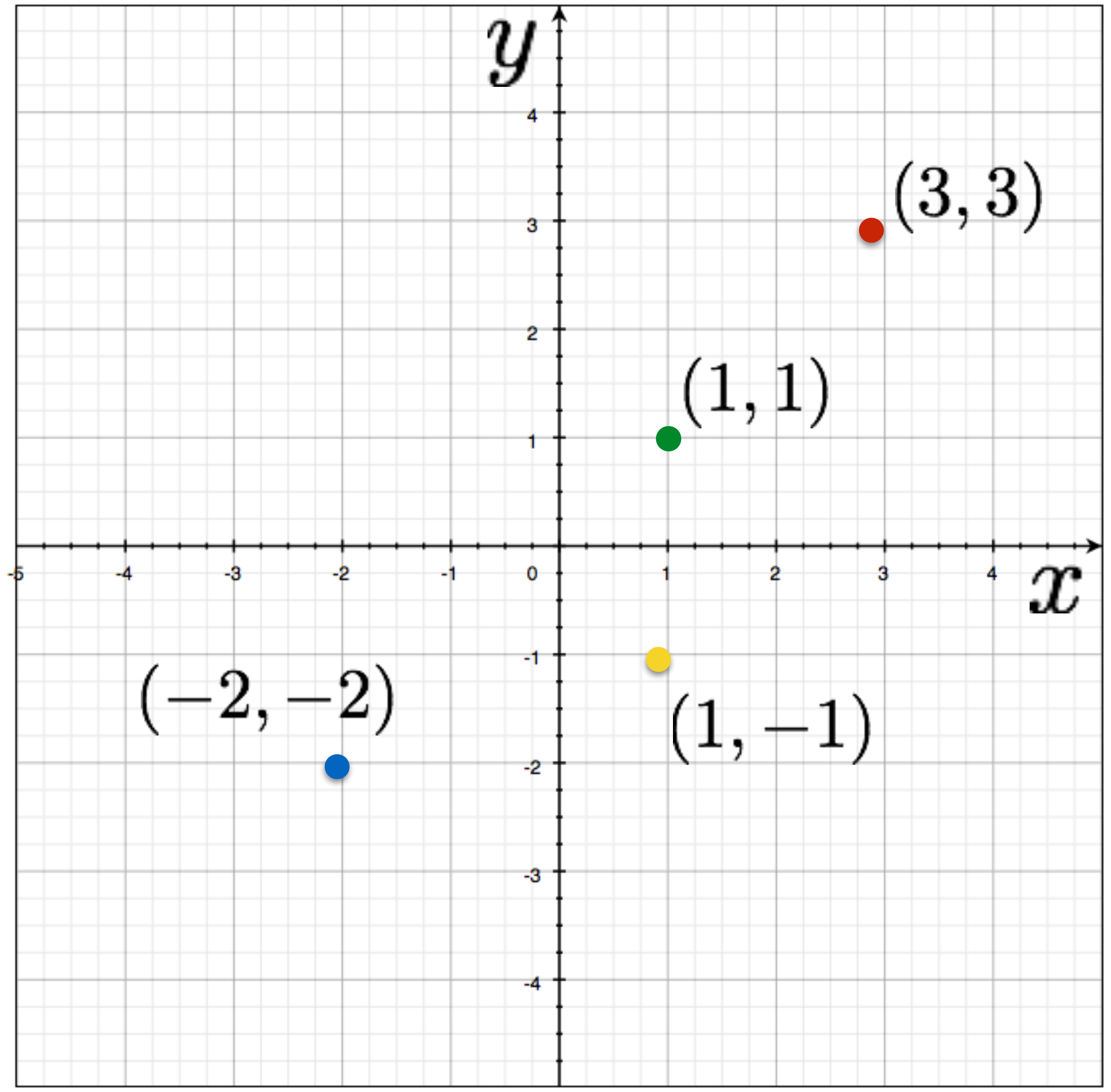
$$y = mx + b$$

parameters

parameters

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

variables



four points become?

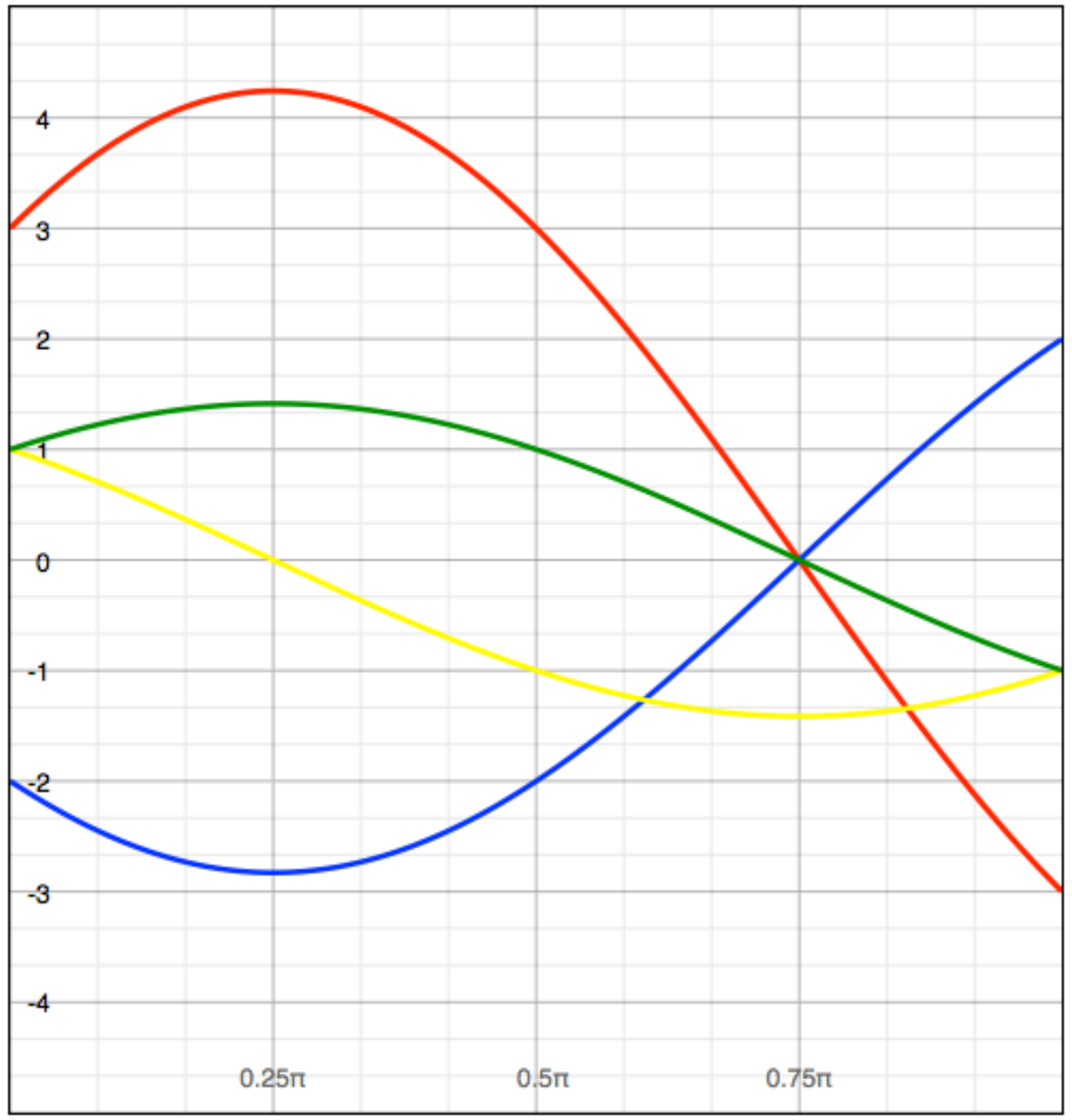


Image space

Parameter space

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Hough Transform for Lines (switching to books notation)

Idea: Each point votes for the lines that pass through it

— A line is the set of points, (x, y), such that

$$x \sin\theta + y \cos\theta + r = 0$$

— Different choices of θ, r give different lines

Hough Transform for Lines (switching to books notation)

Idea: Each point votes for the lines that pass through it

— A line is the set of points, (x, y), such that

$$x \sin\theta + y \cos\theta + r = 0$$

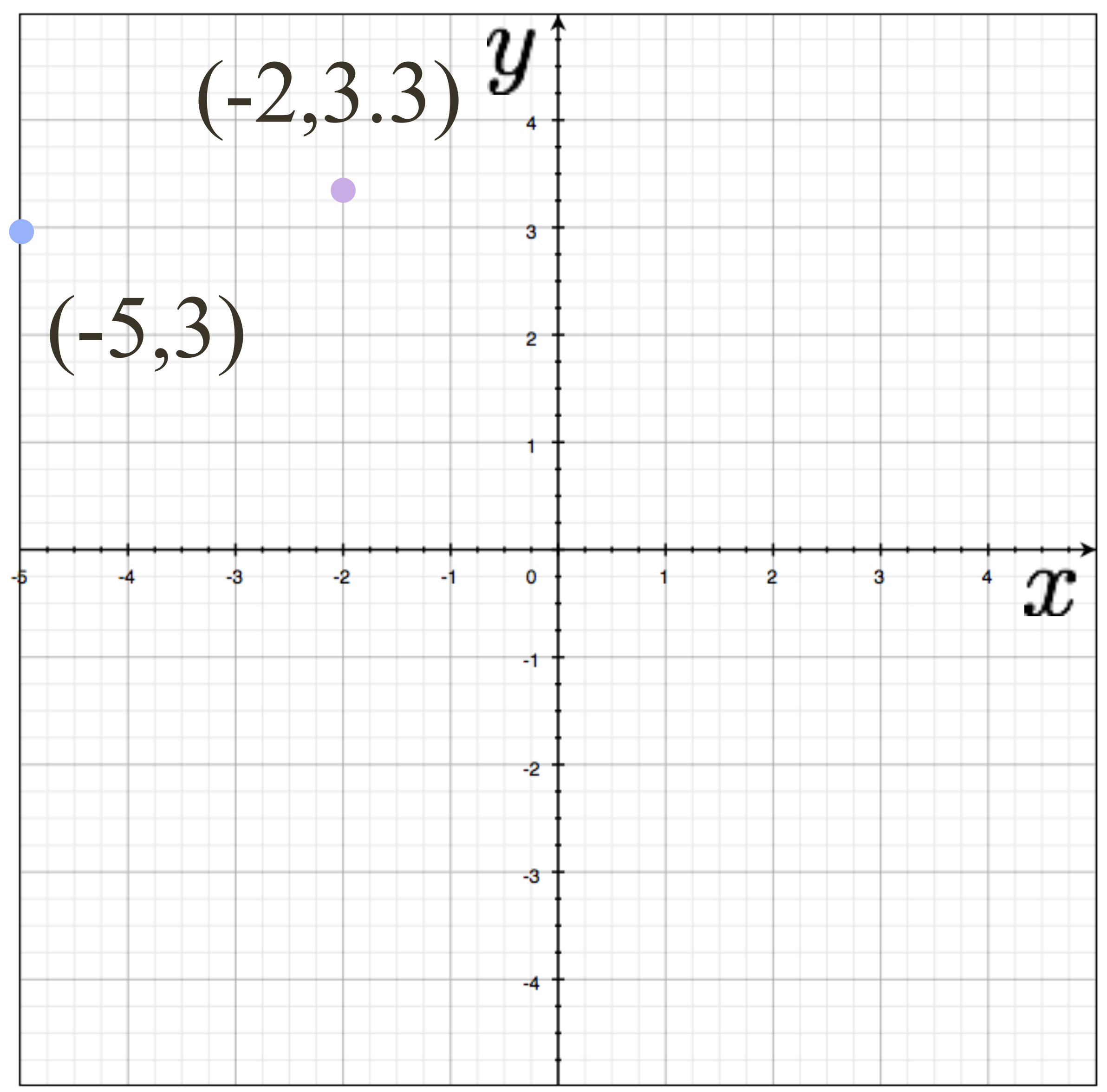
— Different choices of θ, r give different lines

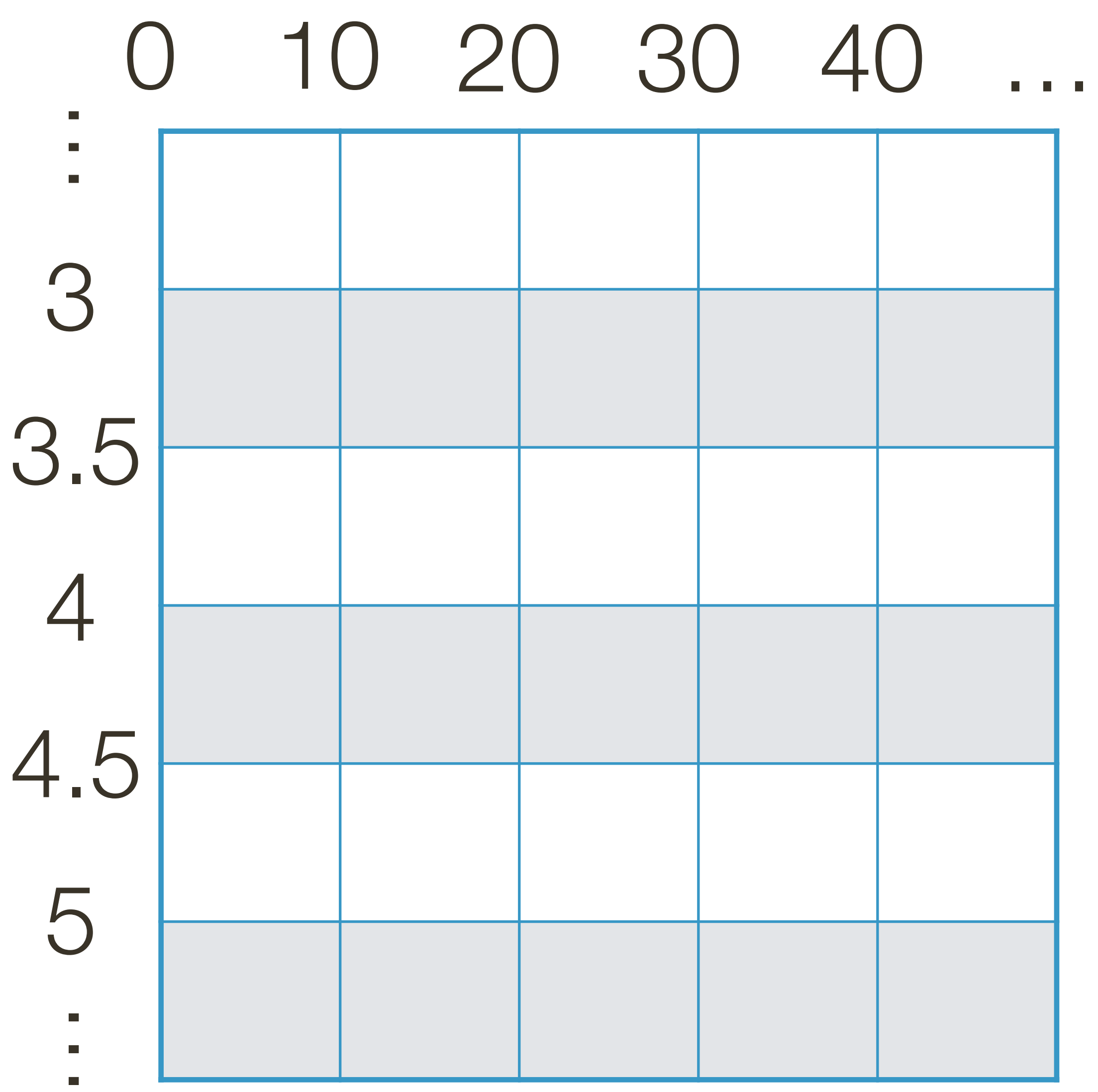
— For any (x, y) there is a one parameter family of lines through this point. Just let (x, y) be constants and for each value of θ the value of r will be determined

— Each point enters votes for each line in the family

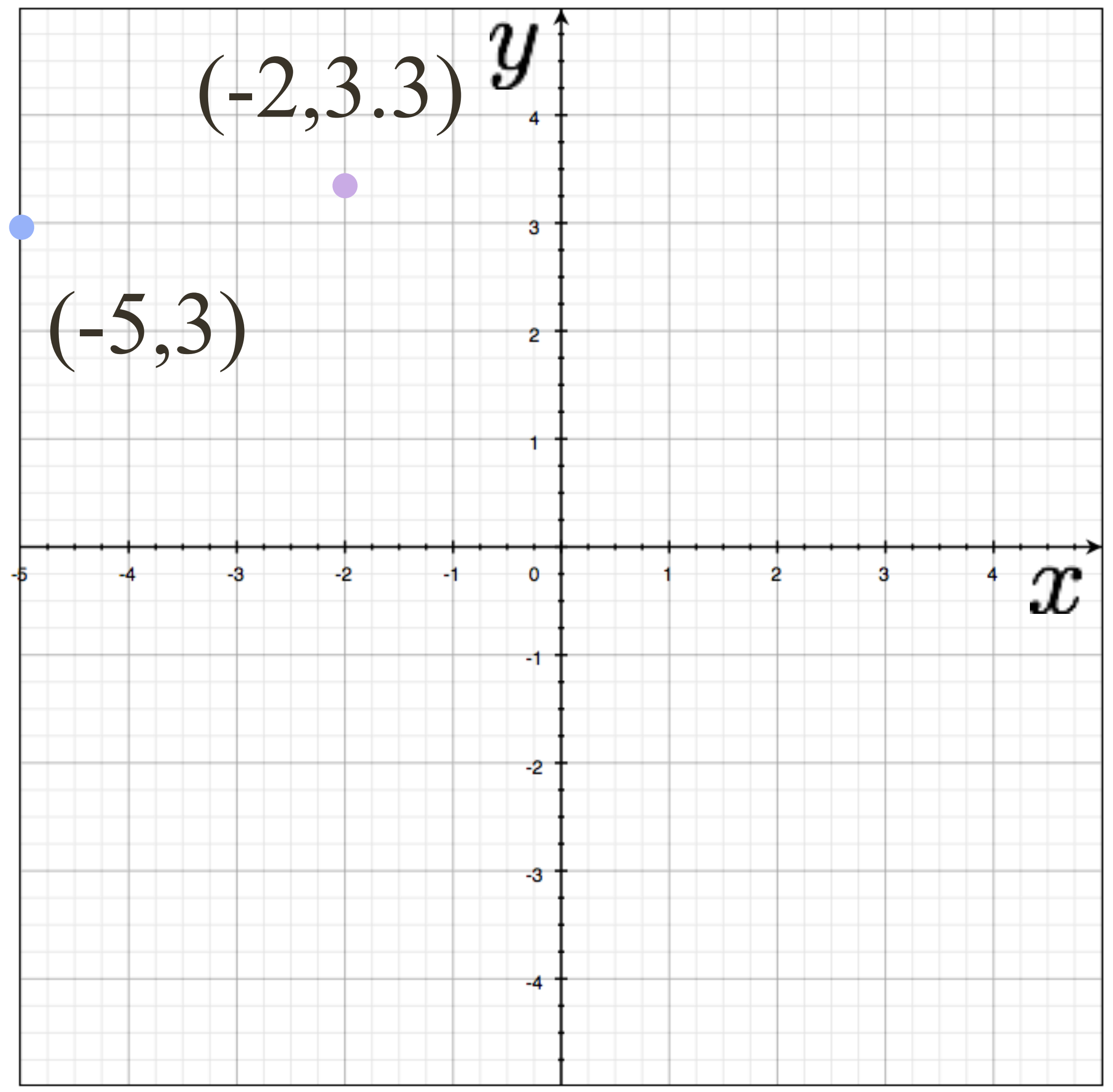
— If there is a line that has lots of votes, that will be the line passing near the points that voted for it

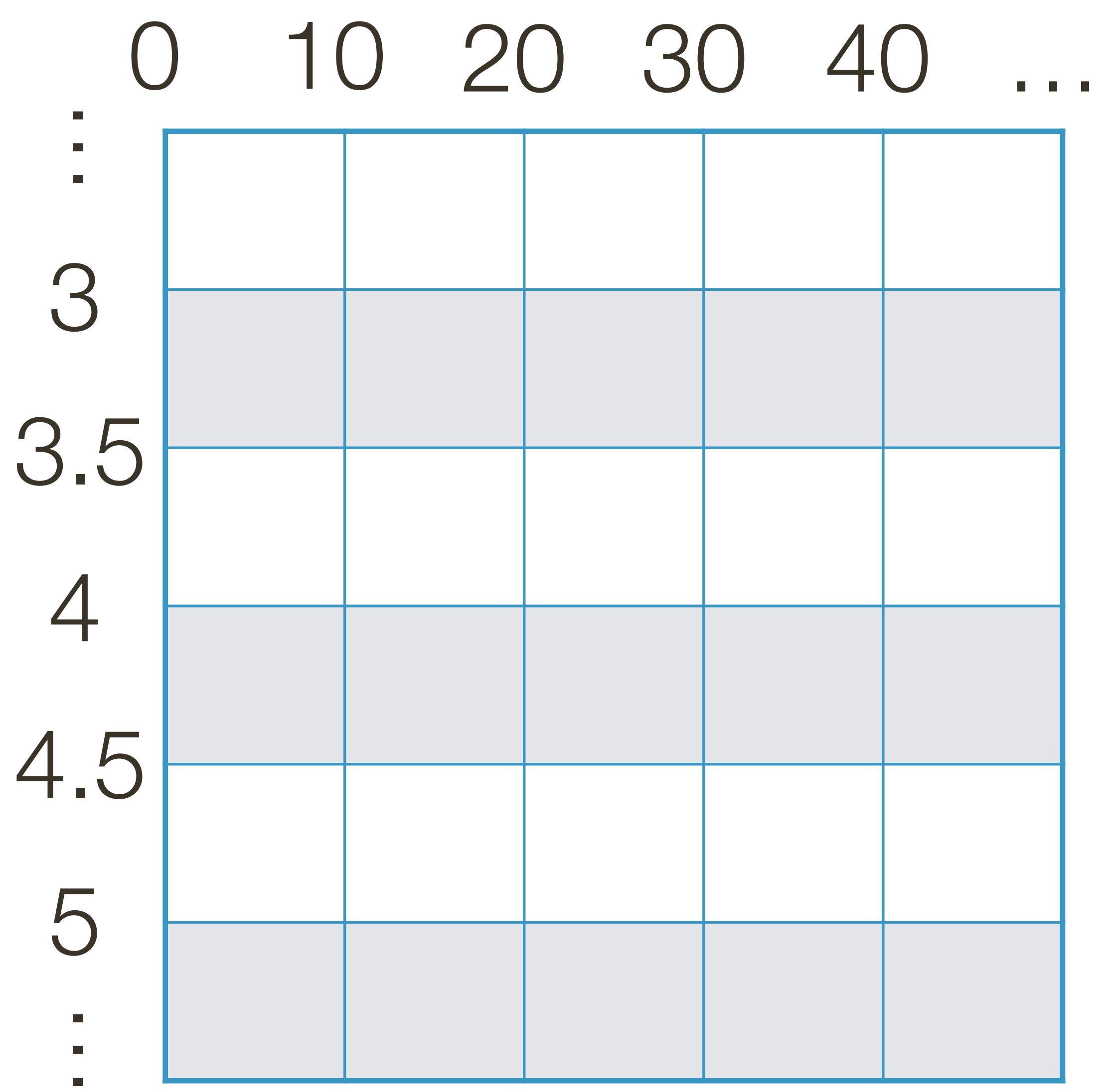
Example: Hough Transform for Lines





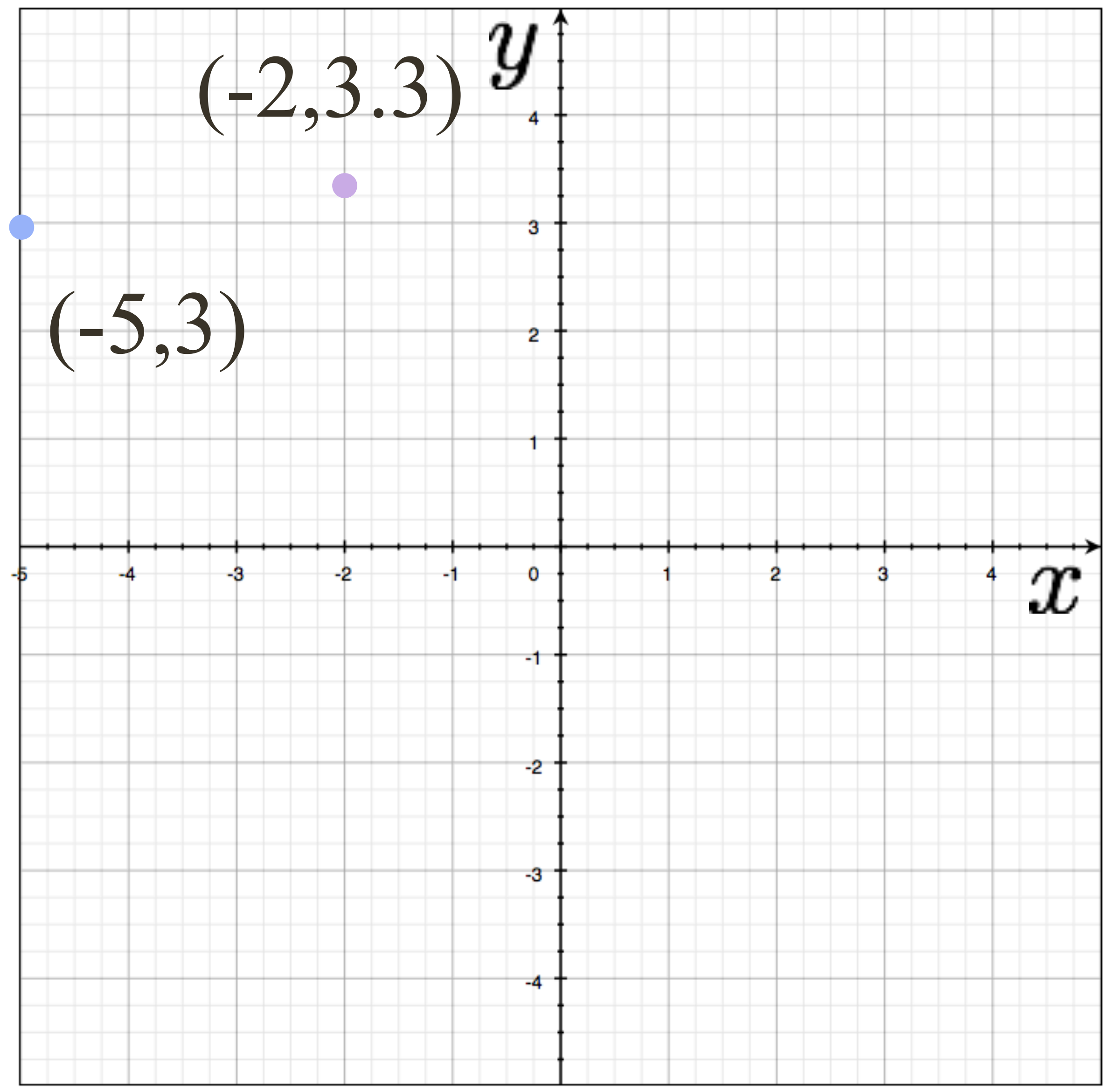
Example: Hough Transform for Lines

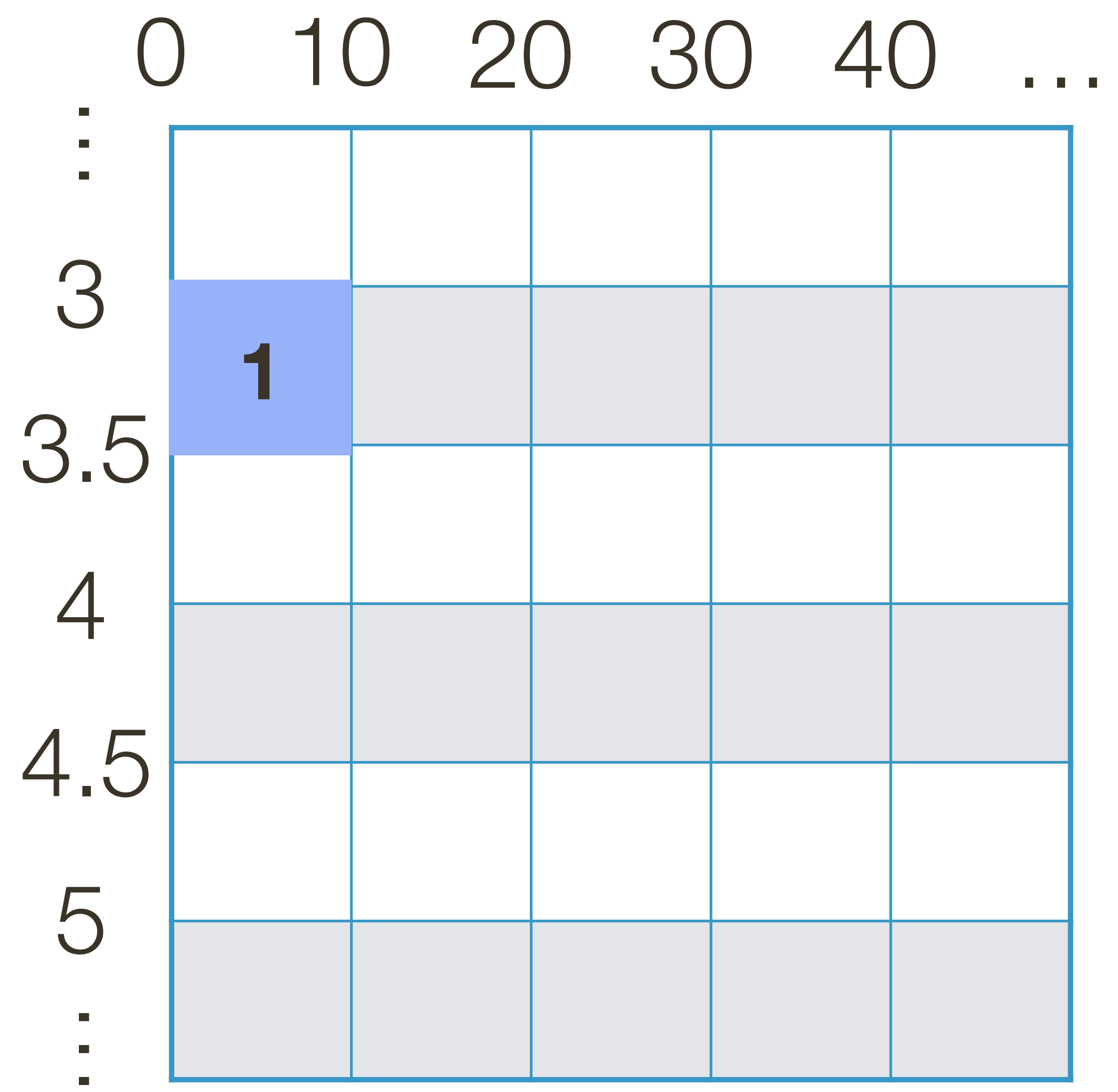




$$-5\sin(5^\circ) - 3\cos(5^\circ) + r = 0 => r = 3.42$$

Example: Hough Transform for Lines





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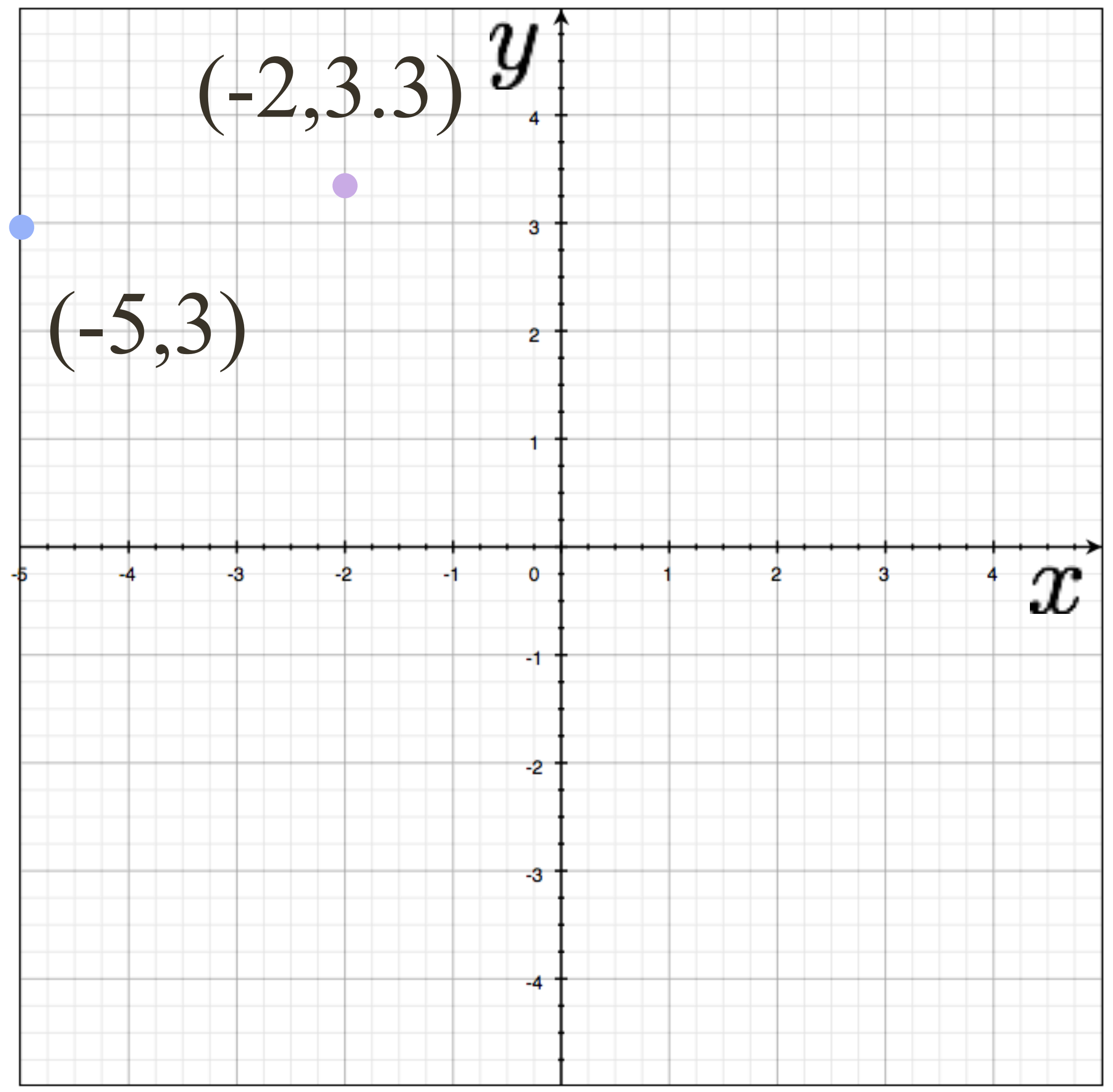
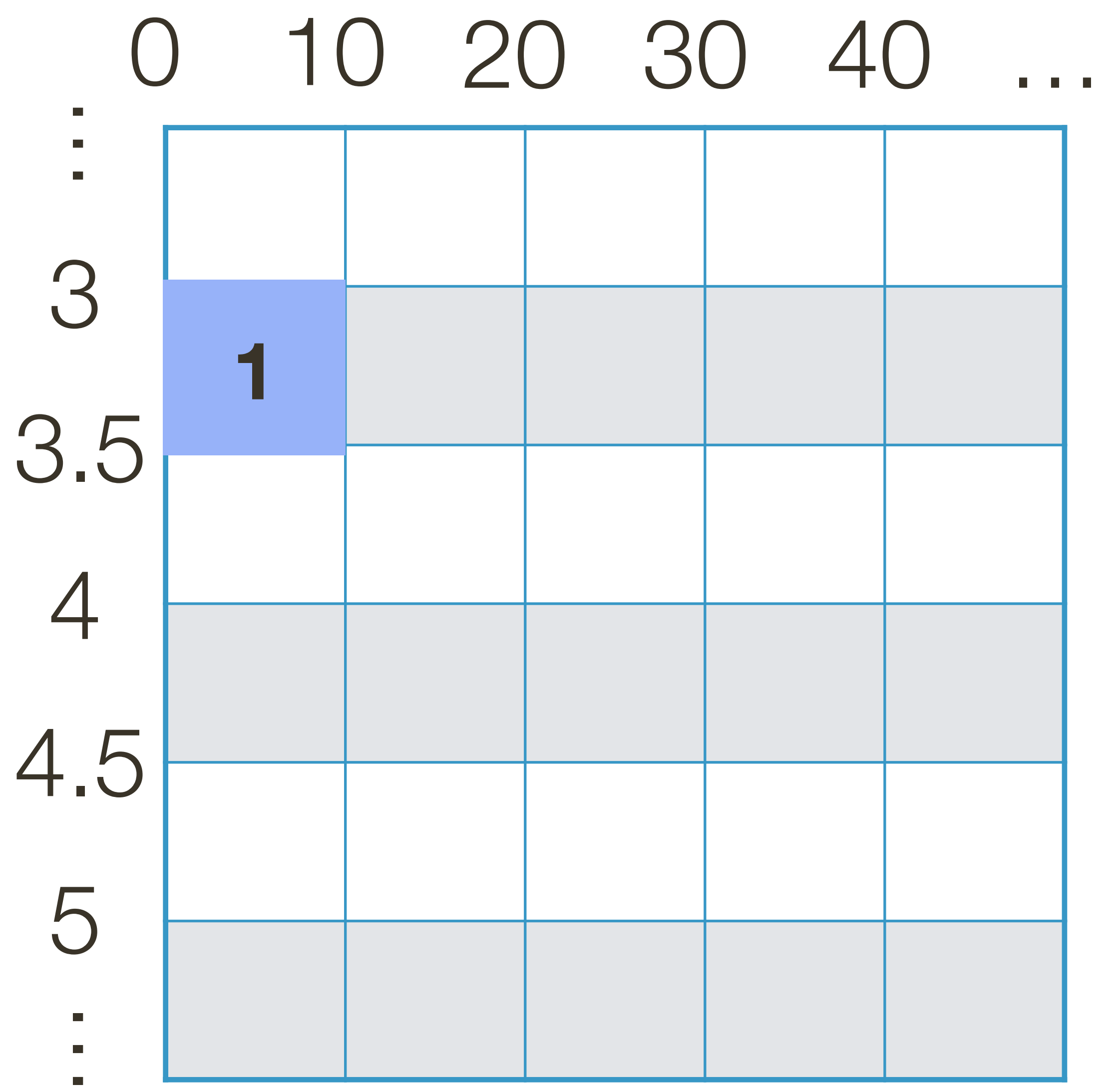
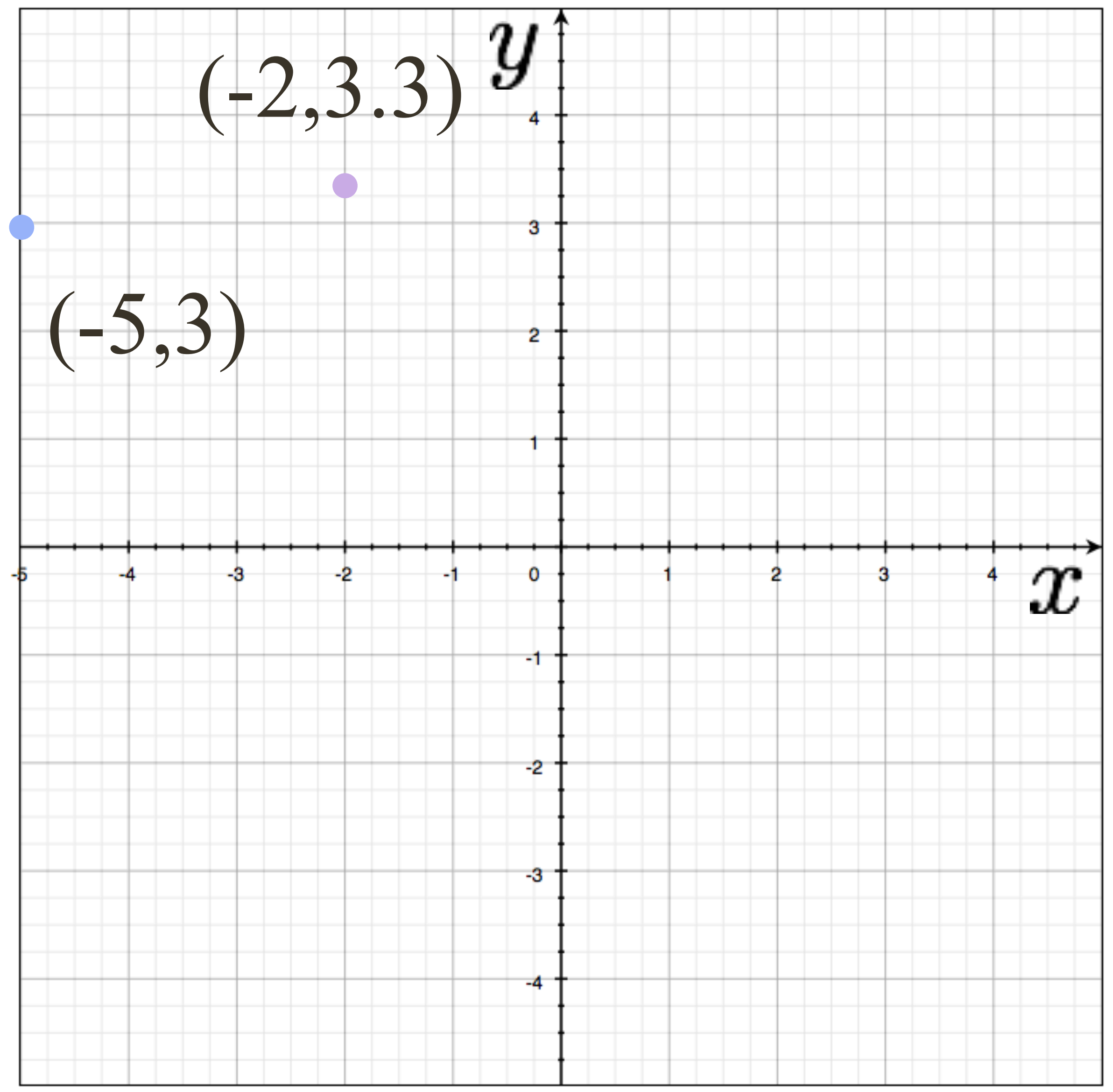


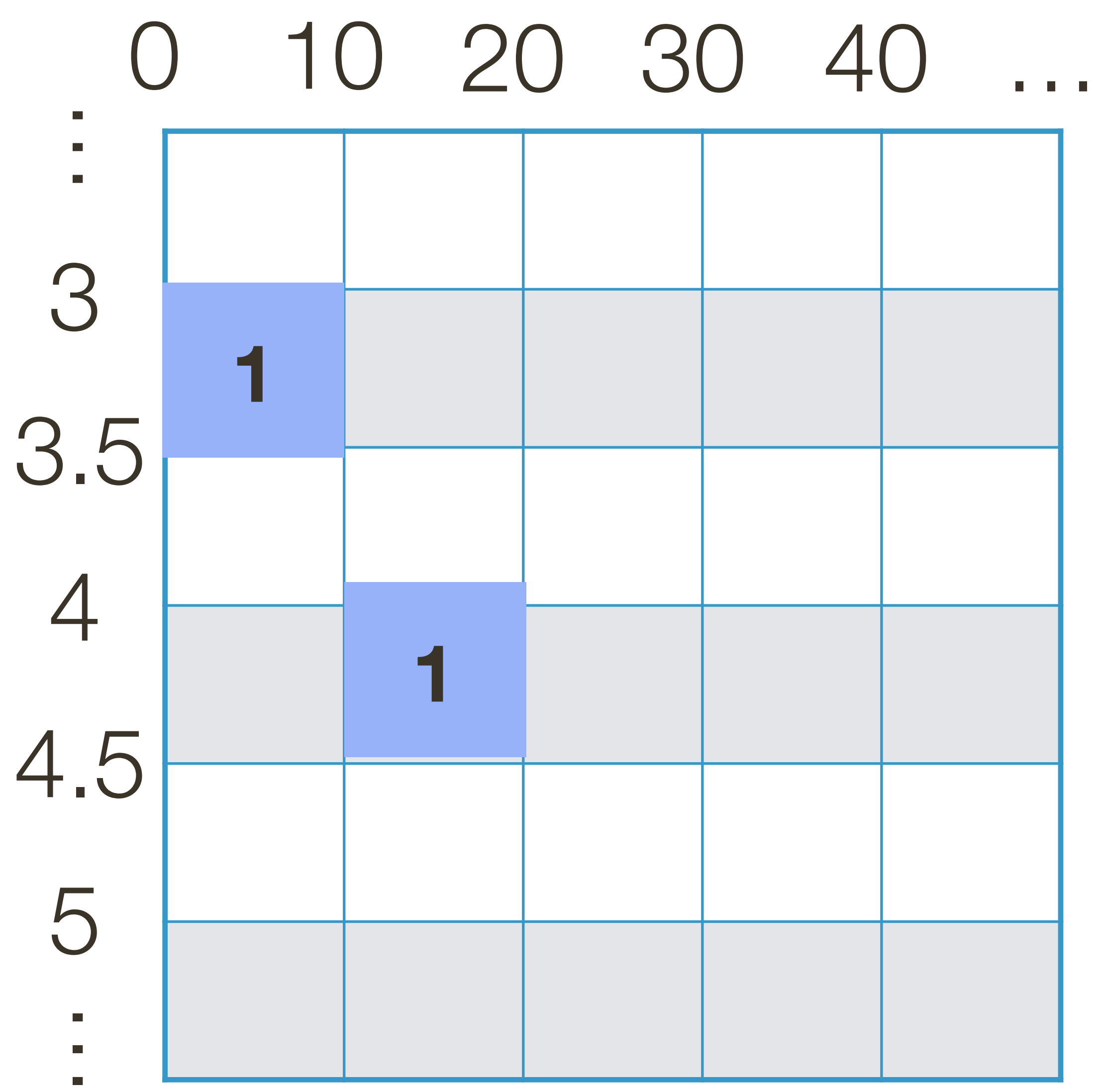


$$-5\sin(5^\circ) - 3\cos(5^\circ) + r = 0 => r = 3.42$$

$$-5\sin(15^\circ) - 3\cos(15^\circ) + r = 0 => r = 4.18$$

Example: Hough Transform for Lines





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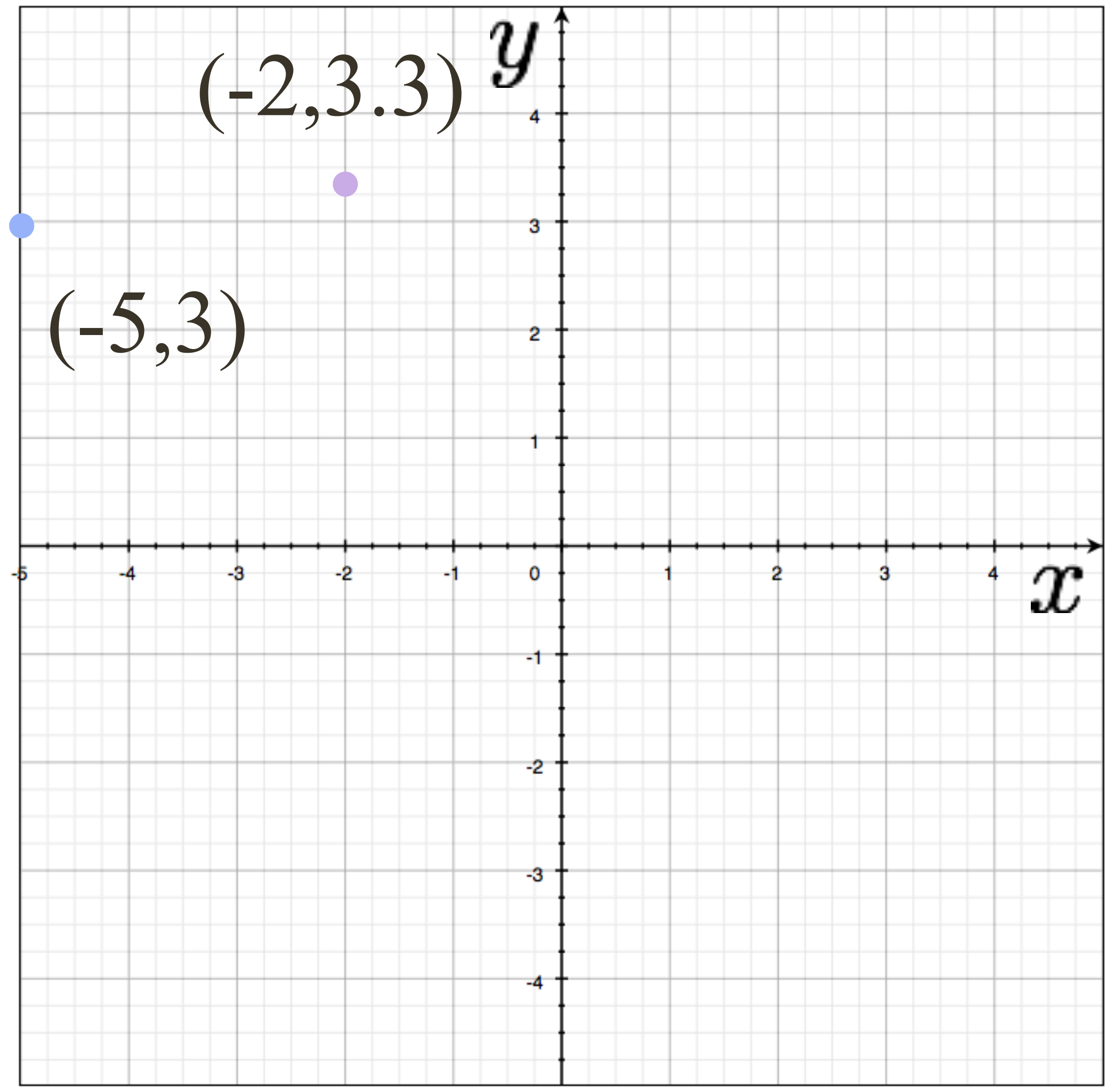
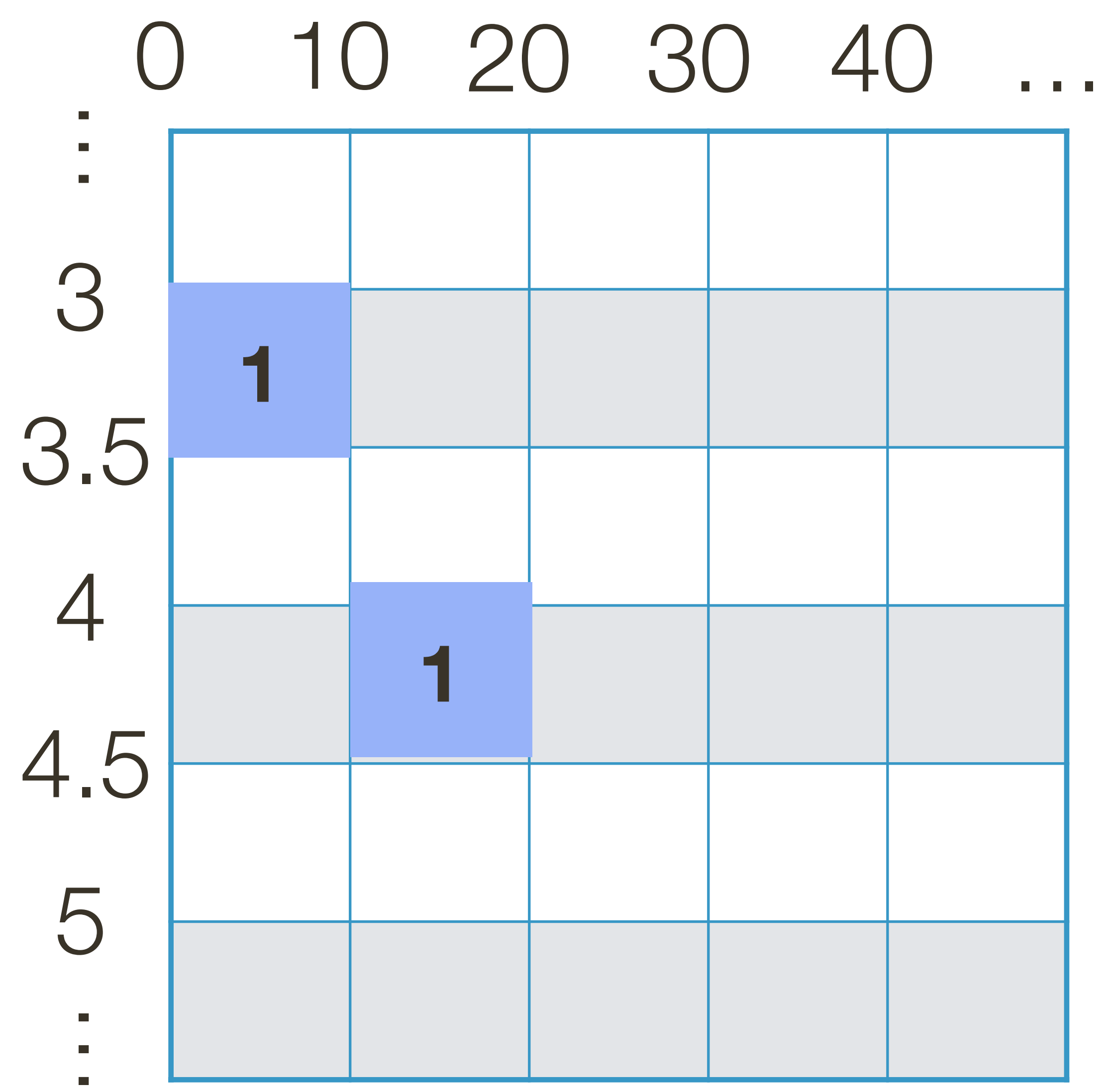


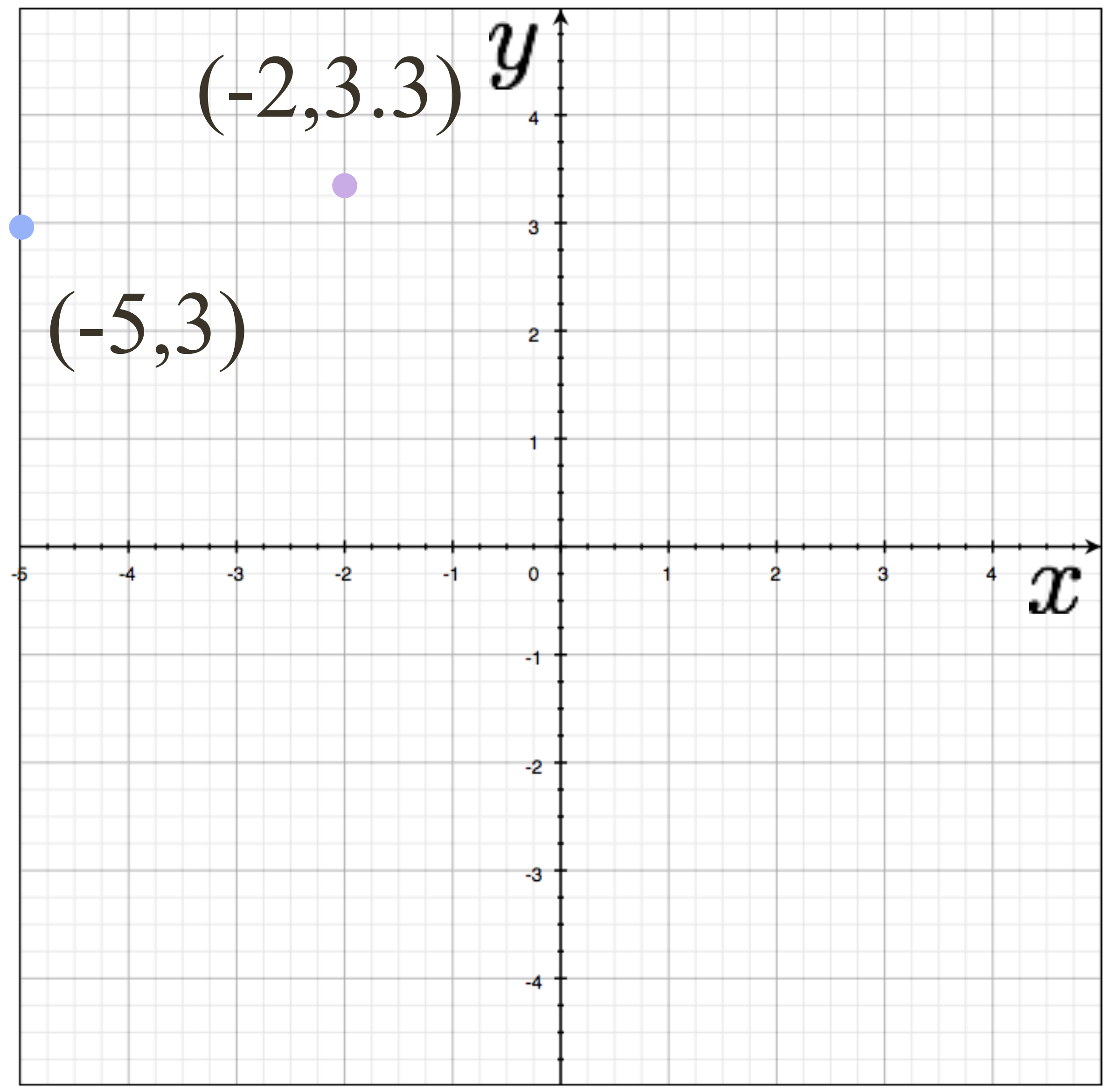


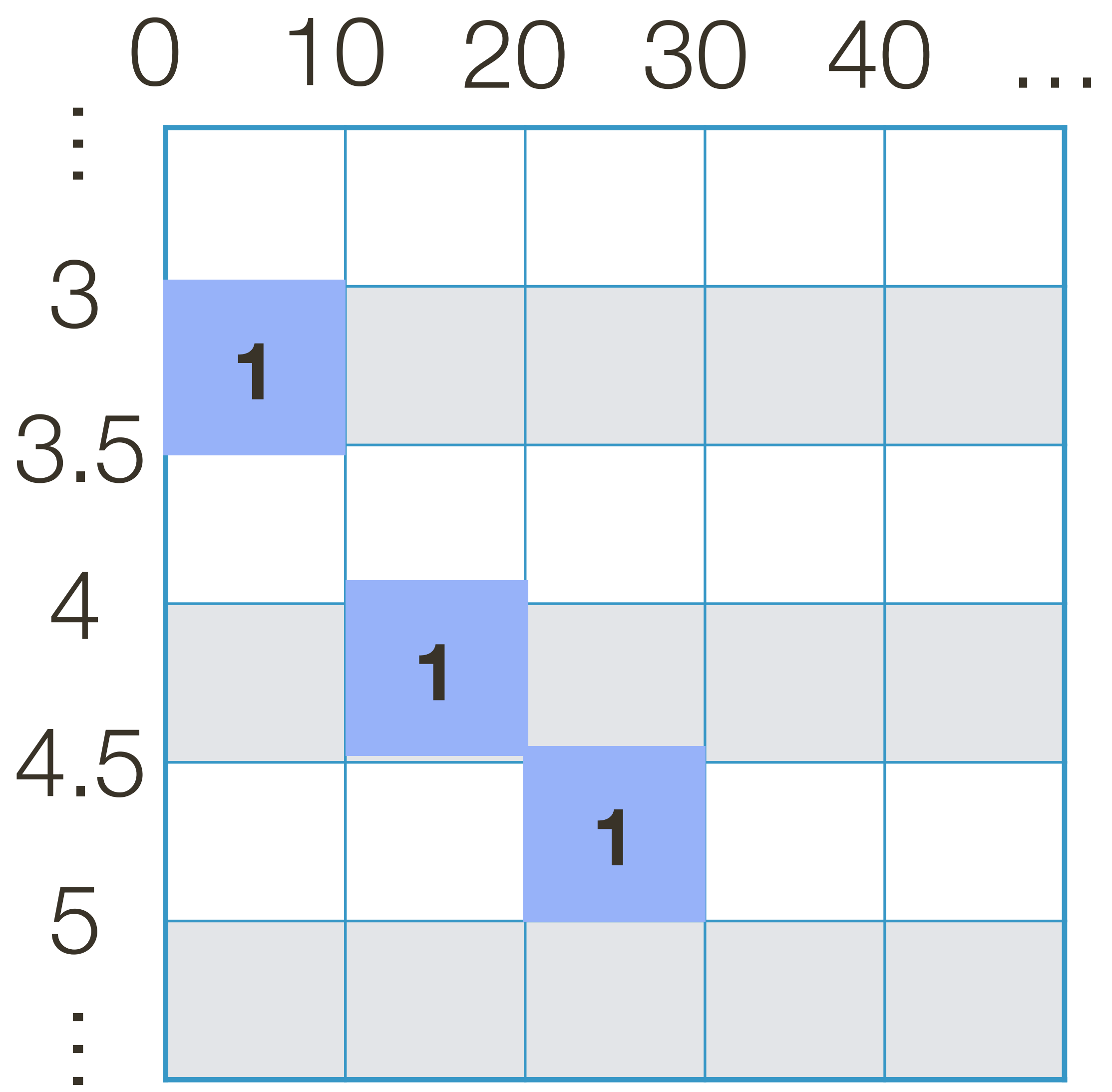
$$-5\sin(5^\circ) - 3\cos(5^\circ) + r = 0 => r = 3.42$$

$$-5\sin(15^\circ) - 3\cos(15^\circ) + r = 0 => r = 4.18$$

$$-5\sin(25^\circ) - 3\cos(25^\circ) + r = 0 => r = 4.83$$

Example: Hough Transform for Lines





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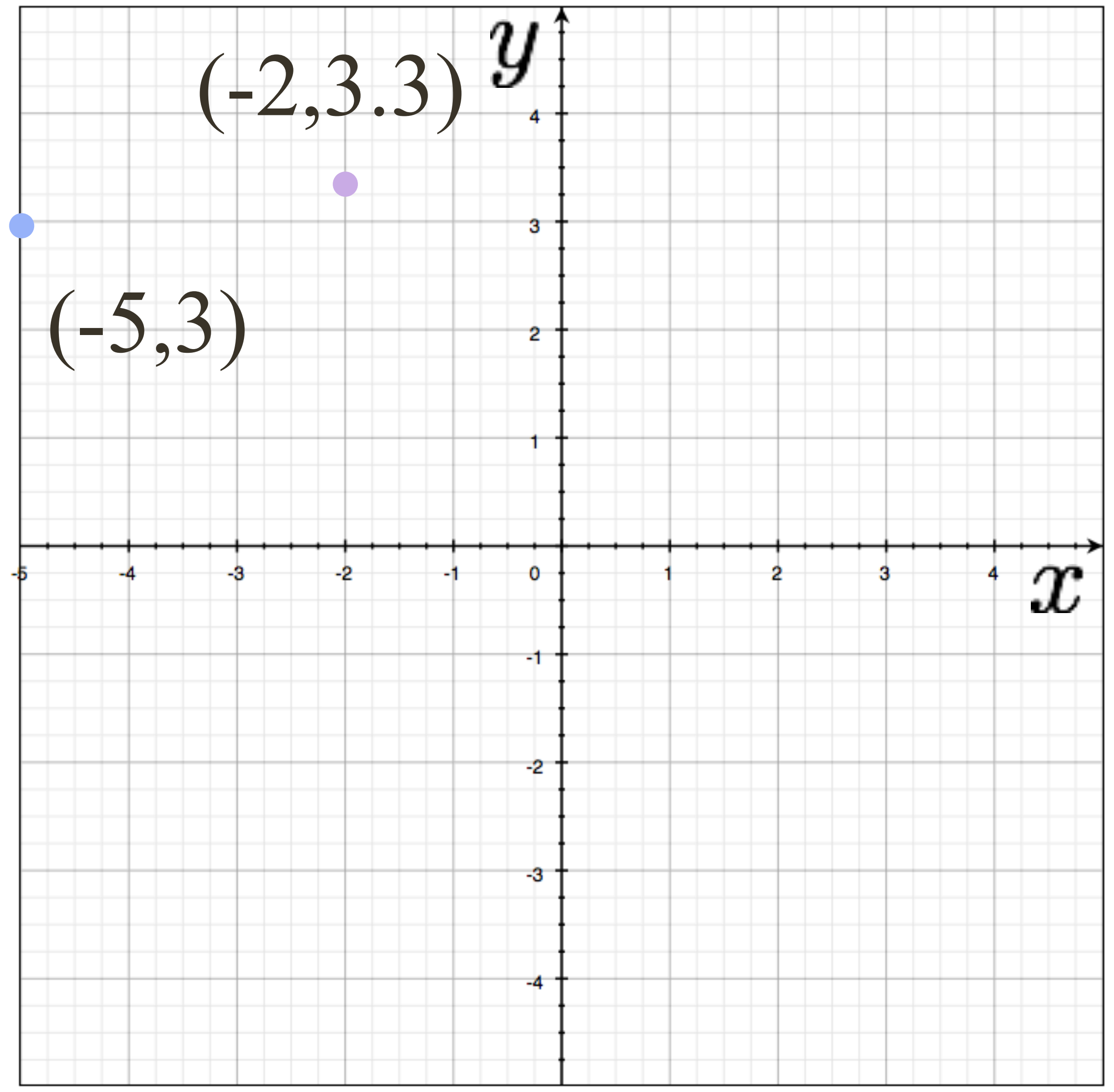

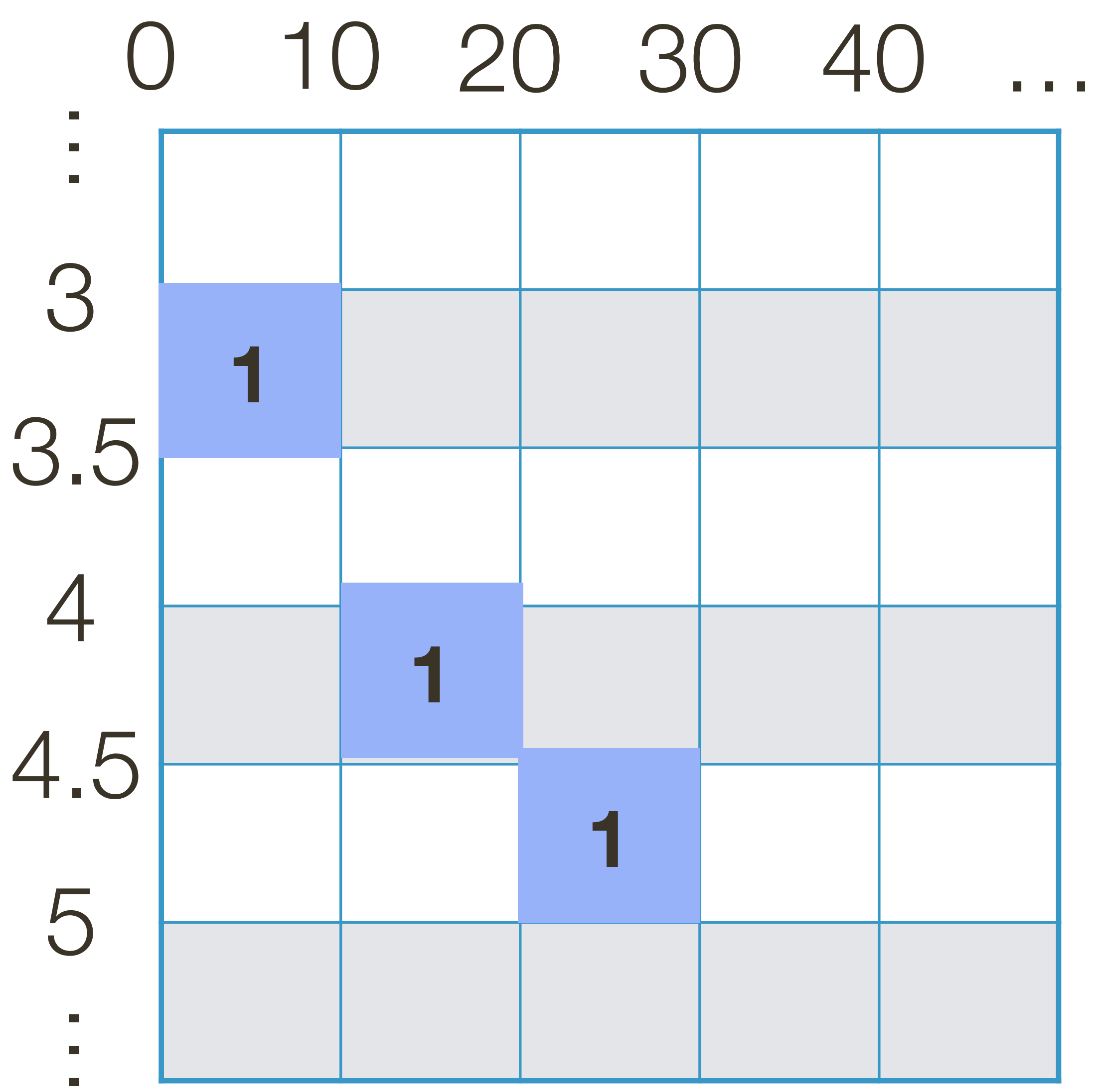

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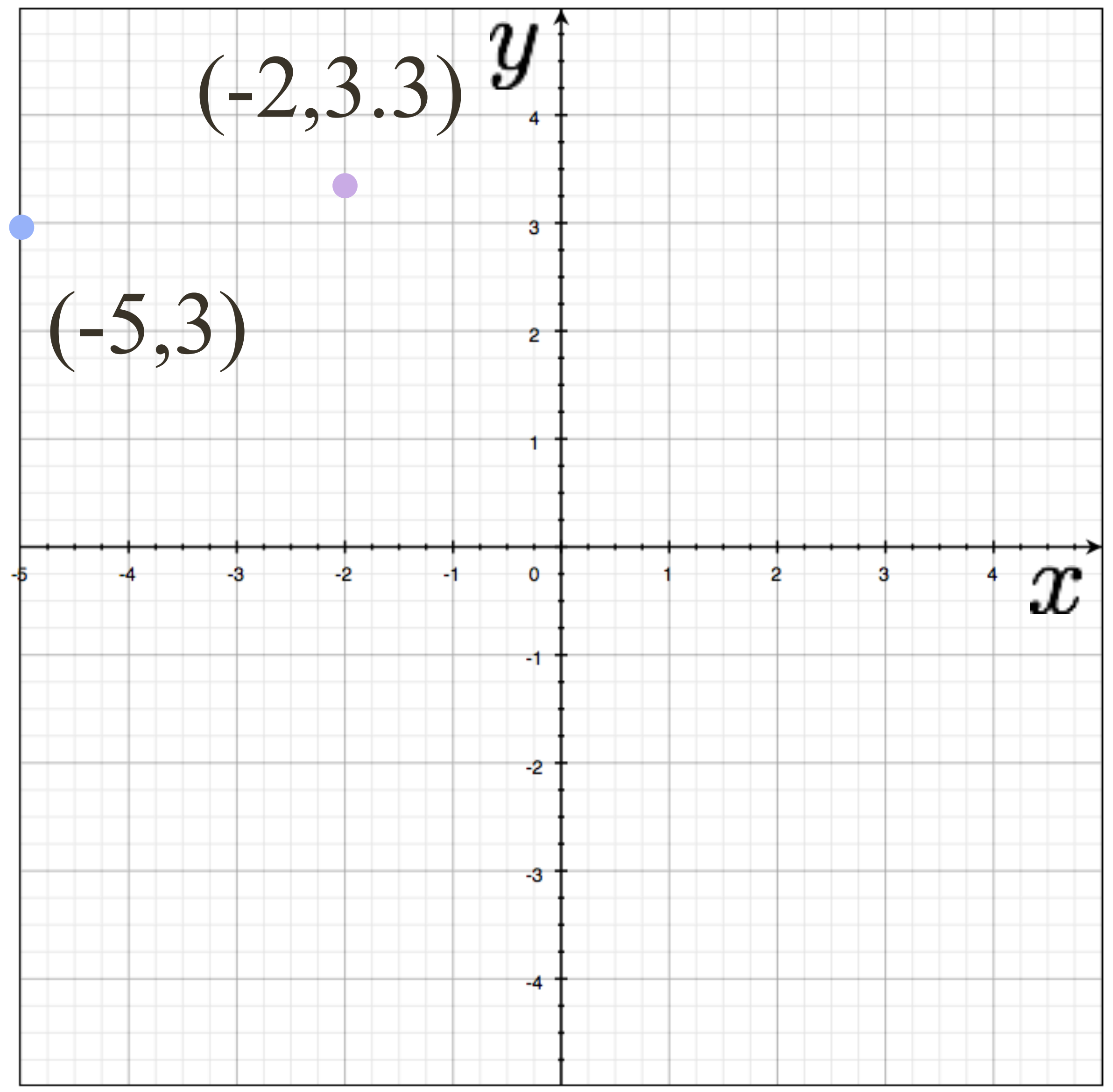
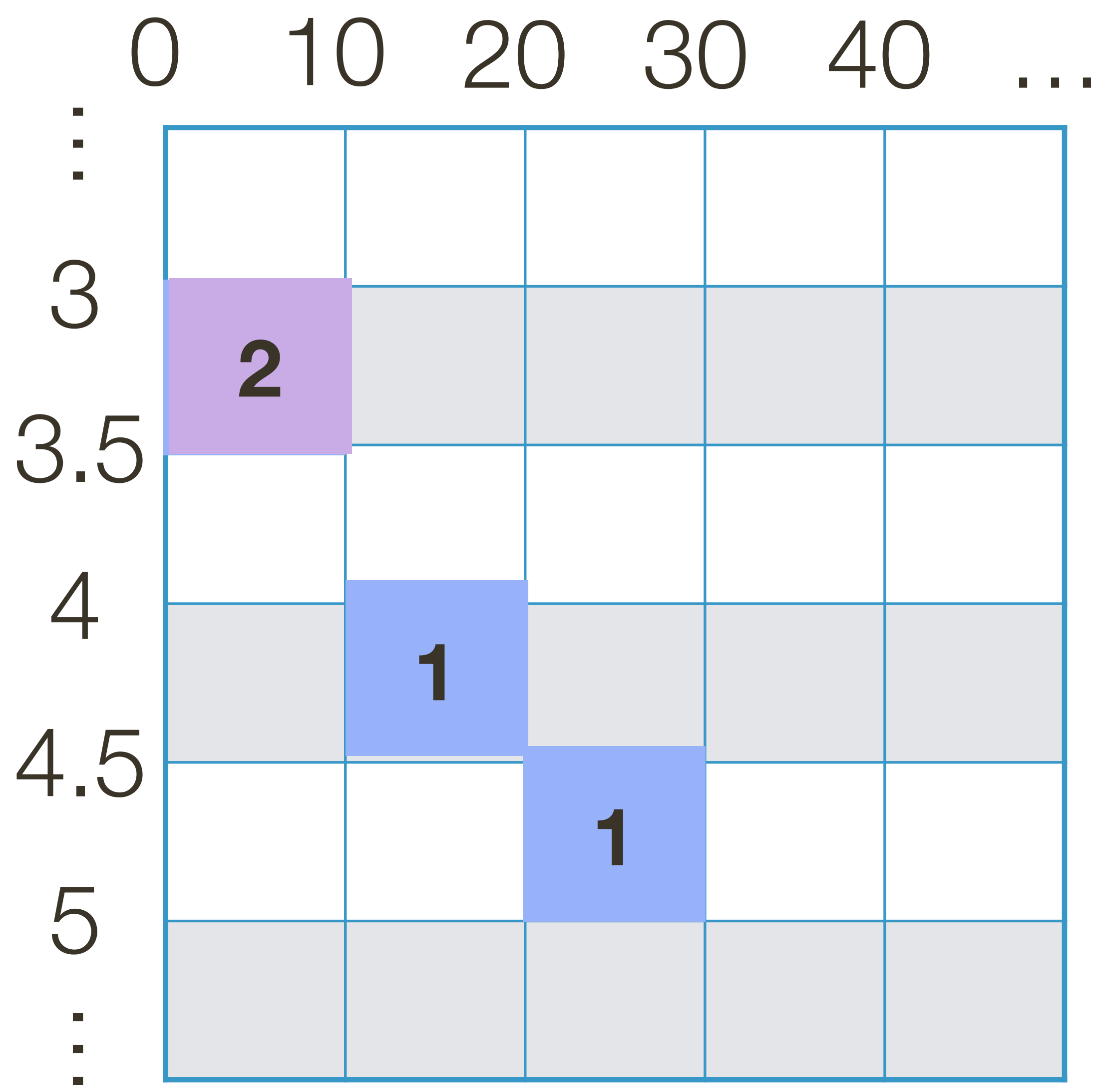
$$-2\sin(5^\circ) - 3.3\cos(5^\circ) + r = 0 => r = 3.46$$

Example: Hough Transform for Lines





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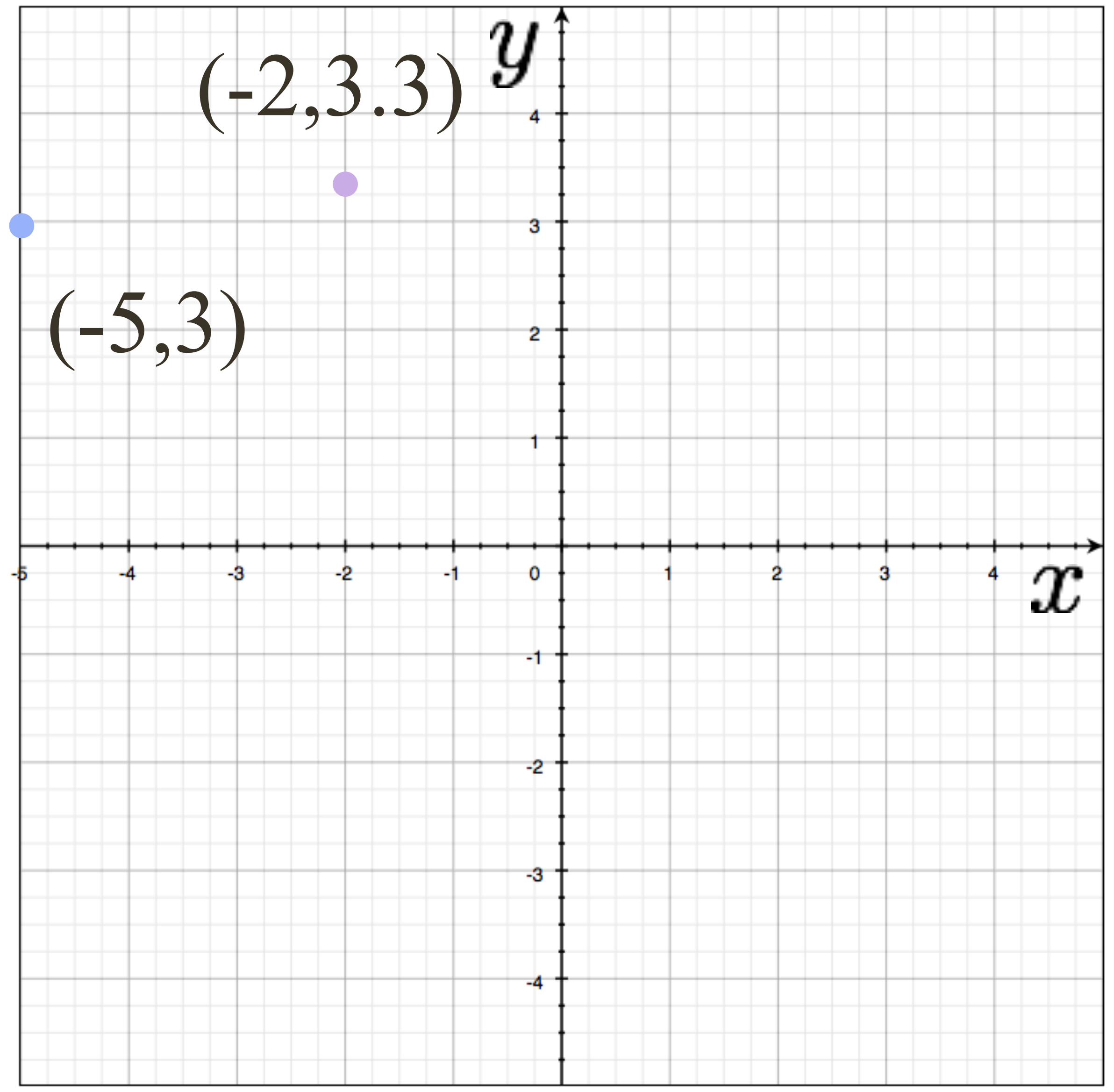

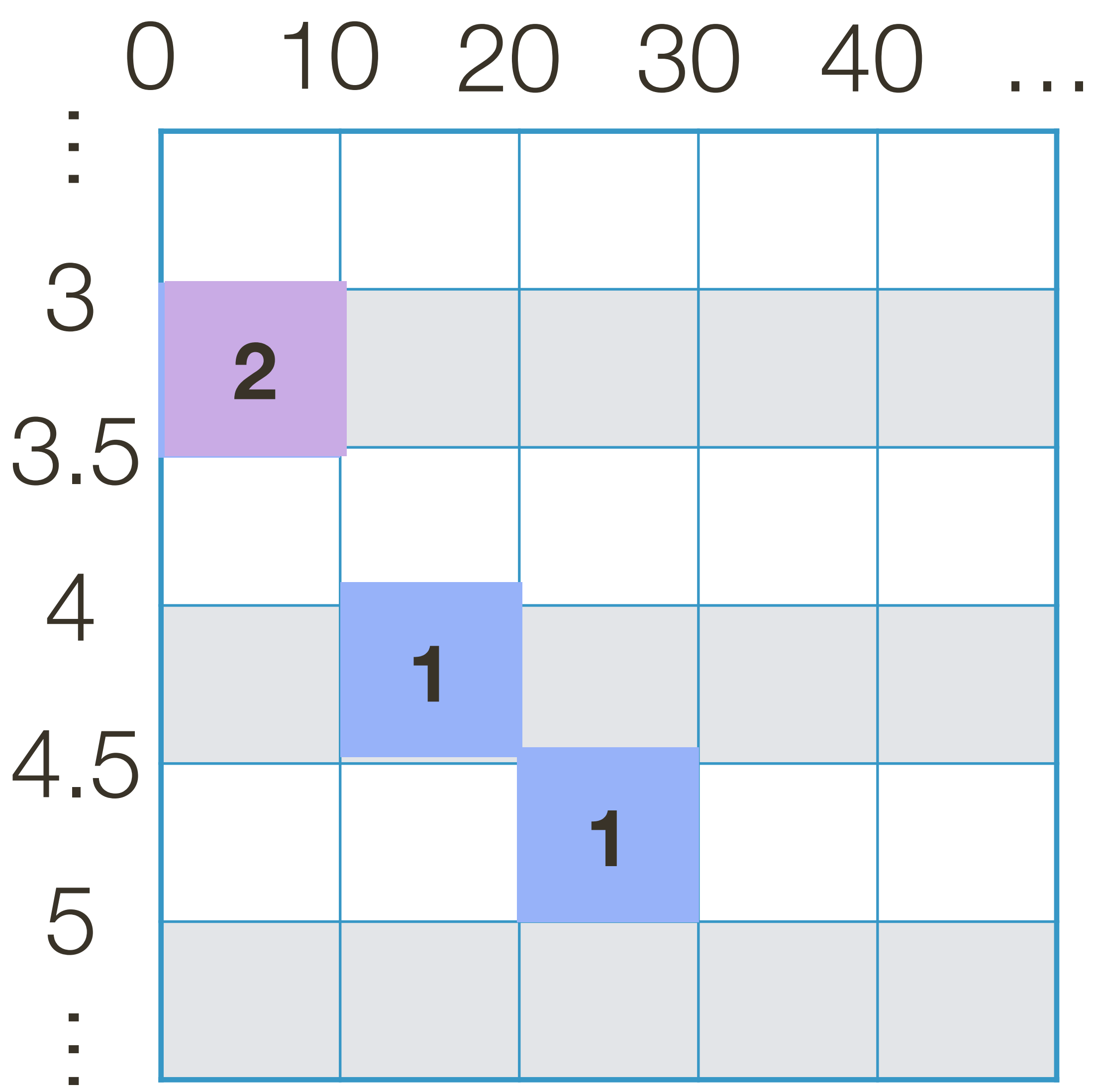

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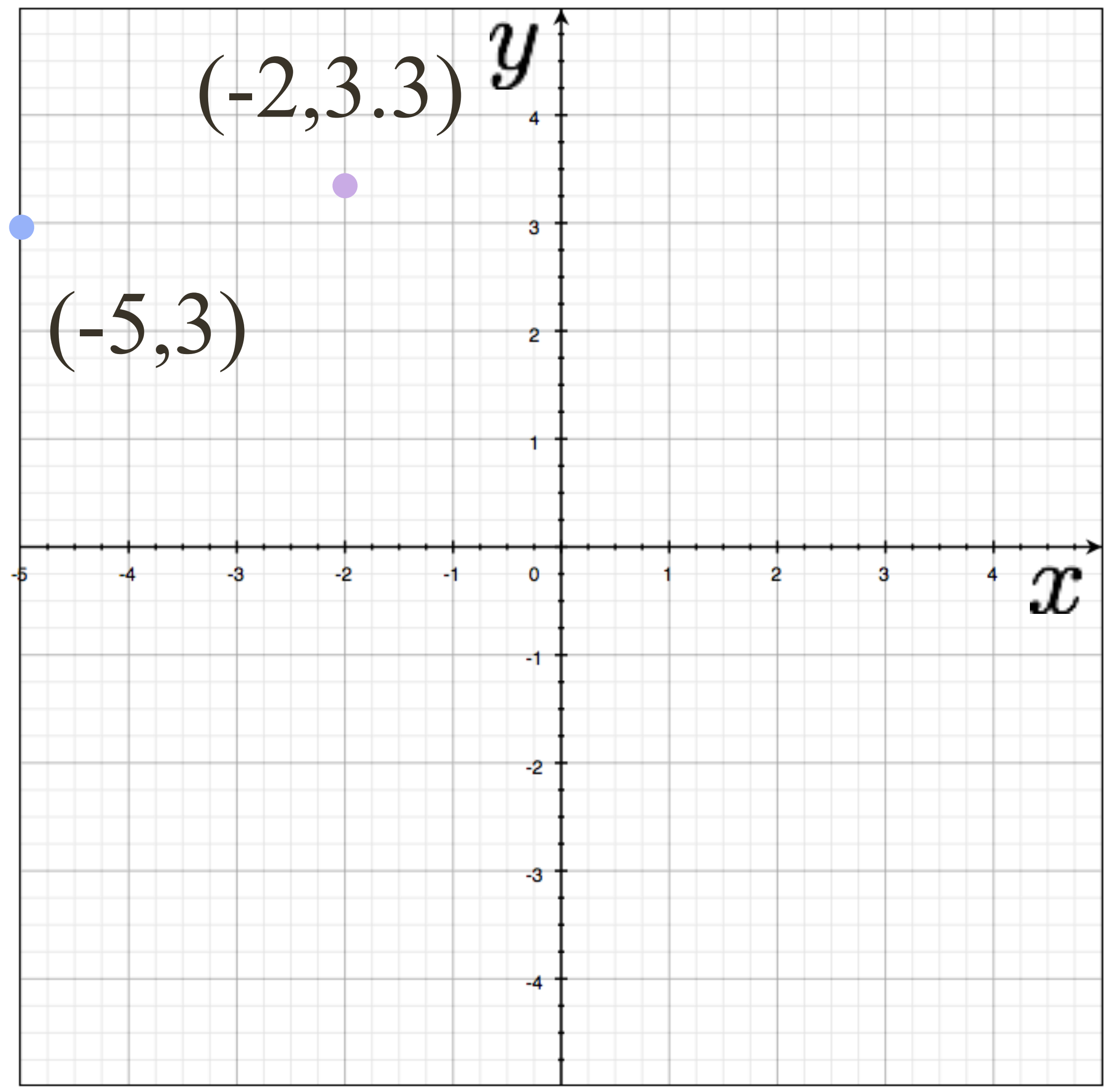
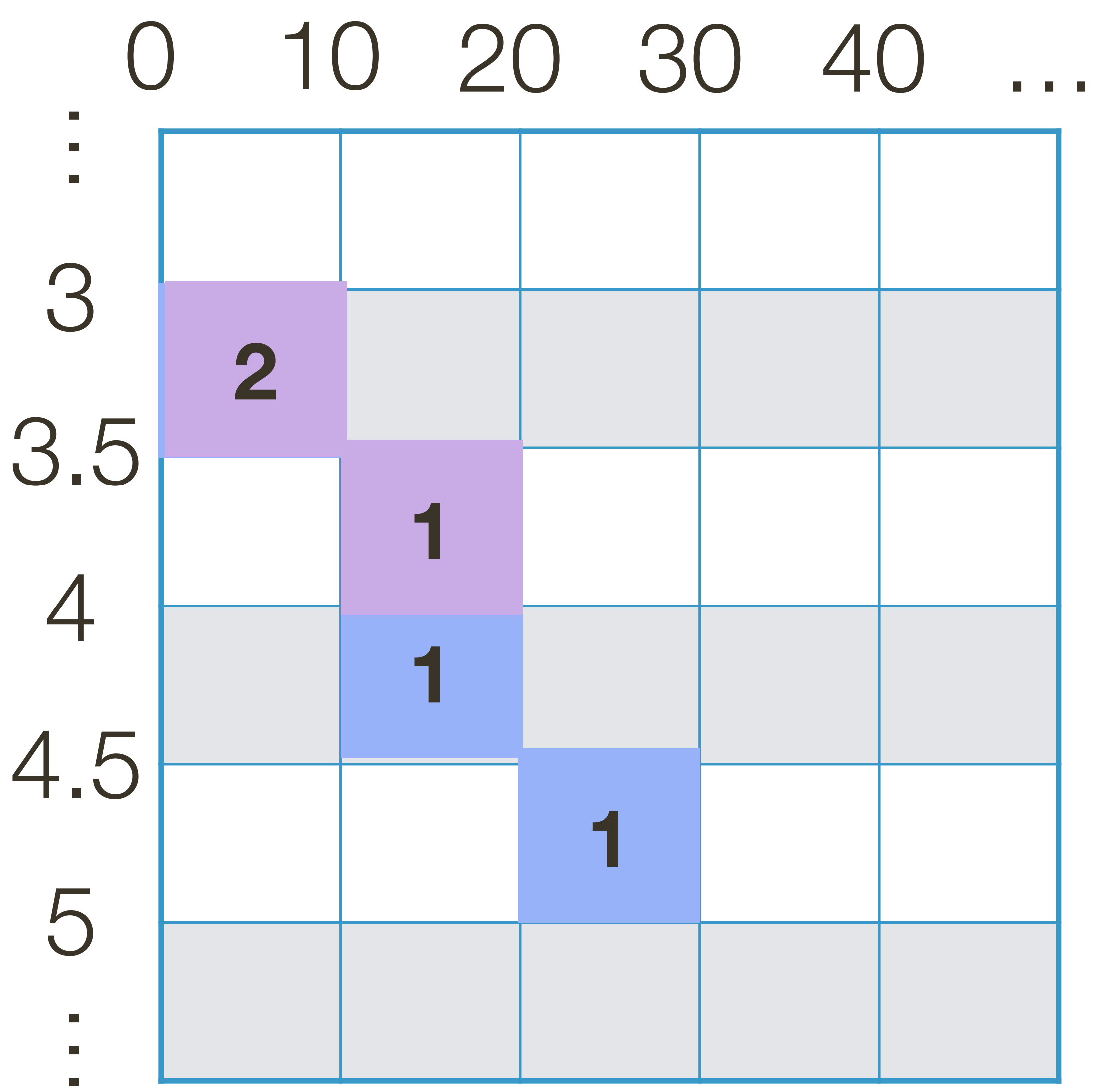
$$-2\sin(5^\circ) - 3.3\cos(5^\circ) + r = 0 => r = 3.46$$
$$-2\sin(15^\circ) - 3.3\cos(15^\circ) + r = 0 => r = 3.71$$

Example: Hough Transform for Lines





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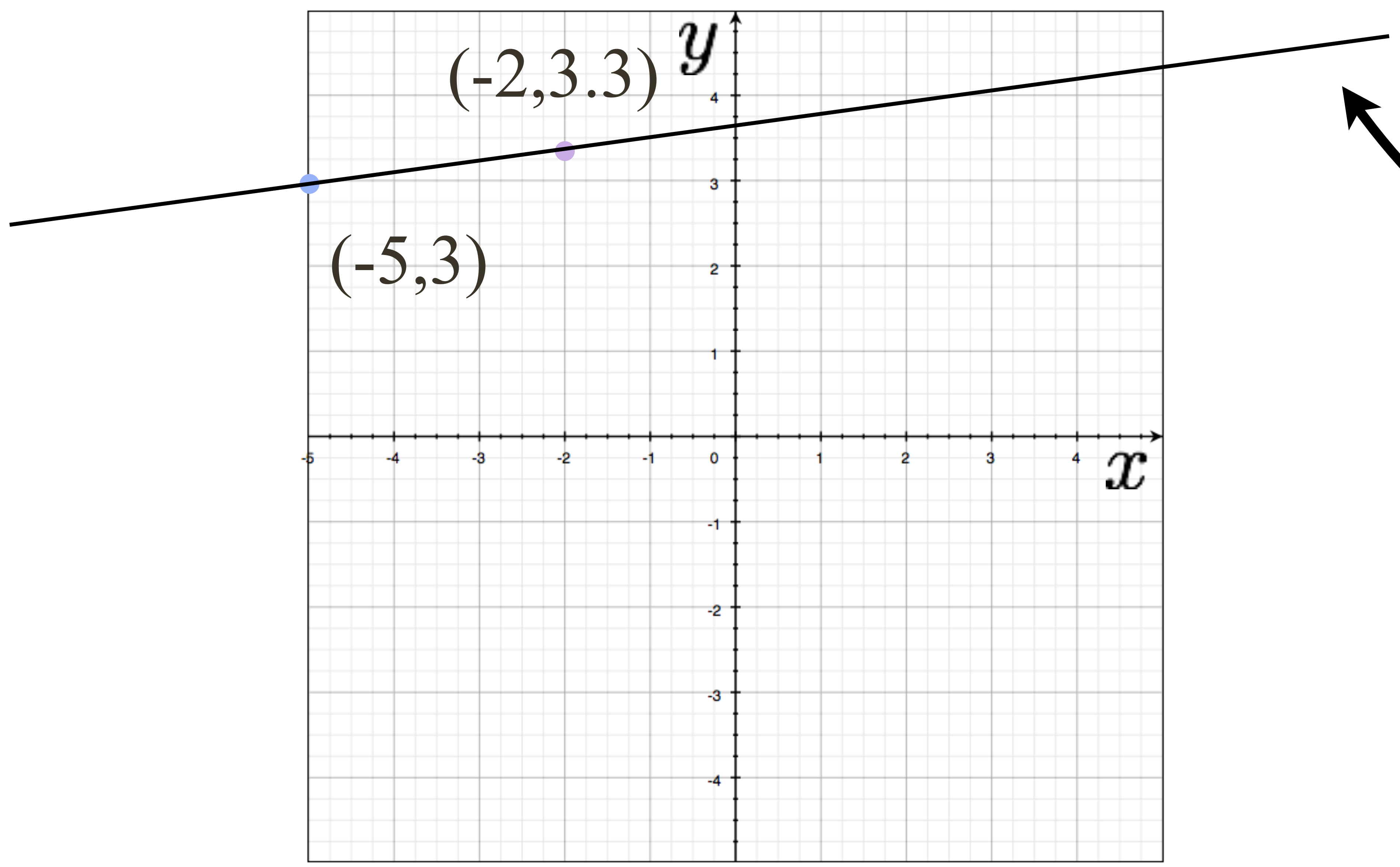
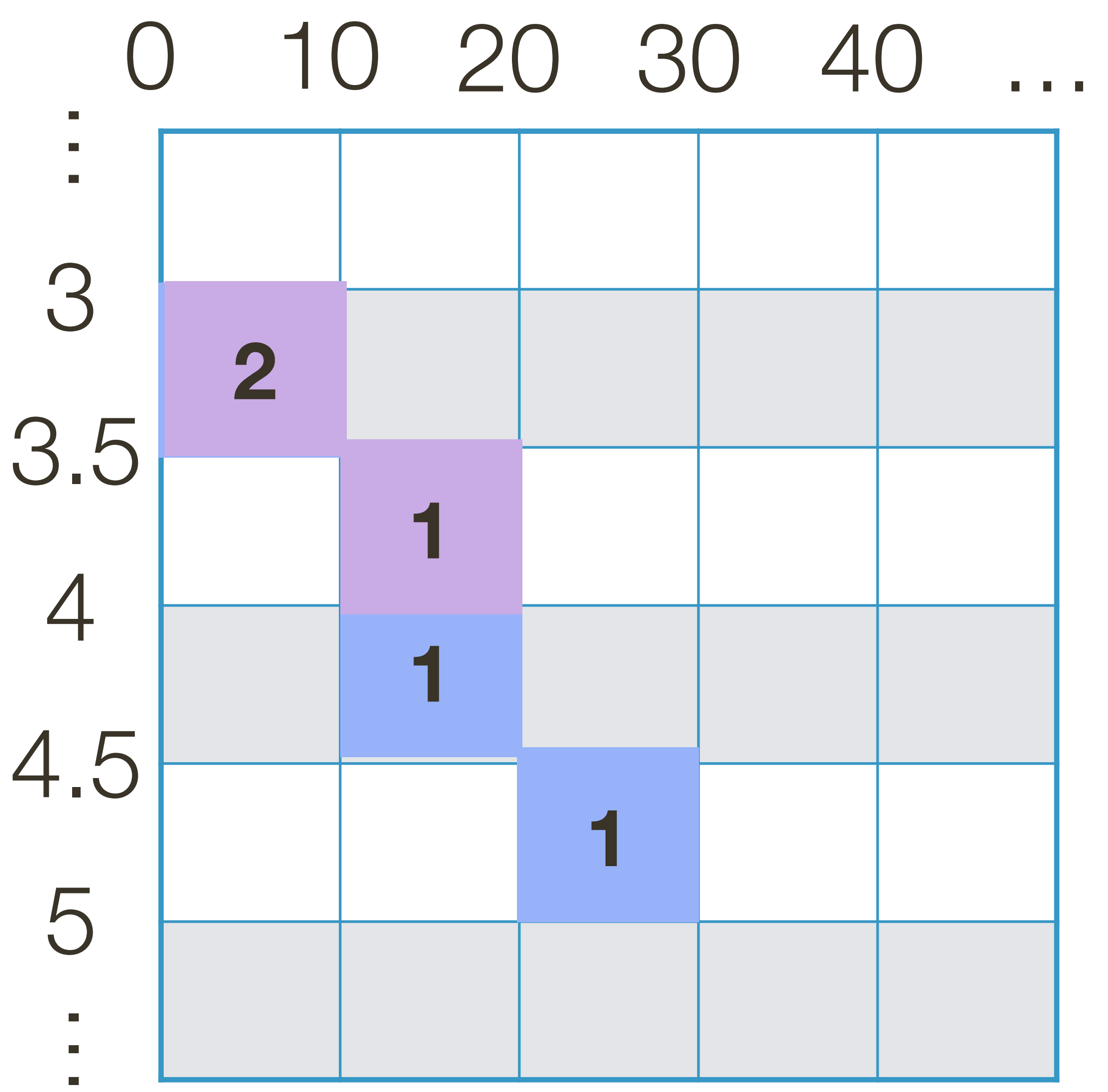
Example: Hough Transform for Lines





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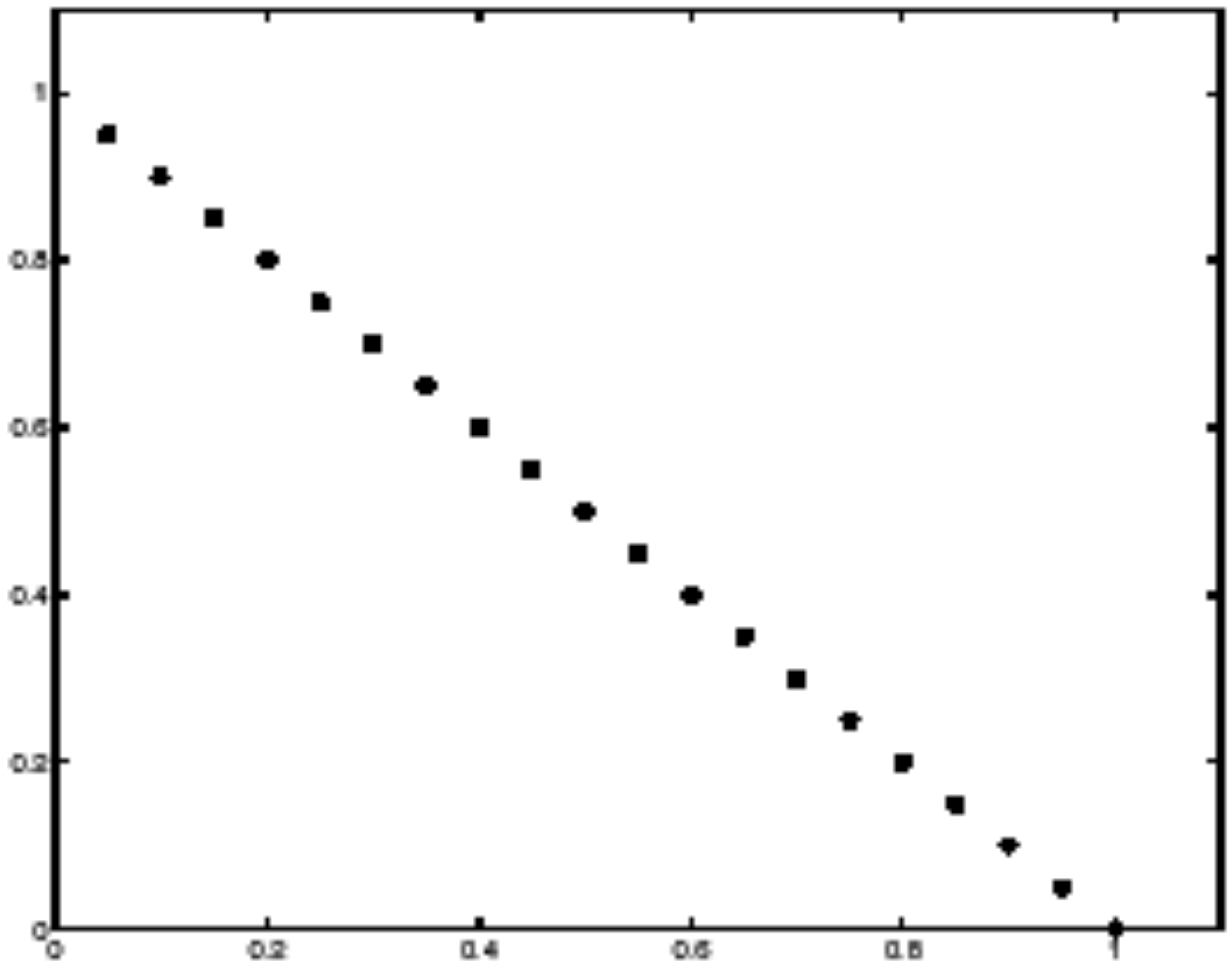
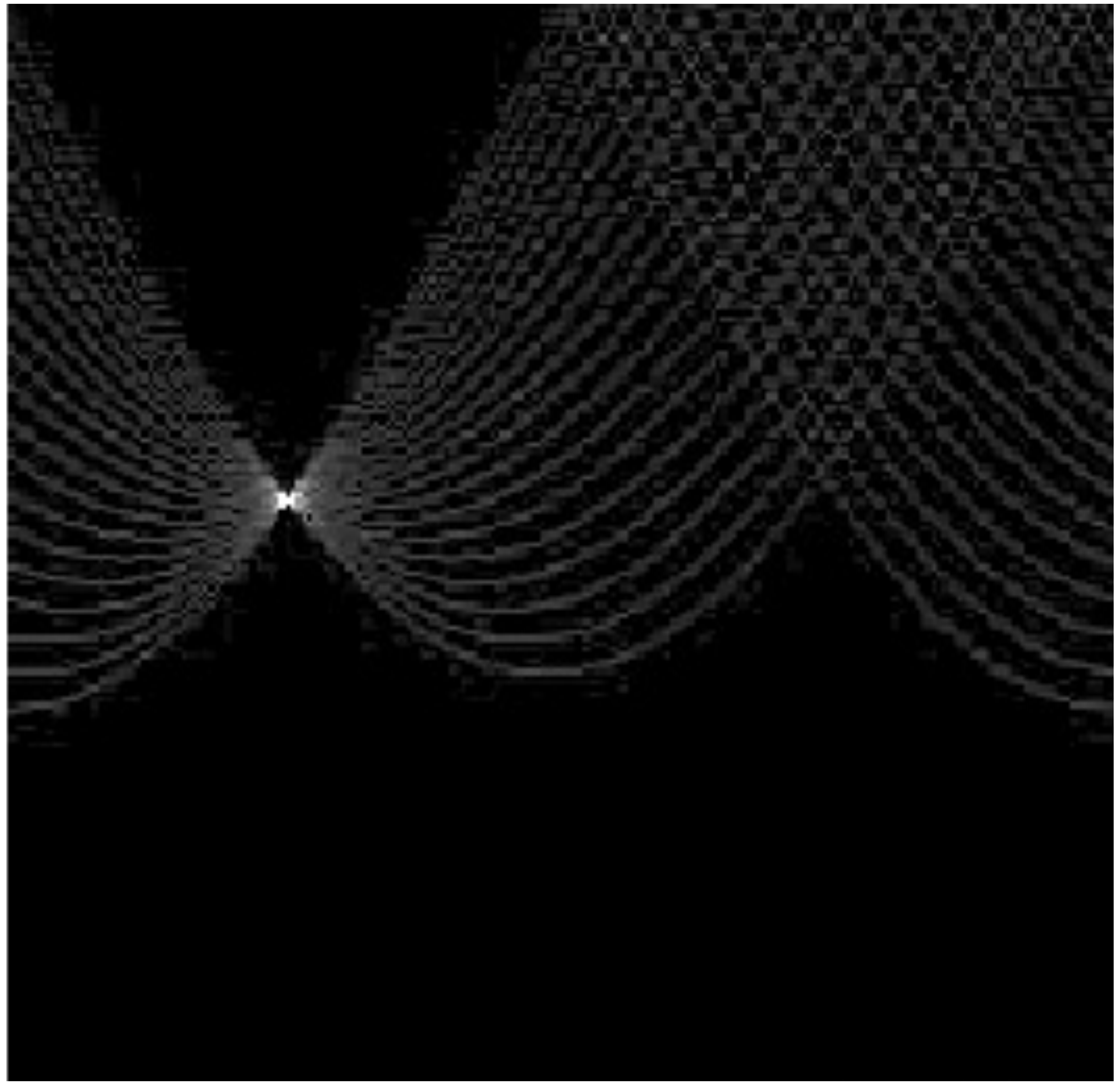
Example: Clean Data



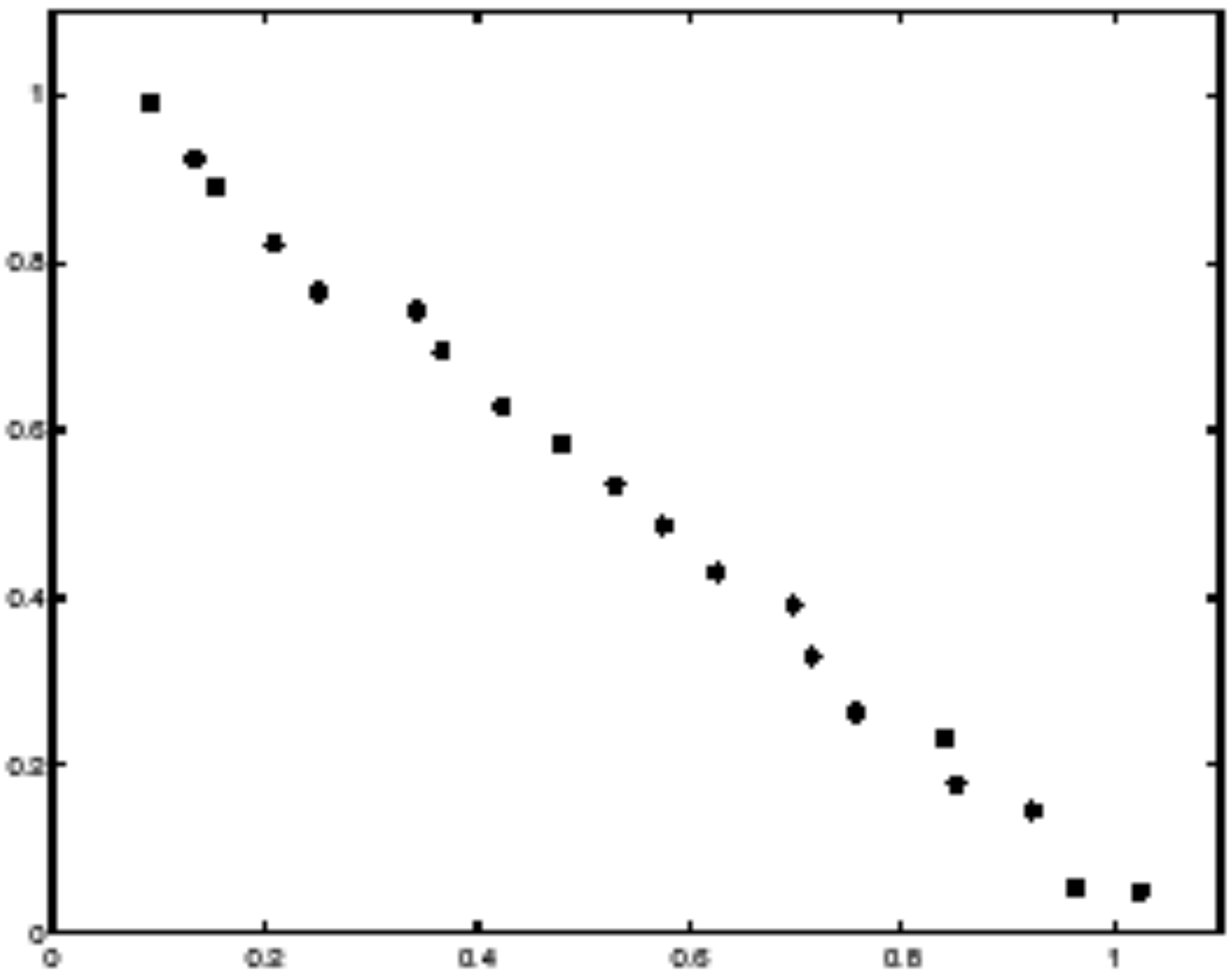
Tokens



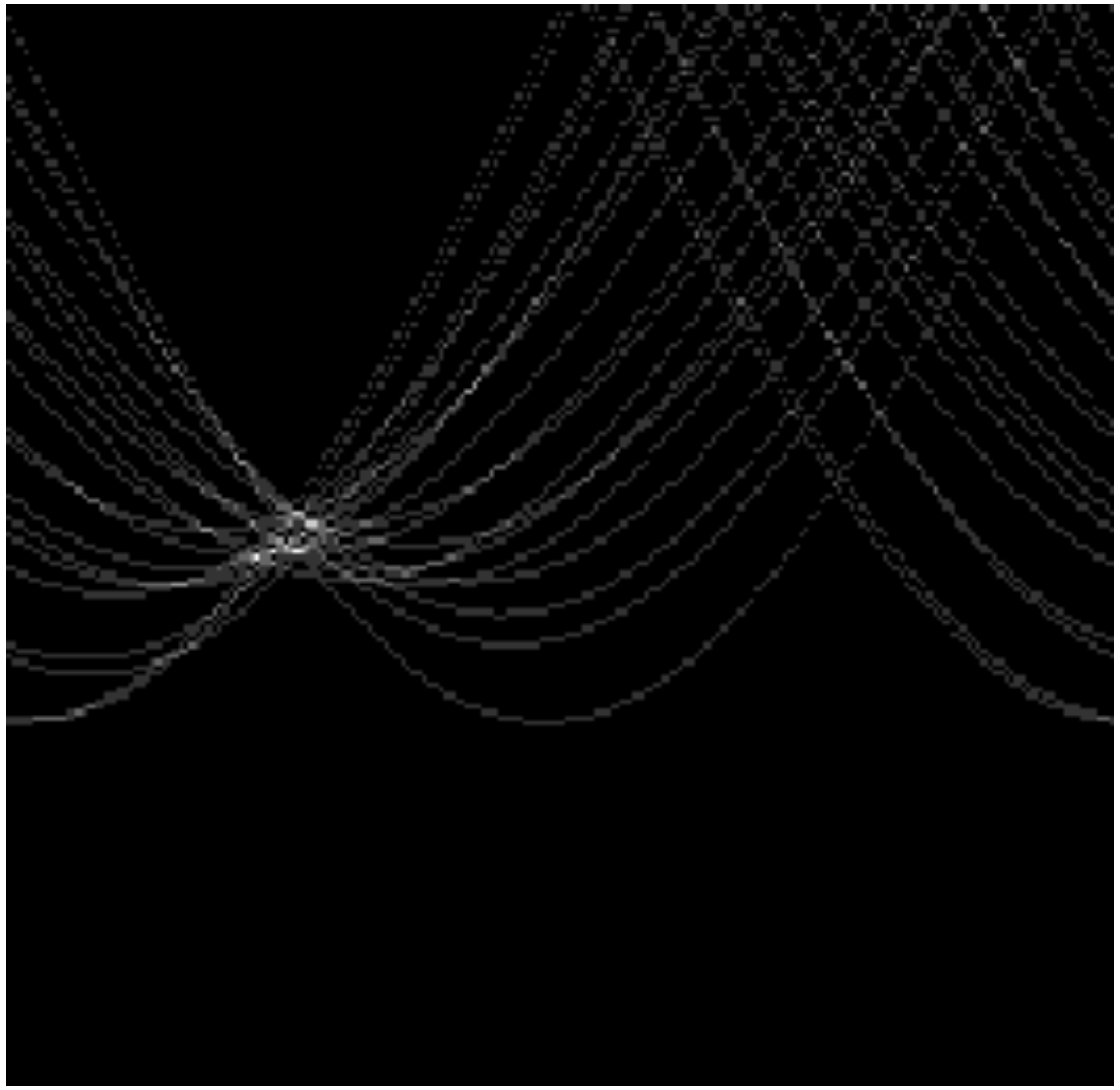
Votes
Horizontal axis is θ
Vertical Axis is r

Forsyth & Ponce (2nd ed.) Figure 10.1 (Top)

Example: Some Noise



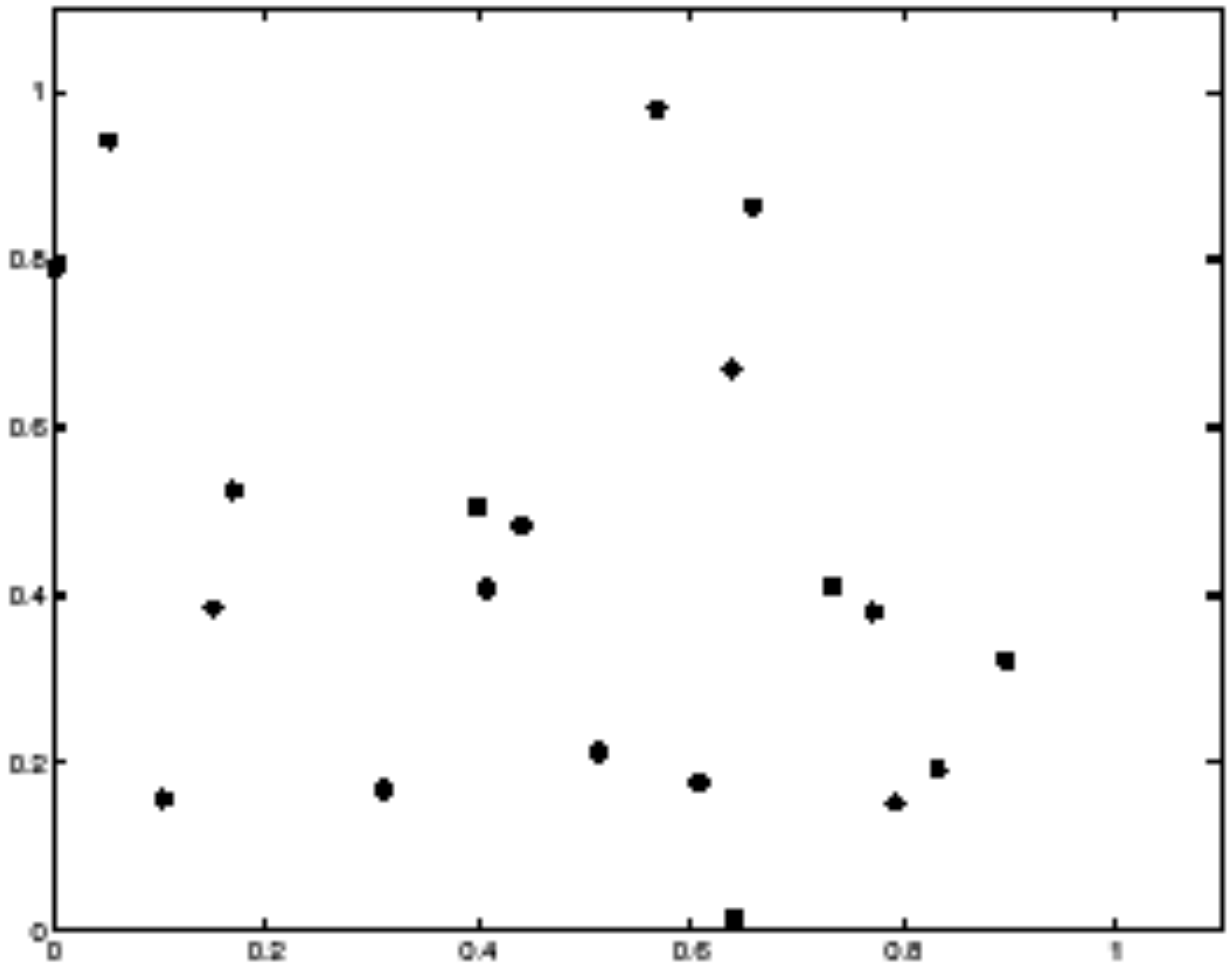
Tokens



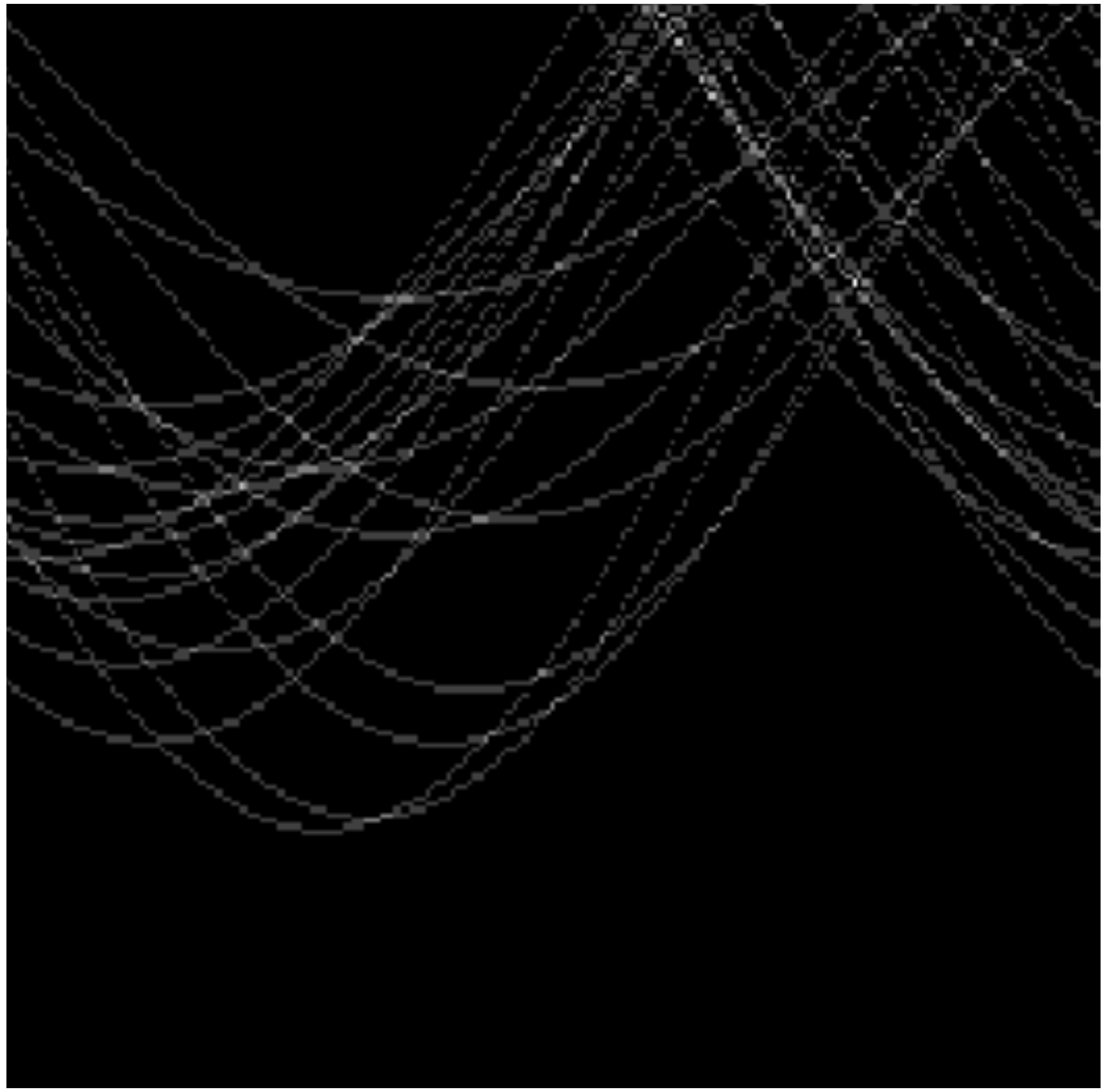
Votes
Horizontal axis is θ
Vertical Axis is r

Forsyth & Ponce (2nd ed.) Figure 10.1 (Bottom)

Example: Too Much Noise



Tokens



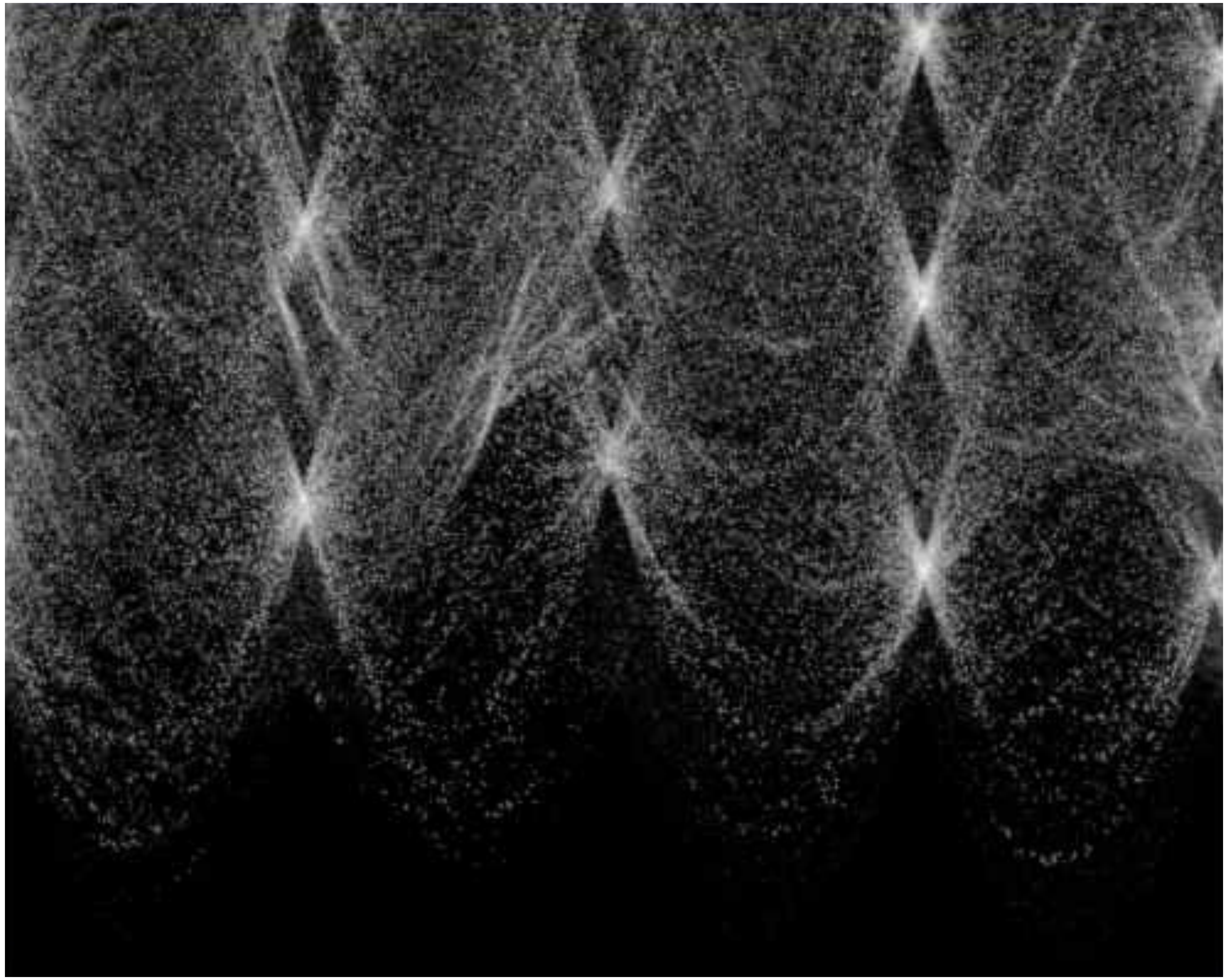
Votes

Horizontal axis is θ

Vertical Axis is r

Forsyth & Ponce (2nd ed.) Figure 10.2

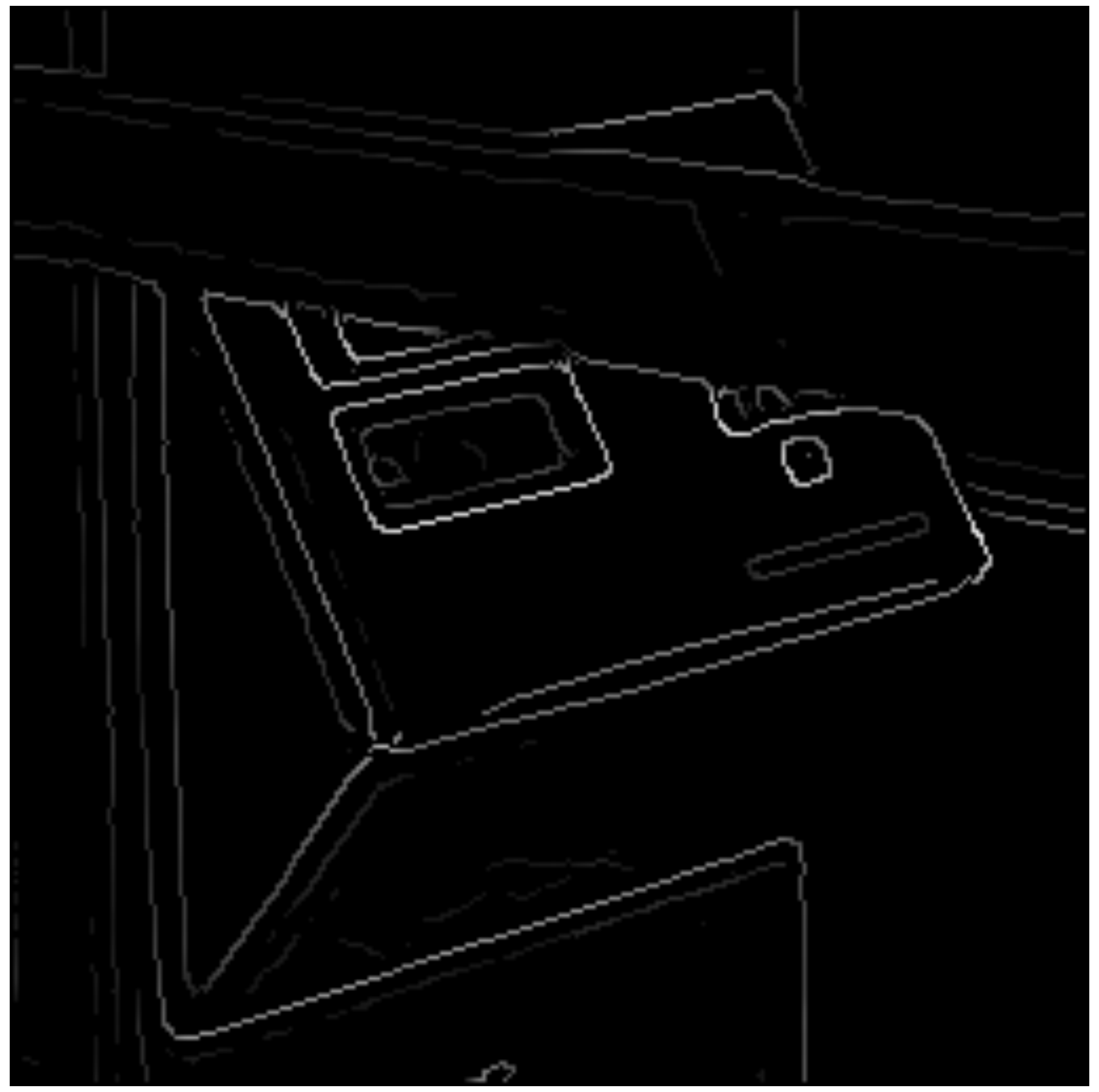
Real World **Example**



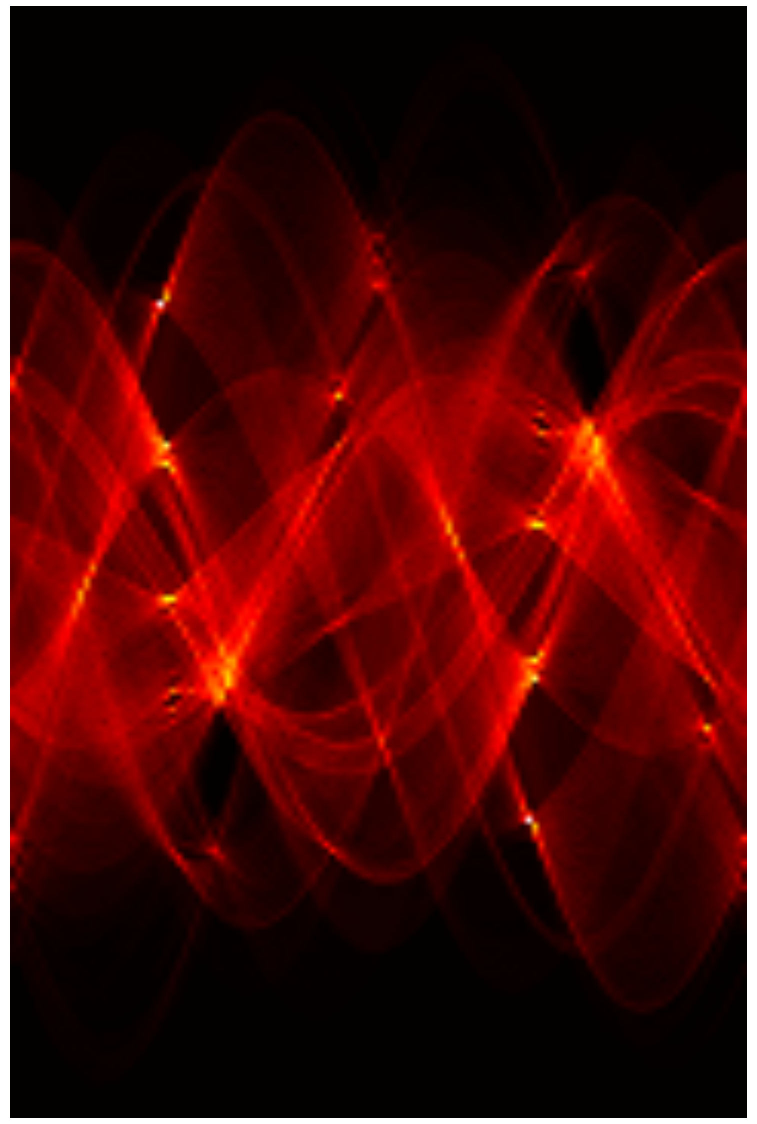
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Real World **Example**

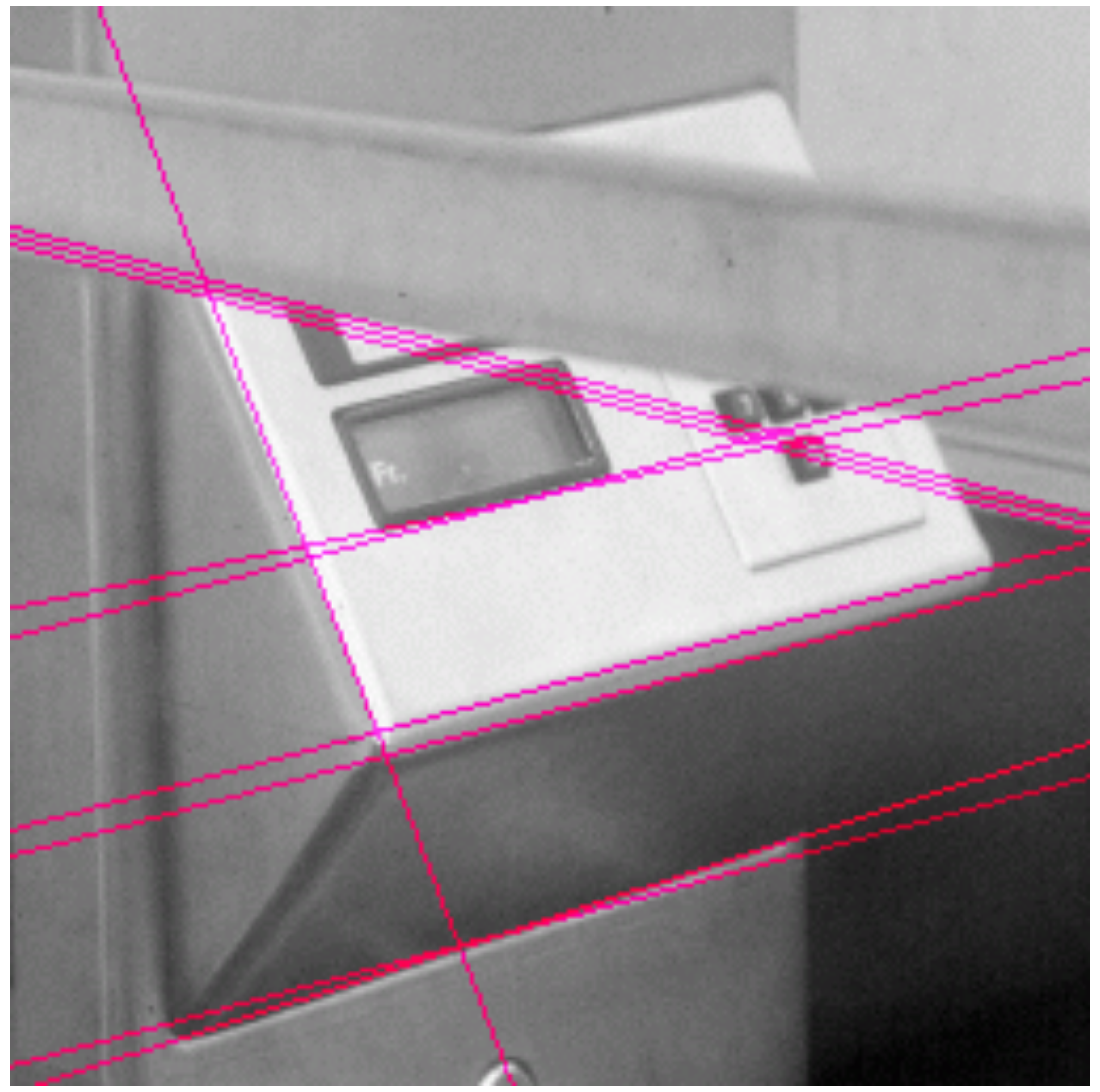
Original



Edges



Parameter space



Hough Lines

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Mechanics of Hough Transform

1. Construct a quantized array to represent θ and r

2. For each point, render curve (θ, r) into this array adding one vote at each cell

Difficulties:
— How big should the cells be? (too big, and we merge quite different lines; too small, and noise causes lines to be missed)

How many lines?

— Count the peaks in the Hough array

— Treat adjacent peaks as a single peak

Some **Practical Details** of Hough Transform

It is best to **vote** for the two closest bins in each dimension, as the locations of the bin boundaries are arbitrary

— This means that peaks are “blurred” and noise will not cause similar votes to fall into separate bins

Can use a **hash table** rather than an array to store the votes

— This means that no effort is wasted on initializing and checking empty bins

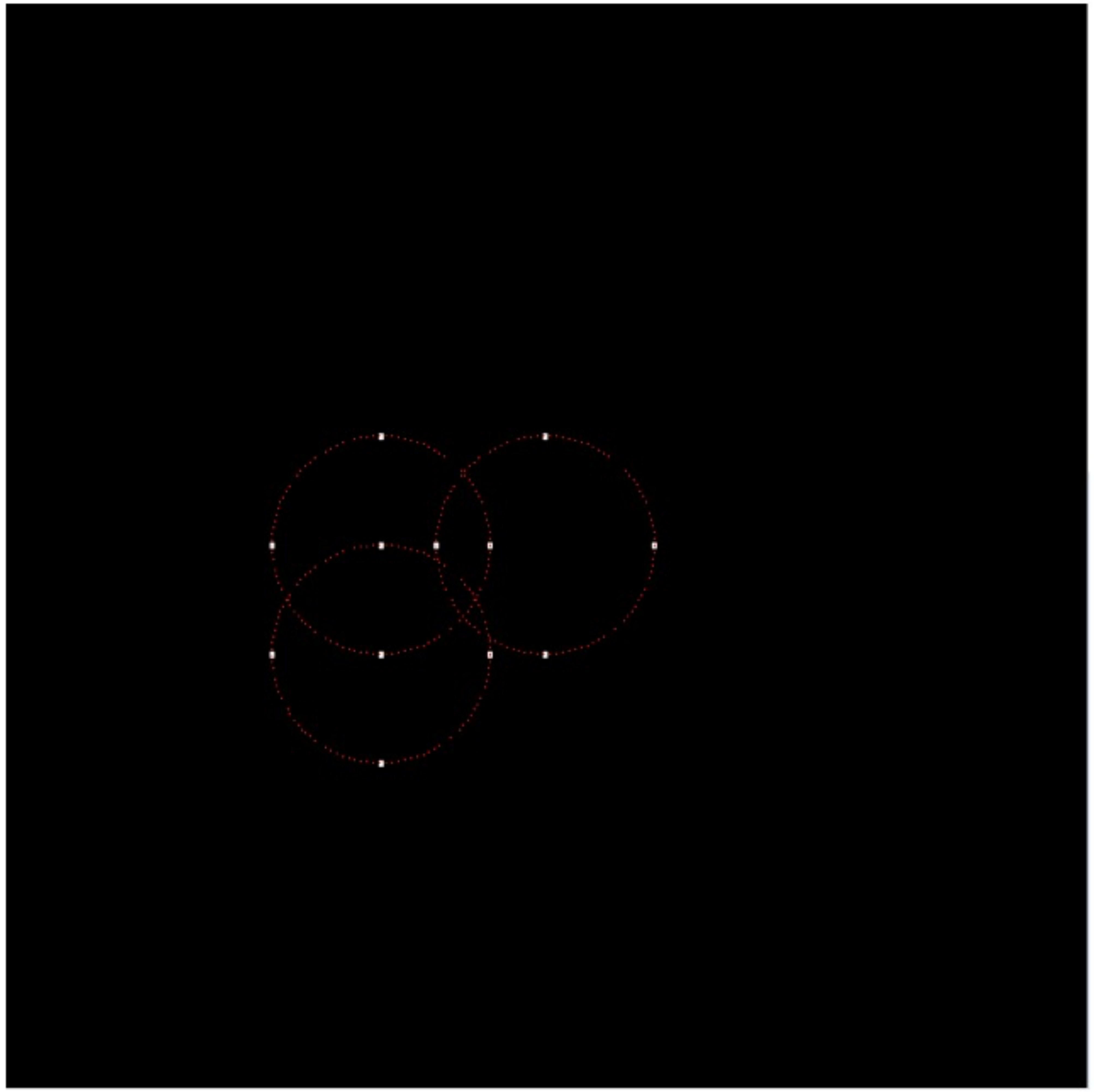
— It avoids the need to predict the maximum size of the array, which can be non-rectangular

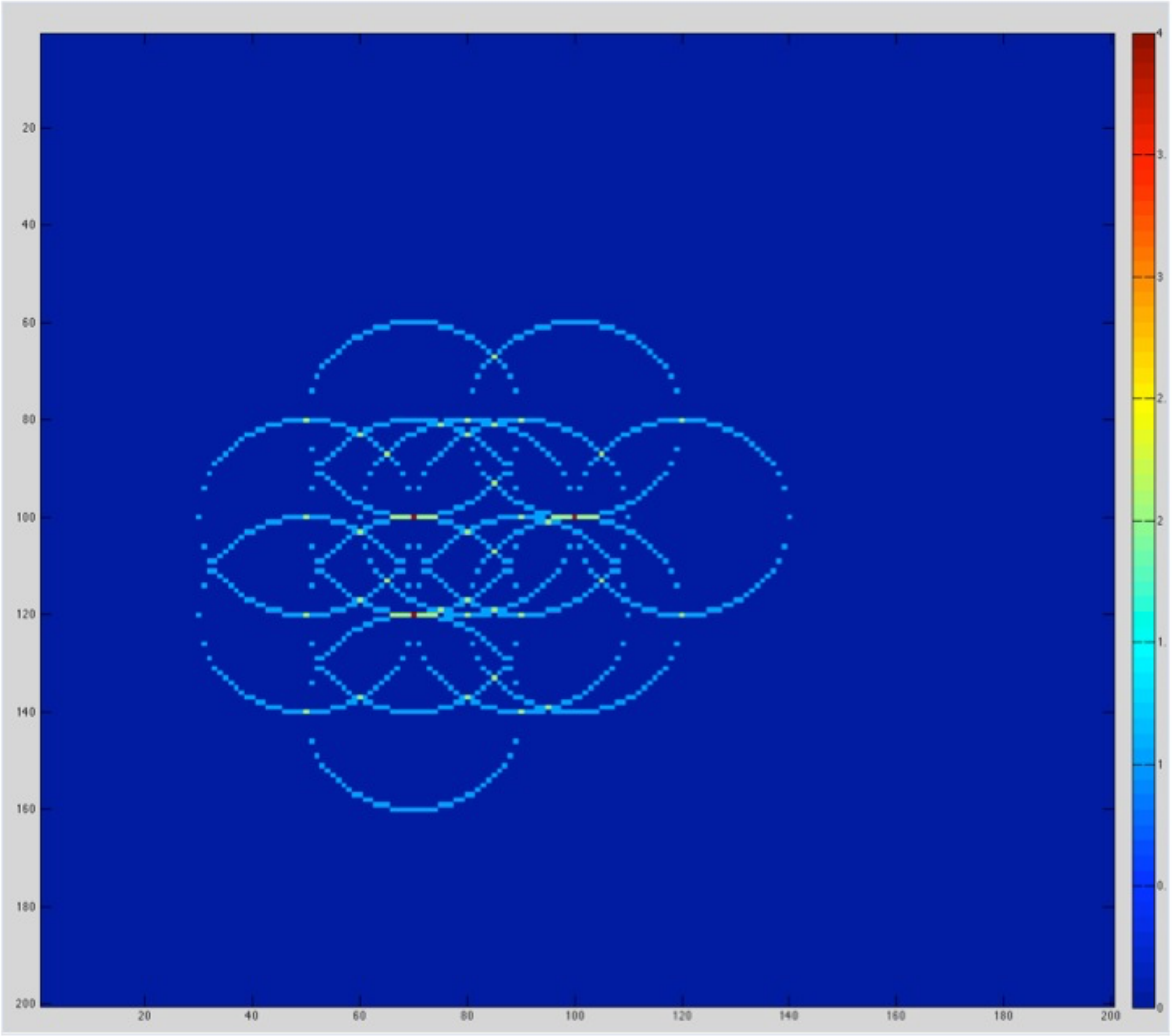
Some **Practical Details** of Hough Transform

A key is to have each feature (token) determine as many parameters as possible
— Lines are detected more effectively from edge elements with
both position and orientation
— For object recognition, each token should predict **position, orientation, and scale**

The Hough transform can extract feature groupings from clutter in linear time

Hough Transform for Circles (of known size)



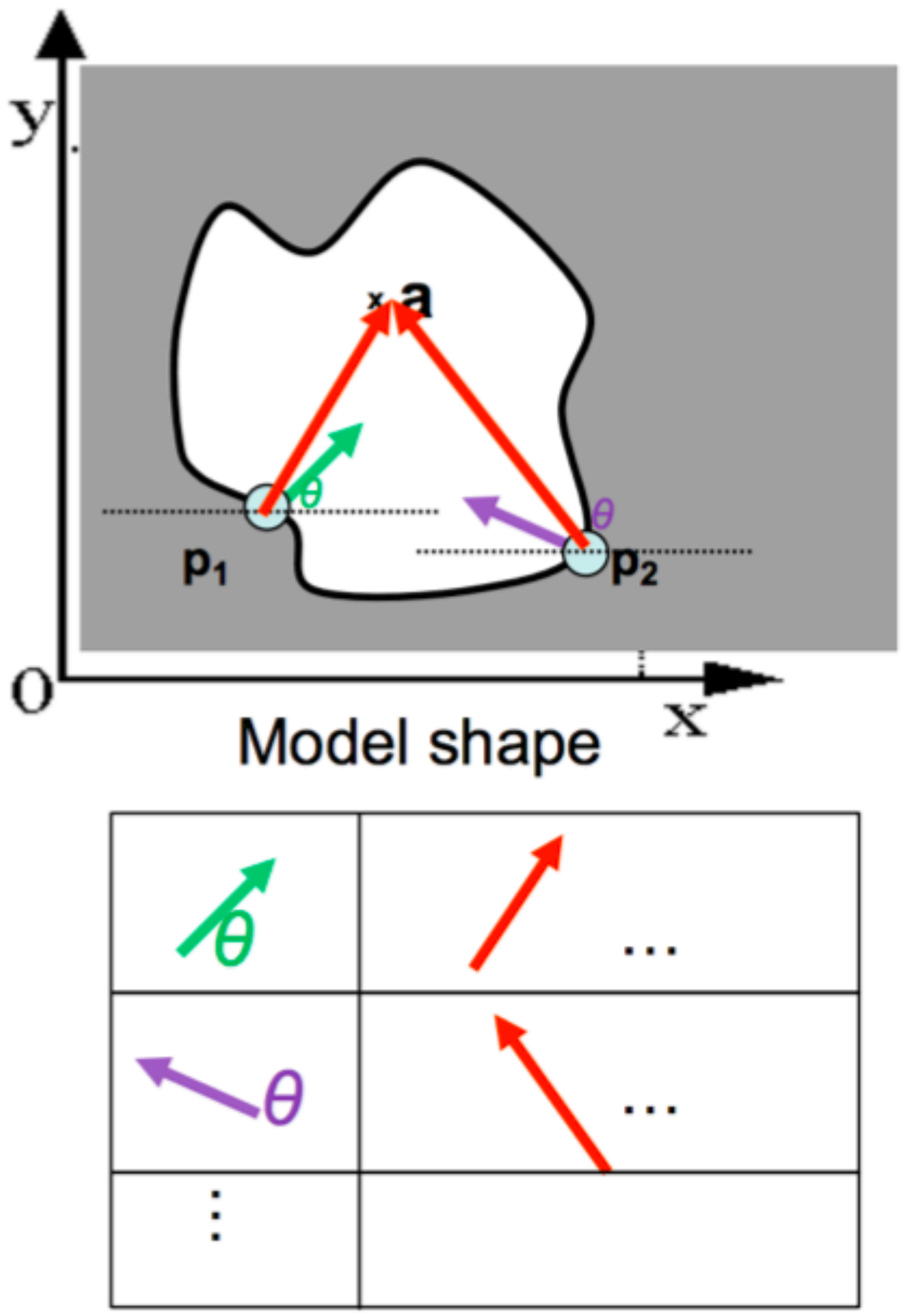


Generalized Hough Transform

What if we want to detect an **arbitrary** geometric shape?

Generalized Hough Transform

What if we want to detect an **arbitrary** geometric shape?



Offline procedure:

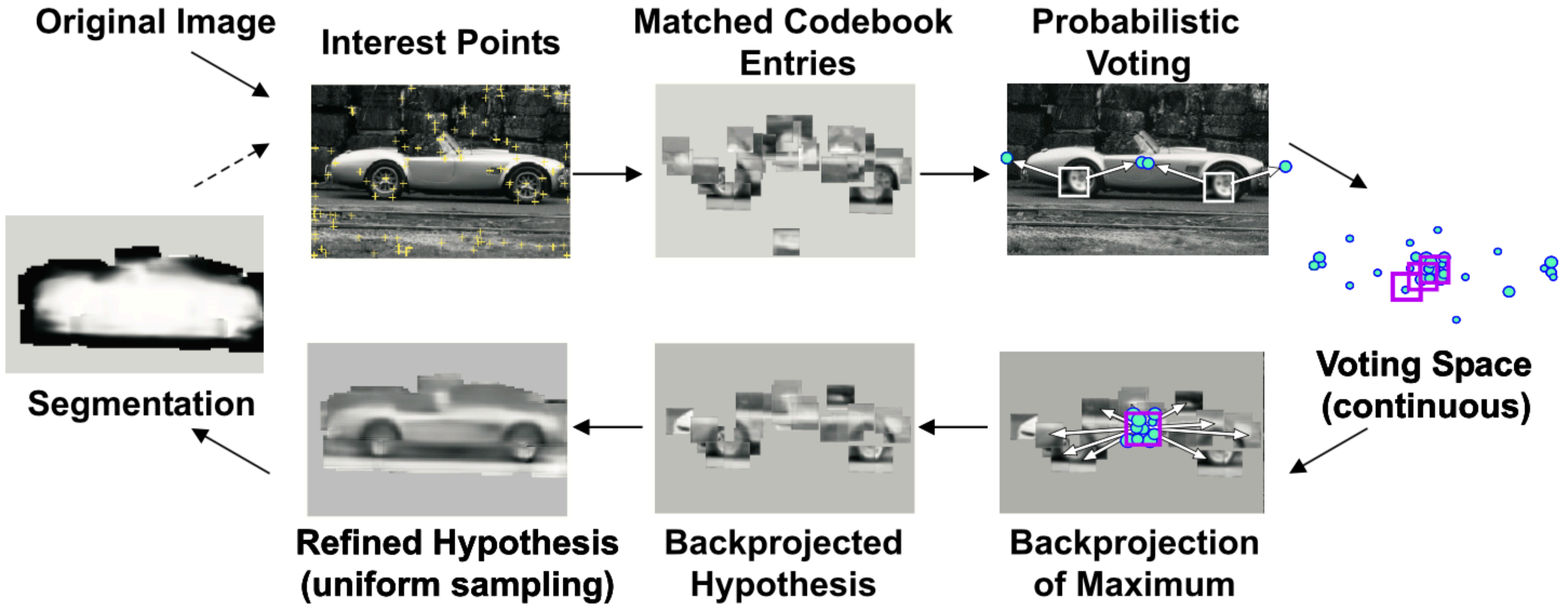
At each boundary point, compute displacement vector: $\mathbf{r} = \mathbf{a} - \mathbf{p}_i$.

Store these vectors in a table indexed by gradient orientation θ.

Dana H. Ballard, Generalizing the Hough Transform to Detect Arbitrary Shapes, 1980

Example 1: Object Recognition — Implicit Shape Model

Combined object detection and segmentation using an implicit shape model.
Image patches cast weighted votes for the object centroid.



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

Example 1: Object Recognition — Implicit Shape Model

Basic Idea:

— Find **interest points/keypoints** in an image (e.g., SIFT Keypoint detector or Corners)

— **Match patch** around each interest point to a training patch (e.g., SIFT Descriptor)

— **Vote** for object center given that training instances

— Find the patches that voted for the peaks (**back-project**)

Example 1: Object Recognition — Implicit Shape Model

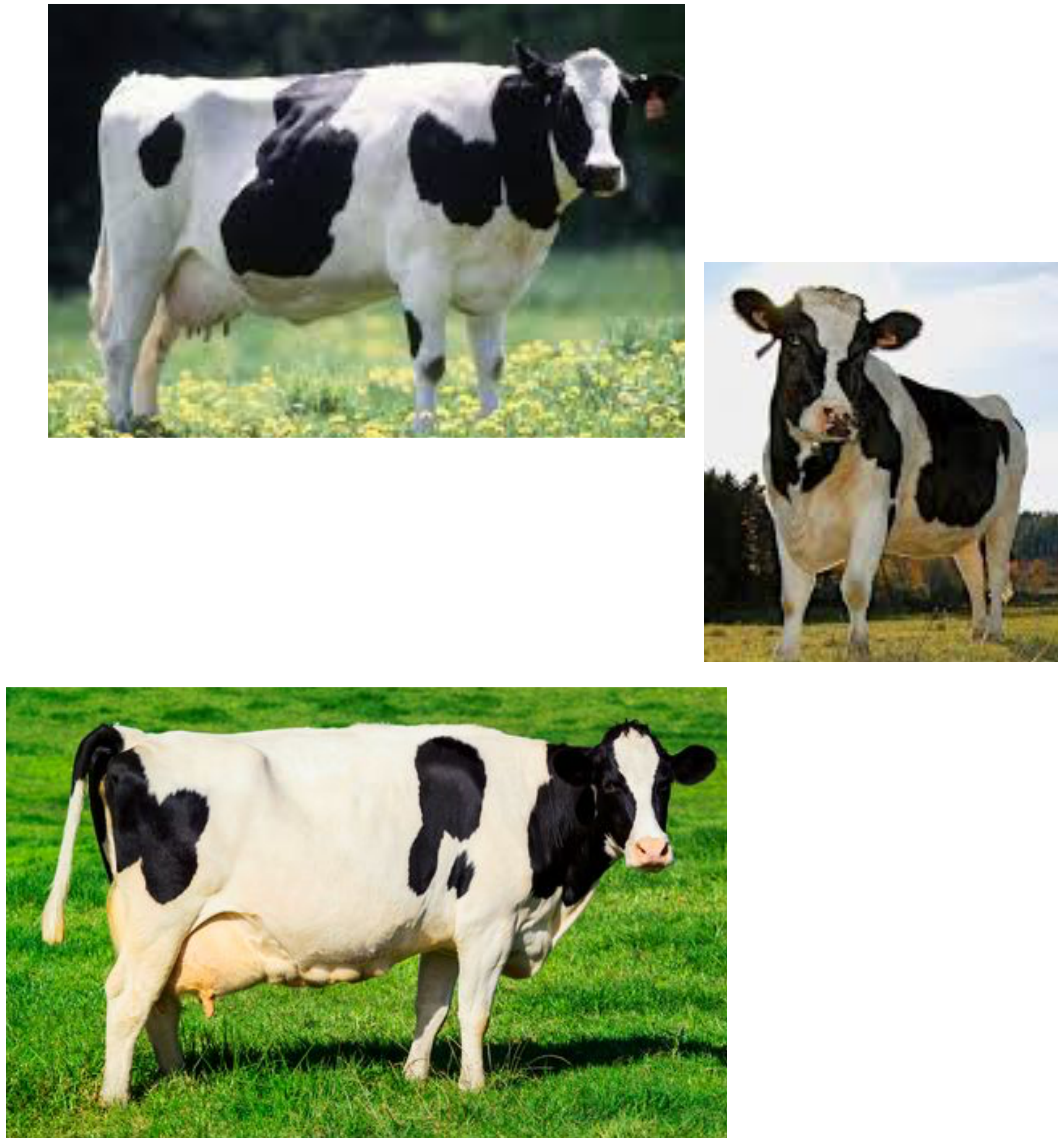
“**Training**” images of cows

“**Testing**” image

* Slide from Sanja Fidler

Example 1: Object Recognition — Implicit Shape Model

“**Training**” images of cows



“**Testing**” image

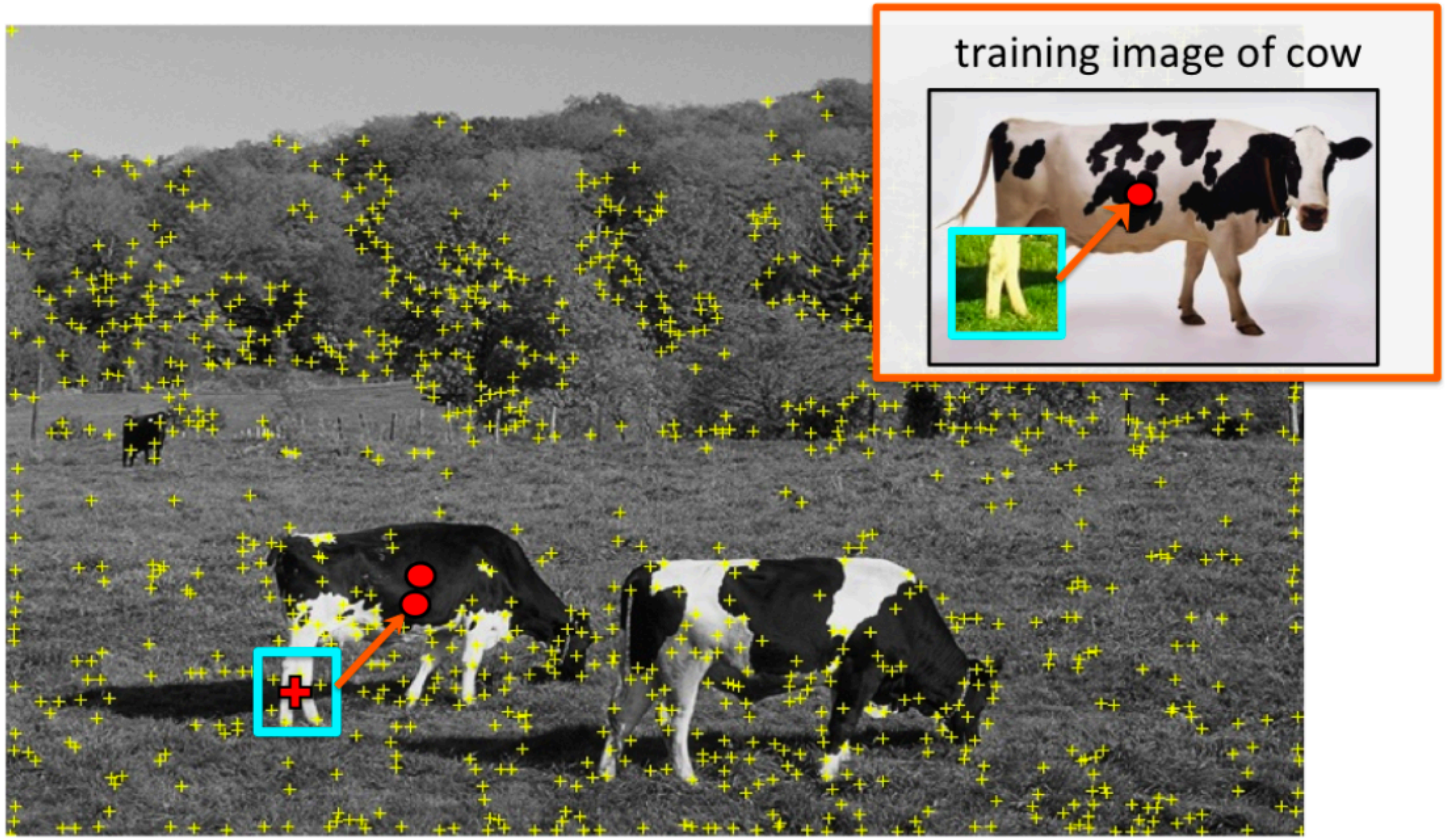
Vote for center of object

* Slide from Sanja Fidler

Example 1: Object Recognition — Implicit Shape Model

“**Training**” images of cows

“**Testing**” image



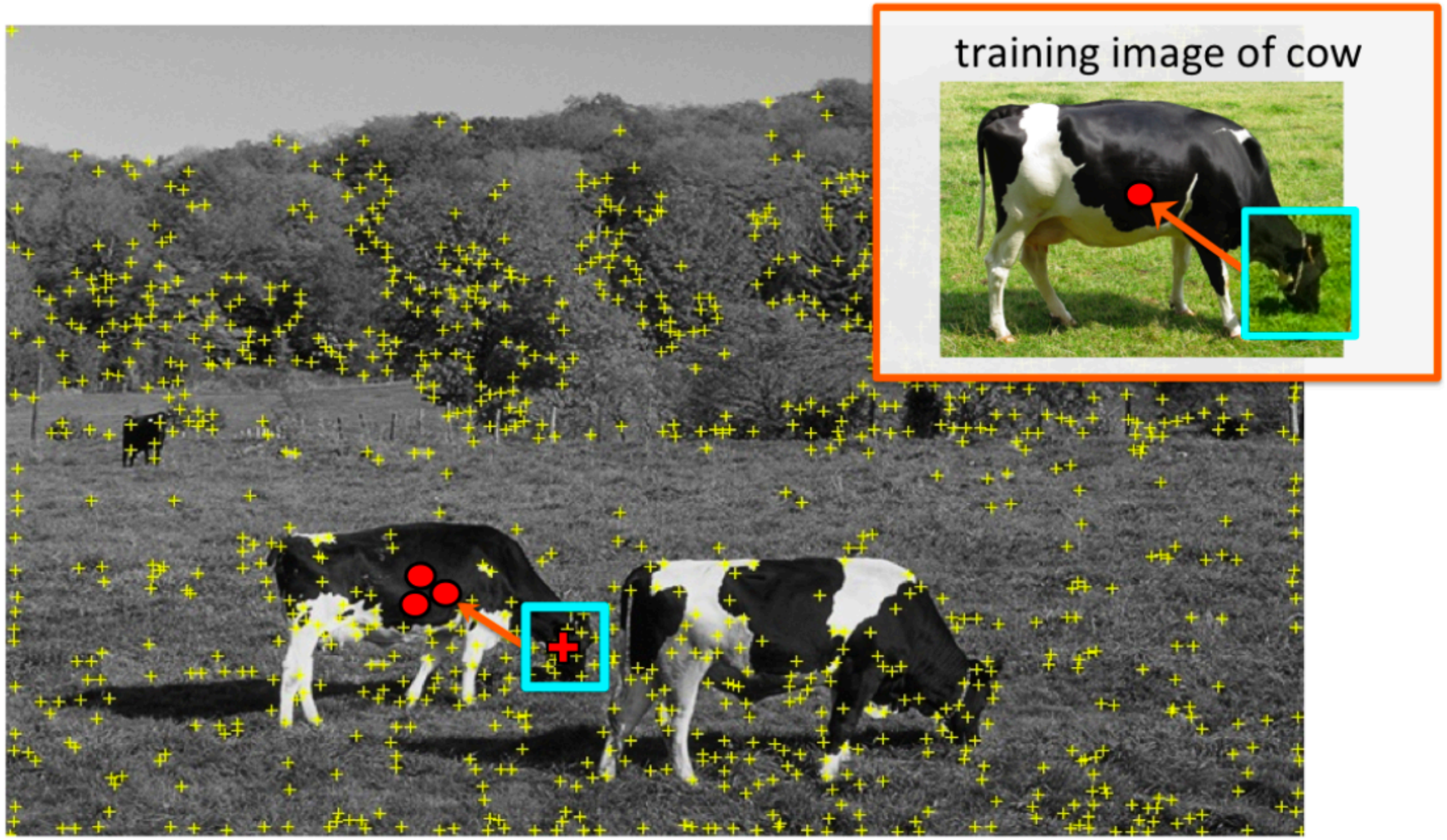
Vote for center of object

* Slide from Sanja Fidler

Example 1: Object Recognition — Implicit Shape Model

“**Training**” images of cows

“**Testing**” image



Vote for center of object

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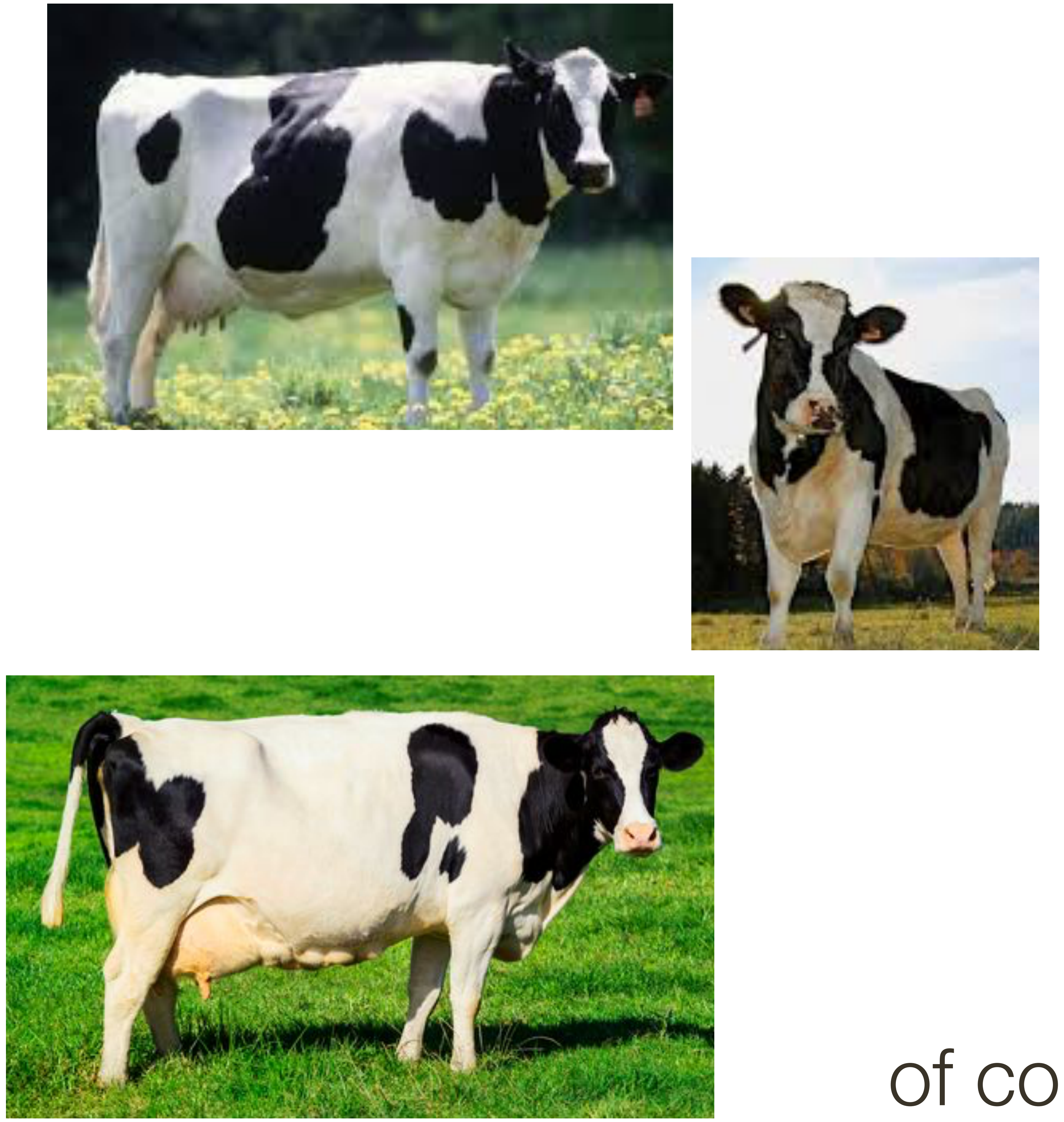
Example 1: Object Recognition — Implicit Shape Model

“**Training**” images of cows



“**Testing**” image

of course sometimes wrong votes are bound to happen

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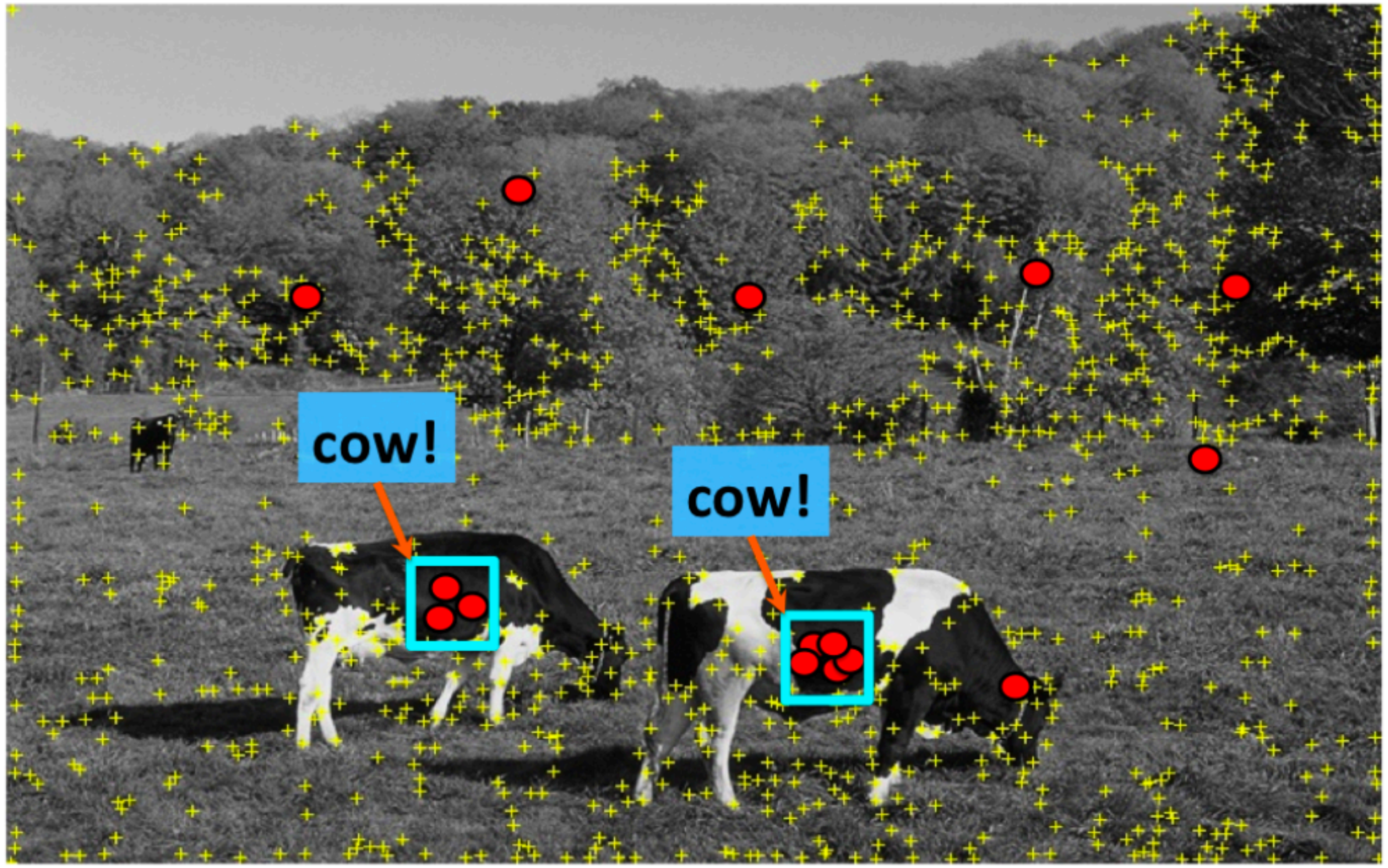
Example 1: Object Recognition — Implicit Shape Model

“**Training**” images of cows

“**Testing**” image



That’s ok. We want only **peaks** in voting space.

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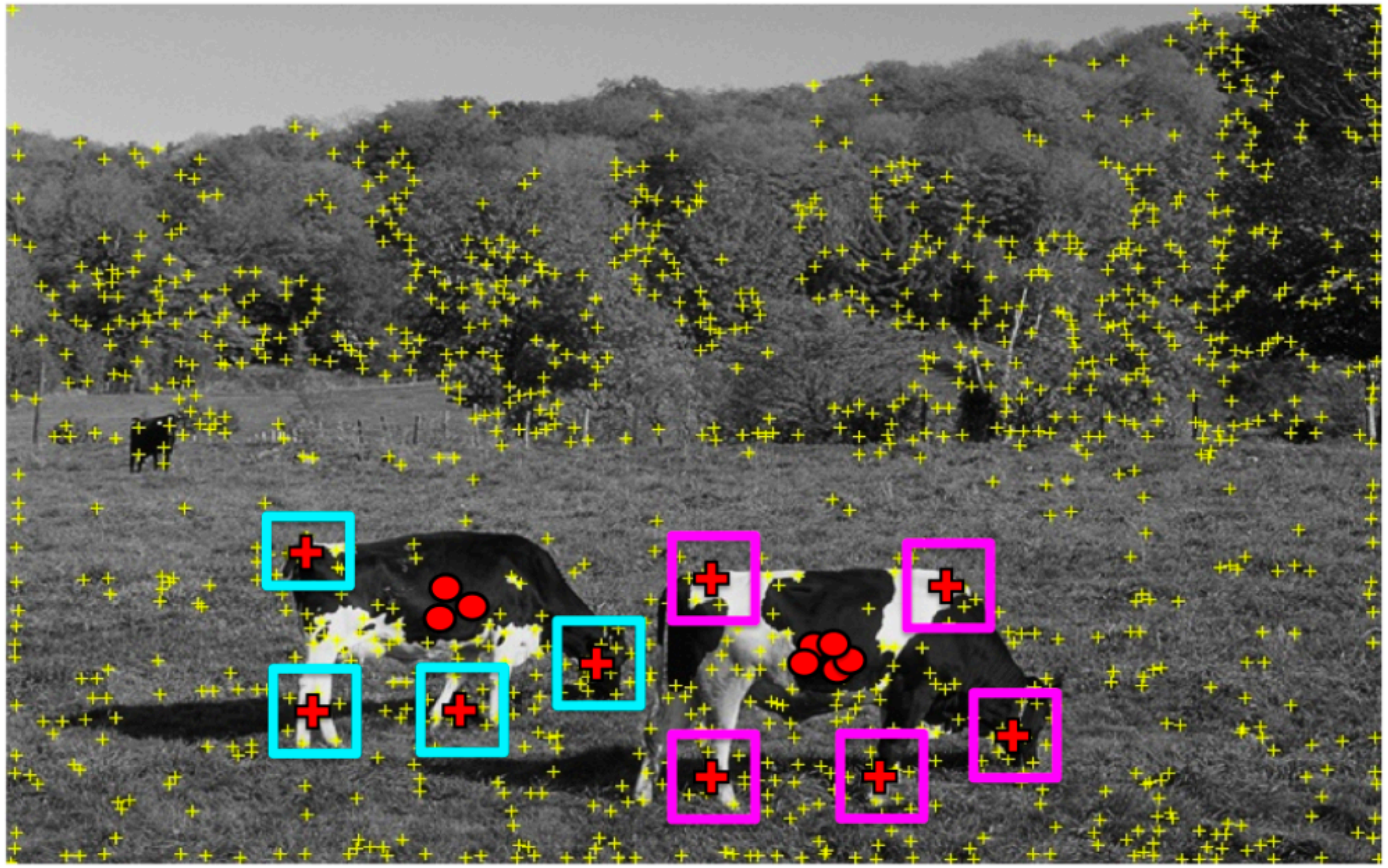
Example 1: Object Recognition — Implicit Shape Model

“**Training**” images of cows

“**Testing**” image



Find patches that voted for the peaks (back-project)

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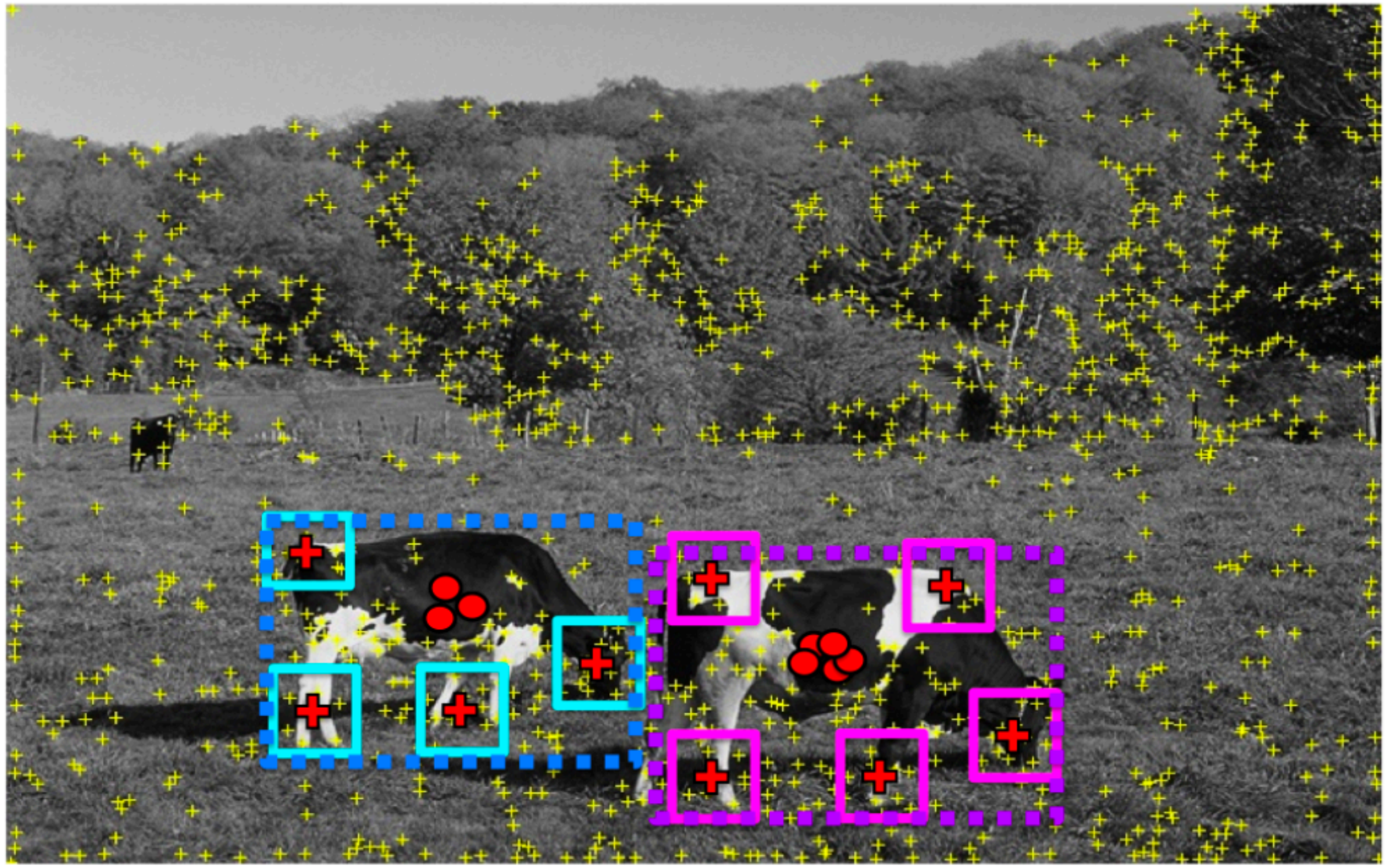
Example 1: Object Recognition — Implicit Shape Model

“**Training**” images of cows

“**Testing**” image

box around patches = object



Find objects based on the back projected patches

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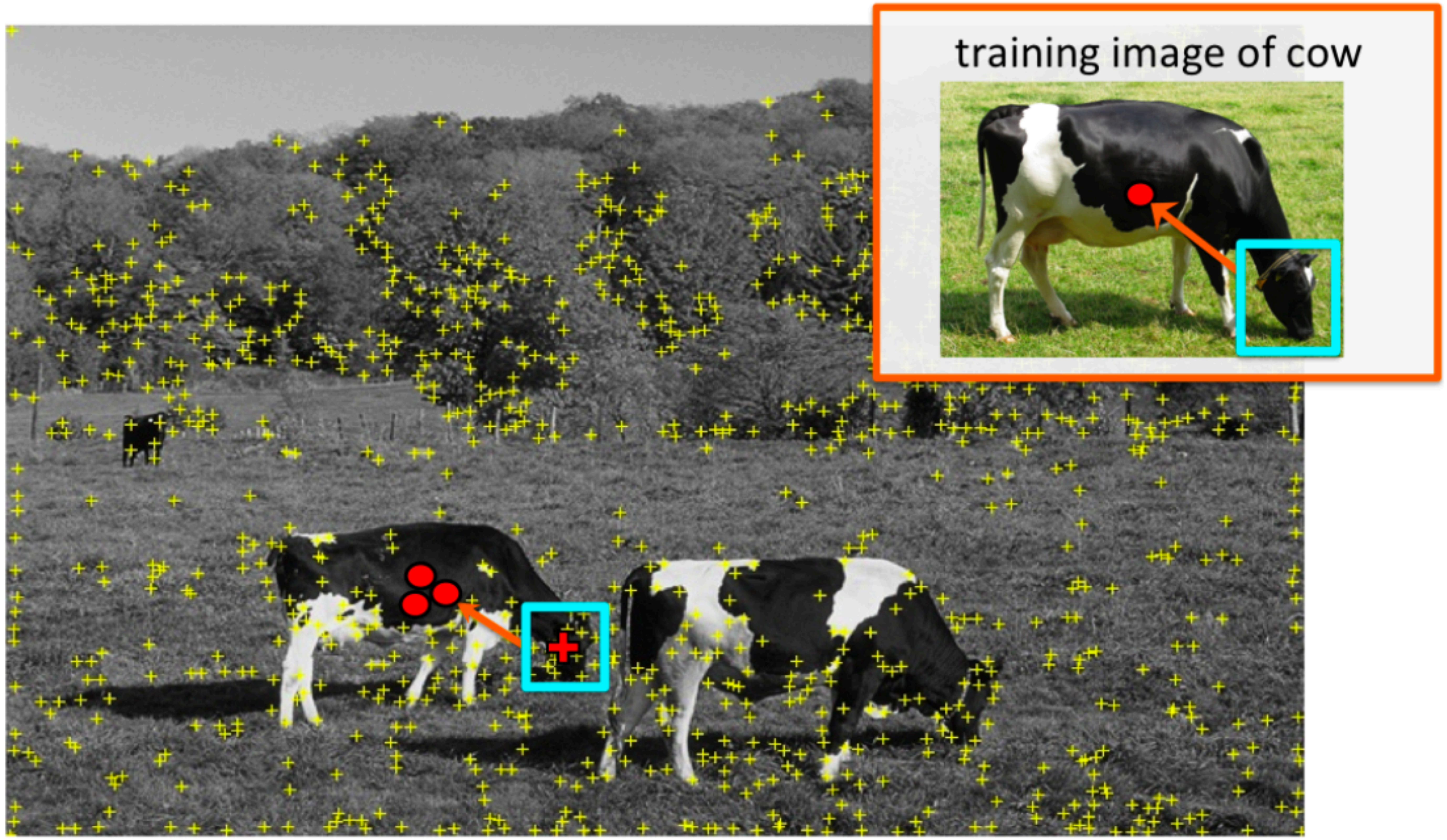
Example 1: Object Recognition — Implicit Shape Model

"**Training**" images of cows

"**Testing**" image

Really easy … but slow … how do we make it fast?



We need to match a patch around each yellow keypoint to all patches in all training images (**slow**)

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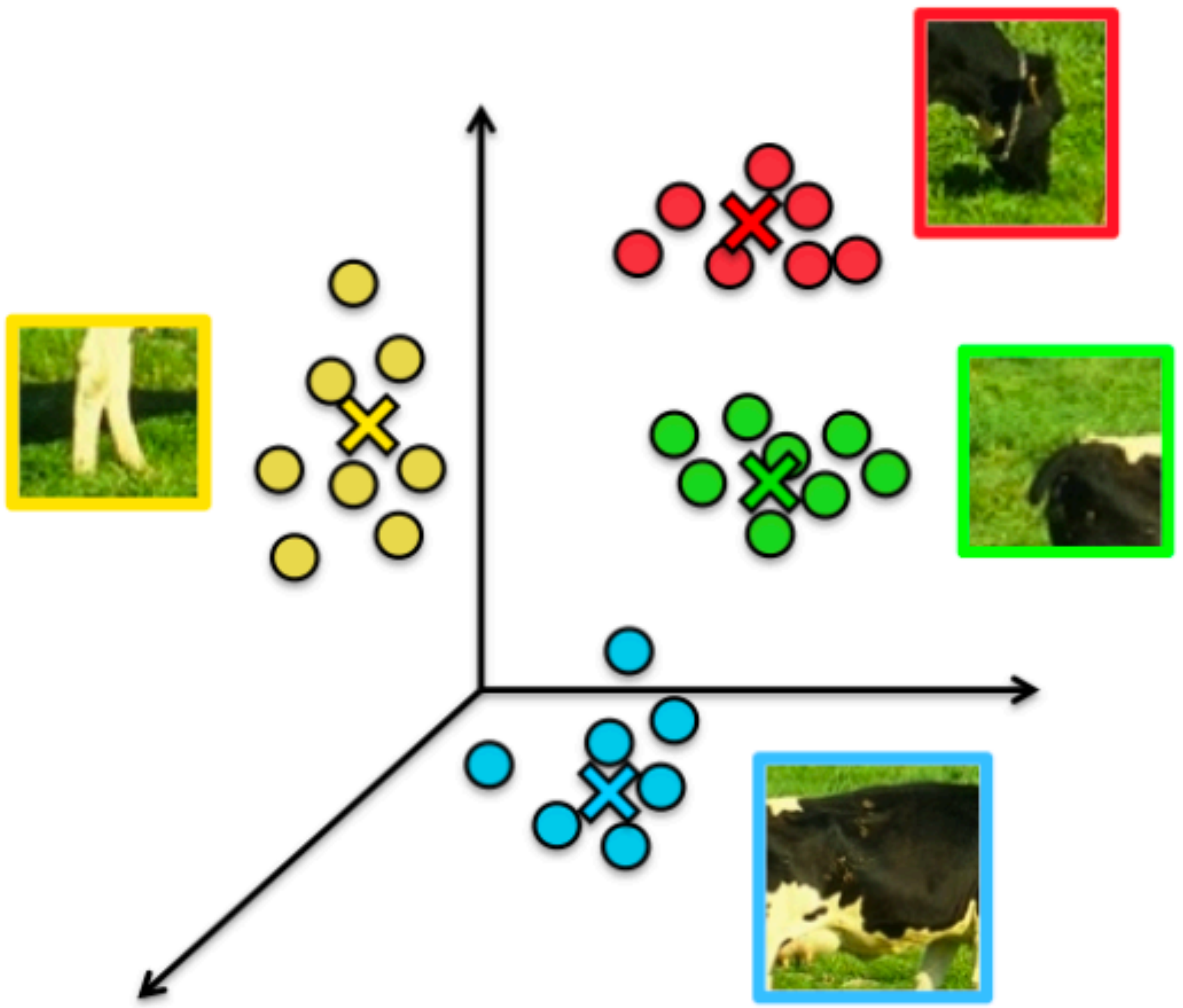
Visual Words

- **Visual vocabulary** (we saw this for retrieval)
- Compare each patch to a small set of visual words (clusters)



Visual words (visual codebook)!

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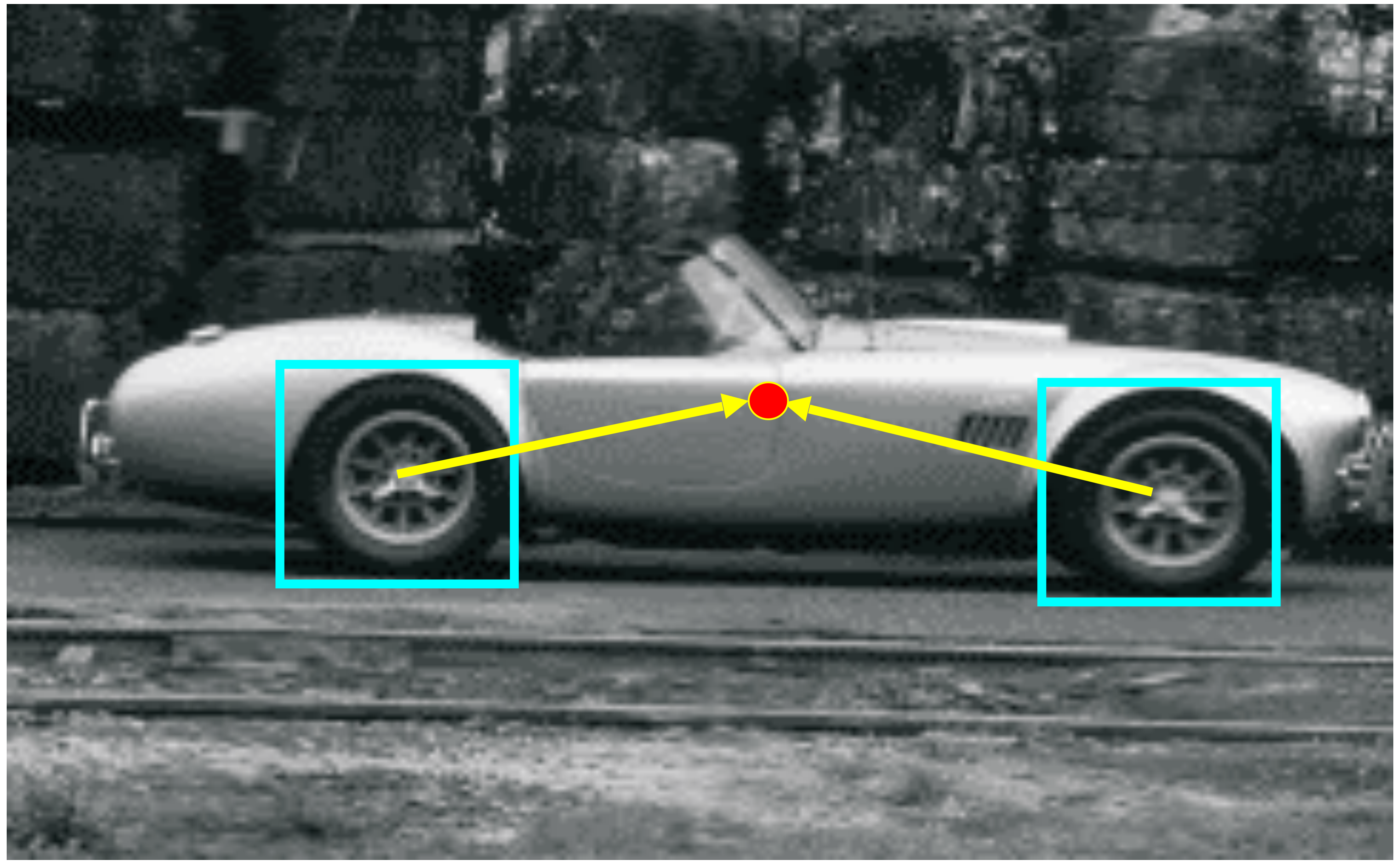
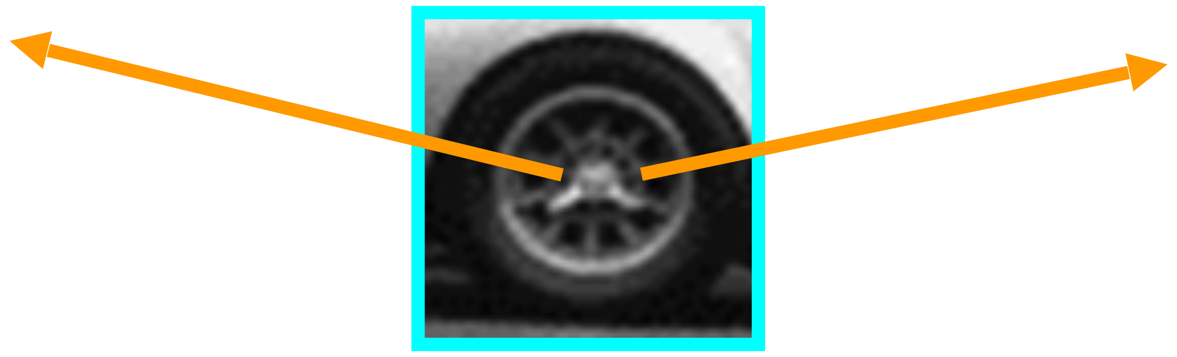
Example 1: Object Recognition — Implicit Shape Model

Index displacements by "visual codeword"



training image



visual codeword with
displacement vectors

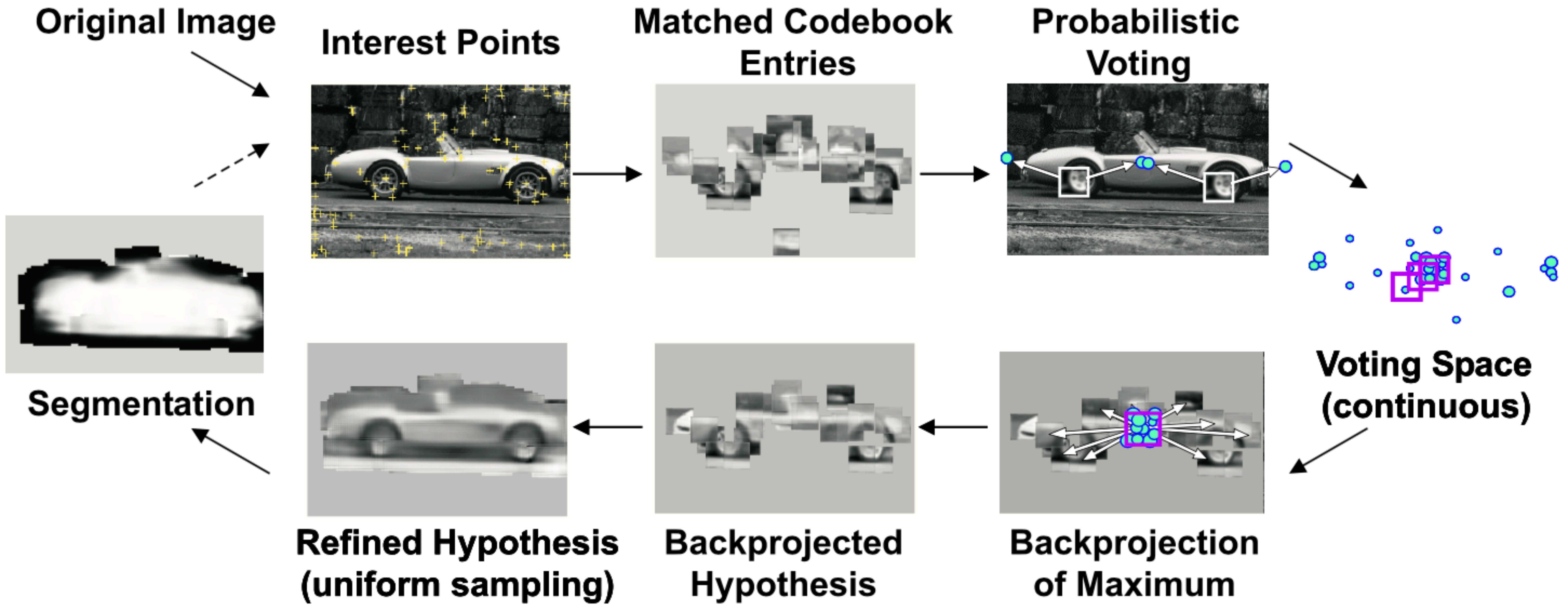
B. Leibe, A. Leonardis, and B. Schiele, Combined Object Categorization and Segmentation with an Implicit Shape Model,
ECCV Workshop on Statistical Learning in Computer Vision 2004

Example 1: Object Recognition — Implicit Shape Model

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

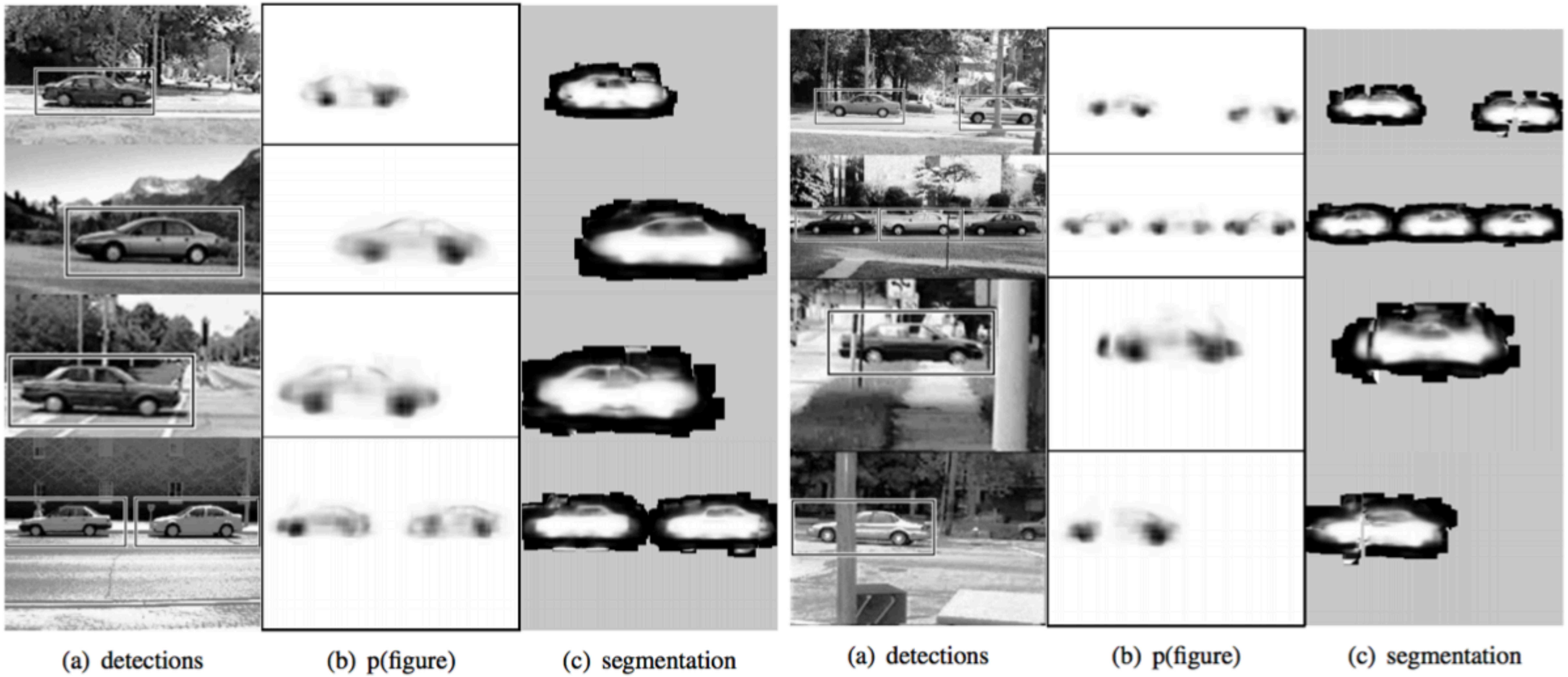
Inferring Other Information: **Segmentation**

Combined object detection and segmentation using an implicit shape model.
Image patches cast weighted votes for the object centroid.



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

Inferring Other Information: **Segmentation**



[Source: B. Leibe]

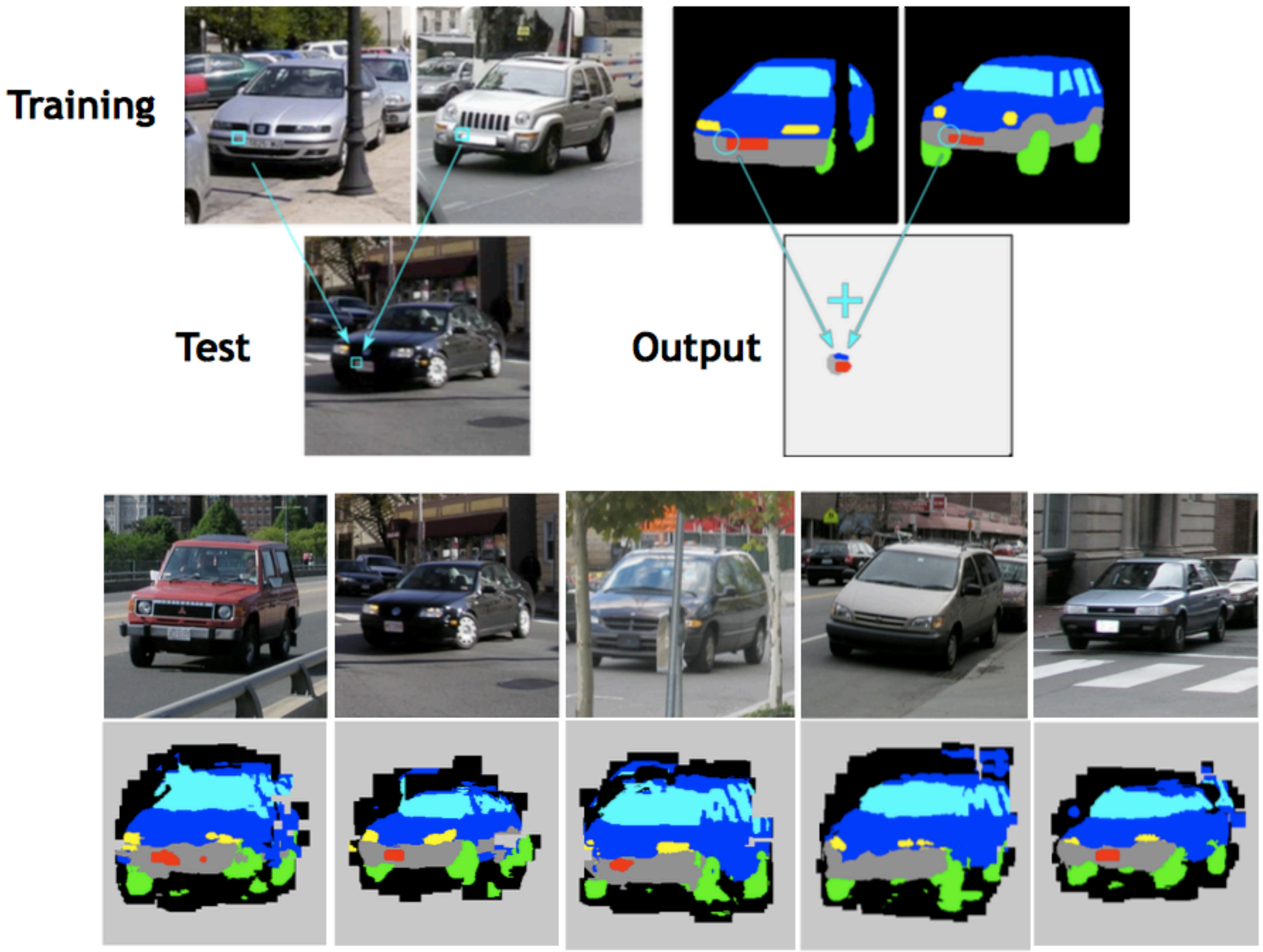
* Slide from Sanja Fidler

Inferring Other Information: **Segmentation**

[Source: B. Leibe]

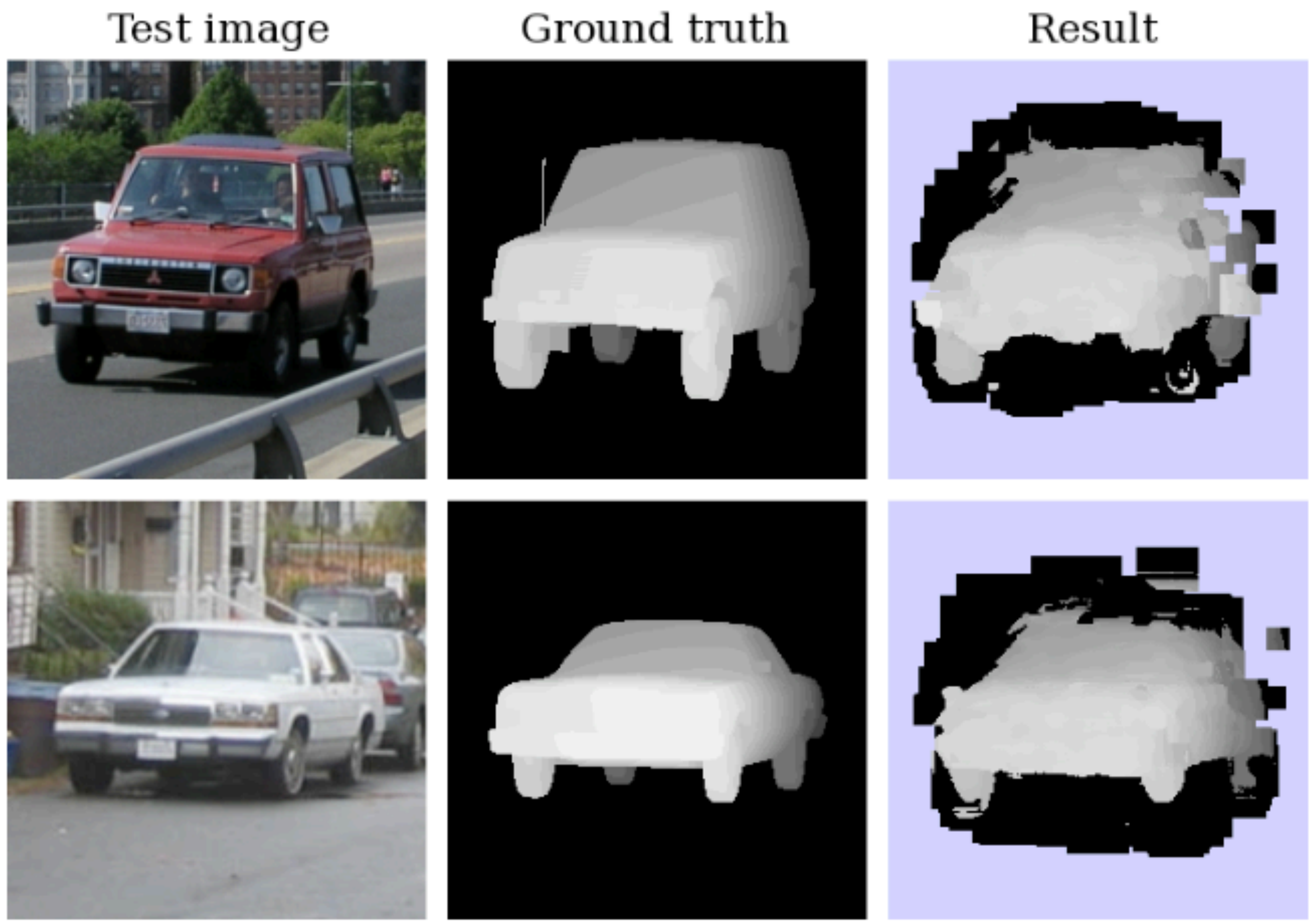
* Slide from Sanja Fidler

Inferring Other Information: **Part Labels**



* Slide from Sanja Fidler

Inferring Other Information: **Depth**



"Depth from a single image"

* Slide from Sanja Fidler

Example 2: Object Recognition — Boundary Fragments

Boundary fragments cast weighted votes for the object centroid. Also obtains an estimate of the object's contour.

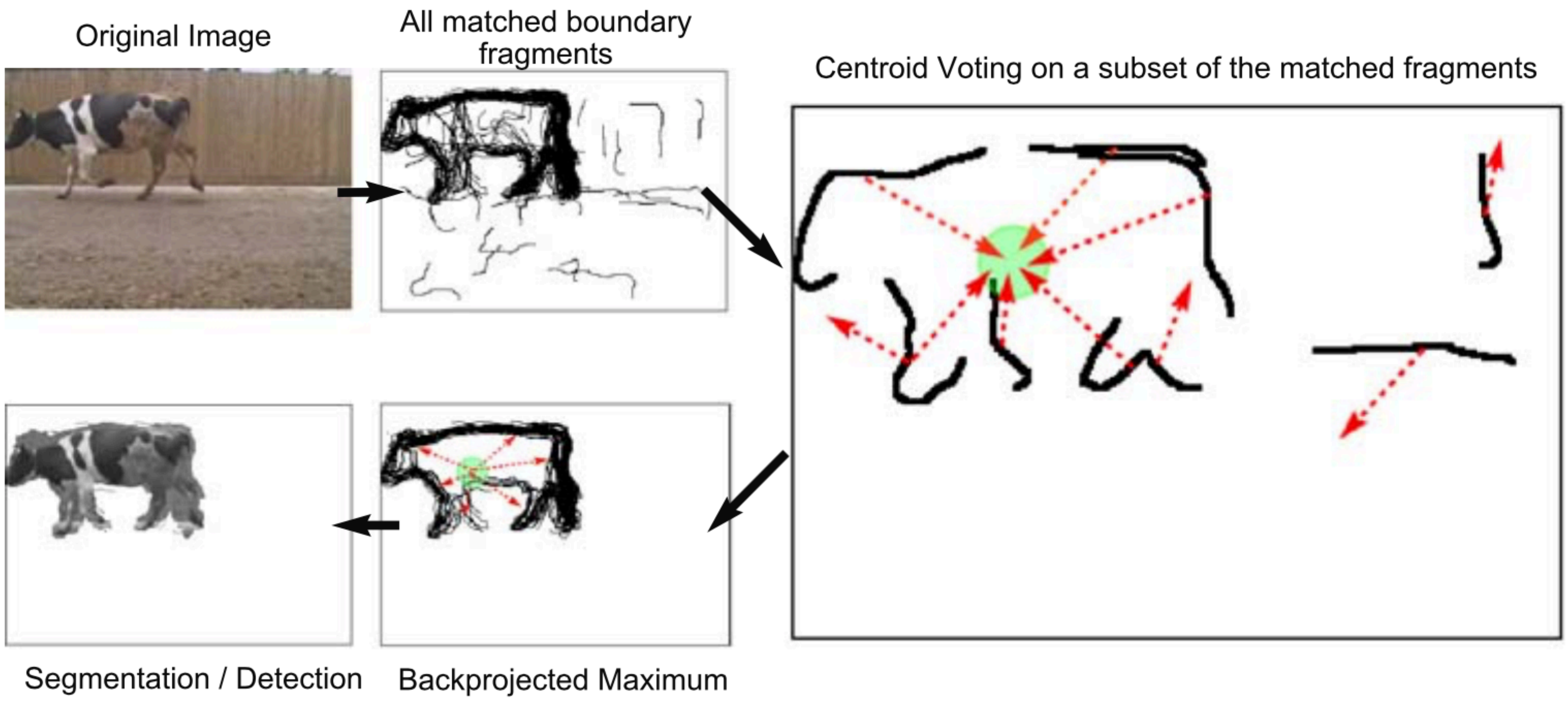


Image credit: Opelt et al., 2006

Example 2: Object Recognition — Boundary Fragments

Boundary fragments cast weighted votes for the object centroid. Also obtains an estimate of the object's contour.

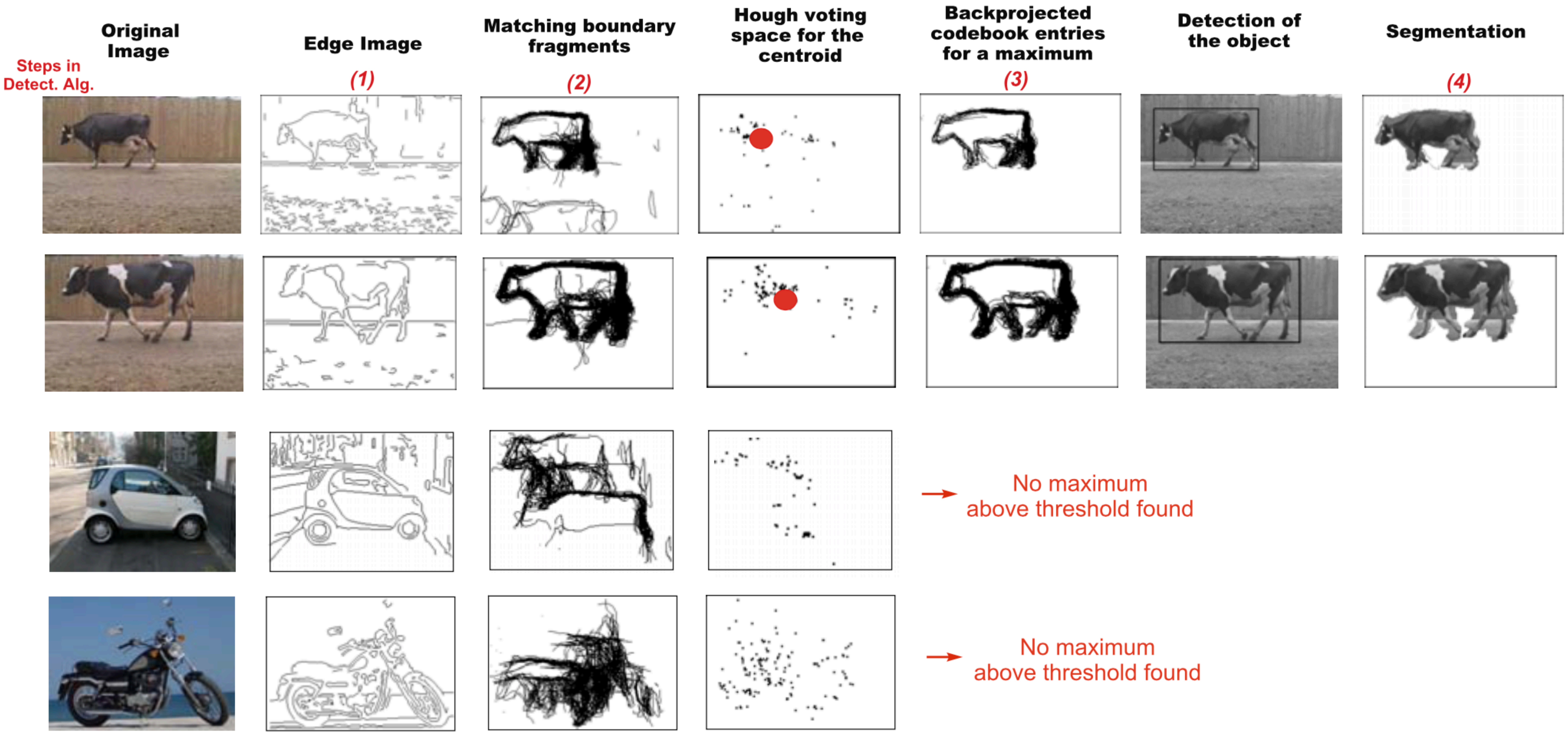


Image credit: Opelt et al., 2006

Example 3: Object Recognition — Poselets

Poselets are image patches that have distinctive appearance and can be used to infer some of the configuration of a parts-based object. Detected poselets vote for the object configuration.

Image credit: Bourdev and Malik, 2009

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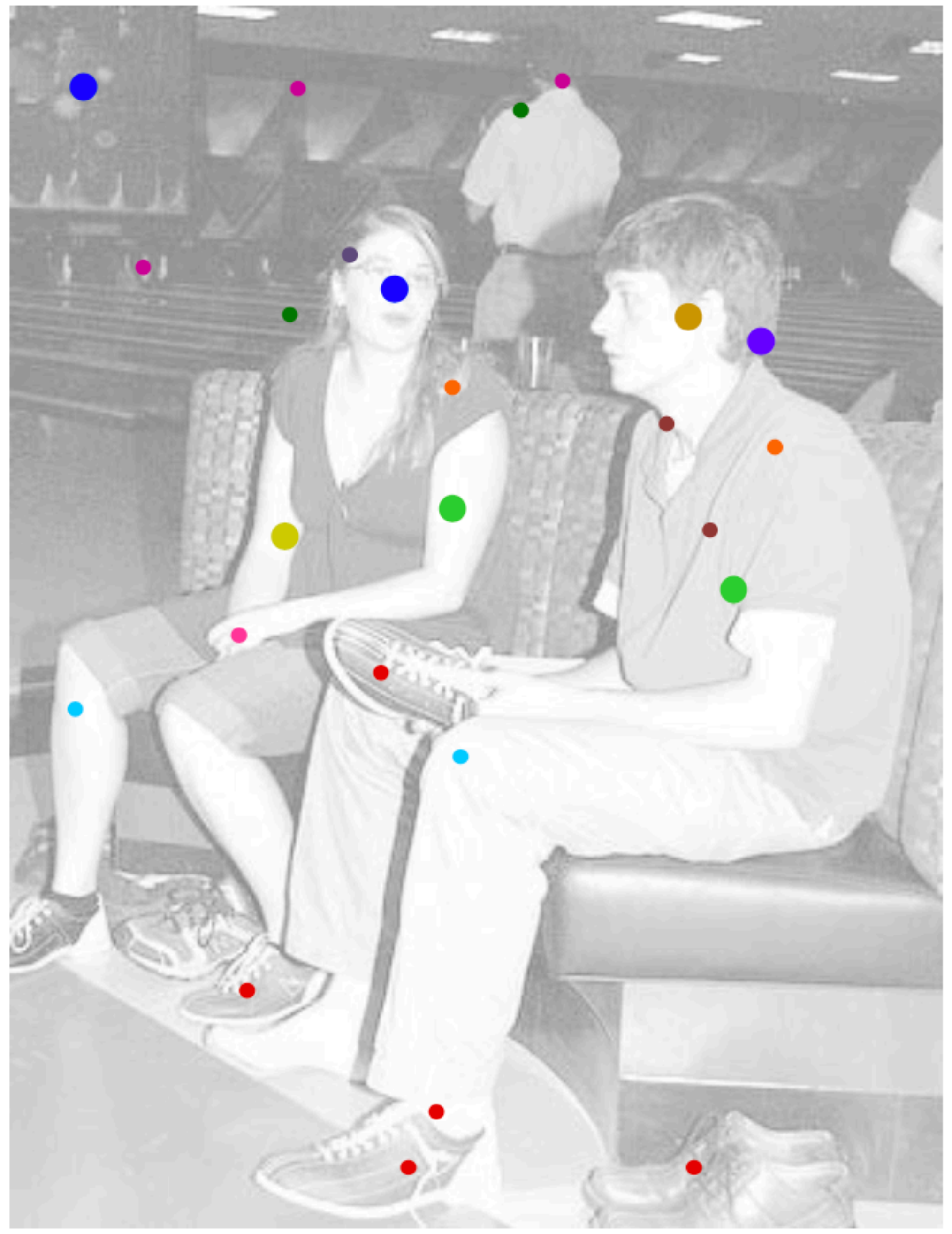
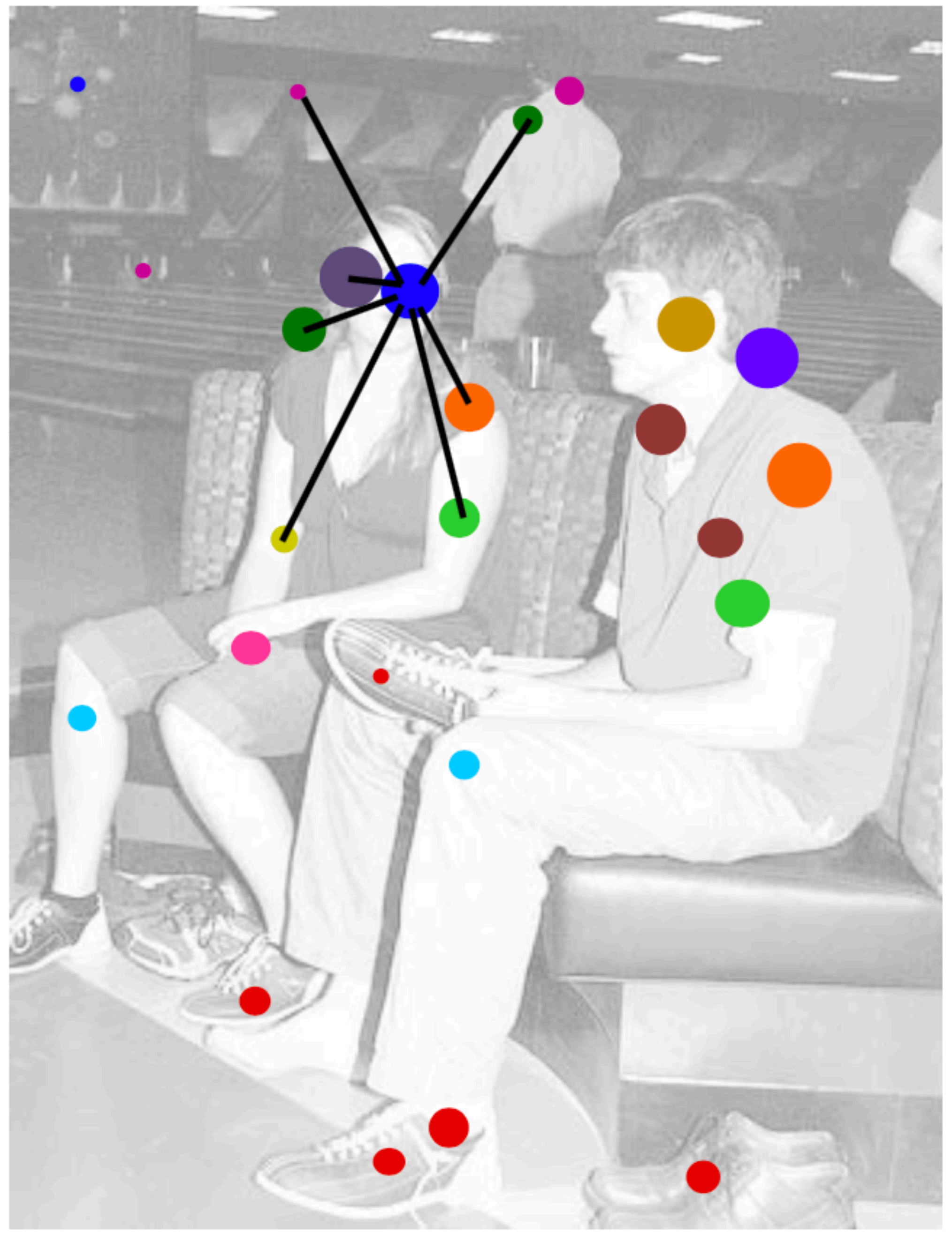
Poselets are image patches that have distinctive appearance and can be used to infer some of the configuration of a parts-based object. Detected poselets vote for the object configuration.

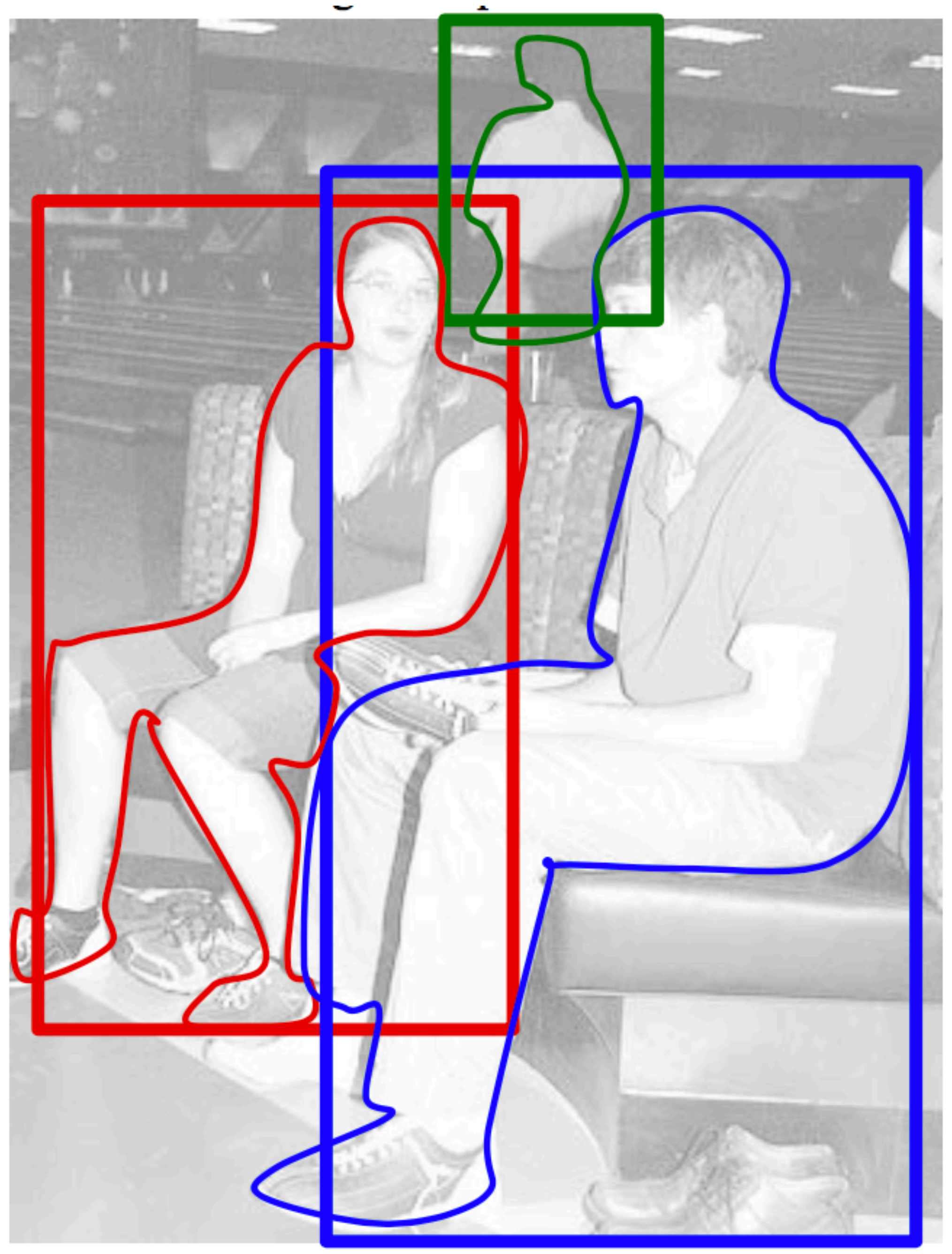


1. q-scores. Different colors illustrate different poselet detectors firing in the image. The blob size illustrates the score of the independent poselet classifier.



2. Q-scores (Section 4). Evidence from consistent poselet activations leads to a reranking based on mutual activation (Q-scores). Weaker activations consistent with others gain importance, whereas inconsistent ones get damped.

3. Clustering (Section 5). Activations are merged in a greedy manner starting with the strongest activation. Merging is based on pairwise consistency.



4. Bounding boxes (Section 6) and segmentations (Section 7). We predict the visible bounds and the contour of the person using the poselets within the cluster.

Image credit: Bourdev and Malik, 2009

Discussion of Hough Transform

Advantages:

— Can handle high percentage of outliers: each point votes separately

— Can detect multiple instances of a model in a single pass

Disadvantages:

— Complexity of search time increases exponentially with the number of model parameters

— Can be tricky to pick a good bin size

Summary of Hough Transform

The **Hough transform** is another technique for fitting data to a model

— a voting procedure

— possible model parameters define a quantized accumulator array

— data points “vote" for compatible entries in the accumulator array

A key is to have each data point (token) constrain model parameters as tightly as possible