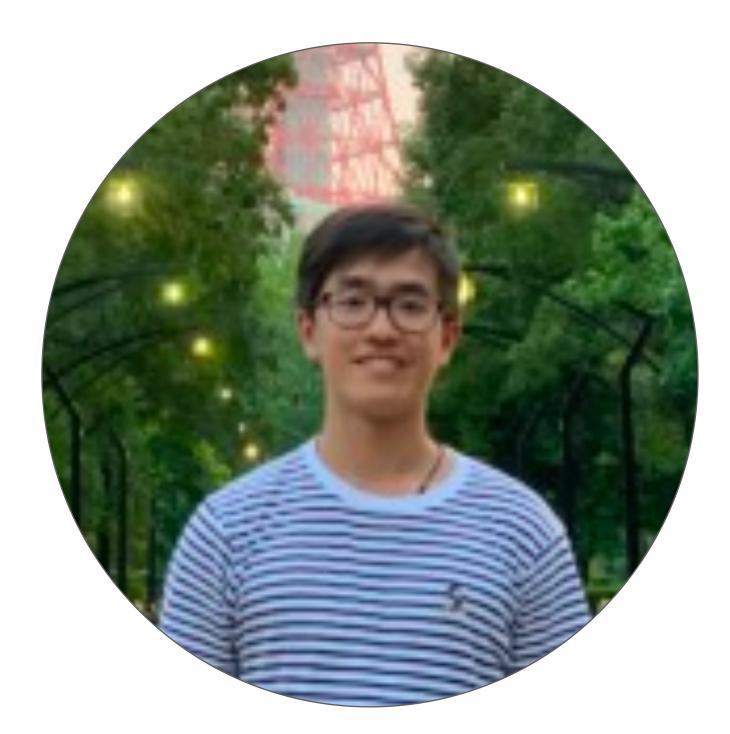
# EECS 504: Foundations of Computer Vision Andrew Owens

# Course staff





Haozhu Wang Graduate student (GSI)



## **Anthony Liang** Instructional aide (IA)

## Bingqi Sun Instructional aide (IA)



# Interacting with us

- Ask questions on Piazza.
  - Sign up: <u>https://bit.ly/36mfYeP</u>
- Submit written work to Gradescope
- Office hours on website:

Name	Office hour times	Location
Andrew Owens	Fri. 3:00pm - 4:00pm	EECS 4231
Haozhu Wang	Thu. 7:30pm - 8:30pm	EECS 3312
Bingqi Sun	Mon. 12:00 - 1:00	EECS 3312
Anthony Liang	Mon. 1:00 - 2:00pm	EECS 3312

## <u>nfYeP</u> Idescope

# Course website

EECS 504: Winter 2	020 × +					
	ich.edu/~ahowens/ee	cs504/w20/				
	EECS 504: Foundations of Computer Vision         Instructor: Andrew Owens       • Tues & Thurs, 12:00 - 1:30 in 1610 IOE       • Winter 2020         Schedule       Staff       Course info       Piazza       Canvas       Gradescope					
		Schedule				
	Lect	ure Date	Торіс	Materials	Assignments	
	Lec. :	L Thu, Jan. 9	Introduction / Image filters 1	Torralba, Freeman, and Isola: A Simple Visual System (optional reading)	ps1 (filtering) out	
	Lec. 2	2 Tue, Jan. 14	Image filters 2			
	Lec. 3	3 Thu, Jan. 16	Signal processing			
	Lec. 4	4 Tue, Jan. 21	Temporal filters		ps1 due ps2 (signal processing) out	
	Lec. S	5 Thu, Jan. 23	Multi-scale pyramids			
	Lec. 6	5 Tue, Jan. 28	Statistical models of images		ps2 due ps3 out (texture)	
	Lec.	7 Thu, Jan. 30	Machine learning			
	Lec. 8	3 Tue, Feb. 4	Neural networks		ps3 due	

## https://web.eecs.umich.edu/~ahowens/eecs504/w20/

# Assignments (70%) • Final project (30%)

# Grading

# Assignments

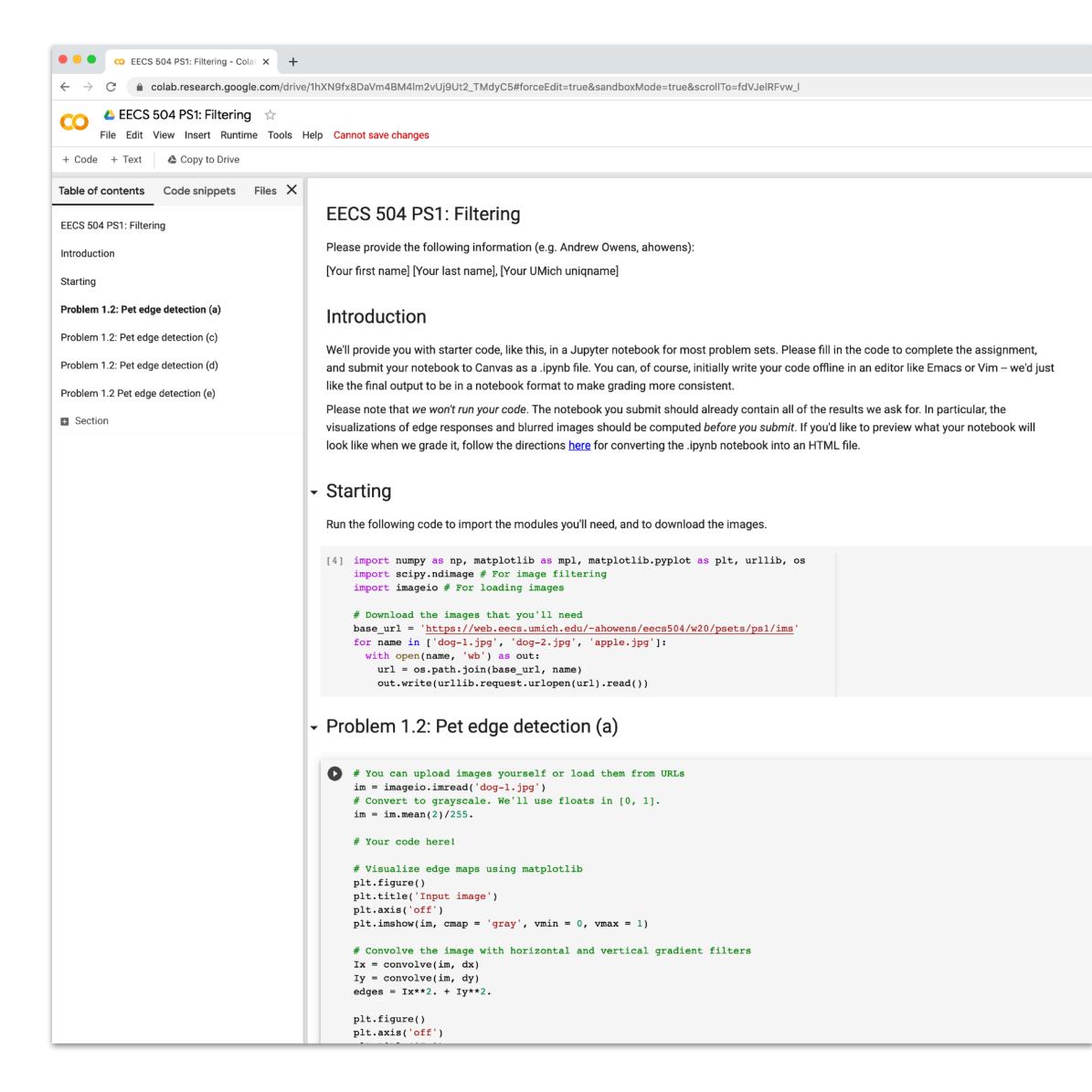
- Weekly homework assignments ( $\approx 10$  total) • Due each Tuesday at midnight
- Late submissions penalized 30% per day
  - You have 5 "late days"
- Assignments should be done independently.
  - Encouraged to discuss them
  - Programming and writing should all be yours

# Assignments

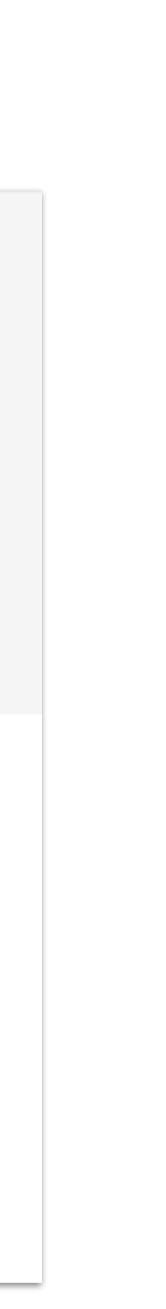
- Mix of programming and written problems
- PyTorch for deep learning
- Linear algebra and multivariable calculus
- Jupyter notebooks and Google Colab for problem sets

# • Python + numerical computing libraries (numpy, scipy, etc.)

# Assignments

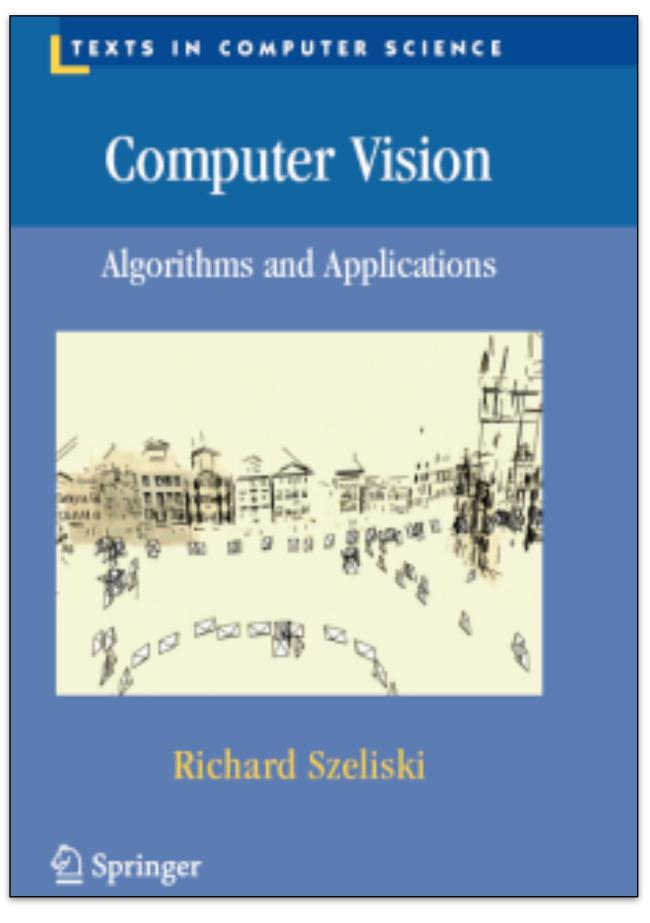


	Iy = convolve(im, dy)
Table of contents         Code snippets         Files         X	<pre>edges = Ix**2. + Iy**2.</pre>
EECS 504 PS1: Filtering	<pre># Visualize edge maps using matplotlib</pre>
ELCS 504 PST. Pittering	<pre>plt.figure() </pre>
Introduction	<pre>plt.title('Input image') plt.axis('off')</pre>
Otentin -	<pre>plt.imshow(im, cmap = 'gray', vmin = 0, vmax = 1)</pre>
Starting	
Problem 1.2: Pet edge detection (a)	<pre>plt.figure() plt.axis('off')</pre>
	<pre>plt.title('Ix')</pre>
Problem 1.2: Pet edge detection (c)	plt.imshow(Ix)
Problem 1.2: Pet edge detection (d)	<pre>plt.figure()</pre>
	<pre>plt.title('Iy')</pre>
Problem 1.2 Pet edge detection (e)	<pre>plt.axis('off')</pre>
+ Section	plt.imshow(Iy)
	<pre>plt.figure()</pre>
	<pre>plt.title('Edges')</pre>
	<pre>plt.axis('off') # Please visualize edge responses using this range of value</pre>
	plt.imshow(edges, vmin = 0., vmax = np.percentile(edges, 9
	<pre> _→ <matplotlib.image.axesimage 0x7f3ab8d60160="" at=""> </matplotlib.image.axesimage></pre>
	Input image
	Cuite
	Jan Jan
	Mar.
	S. Barthe
	1 Low 28 Staller
	SA Sand AV
	Mr. rassing
	Mr. Constant

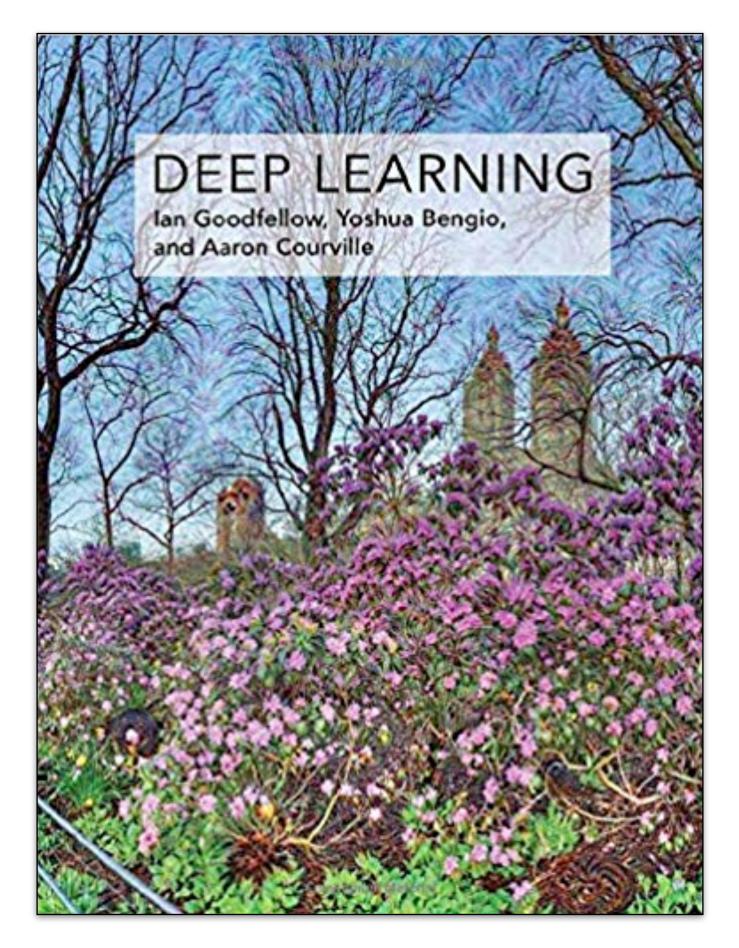


# Project

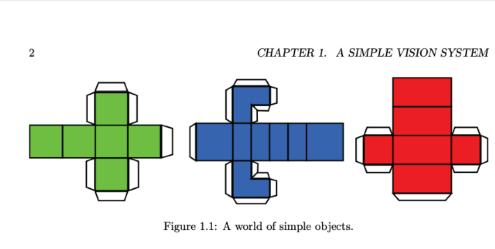
- Open-ended! Example projects:
  - Implement and extend a recent computer vision paper
  - Use computer vision in your research
  - We'll also provide a list of project ideas
- Work in small groups (up to 4 people)
- Complete in last month of class.
  - Project proposal (after spring break)
  - Short presentation (finals period)
  - Writeup (finals period)



http://szeliski.org/Book



# Readings



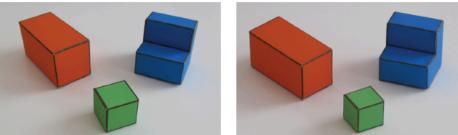


Figure 1.2: a) Close up picture without zoom. Note that near edges are larger than far edges, and parallel lines in 3D are not parallel in the image, b) Picture taken from far away but using zoom. This creates an image that can be approximately described by parallel projection.

One way of generating images that can be described by parallel projection is to use the camera zoom. If we increase the distance between the camera and the object while zooming, we can keep the same approximate image size of the objects, but with reduced perspective effects (fig. 1.2.b). Note how, in fig. 1.2.b, 3D parallel lines in the world are almost parallel in the image (some weak perspective effects remain)

The first step we need to is to characterize how a point in world coordinates (X, Y, Z)projects into the image plane. Figure 1.3.a shows our parameterization of the world and camera. The camera center is inside the plane X = 0, and the horizontal axis of the camera (x) is parallel to the ground plane (Y = 0). The camera is tilted so that the line connecting the origin of the world coordinates system and the image center is perpendicular to the image plane. The angle  $\theta$  is the angle between this line and the Z axis. We will see a more general projection transformation in lectures 11-13. The image is parametrized by coordinates (x, y). In this simple projection model, the origin of the world coordinates projects on the origin of the image coordinates. Therefore, the world point (0,0,0) projects into (0,0). The resolution of the image (the number of pixels) will also affect the transformation from world coordinates to image coordinates via a constant factor  $\alpha$  (for now we assume that pixels are square and we will see a more general form in lectures 11-13) and that this constant is  $\alpha = 1$ . Taking into account all these assumptions, the transformation between world coordinates and image coordinates can be written as:

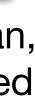
$$x = X$$
(1.1)  
$$y = \cos(\theta)Y - \sin(\theta)Z$$
(1.2)

For this particular parametrization, the world coordinates Y and Z are mixed.

## https://www.deeplearningbook.org

Manuscript chapters by Torralba, Freeman, and Isola (on course website). Class based on this coursework.

## And also occasional paper readings



Class topics

Lec. 1	Thu, Jan. 9	Introduction / Image filters 1
Lec. 2	Tue, Jan. 14	Image filters 2
Lec. 3	Thu, Jan. 16	Signal processing
Lec. 4	Tue, Jan. 21	Temporal filters
Lec. 5	Thu, Jan. 23	Multi-scale pyramids
Lec. 6	Tue, Jan. 28	Statistical models of images
Lec. 7	Thu, Jan. 30	Machine learning
Lec. 8	Tue, Feb. 4	Neural networks
Lec. 9	Thu, Feb. 6	Optimization
Lec. 10	Tue, Feb. 11	Convolutional networks
Tutorial	Tue, Feb. 11	PyTorch tutorial

Signa

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## Homework problem:



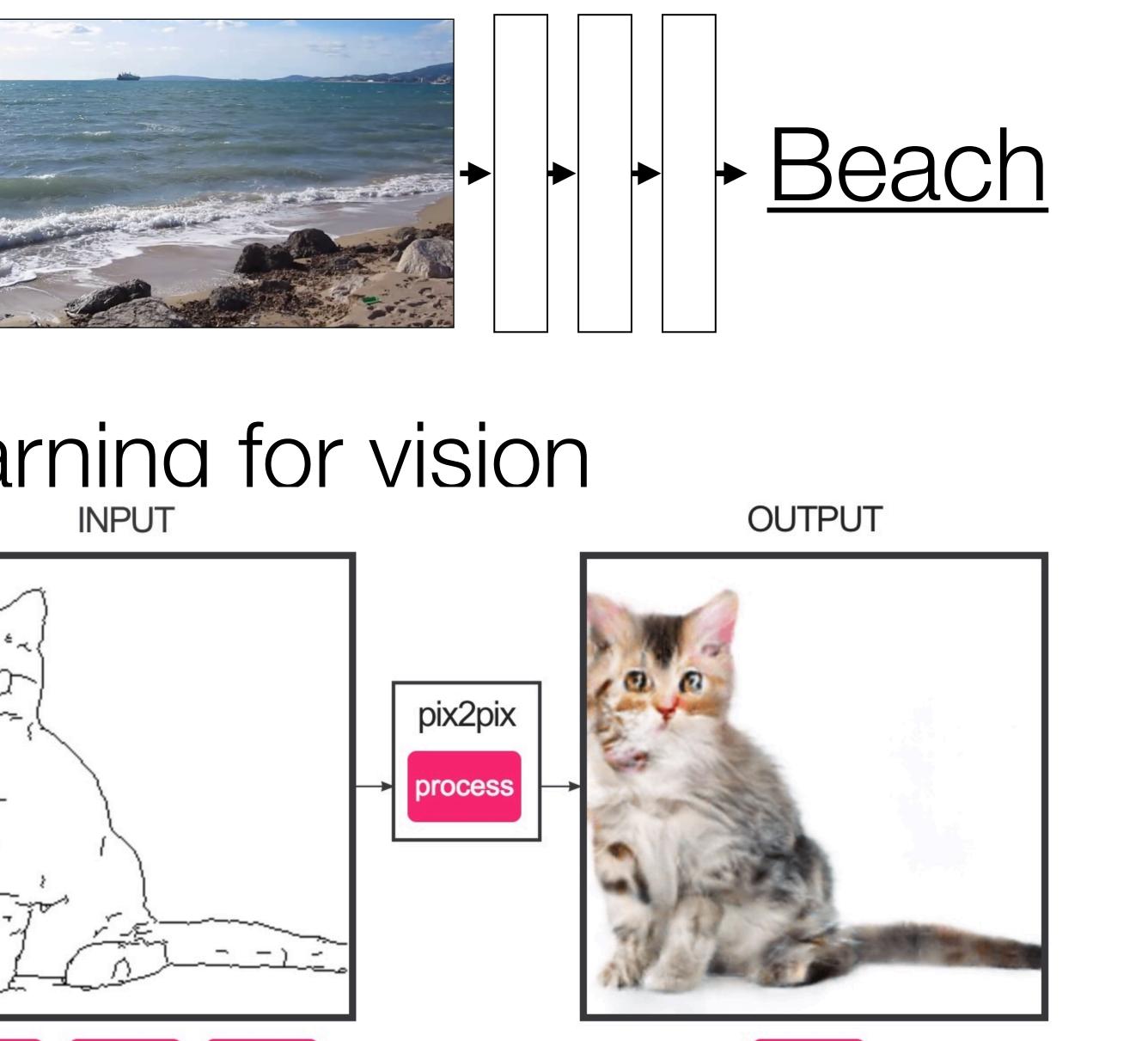


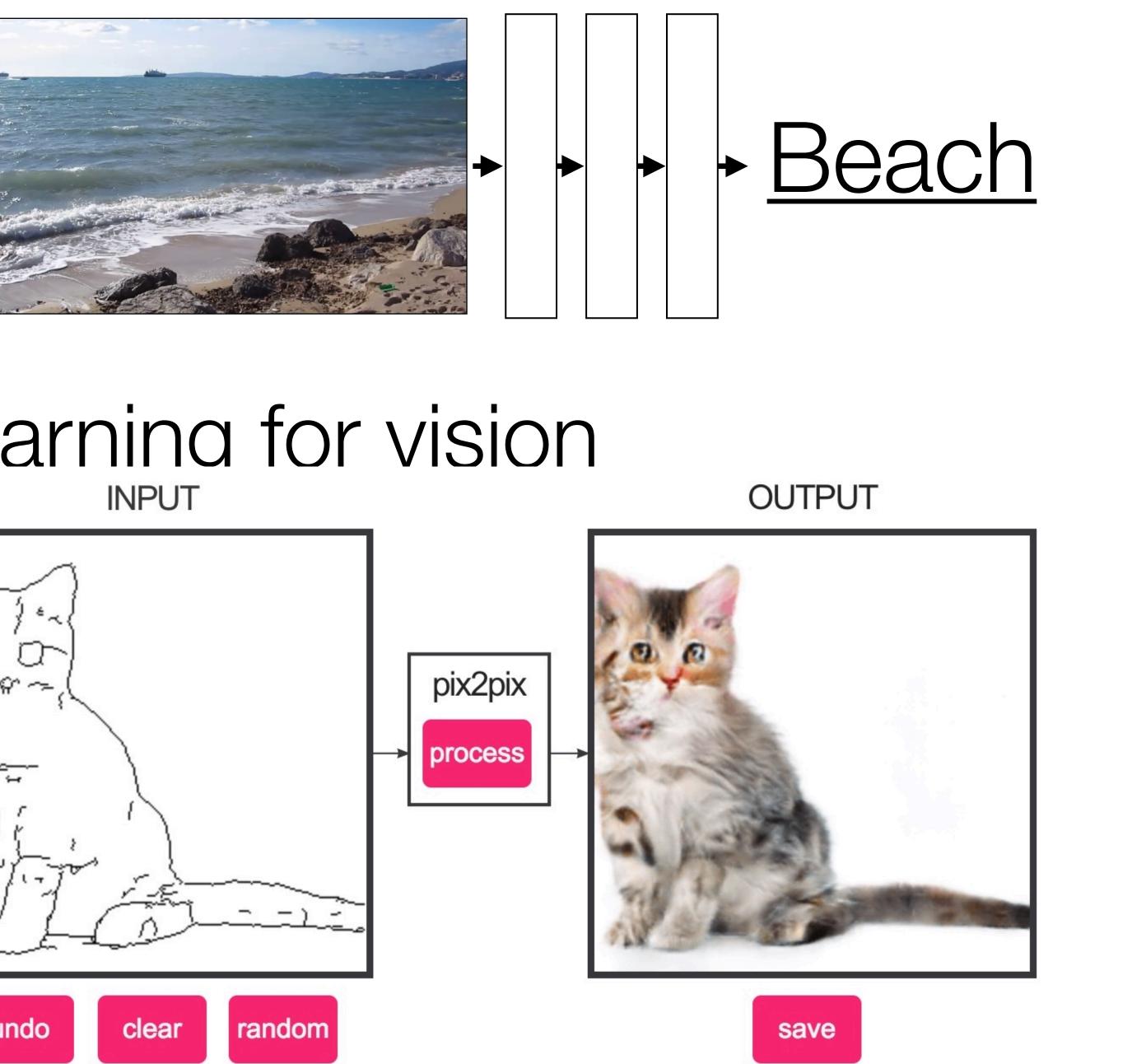
Thu, Jan. 9	Introduction / Image filters 1	
Tue, Jan. 14	Image filters 2	
Thu, Jan. 16	Signal processing	
Tue, Jan. 21	Temporal filters	
Thu, Jan. 23	Multi-scale pyramids	
Tue, Jan. 28	Statistical models of images	
Thu, Jan. 30	Machine learning	
Tue, Feb. 4	Neural networks	
Thu, Feb. 6	Optimization	
Tue, Feb. 11	Convolutional networks	
Tue, Feb. 11	PyTorch tutorial	J
	Гие, Jan. 14 Гhu, Jan. 16 Гие, Jan. 21 Гие, Jan. 23 Гие, Jan. 28 Гhu, Jan. 30 Гие, Feb. 4 Гhu, Feb. 6 Гие, Feb. 11	Fue, Jan. 14Image filters 2Fhu, Jan. 16Signal processingFue, Jan. 21Temporal filtersFhu, Jan. 23Multi-scale pyramidsFue, Jan. 28Statistical models of imagesFue, Feb. 4Neural networksFue, Feb. 4OptimizationFue, Feb. 11Convolutional networks

Intro to eep learning

				-
Tutorial	Tue, Feb. 11	PyTorch tutorial		3.1 1720 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.
Lec. 11	Thu, Feb. 13	Scene understanding		
Lec. 12	Tue, Feb. 18	Object detection		
Lec. 13	Thu, Feb. 20	Action recognition		
Lec. 14	Tue, Feb. 25	GANs		
Lec. 15	Thu, Feb. 27	Image synthesis		.65
	Spring	break		
Lec. 16	Tue, Mar. 10	Representation learning	}	11
Lec. 17	Thu, Mar. 12	Sight, sound, and touch		/ C { /~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Lec. 18	Tue, Mar. 17	Optical flow	( 2	/₩ ~~=
Lec. 19	Thu, Mar. 19	Multi-view geometry		
				$\int \frac{1}{6} \int $

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Lec. 17	Thu, Mar. 12	Sight, sound, and touch	
Lec. 18	Tue, Mar. 17	Optical flow	
Lec. 19	Thu, Mar. 19	Multi-view geometry	
Lec. 20	Tue, Mar. 24	Structure from motion	
Lec. 21	Thu, Mar. 26	Depth estimation	opt
Lec. 22	Tue, Mar. 31	Graphical models	
Lec. 23	Thu, Apr. 2	Color	J
Lec. 24	Tue, Apr. 7	Embodied vision	
Lec. 25	Thu, Apr. 9	Modern CNNs	
Lec. 26	Tue, Apr. 14	Image forensics	
Lec 27	Thu Apr 16	Language and vision	

## Homework problem:





Lec. 19	Thu, Mar. 19	Multi-view geometry	
Lec. 20	Tue, Mar. 24	Structure from motion	
Lec. 21	Thu, Mar. 26	Depth estimation	
Lec. 22	Tue, Mar. 31	Graphical models	
Lec. 23	Thu, Apr. 2	Color	
Lec. 24	Tue, Apr. 7	Embodied vision	
Lec. 25	Thu, Apr. 9	Modern CNNs	(Ad
Lec. 26	Tue, Apr. 14	Image forensics	l and
Lec. 27	Thu, Apr. 16	Language and vision	
Lec. 28	Tue, Apr. 21	Datasets and bias	J

# vanced topics d applications



# 1. A bit of vision history 2. Why vision is hard 3. A simple visual system

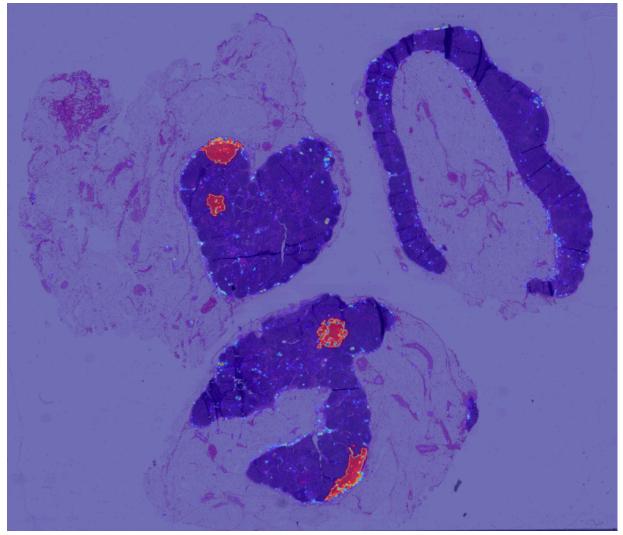
# Today

## Exciting times for computer vision Robotics Medical applications 3D modeling



Driving





Mobile devices







Slide credit: Torralba, Freeman, Isola

## Accessibility





# IO SEE

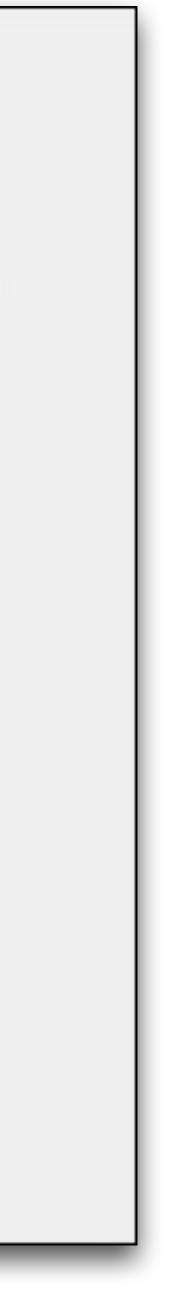
"What does it mean, to see? The plain man's answer (and Aristotle's, too) would be, to know what is where by looking."

To discover from images what is present in the world, where things are, what actions are taking place, to predict and anticipate events in the world.

# VISION David Marr FOREWORD BY Shimon Uliman

Tomaso Poggio

Slides from MIT 6.869 class by Torralba, Freeman, and Isola





## MASSACHUSETTS INSTITUTE OF TECHNOLOGY PROJECT MAC

Artificial Intelligence Group Vision Memo. No. 100.

## THE SUMMER VISION PROJECT

Seymour Papert

The summer vision project is an attempt to use our summer workers effectively in the construction of a significant part of a visual system. The particular task was chosen partly because it can be segmented into sub-problems which will allow individuals to work independently and yet participate in the construction of a system complex enough to be a real landmark in the development of "pattern recognition".

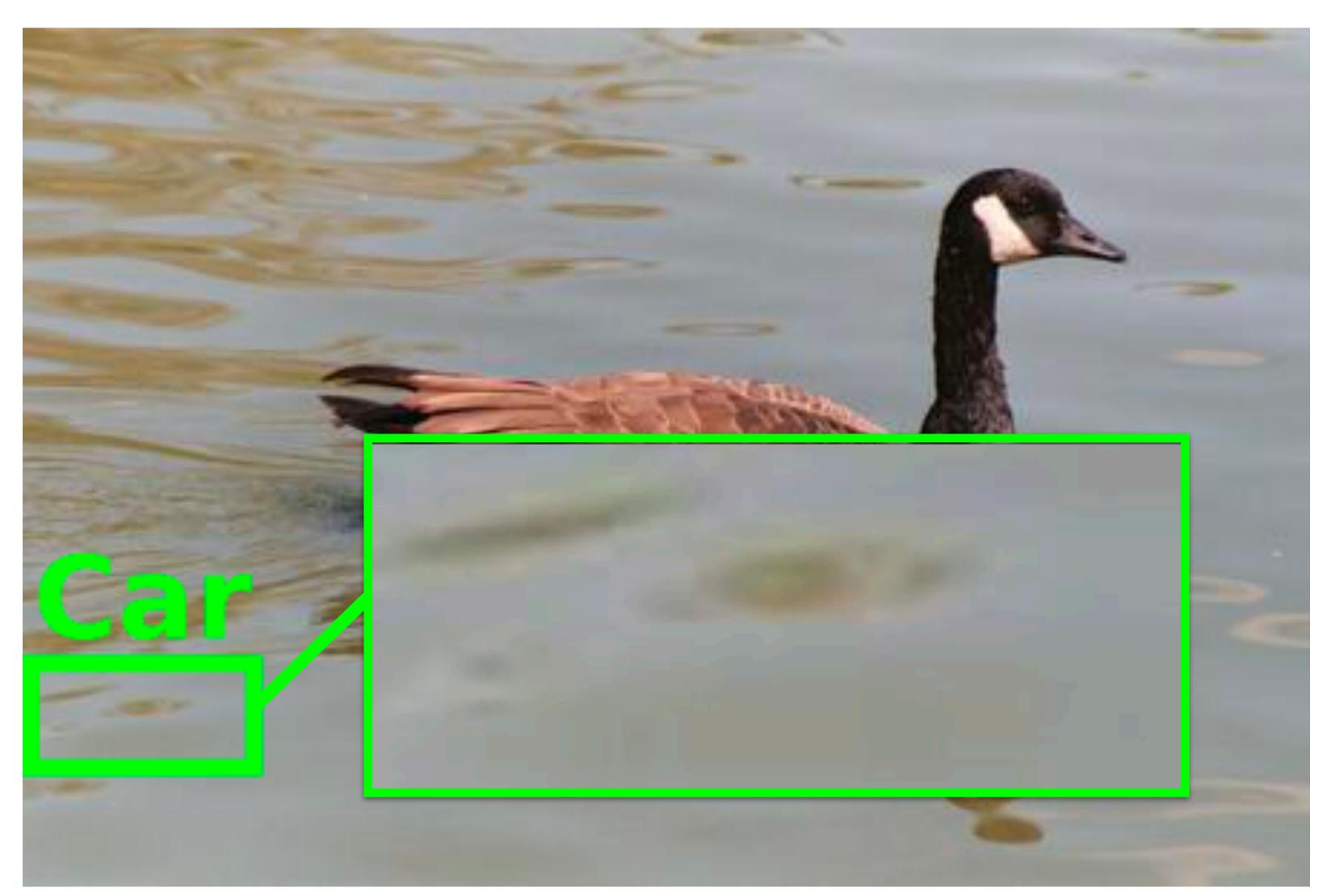
## July 7, 1966

4.1

## Slide credit: Torralba, Freeman, Isola



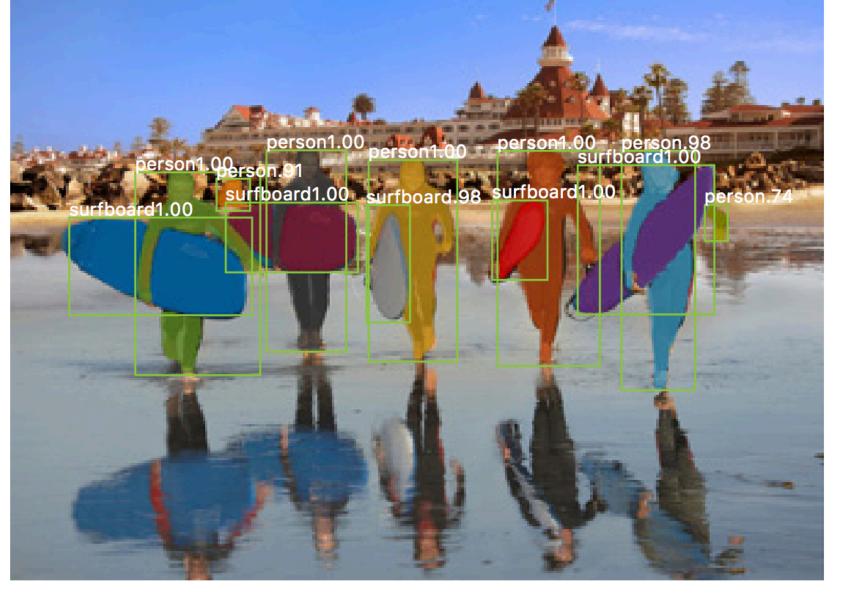
# Just a few years ago...



## ["HOGgles", Vondrick et al., ICCV 2013]



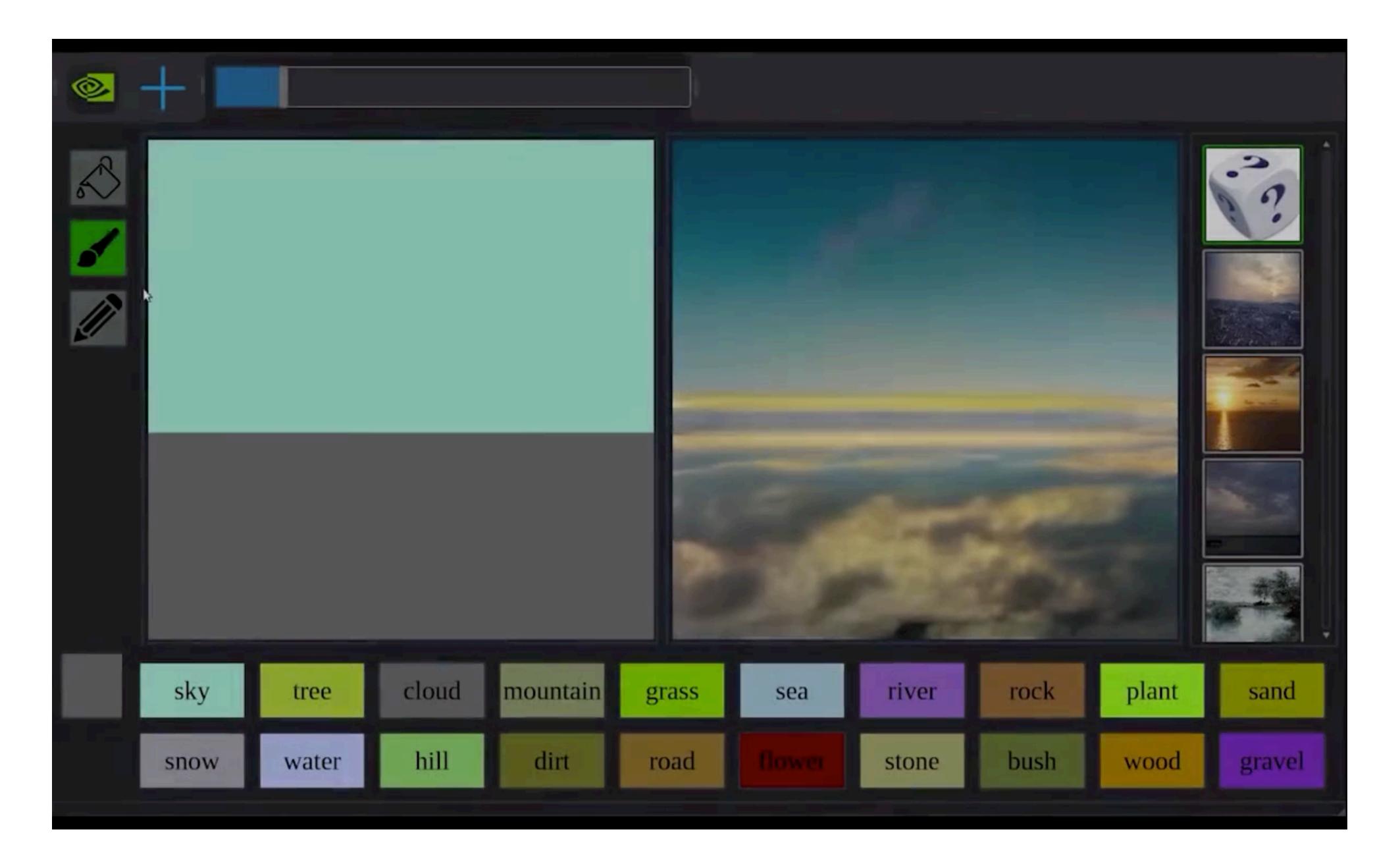
Slide credit: Torralba, Freeman, Isola





["Mask RCNN", He et al., ICCV 2017]





["GauGAN", Park et al., CVPR 2019]



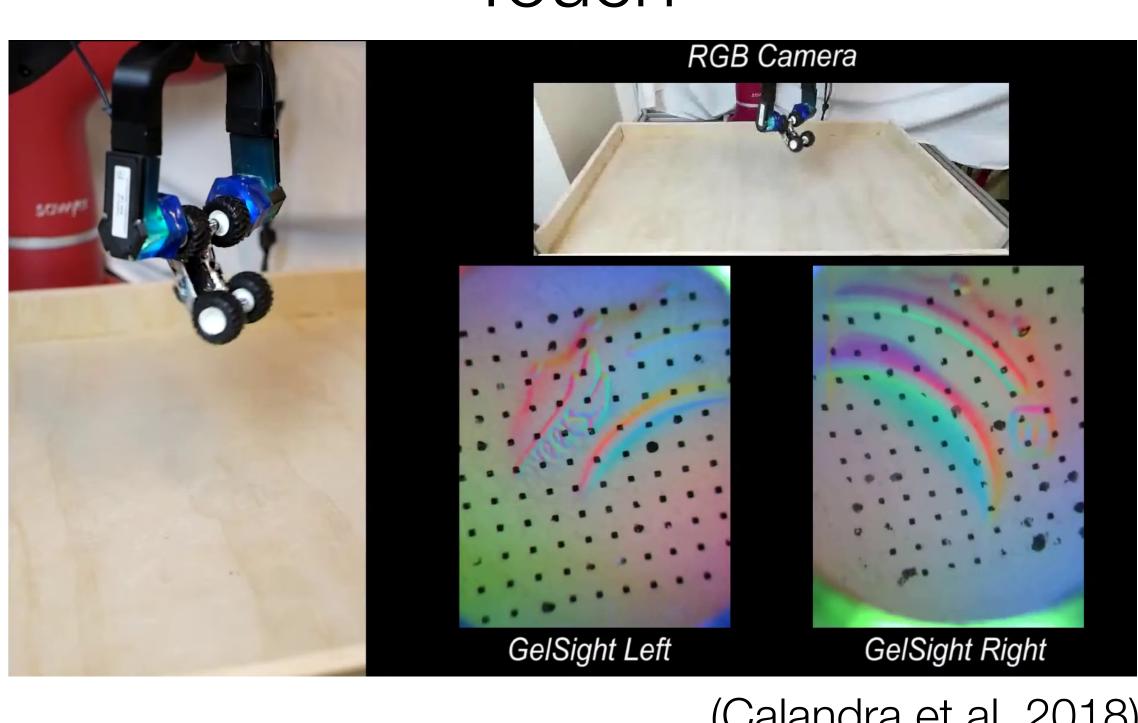
## Different signals, same methods Sound Touch Amplitude **RGB** Camera Time→

WiFi

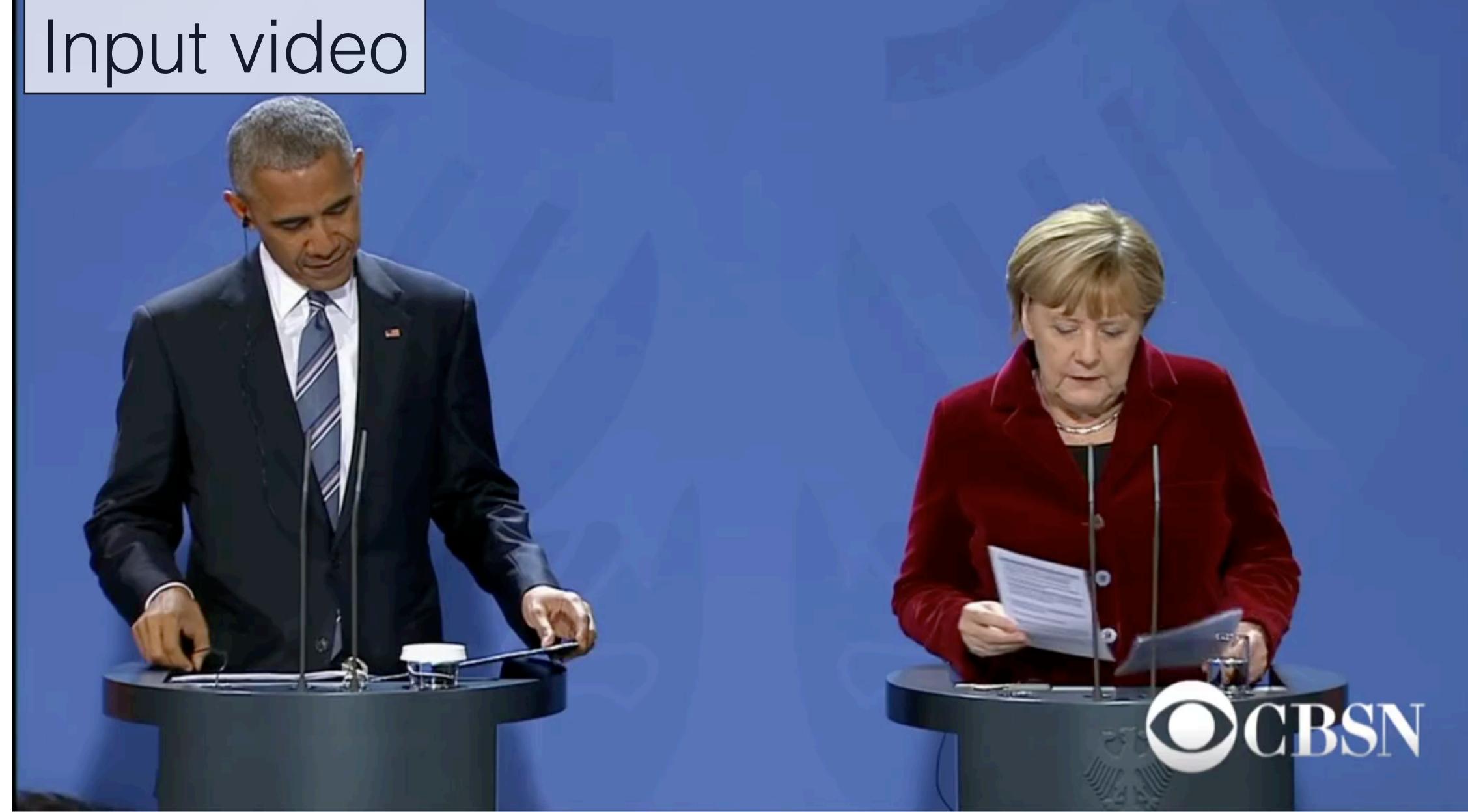


(Zhao et al. 2019)





(Calandra et al. 2018)



(Owens and Efros 2018)



# On-screen audio



(Owens and Efros 2018)



# Off-screen audio

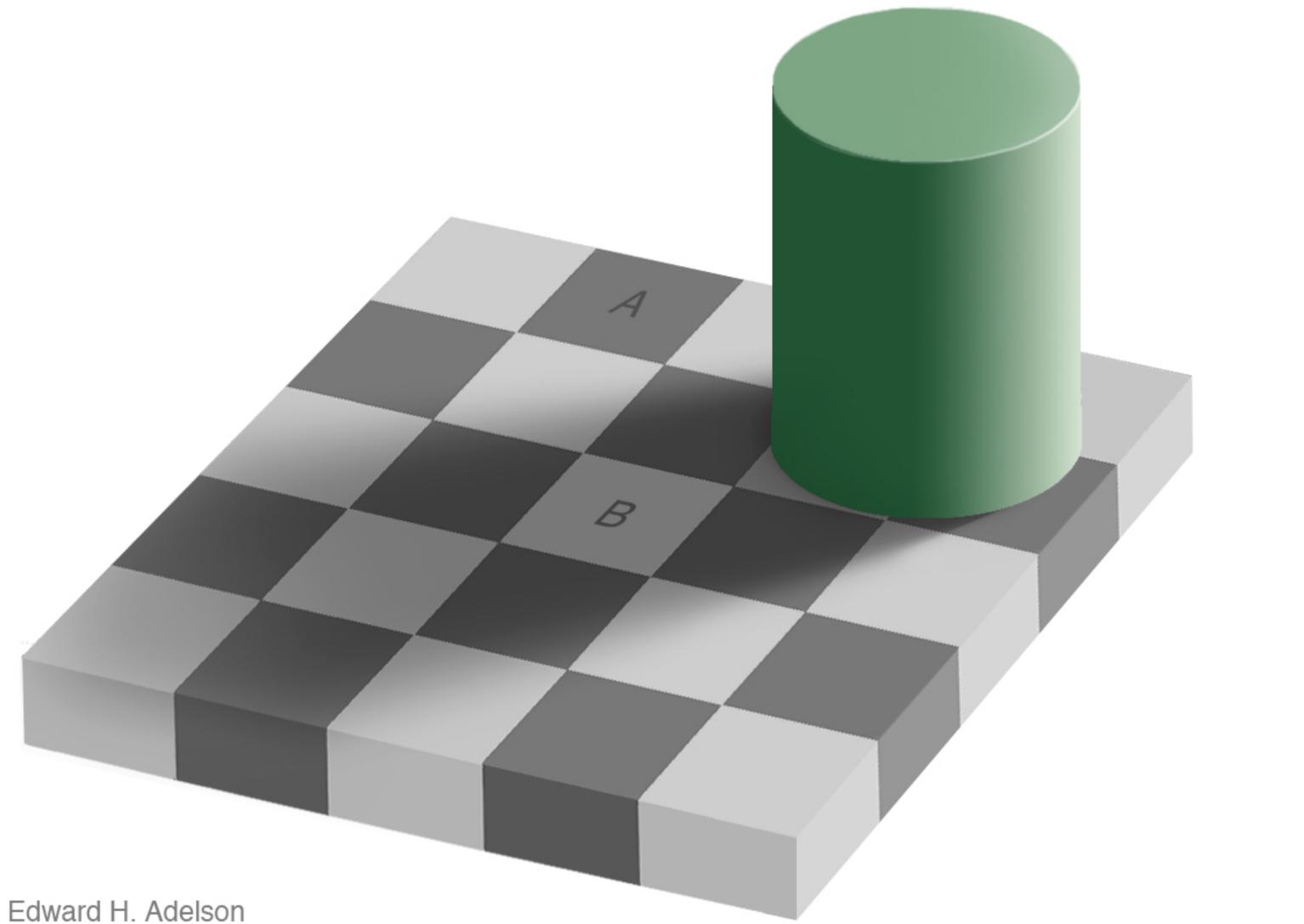


(Owens and Efros 2018)



# What makes vision hard?

# To see: perception vs. measurement



Slide credit: Torralba, Freeman, Isola



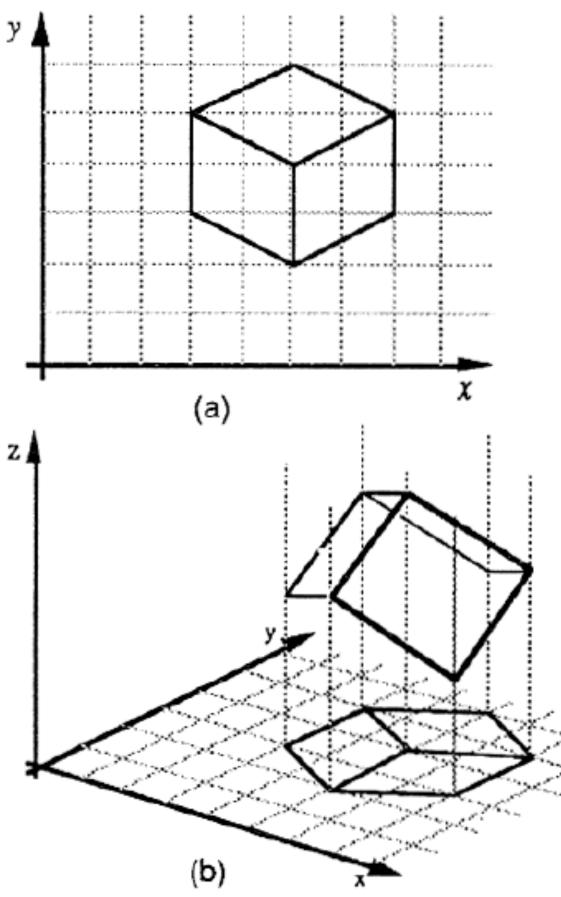
## To see: perception vs. measurement

A B

Slide credit: Torralba, Freeman, Isola

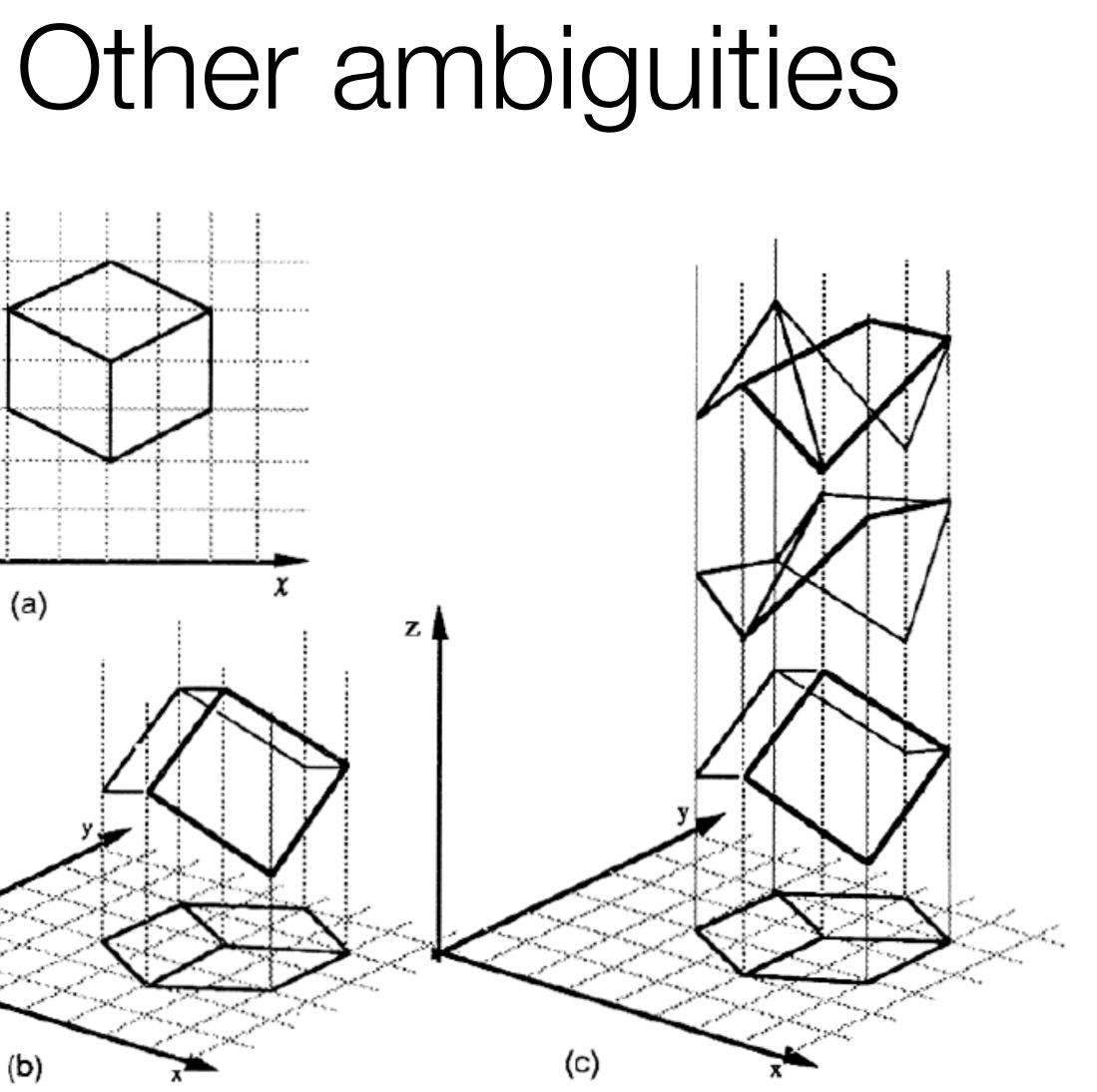


# Other ambiguities



## Sinha & Adelson 93





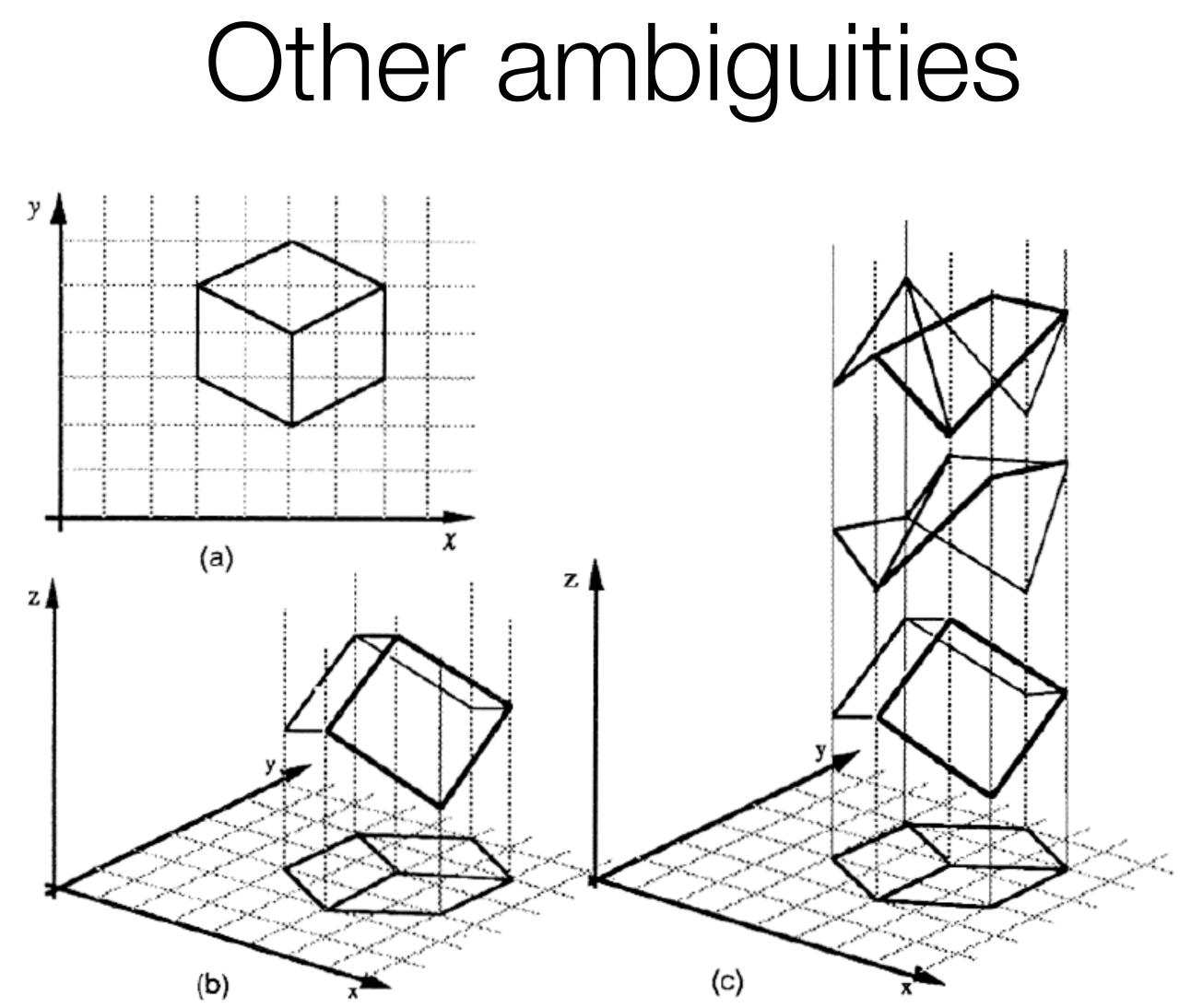


Figure 1. (a) A line drawing provides information only about the x, y coordinates of points lying along the object contours. (b) The human visual system is usually able to reconstruct an object in three dimensions given only a single 2D projection (c) Any planar line-drawing is geometrically consistent with infinitely many 3D structures.

Sinha & Adelson 93

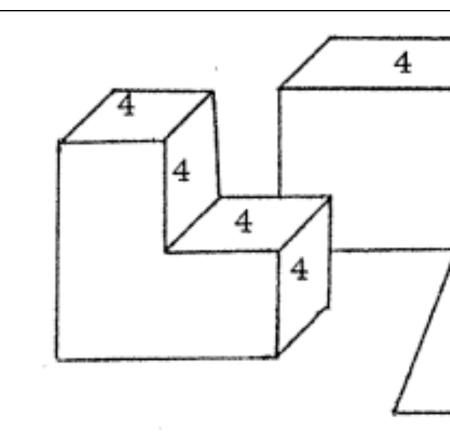


# A simple visual system

# A simple world A simple image formation model A simple goal

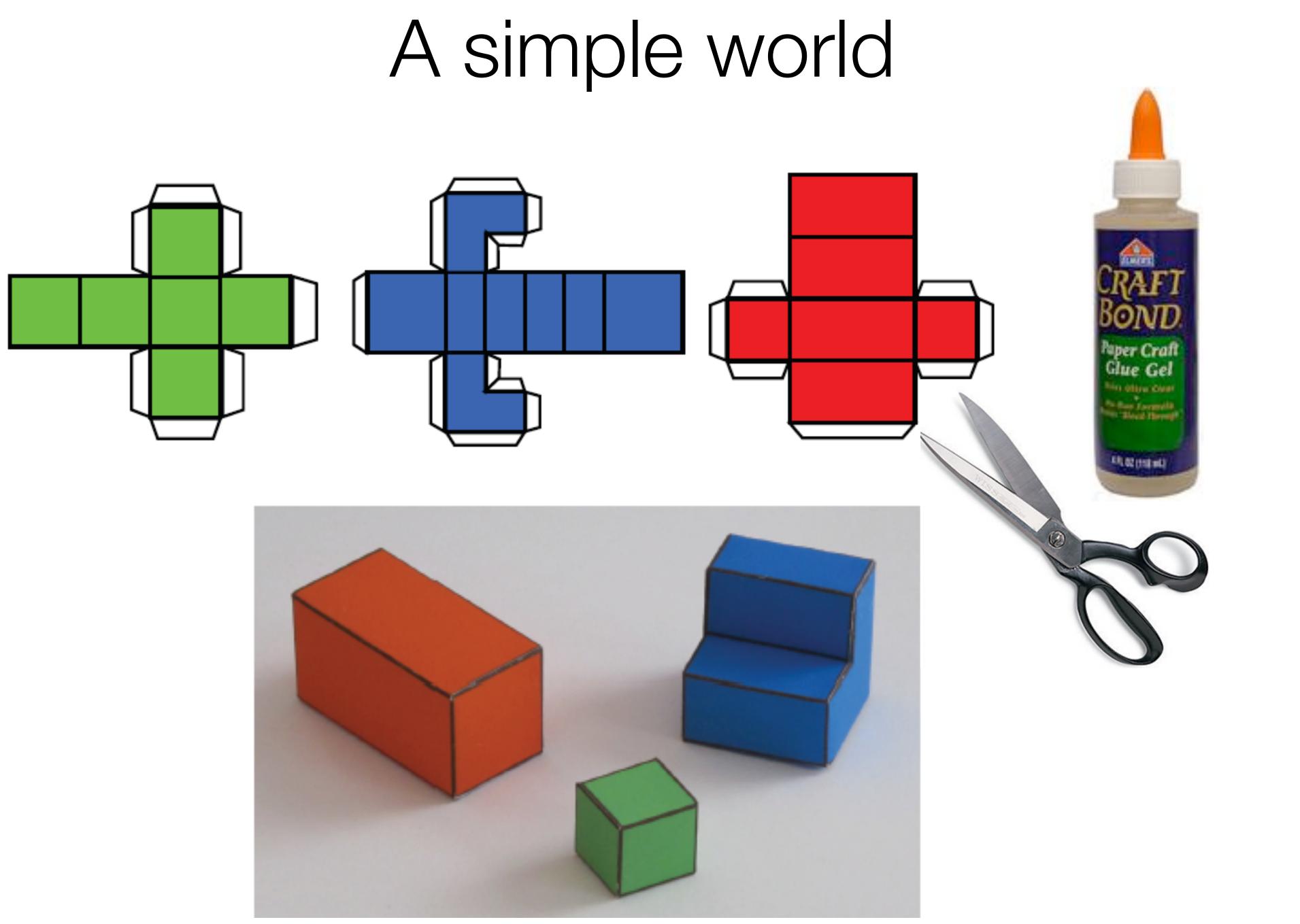
# A simple world

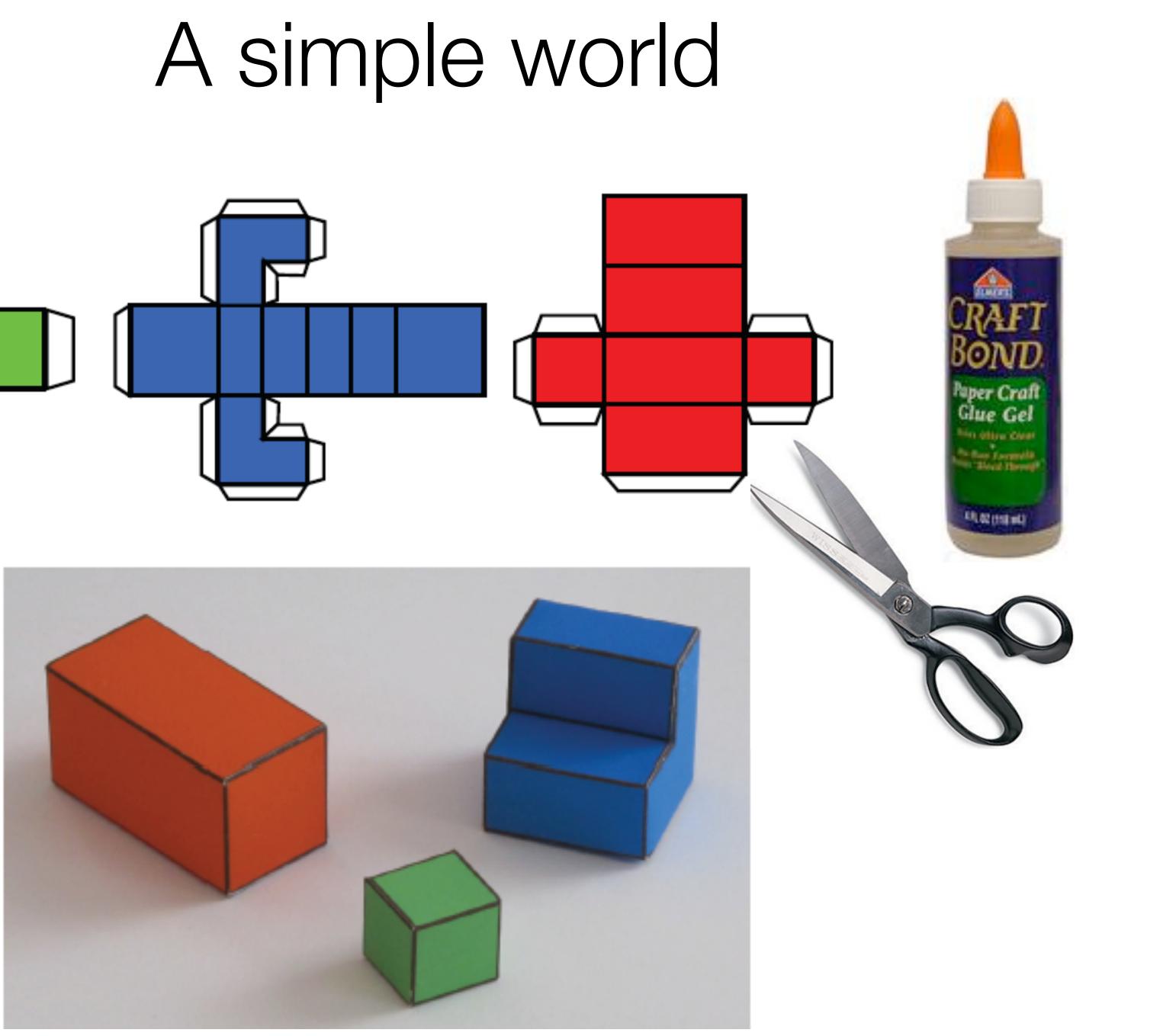
The problem of machine recognition of pictorial data has long MACHINE PERCEPTION OF THREE-DIMENSIONAL SOLIDS been a challenging goal, but has seldom been attempted with anything more complex than alphabetic characters. Many people have felt that by research on character recognition would be a first step, leading the LAWRENCE GILMAN ROBERTS way to a more general pattern recognition system. However, the multitudinous attempts at character recognition, including my own, have not led very far. The reason, I feel, is that the study of abstract, two-Submitted to the Department of Electrical Engineering on May 10, 1963, in partial fulfillment of the requiredimensional forms leads us away from, not toward, the techniques ments for the degree of Doctor of Philosophy. necessary for the recognition of three-dimensional objects. The per-



4 Complete Convex Polygons. The polygon selection procedure would select the numbered polygons as complete and convex. The number indicates the probable number of sides. A polygon is incomplete if one of its points is a collinear joint of another polygon.





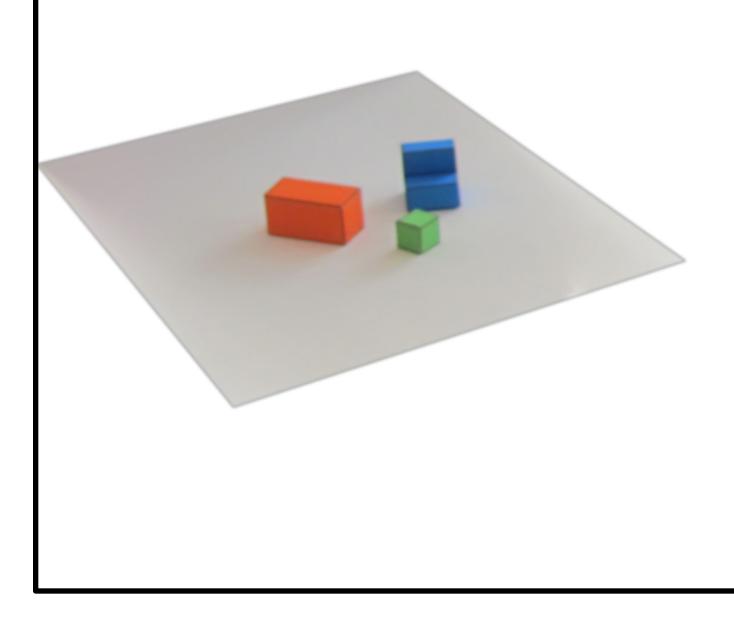




# A simple image formation model

Simple world rules:

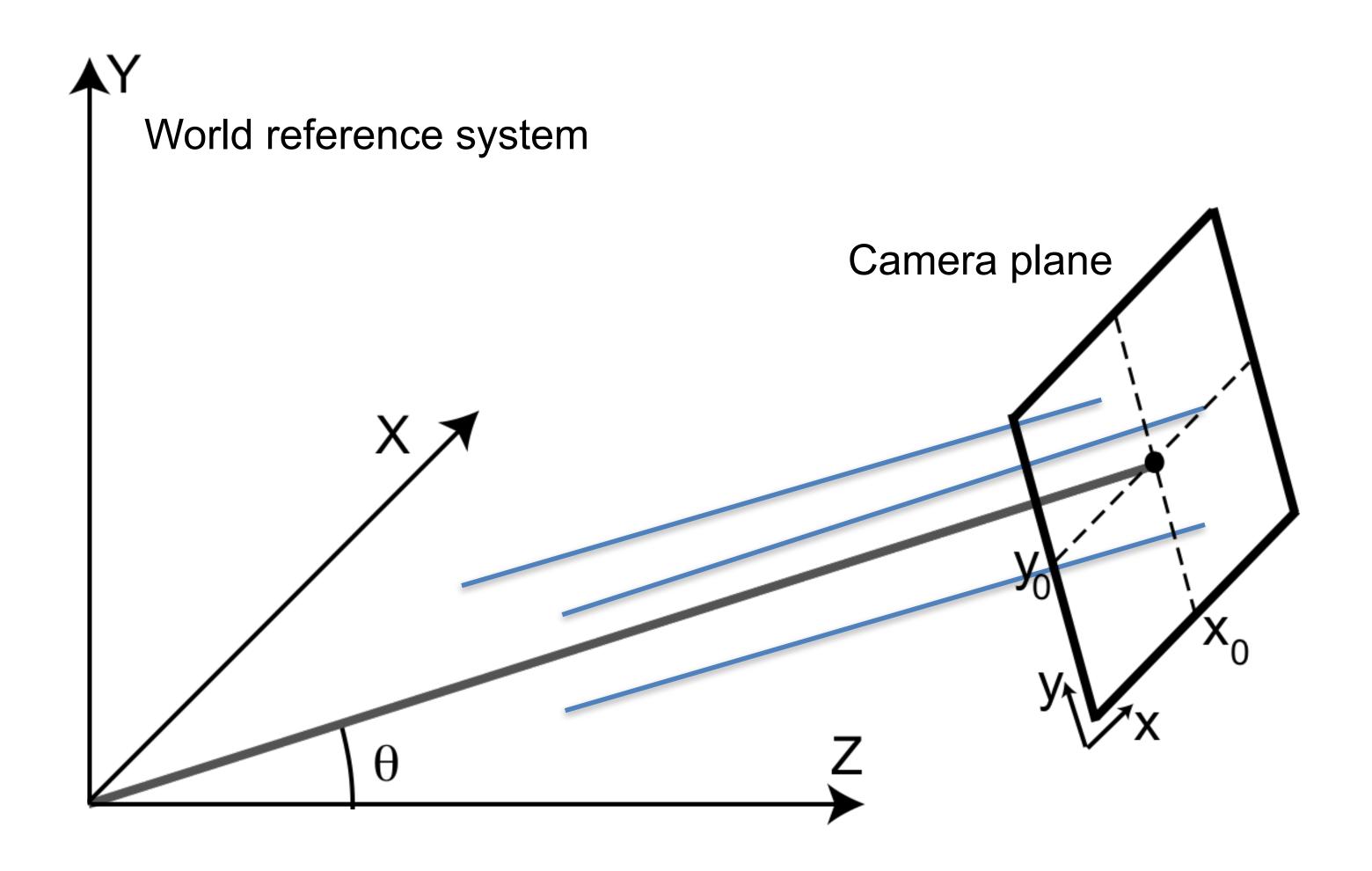
- Surfaces can be horizontal or vertical.
- Objects will be resting on a white horizontal ground plane







### A simple image formation model





### A simple image formation model

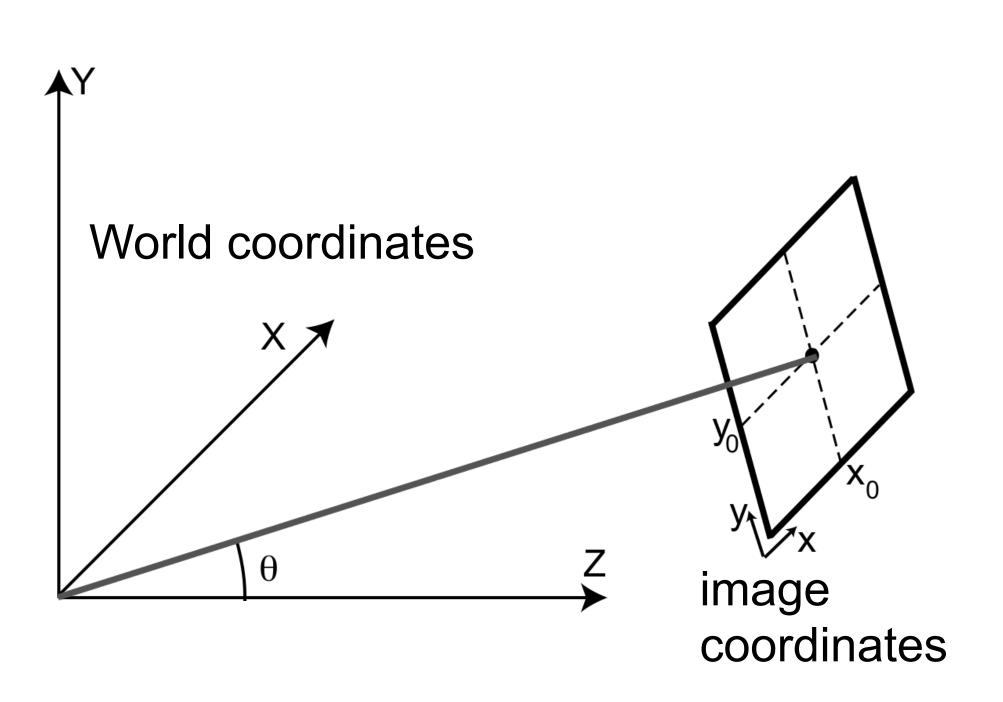
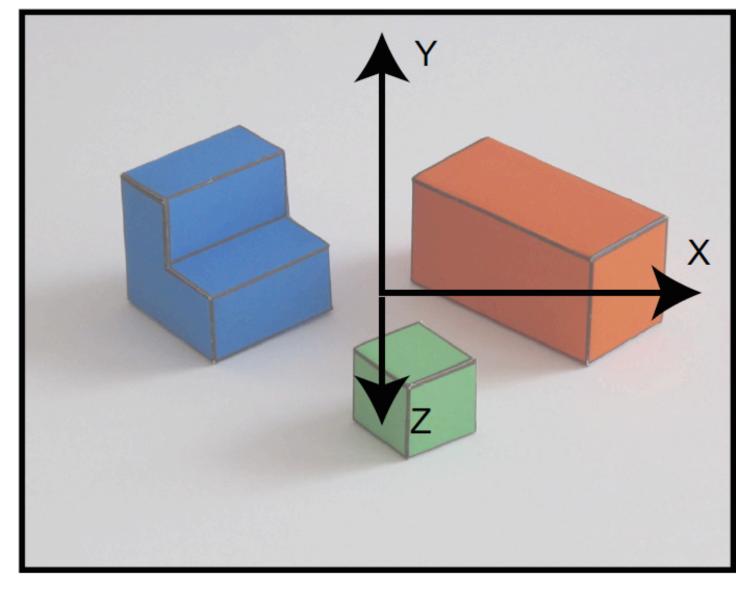


Image and projection of the world coordinate axes into the image plane



World coordinates

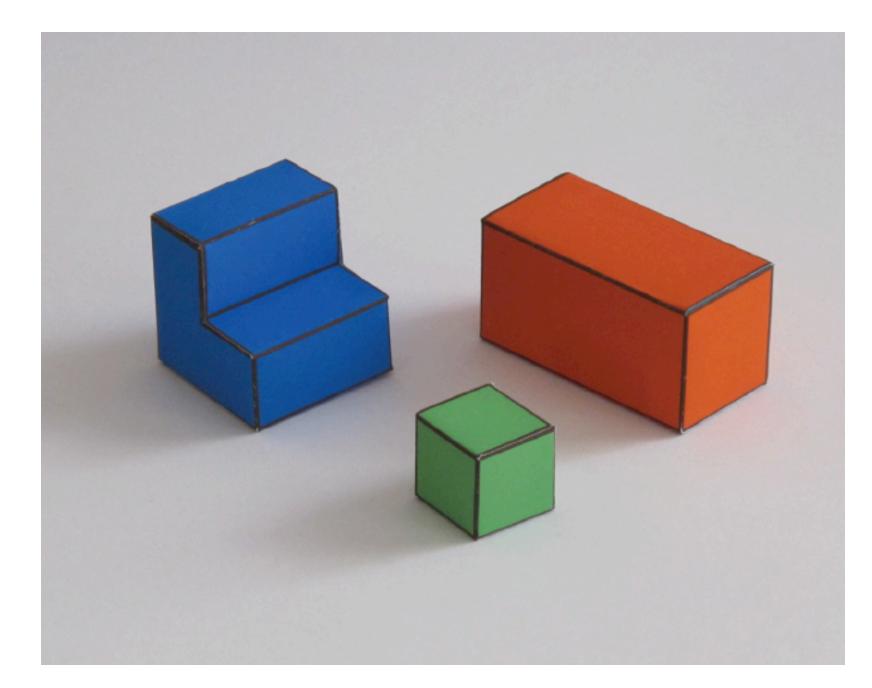
$$x = X + x_0$$
  
$$y = \cos(\theta) Y - \sin(\theta) Z + y_0$$

image coordinates



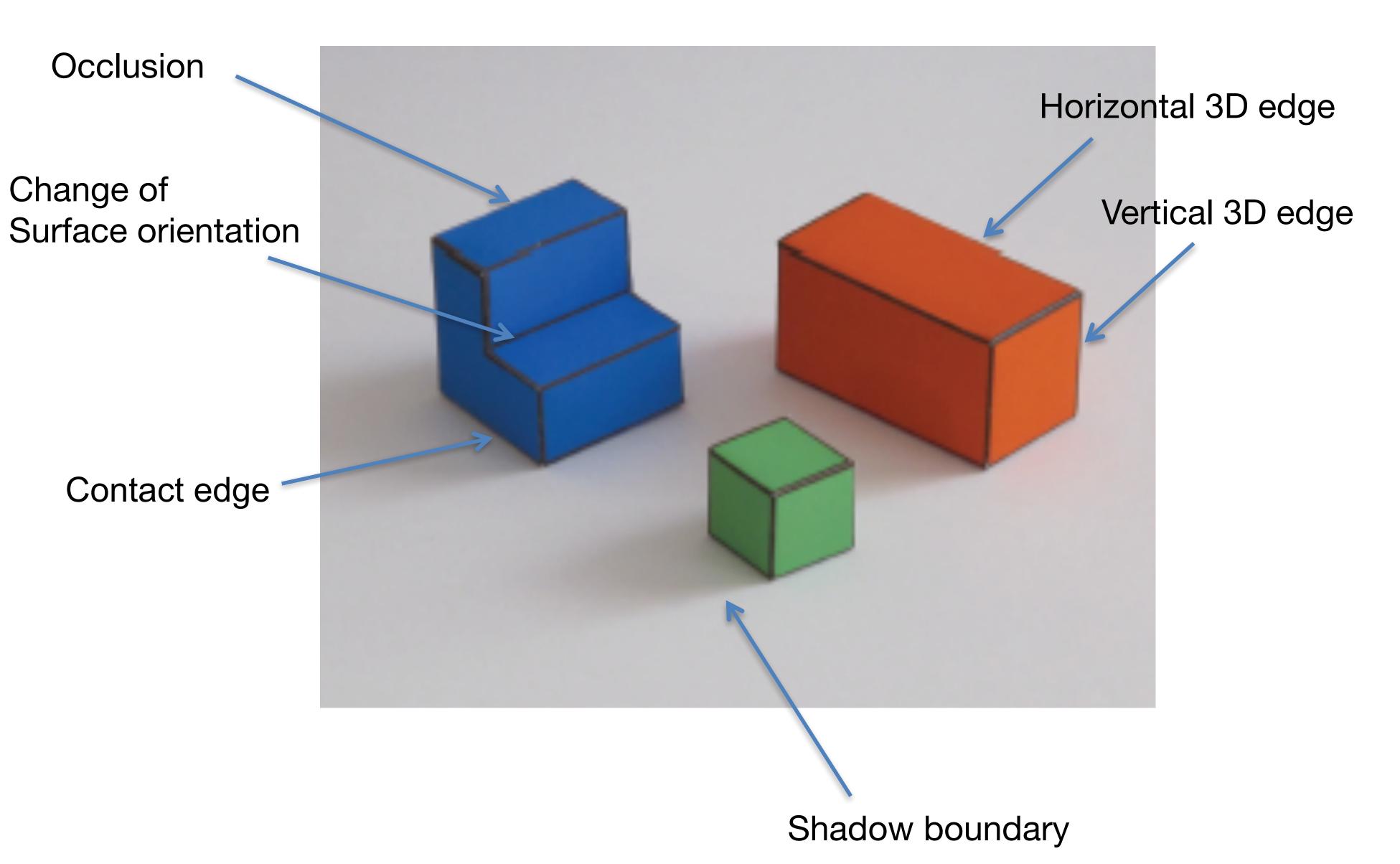
### A simple goal

#### Recover the 3D structure of the world



#### We want to recover X(x,y), Y(x,y), Z(x,y) using as input I(x,y)

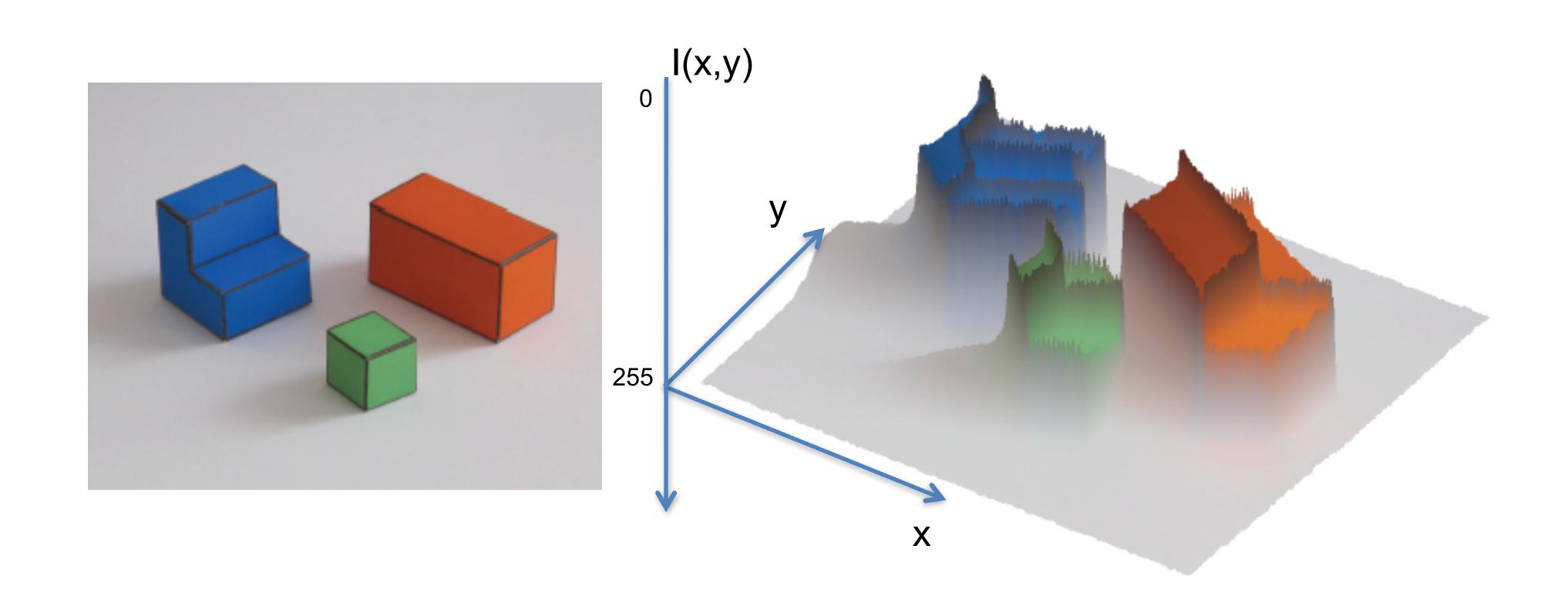




### Edges



### Treating the image as a function





### Finding edges in the image



Edge strength

Edge orientation:

Edge normal:

Image gradient:

$$\nabla \mathbf{I} = \left(\frac{\partial \mathbf{I}}{\partial x}, \frac{\partial \mathbf{I}}{\partial y}\right)$$

Approximation image derivative:

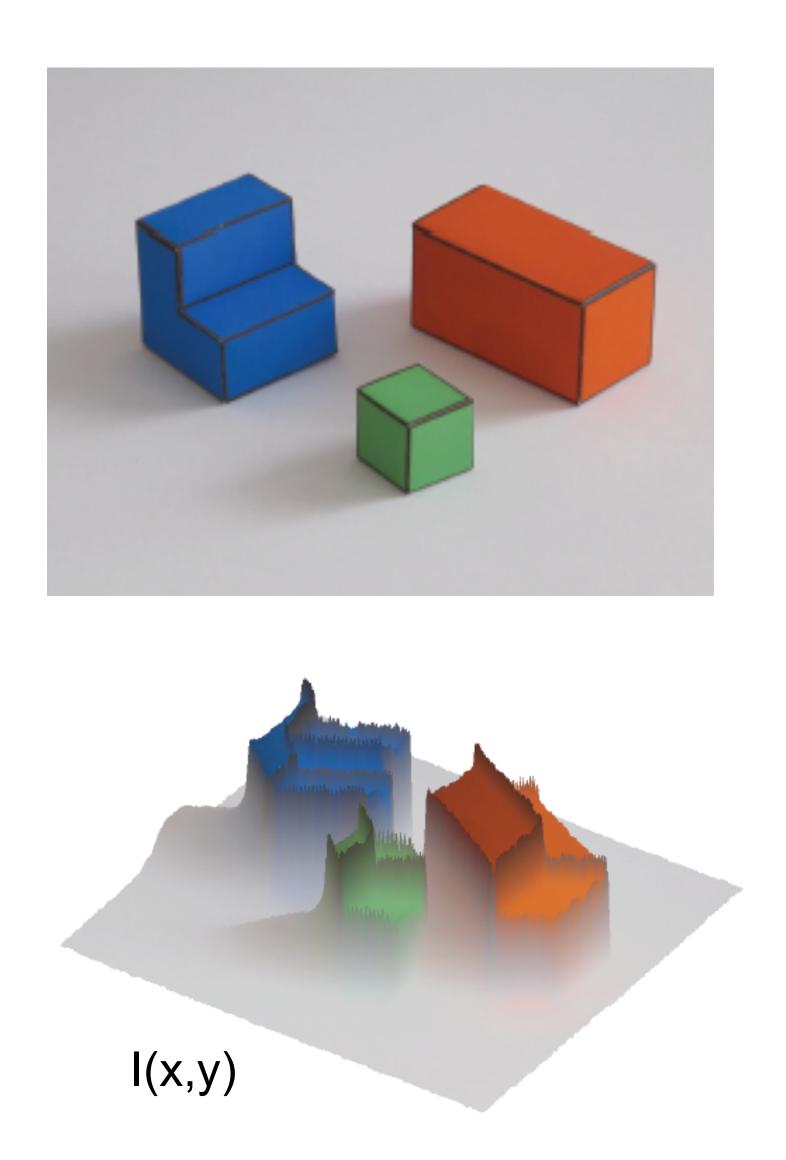
$$\frac{\partial \mathbf{I}}{\partial x} \simeq \mathbf{I}(x, y) - \mathbf{I}(x - 1, y)$$

 $E(x,y) = |\nabla \mathbf{I}(x,y)|$ 

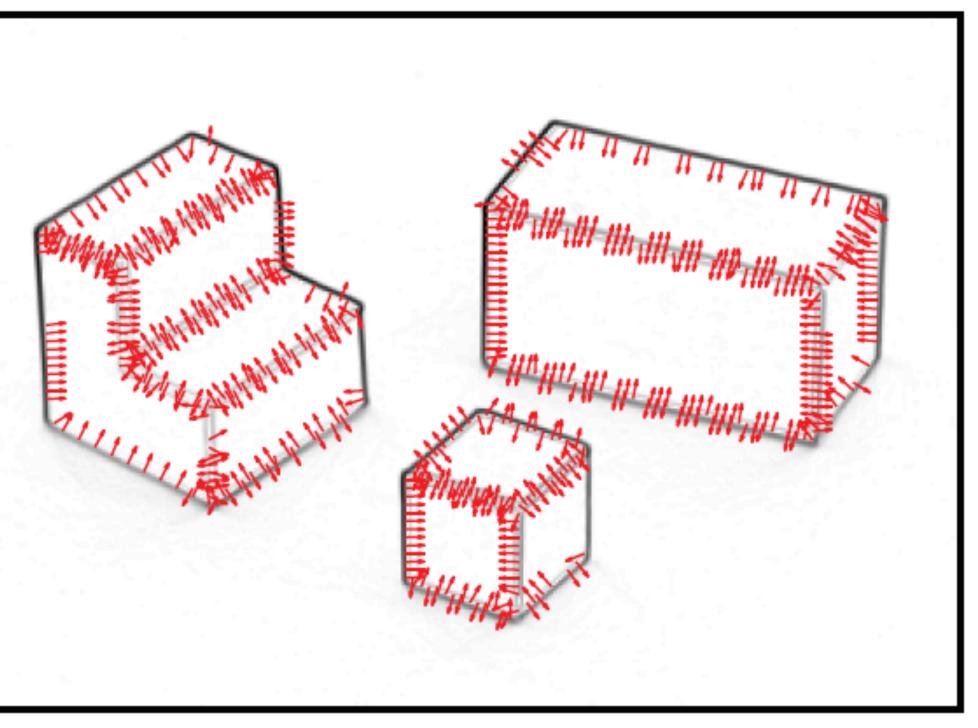
$$\theta(x, y) = \angle \nabla \mathbf{I} = \arctan \frac{\partial \mathbf{I} / \partial y}{\partial \mathbf{I} / \partial x}$$
$$\mathbf{n} = \frac{\nabla \mathbf{I}}{|\nabla \mathbf{I}|}$$



### Finding edges in the image



 $\nabla \mathbf{I} = \left(\frac{\partial \mathbf{I}}{\partial x}, \frac{\partial \mathbf{I}}{\partial y}\right) \qquad \mathbf{n} = \frac{\nabla \mathbf{I}}{|\nabla \mathbf{I}|}$ 



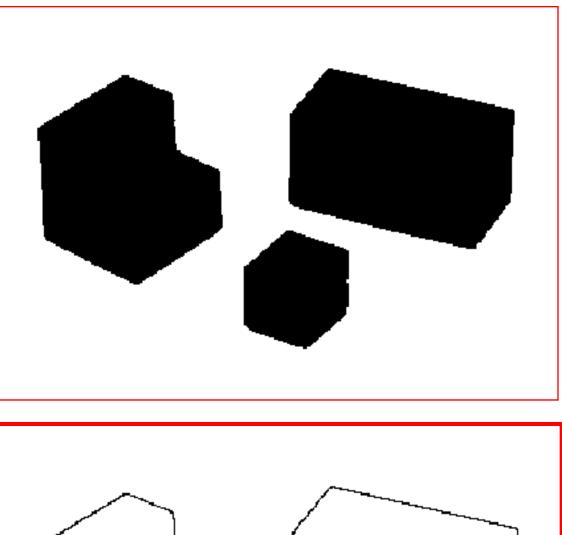
E(x,y) and n(x,y)

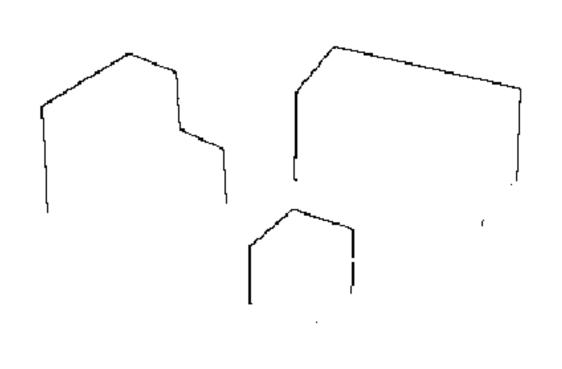


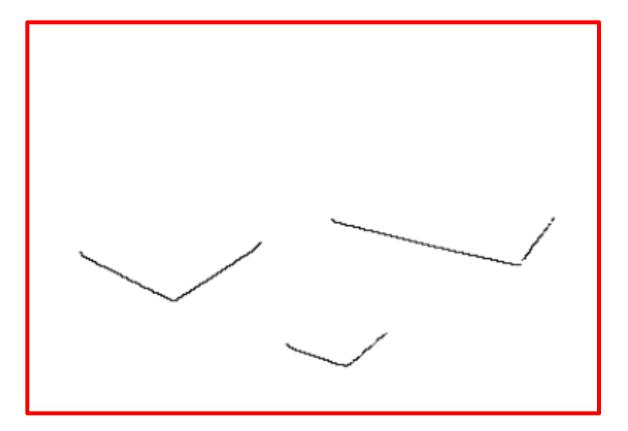
### Edge classification

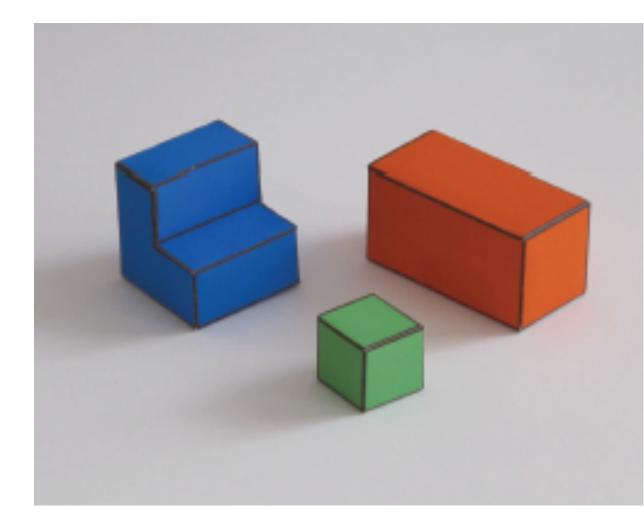
- Figure/ground segmentation Using the fact that objects have color
- Occlusion edges - Occlusion edges are owned by the foreground

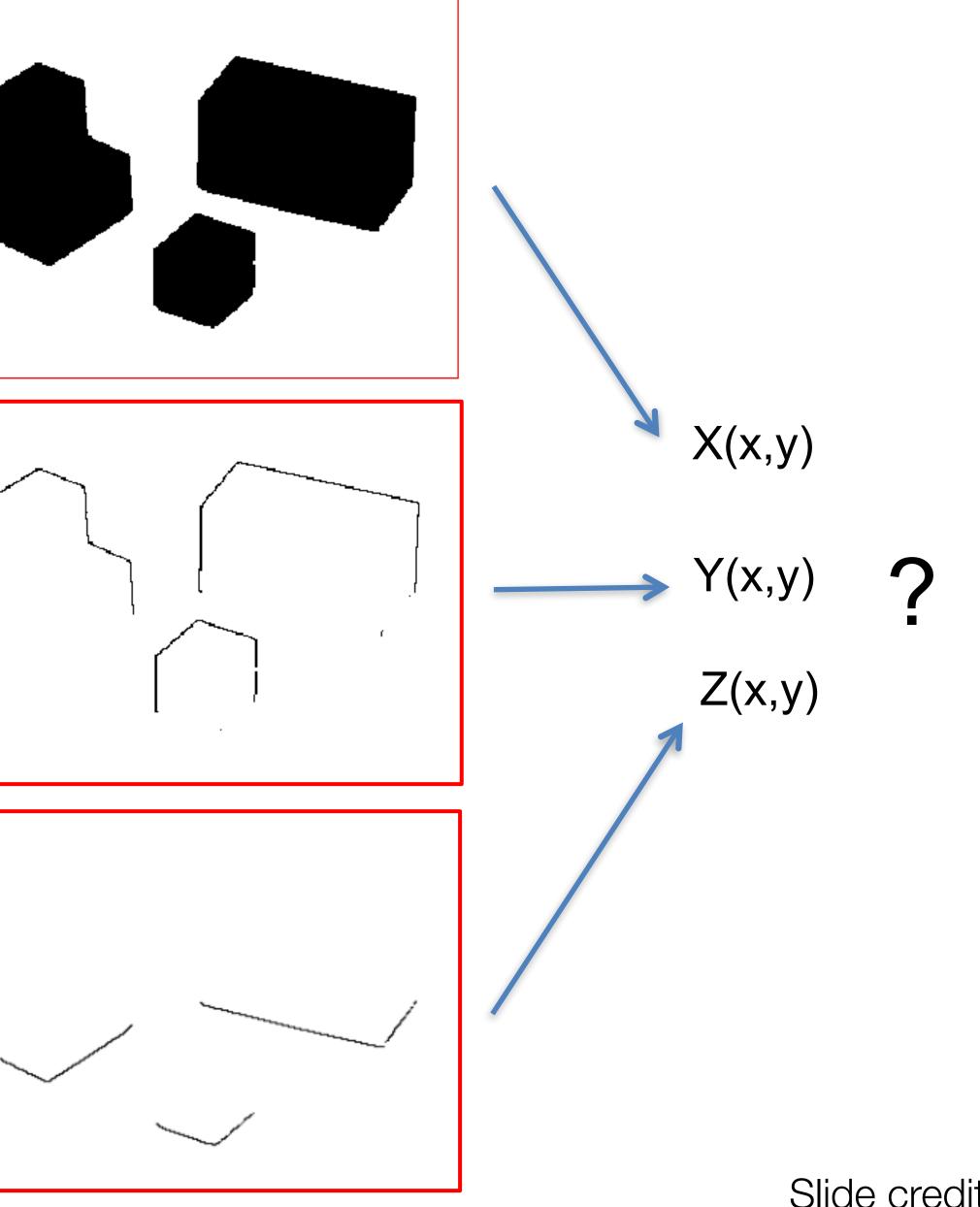
#### Contact edges



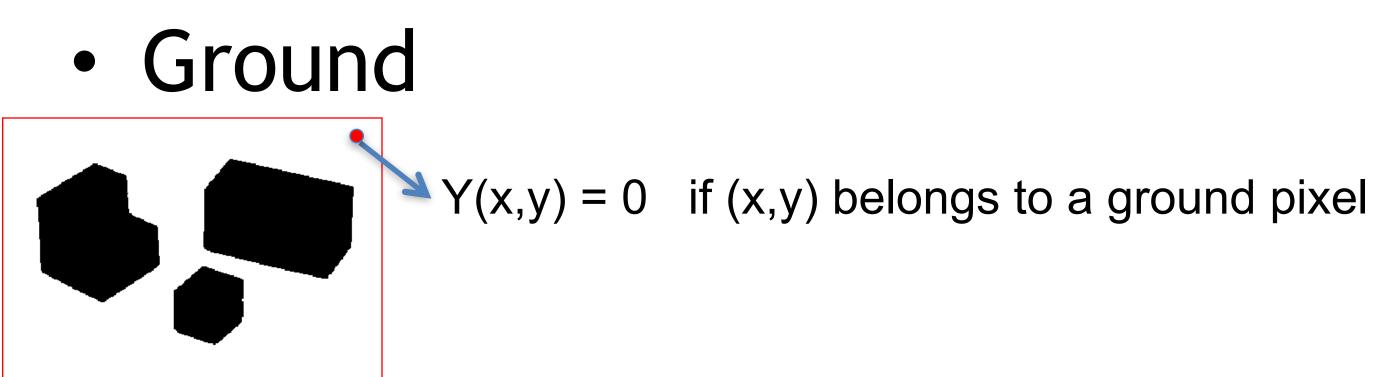




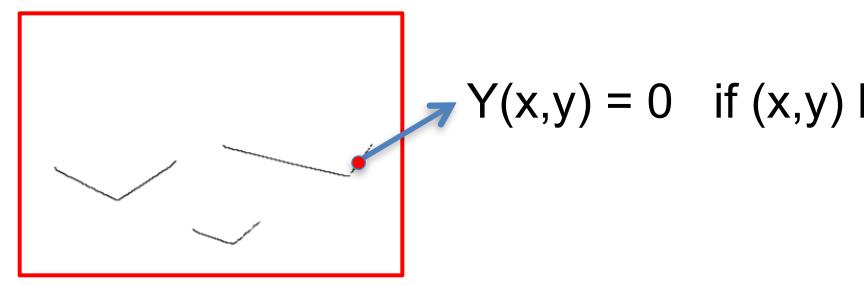








#### Contact edge



#### • What happens inside the objects?

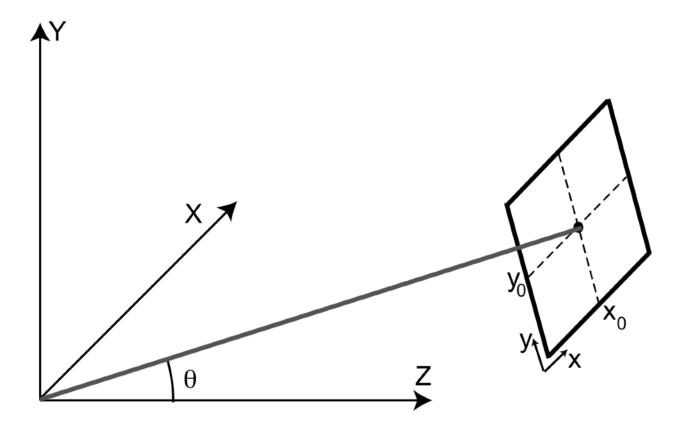
... now things get a bit more complicated.

Y(x,y) = 0 if (x,y) belongs to foreground and is a contact edge

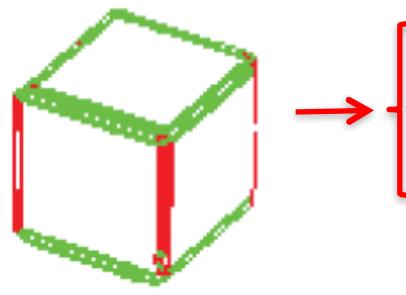


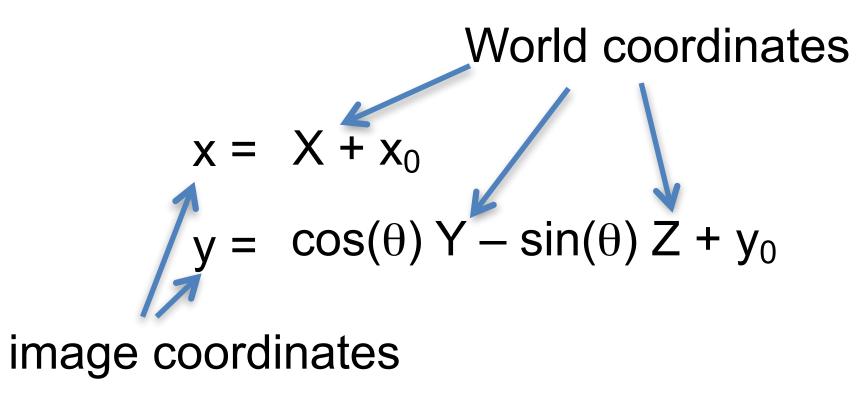
How can we relate the information in the pixels with 3D surfaces in the world?

#### Vertical edges



Given the image, what can we say about X, Y and Z in the pixels that belong to a vertical edge?

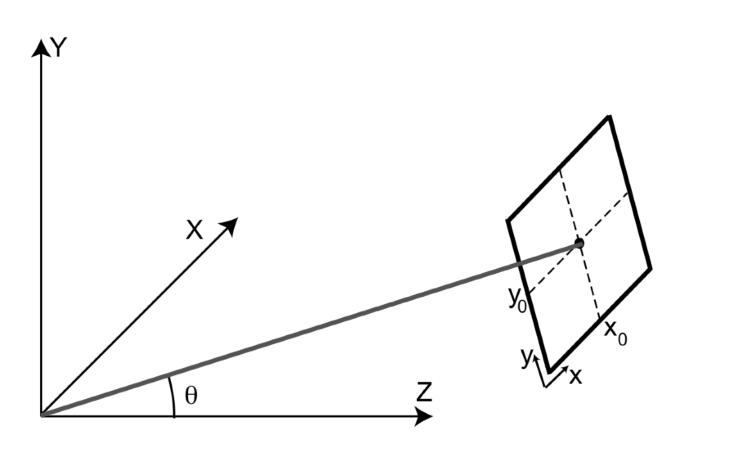




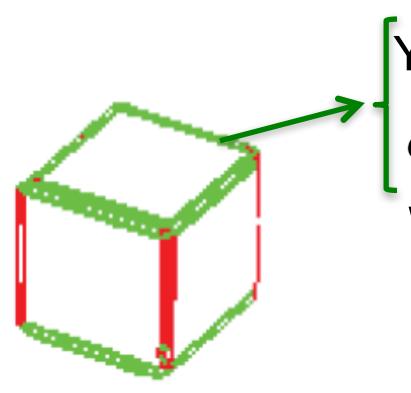
Z = constant along the edge 
$$\partial Y/\partial y = 1/\cos(\theta)$$



# From edges to surface constraintsHorizontal edges



Given the image, what can we say about X, Y and Z in the pixels that belong to an horizontal 3D edge?



Slide credit: Antonio Torralba

World coordinates  

$$x = X + x_0$$
  
 $y = \cos(\theta) Y - \sin(\theta) Z + y_0$ 

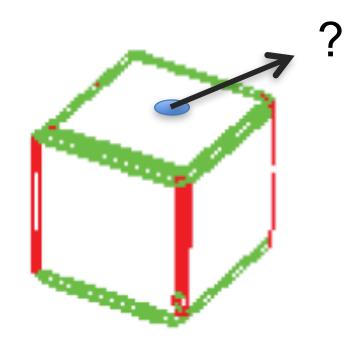
image coordinates

Y = constant along the edge

 $\partial Y / \partial \mathbf{t} = 0$ 

Where **t** is the vector parallel to the edge  $\mathbf{t} = (-n_y, n_x)$ 

 $\partial Y / \partial \mathbf{t} = -n_y \partial Y / \partial x + n_x \partial Y / \partial y$ 



Information has to be propagated from the edges

Slide credit: Antonio Torralba

#### What happens where there are no edges?

Assumption of planar faces:

$$\frac{\partial^2 Y}{\partial x^2} = 0$$
$$\frac{\partial^2 Y}{\partial y^2} = 0$$
$$\frac{\partial^2 Y}{\partial y \partial x} = 0$$

### A simple inference scheme

#### All the constraints are linear!

Y(x,y)=0

$$\partial Y/\partial y = 1/\cos(\theta)$$

 $\partial Y / \partial \mathbf{t}$ = 0

$$\frac{\partial^2 Y}{\partial x^2} = 0$$
$$\frac{\partial^2 Y}{\partial y^2} = 0$$
$$\frac{\partial^2 Y}{\partial y \partial x} = 0$$

Slide credit: Antonio Torralba

- if (x,y) belongs to a ground pixel
- if (x,y) belongs to a vertical edge
- if (x,y) belongs to an horizontal edge
- if (x,y) is not on an edge

#### A similar set of constraints could be derived for Z

### Discrete approximation

## We can transform every differential constraint into a linear constraint on Y(x,y)

Y(x,y)

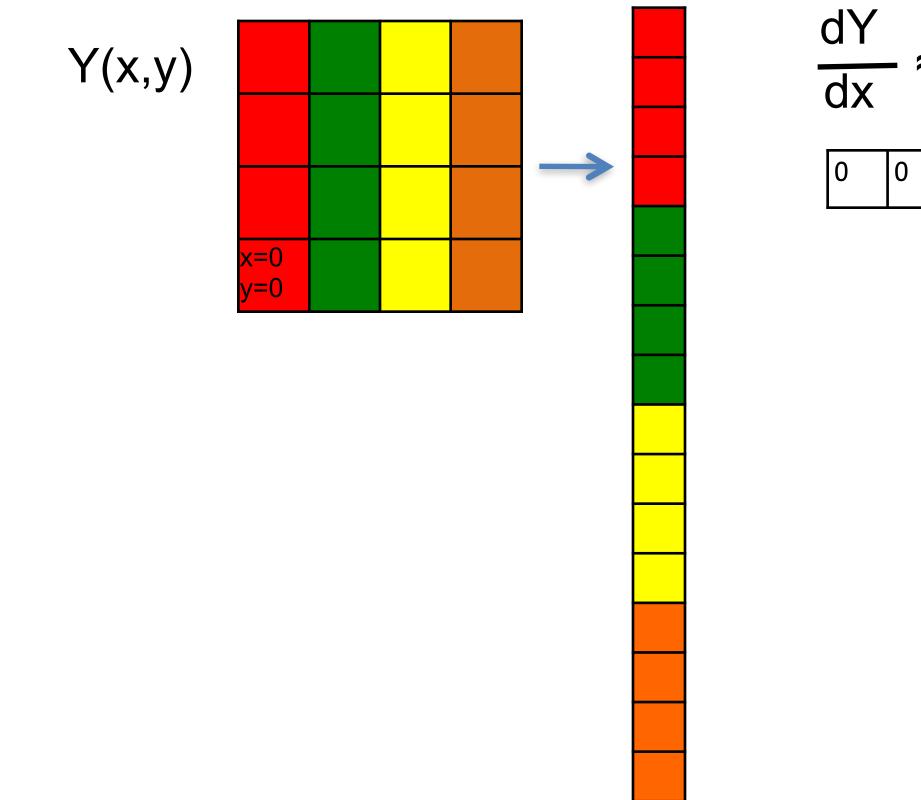
111	115	113	111	112	111	112	111
135	138	137	139	145	146	149	147
163	168	188	196	206	202	206	207
180	184	206	219	202	200	195	193
189	193	214	216	104	79	83	77
191	201	217	220	103	59	60	68
195	205	216	222	113	68	69	83
199	203	223	228	108	68	71	77

$$\frac{dY}{dx} \approx Y(x,y) - Y(x-1,y)$$



### Discrete approximation

Transform the "image" Y(x,y) into a column vector:



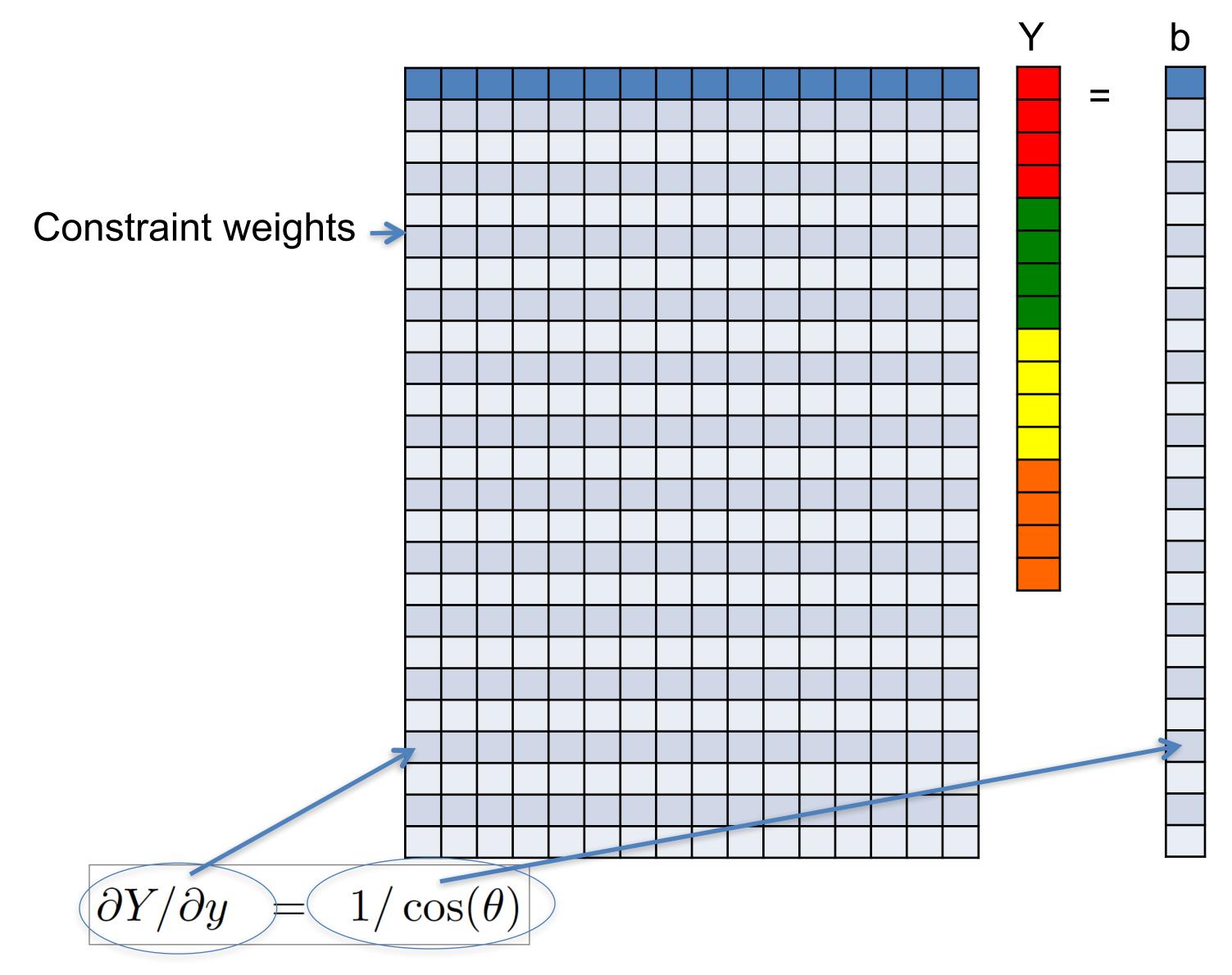
x=2, y=2

### $\frac{dY}{dx} \approx Y(x,y) - Y(x-1,y) \stackrel{\checkmark}{=} Y(2,2) - Y(1,2) =$

0	0	0	0	-1	0	0	0	1	0	0	0	0	0	0	
														-	
														-	



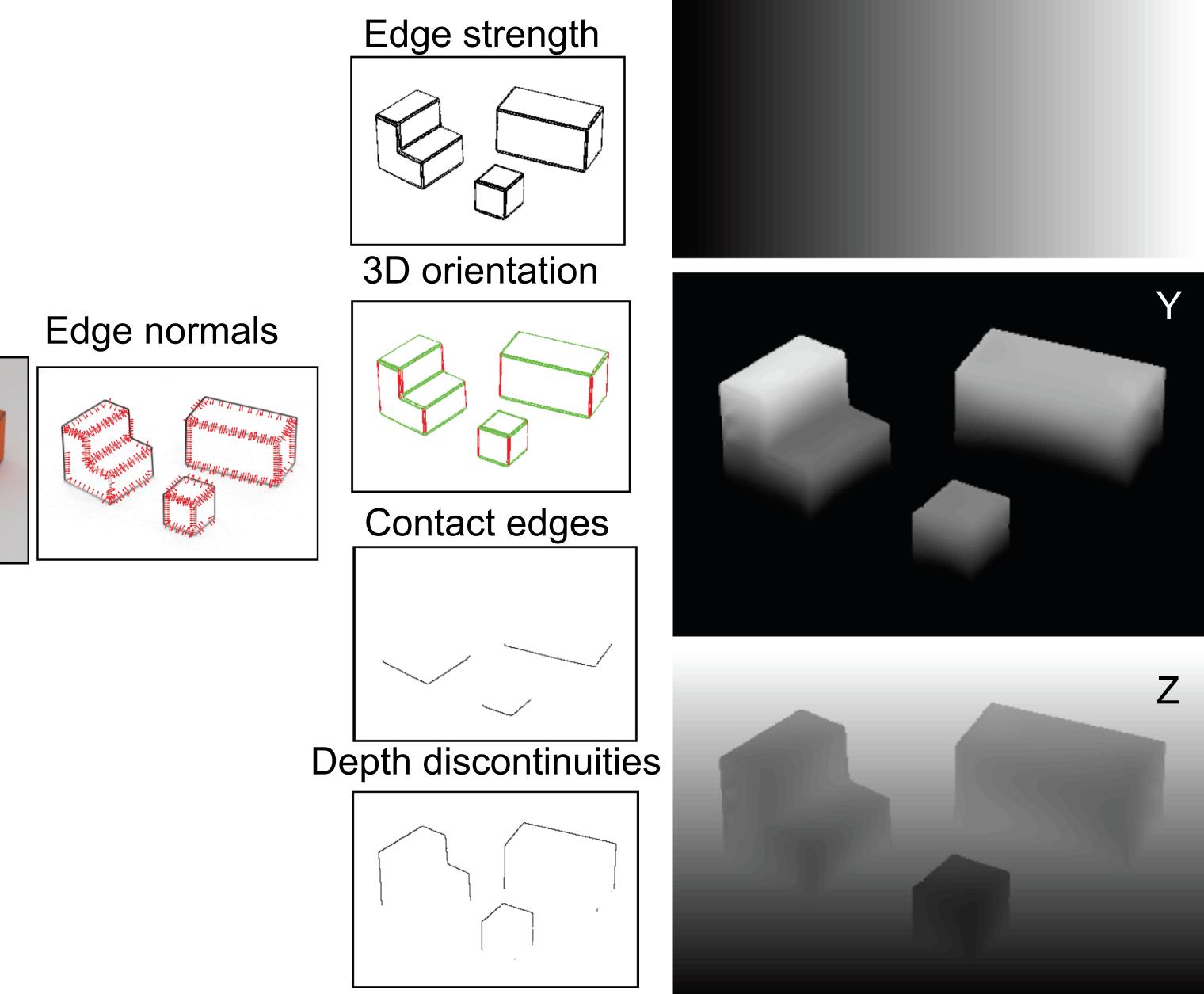
#### A simple inference scheme: solve for Y

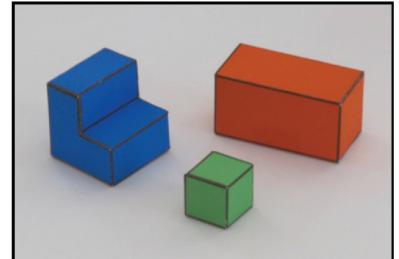


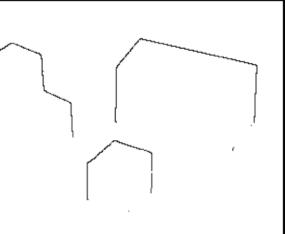
AY = b



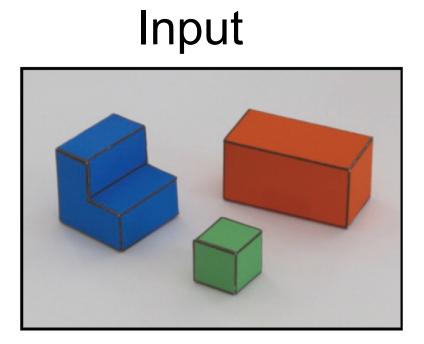
### Results





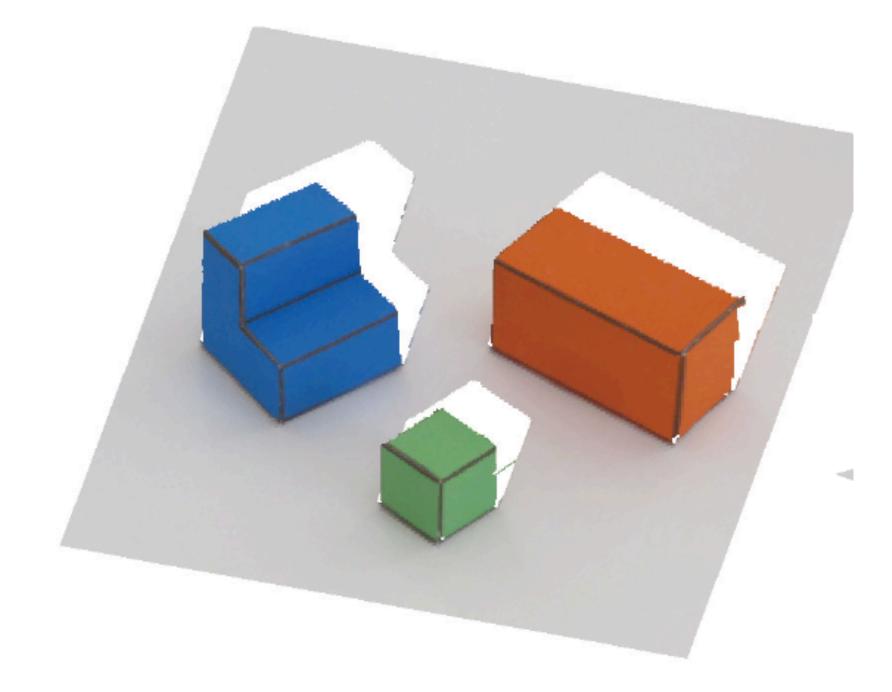


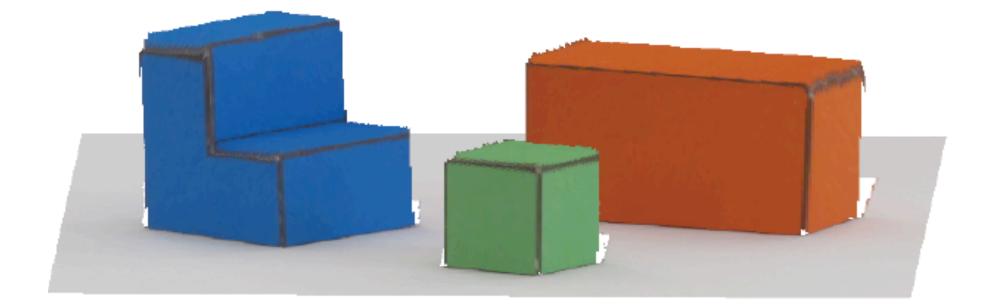


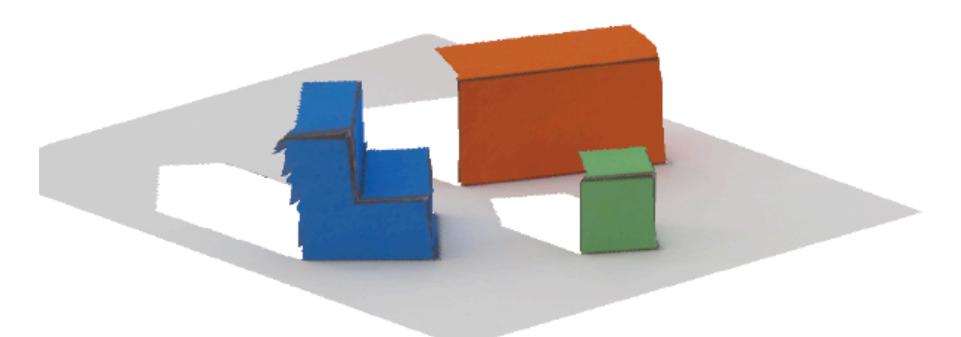


### Changing view point

#### New view points:

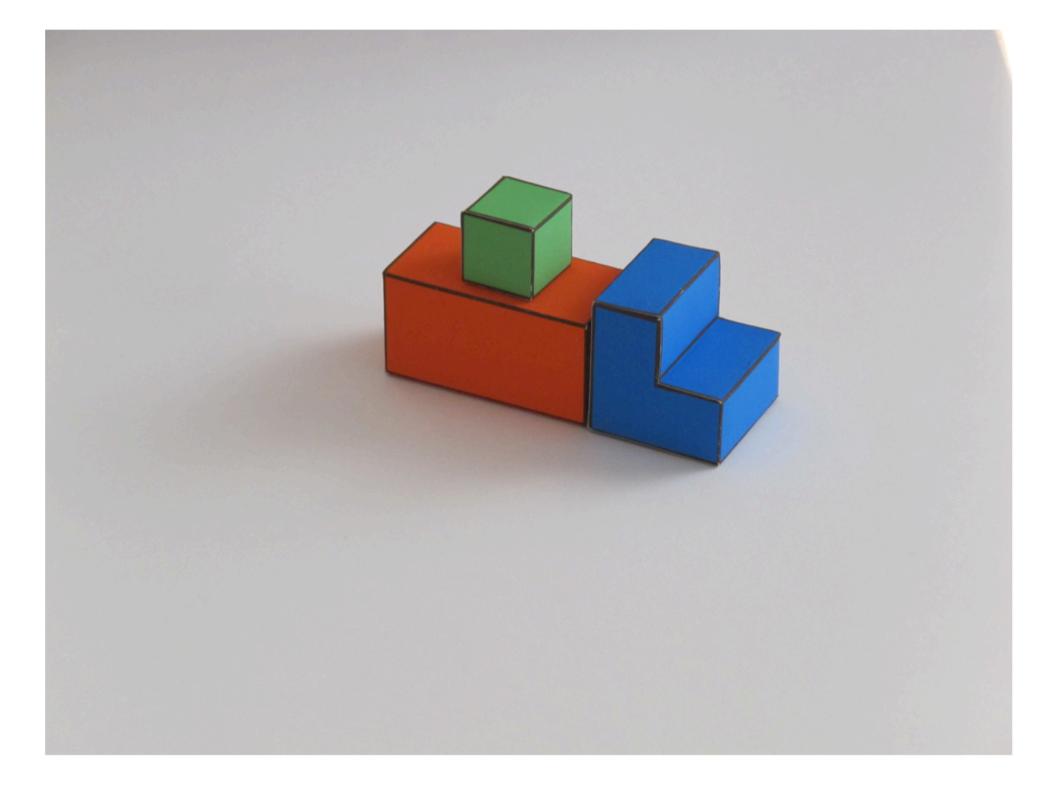


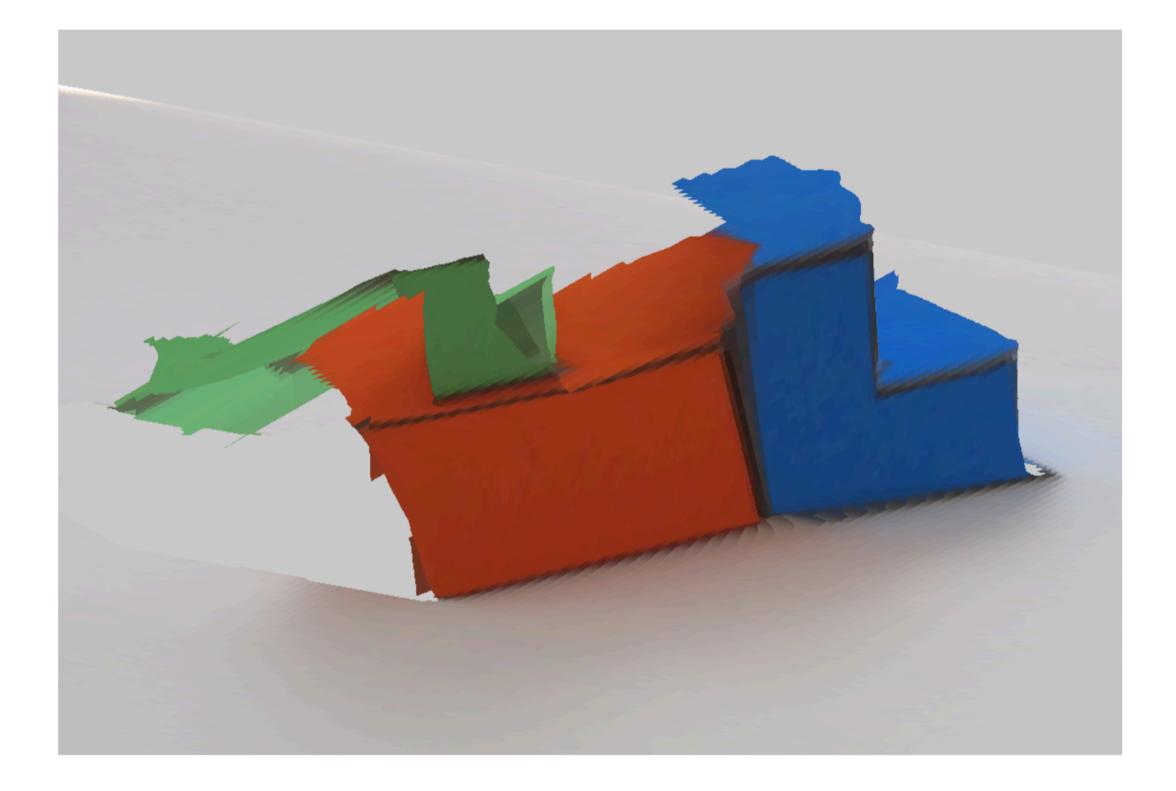




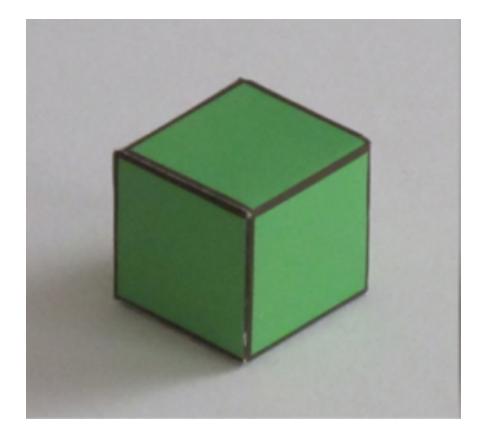


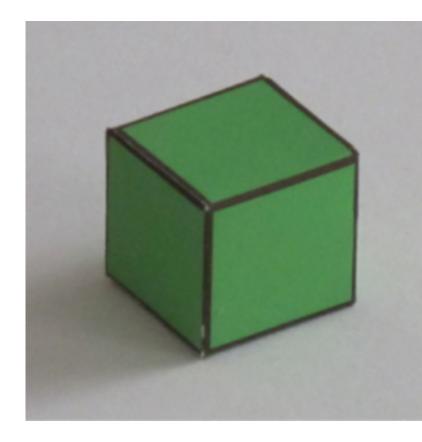
#### Failure cases... even in a simple world!

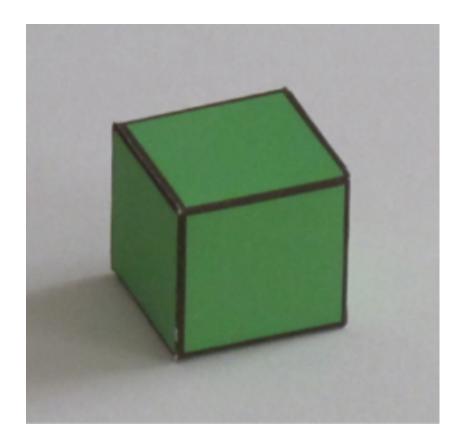


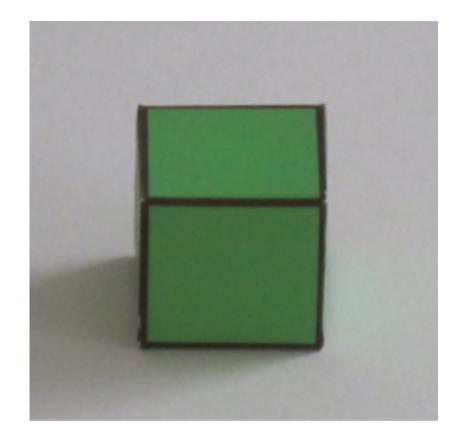


#### Failure cases... even in a simple world!

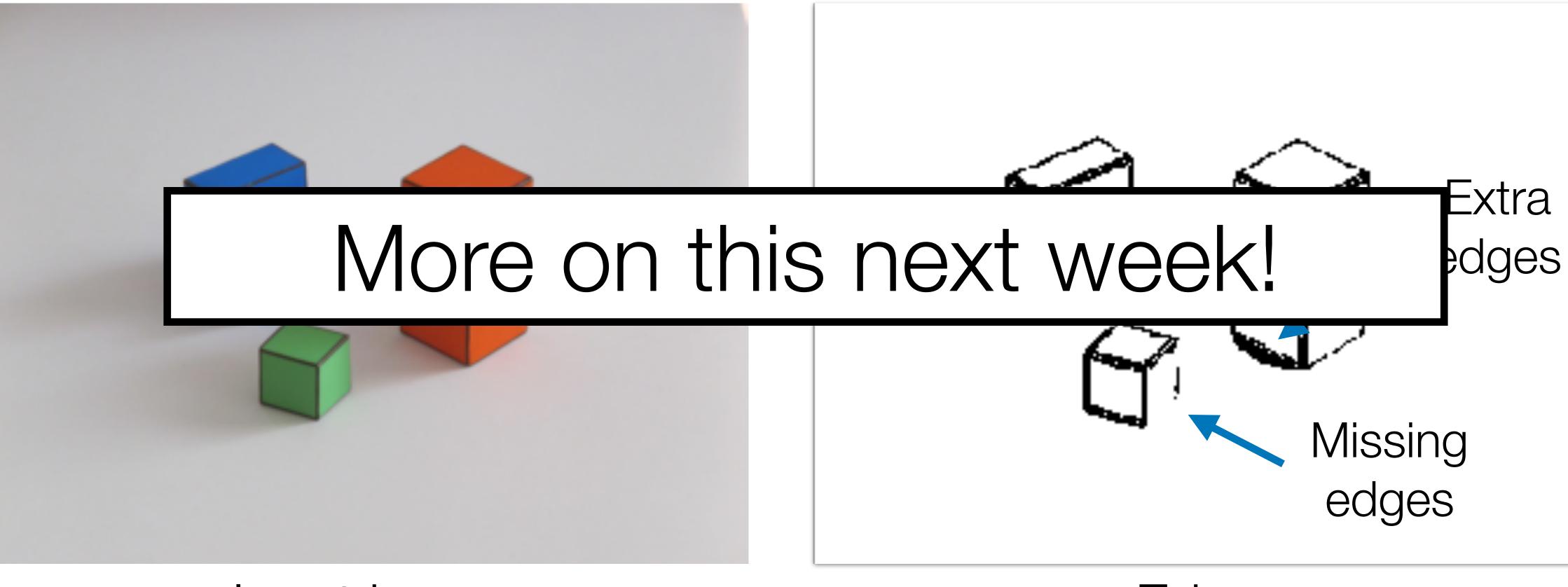








#### Failure cases... even in a simple world!



Input image





### Questions about the course?