CS 4476-A and 6476-A: Computer Vision

Instructor: James Hays

TAs: **Otis Smith**, **Sooraj Karthik** (head TAs), Mohit Aggarwal, Mansi Bhandari, SooHoon Choi, Deepanshi, Jesse Dill, Akhil Goel, Nikith Hosangadi, Haris Hussain, Jim James, Mark Kahoush, Xueqing Li, Alex Liu, Michael Propp, Aditya Sarma, Kelin Yu, Sili Zeng.

Image by
kirkh.deviantart.com

Today’s Class

- Who am I?
- What is Computer Vision?
- Specifics of this course
- Geometry of Image Formation
- Questions

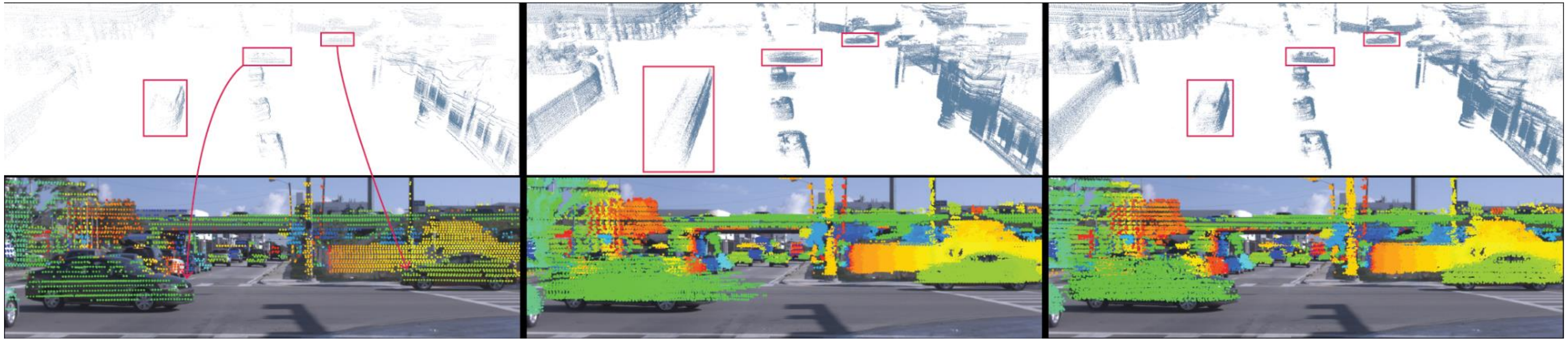
A bit about me

La Crosse
Fond Du Lac
Madison
Dubuque
Janesville
Rockford
Cedar Rapids
Elgin
Aurora
Davenport
Galesburg
Burlington
Peoria
Illinois
Quincy
Springfield
Decatur
Indianapolis
Carmel
Dayton
Columbus
Lancaster
Terre Haute
Hamilton
Columbus
Bloomington
Cincinnati
Parkersburg
St Louis
Ballwin
Belleville
Louisville
Huntington
West Virginia
Harrisonburg
Evansville
Lexington
Owensboro
Cape Girardeau
Bowling Green
Kentucky
Glasgow
Roanoke
Blacksburg
Virginia
Petersburg
Richmond
Norfolk
Danville
Kingsport
Nashville
Cookeville
Knoxville
Jonesboro
Blytheville
Tennessee
Jackson
Wynne
Memphis
Germantown
Cleveland
Chattanooga
Huntsville
Decatur
Clarksdale
Tupelo
Rome
Gadsden
Johns Creek
Marietta
Athens
Grenada
Greenville
Mississippi
Birmingham
Atlanta
Tuscaloosa
Macon
Mississauga
Toronto
Hamilton
St. Catharines
Norfolk
Erie
Youngstown
Pittsburgh
Altoona
Pennsylvania
Morgantown
Maryland
Rockville
Annapolis
Washington DC
Charlottesville
York
Lancaster
Trenton
Allentown
Scranton
New York
Brentwood
Edison
Danbury
Bridgeport
Connecticut
Portland
New Hampshire
Haverhill
Boston
Brockton
New Bedford
Rhode Island
Kill Devil Hills

ARGO AI
Ford
self-driving test vehicle
vehículo de manejo autónomo
ARGO

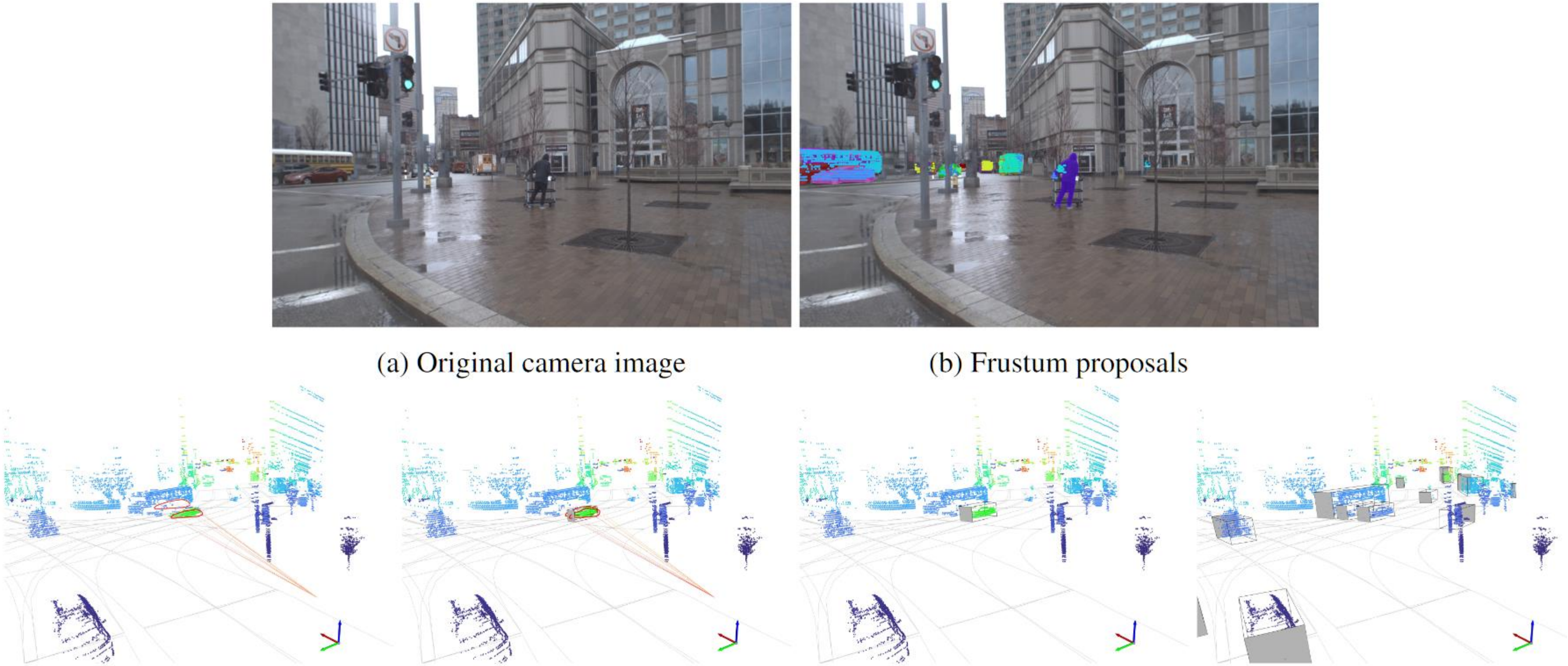
What type of stuff do I work on?

Understanding Lidar



Scene Flow from Point Clouds with or without Learning
Jhony Kaesemodel Pontes, James Hays, Simon Lucey
https://jhonykaesemodel.com/publication/sceneflow-3dv2020/

Understanding Lidar



(a) Original camera image

(b) Frustum proposals

(c) Object frustum proposal

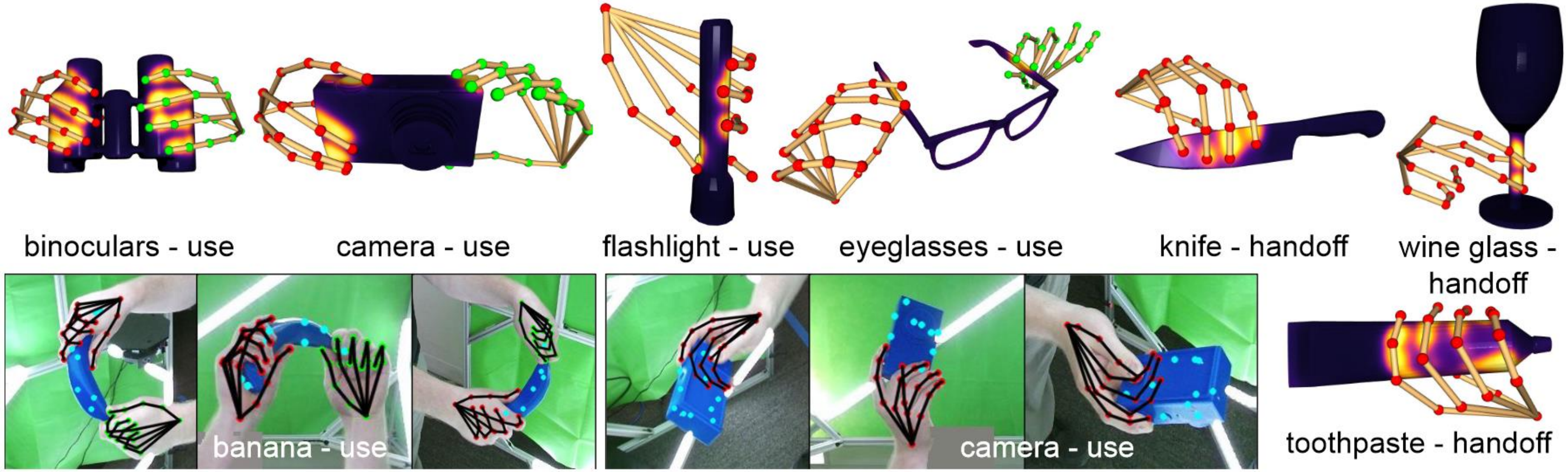
(d) LiDAR instance segmentation

(e) Amodal completion

(f) Final cuboids

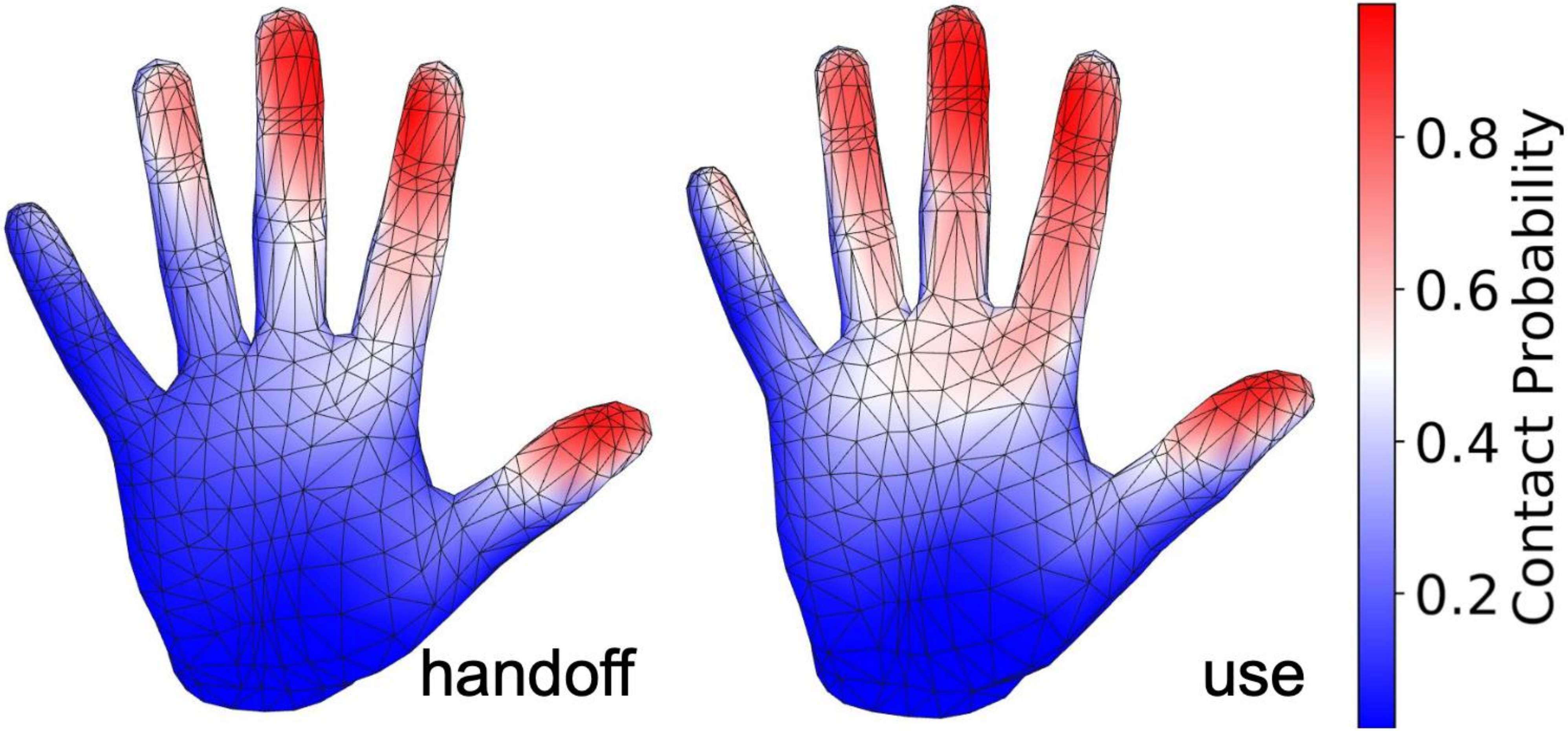
3D for Free: Crossmodal Transfer Learning using HD Maps
Benjamin Wilson, Zsolt Kira, James Hays
https://arxiv.org/abs/2008.10592

Exploring new data sources

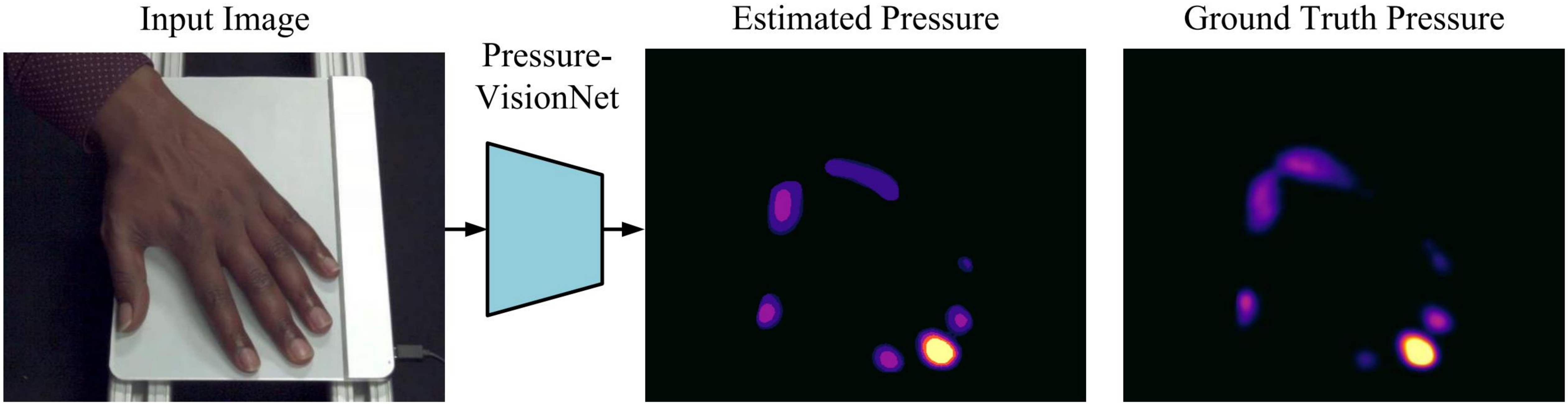


ContactPose: A Dataset of Grasps with Object Contact and Hand Pose
Samarth Brahmbhatt, Chengcheng Tang, Christopher D. Twigg, Charles C. Kemp, James Hays ECCV 2020

Hand Contact Probability



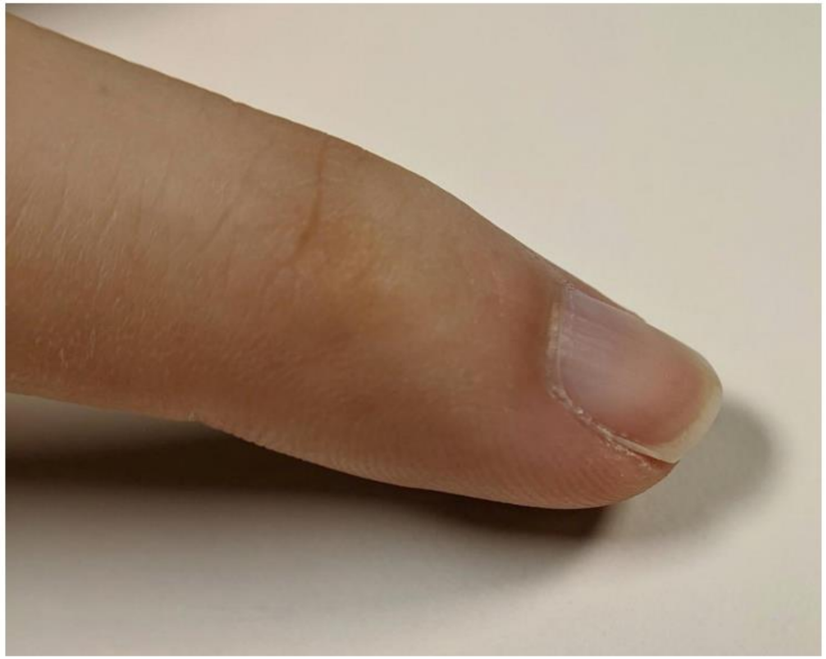
PressureVision: Estimating Hand Pressure from a Single RGB Image



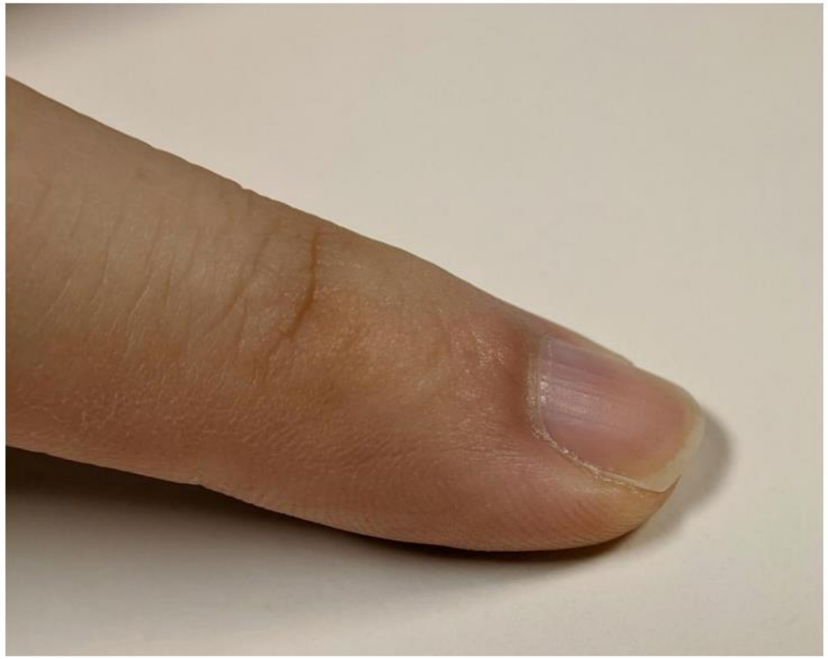
Patrick Grady, Chengcheng Tang, Samarth Brahmbhatt, Christopher D. Twigg,
Chengde Wan, James Hays, and Charles C. Kemp

ECCV 2022 Oral

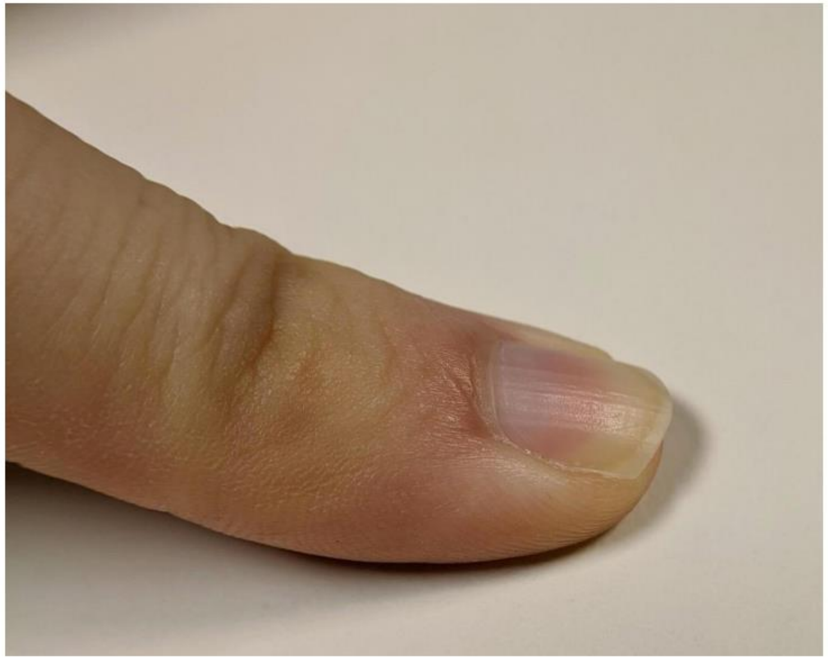
No Contact



Low Force



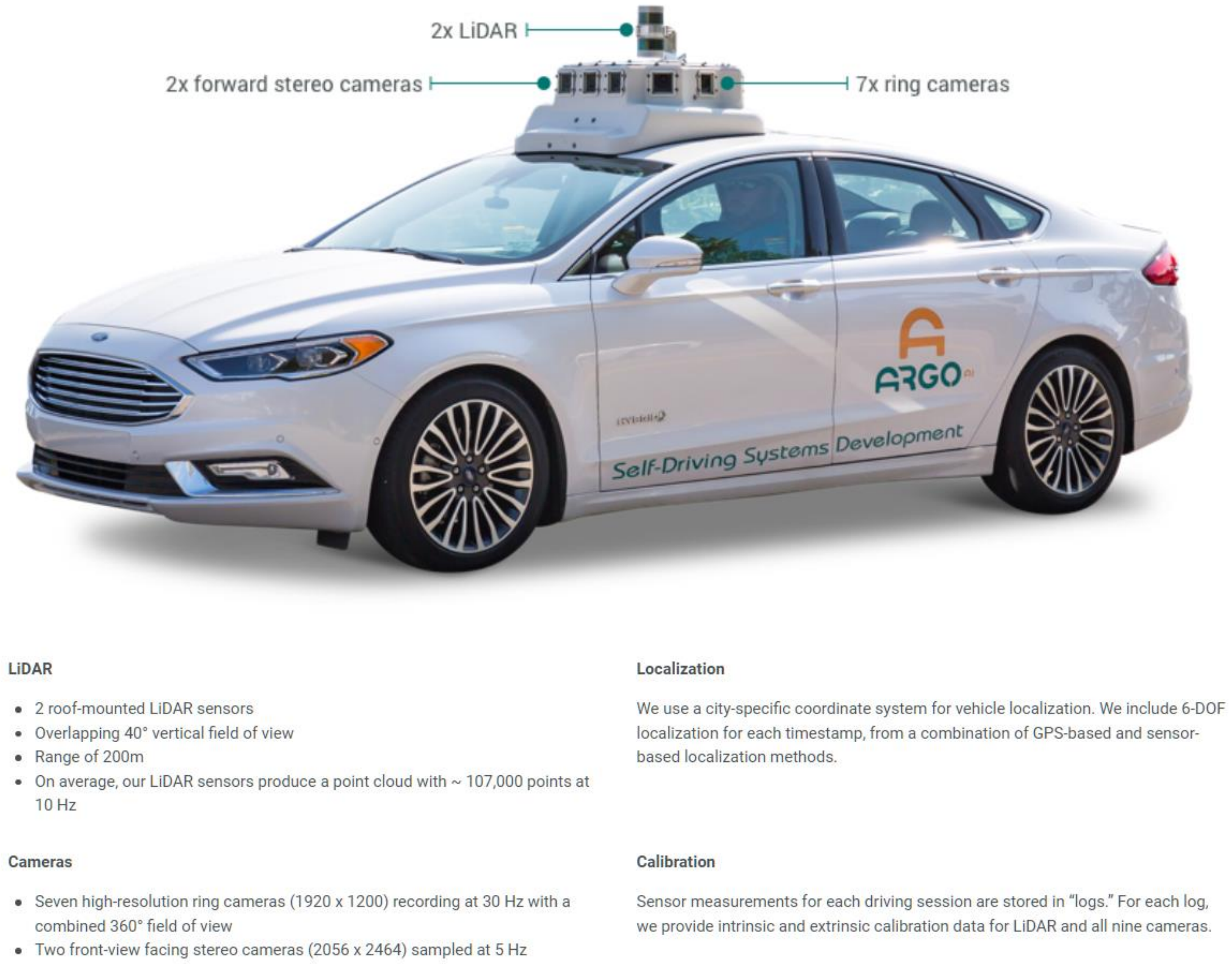
High Force



We train a deep network, PressureVisionNet,
to estimate pressure from a single RGB image.

The pressure for each frame is calculated independently.

Exploring new data sources



LiDAR

- 2 roof-mounted LiDAR sensors
- Overlapping 40° vertical field of view
- Range of 200m
- On average, our LiDAR sensors produce a point cloud with ~ 107,000 points at 10 Hz

Cameras

- Seven high-resolution ring cameras (1920 x 1200) recording at 30 Hz with a combined 360° field of view
- Two front-view facing stereo cameras (2056 x 2464) sampled at 5 Hz

Localization

We use a city-specific coordinate system for vehicle localization. We include 6-DOF localization for each timestamp, from a combination of GPS-based and sensor-based localization methods.

Calibration

Sensor measurements for each driving session are stored in "logs." For each log, we provide intrinsic and extrinsic calibration data for LiDAR and all nine cameras.

https://www.argoverse.org/

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- Specifics of this course
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- Questions

What is Computer Vision?

Derogatory summary of computer vision:
Machine learning applied to visual data

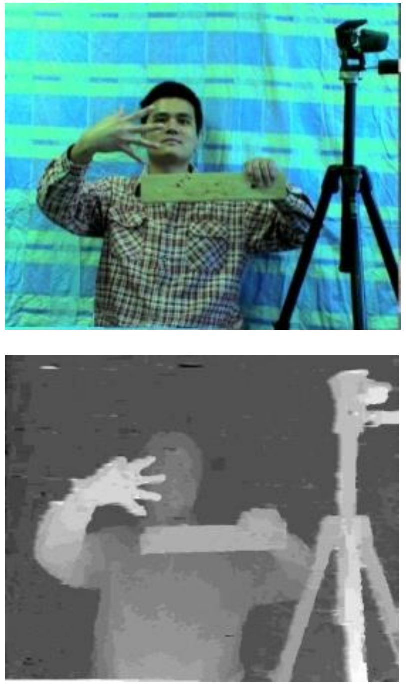
Computer Vision

- Automatic understanding of images and video
    1. Computing properties of the 3D world from visual data *(measurement)*

Slide credit: Kristen Grauman

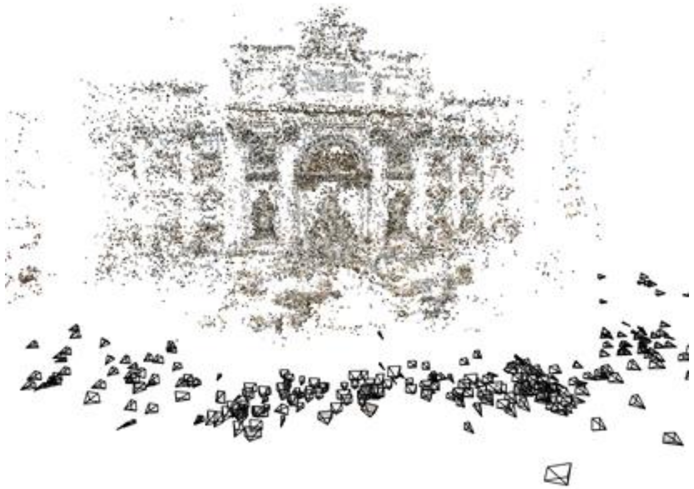
1. Vision for measurement

Real-time stereo



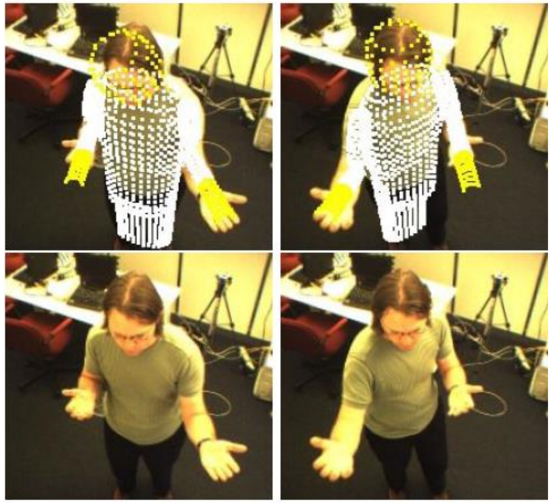
Wang et al.

Structure from motion



Snavely et al.

Tracking



Demirdjian et al.

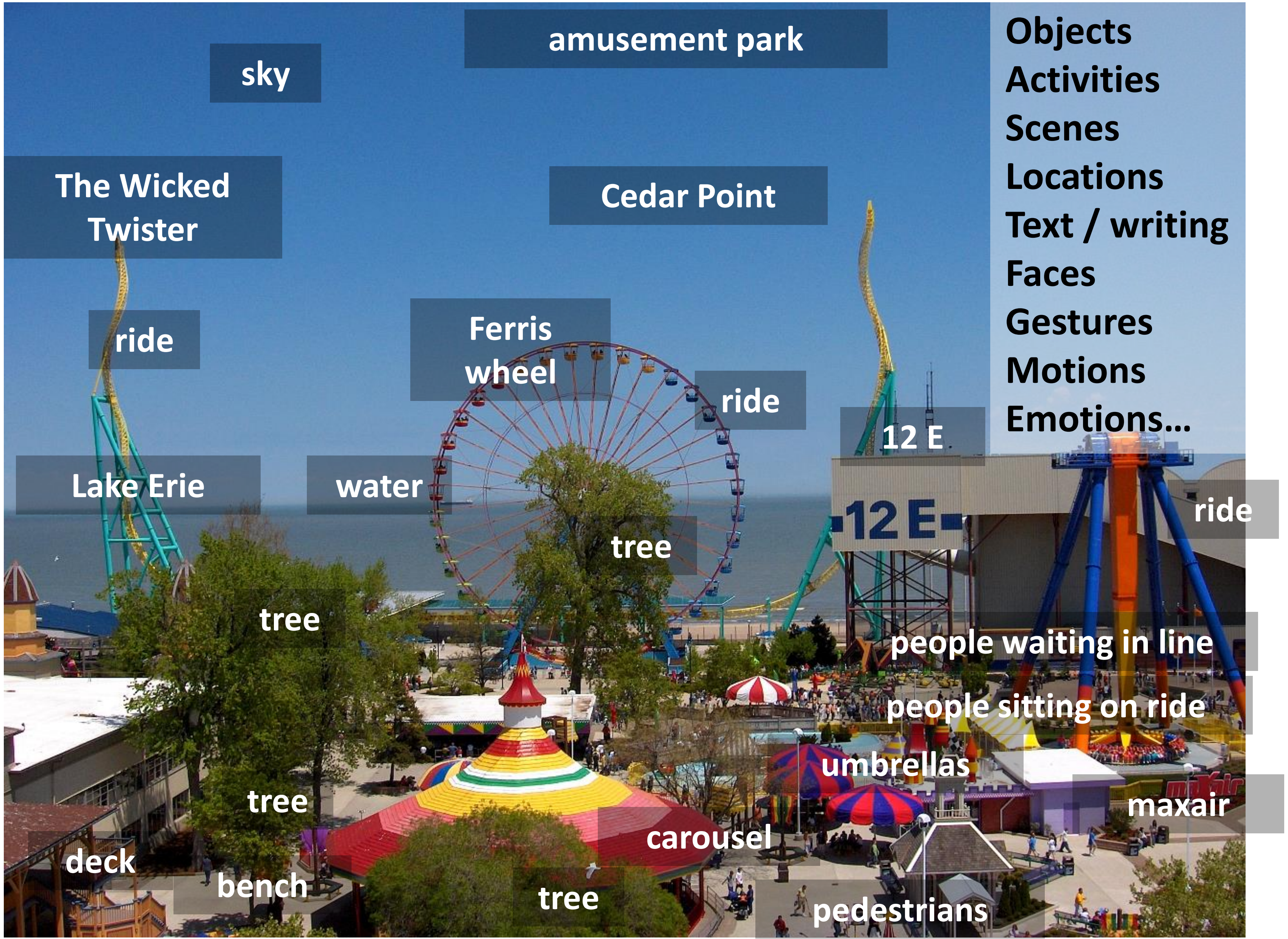
Slide credit: Kristen Grauman

Computer Vision

- Automatic understanding of images and video
  1. Computing properties of the 3D world from visual data *(measurement)*
  2. Algorithms and representations to allow a machine to recognize objects, people, scenes, and activities. *(perception and interpretation)*

Slide credit: Kristen Grauman

2. Vision for perception, interpretation



Objects
Activities
Scenes
Locations
Text / writing
Faces
Gestures
Motions
Emotions…

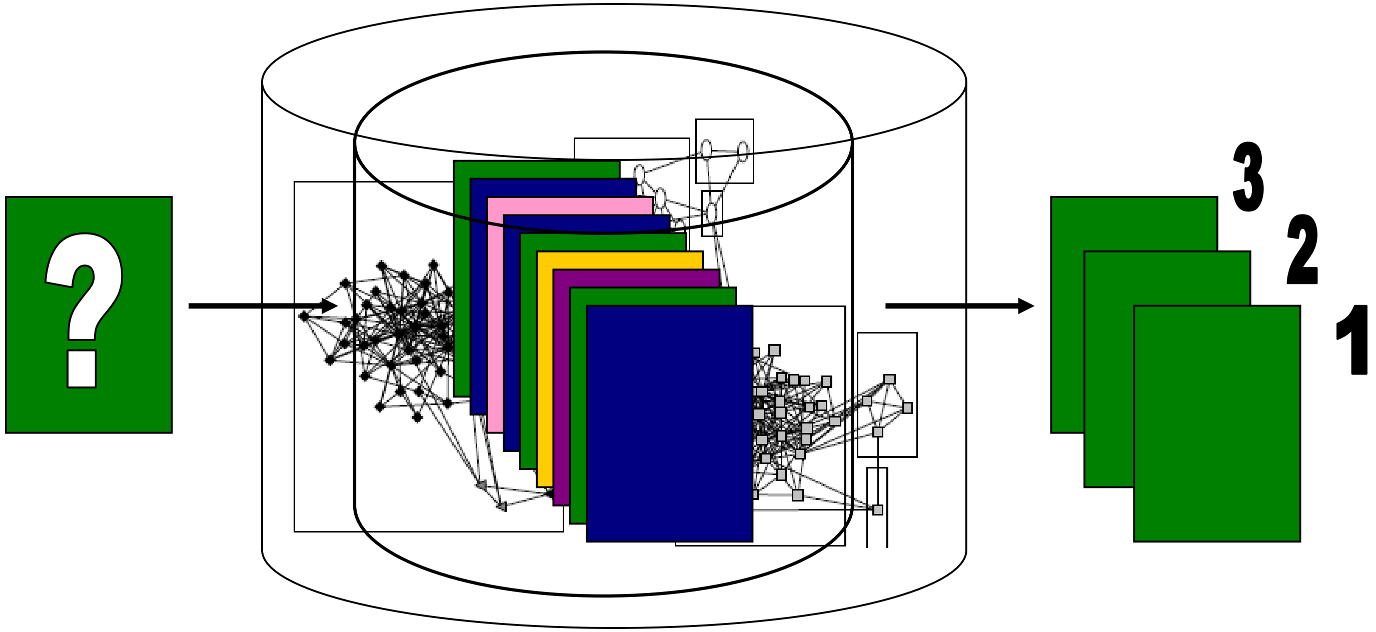
Slide credit: Kristen Grauman

Computer Vision

- Automatic understanding of images and video
  1. Computing properties of the 3D world from visual data *(measurement)*
  2. Algorithms and representations to allow a machine to recognize objects, people, scenes, and activities. *(perception and interpretation)*
  3. Algorithms to mine, search, and interact with visual data (*search and organization*)

Slide credit: Kristen Grauman

3. Visual search, organization



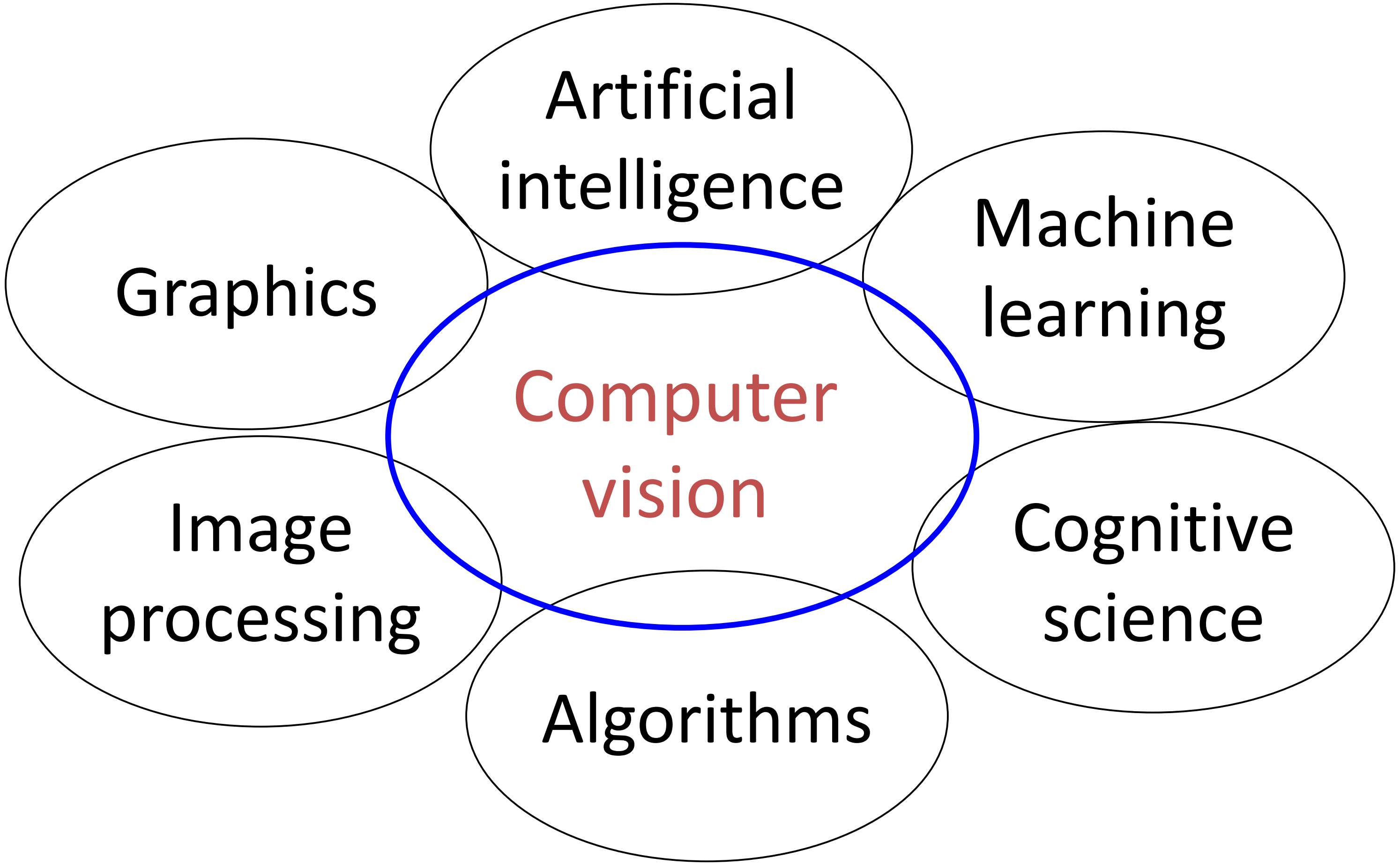
Query

Image or video archives

Relevant content

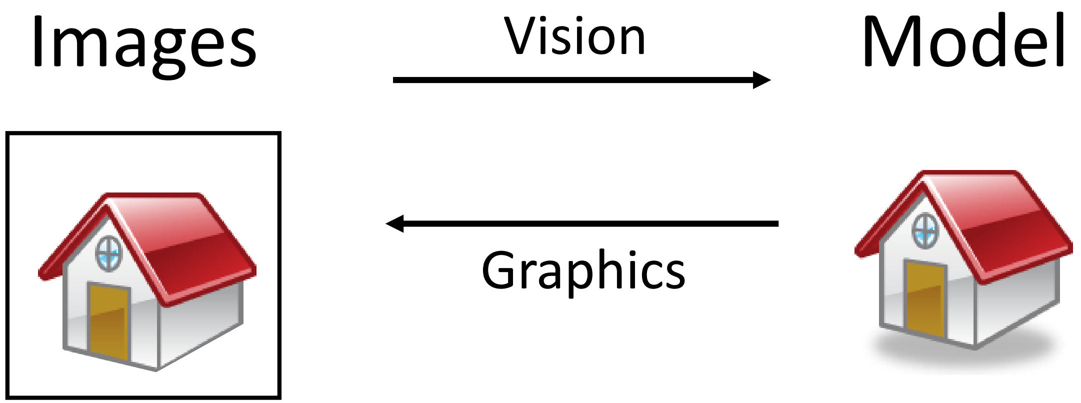
Slide credit: Kristen Grauman

Related disciplines



Slide credit: Kristen Grauman

Vision and graphics



Images

Vision

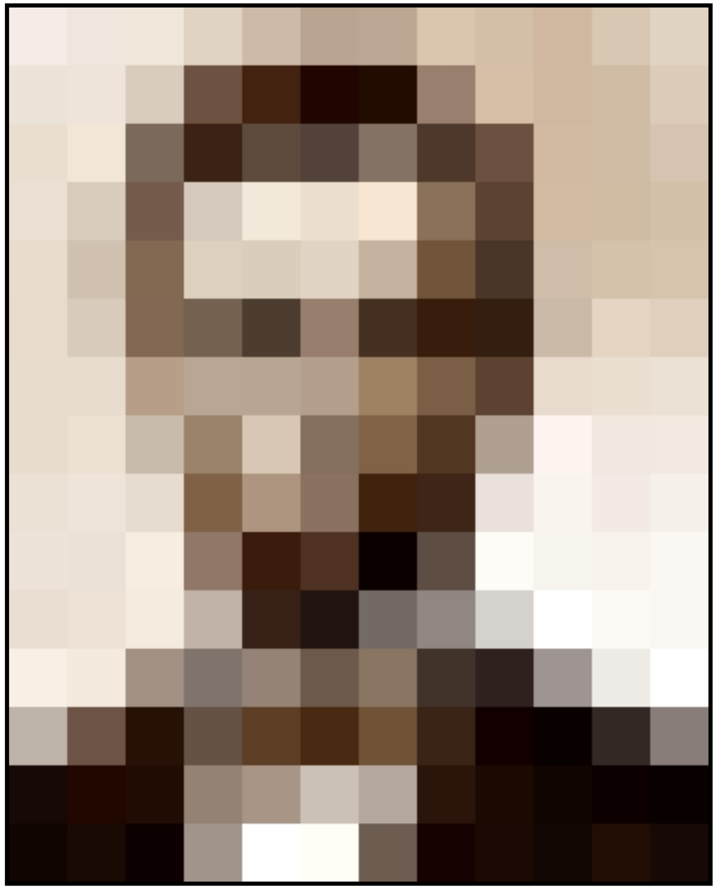
Model

Graphics

Inverse problems: analysis and synthesis.

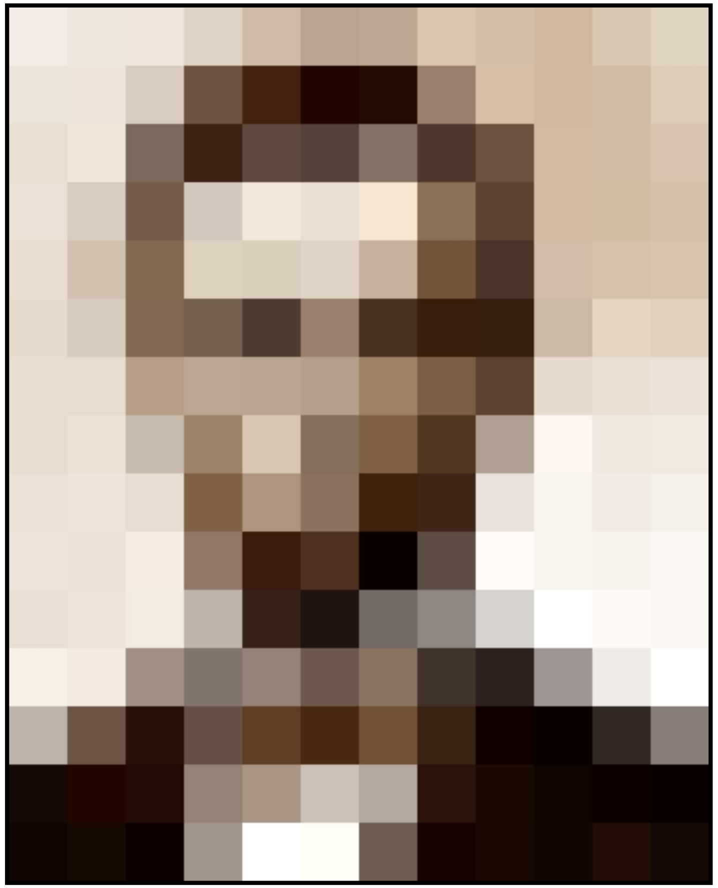
Slide credit: Kristen Grauman

What humans see



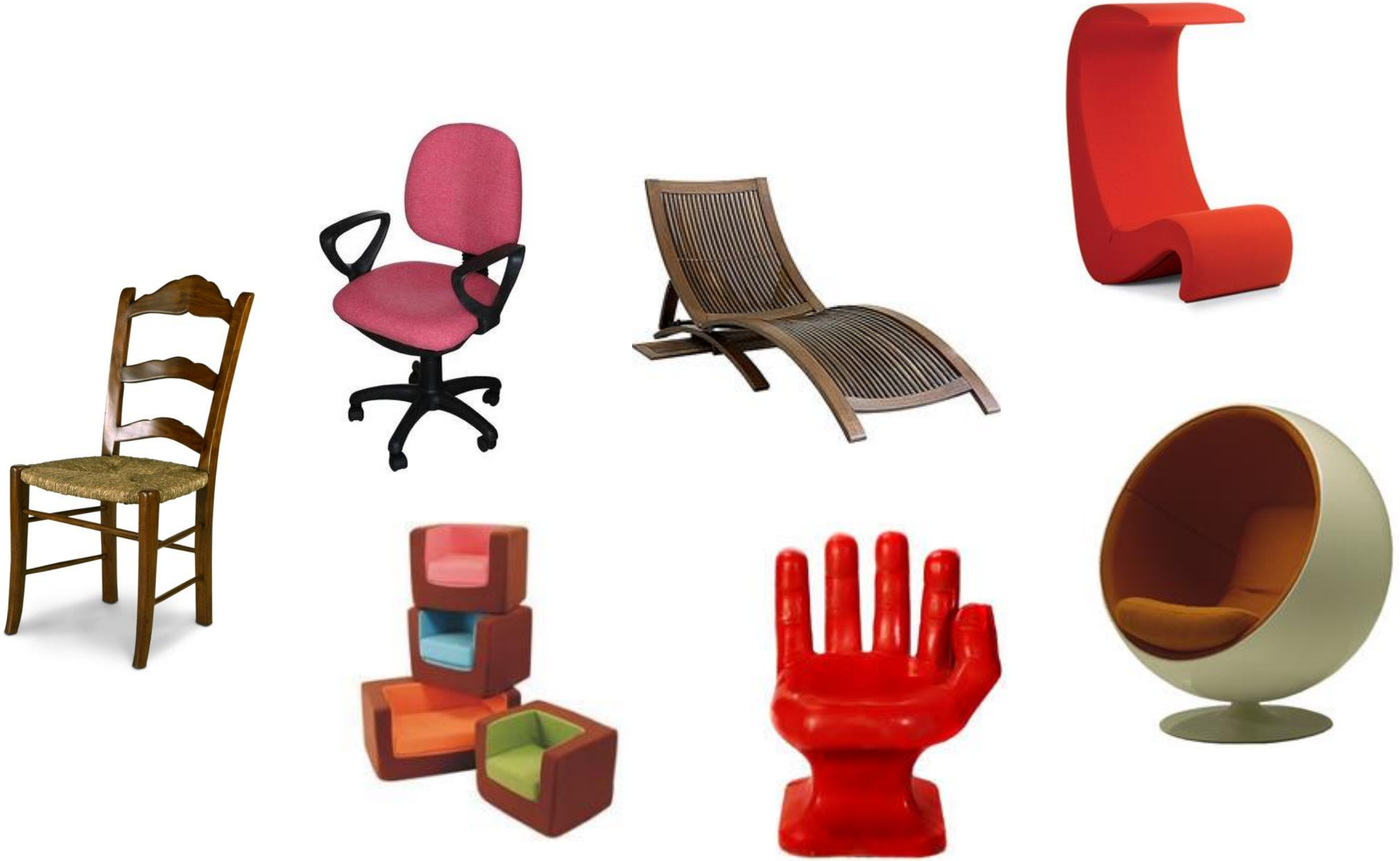
Slide credit: Larry Zitnick

What computers see



Slide credit: Larry Zitnick

What do humans see?



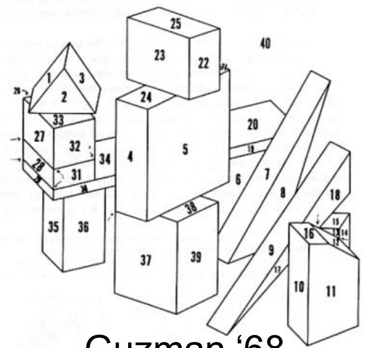
Slide credit: Larry Zitnick

Vision is really hard

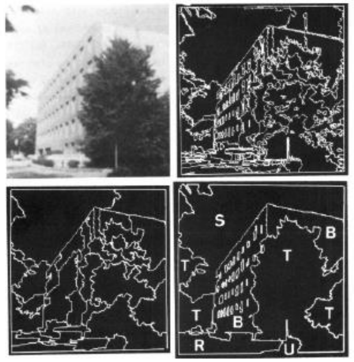
- Vision is an amazing feat of natural intelligence
  - Visual cortex occupies about 50% of Macaque brain
  - One third of human brain devoted to vision (more than anything else)

Ridiculously brief history of computer vision

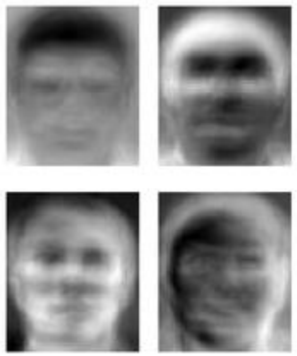
- 1966: Minsky assigns computer vision as an undergrad summer project
- 1960’s: interpretation of synthetic worlds
- 1970’s: some progress on interpreting selected images
- 1980’s: ANNs come and go; shift toward geometry and increased mathematical rigor
- 1990’s: face recognition; statistical analysis in vogue
- 2000’s: broader recognition; large annotated datasets available; video processing starts
- 2010’s: Deep learning with ConvNets
- 2020’s: Widespread autonomous vehicles?
- 2030’s: robot uprising?



Guzman ‘68



Ohta Kanade ‘78



Turk and Pentland ‘91

How vision is used now

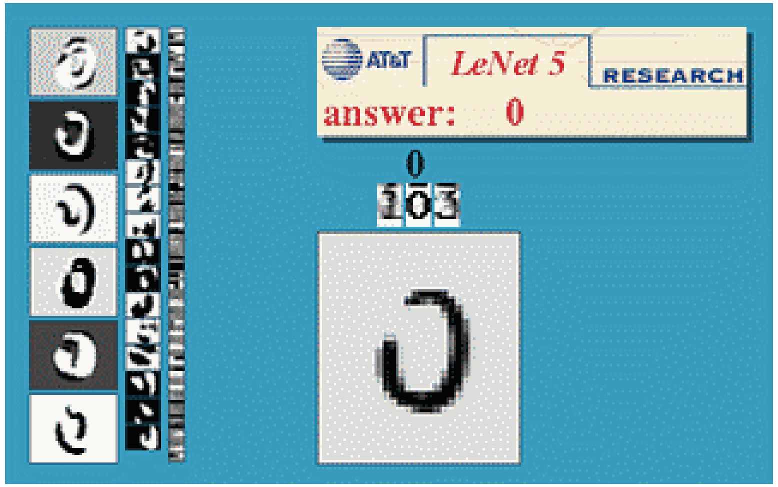
- Examples of real-world applications

Some of the following slides by Steve Seitz

Optical character recognition (OCR)

Technology to convert scanned docs to text

- If you have a scanner, it probably came with OCR software



Digit recognition, AT&T labs
http://www.research.att.com/~yann/

License plate readers
http://en.wikipedia.org/wiki/Automatic_number_plate_recognition

Optical character recognition (OCR)

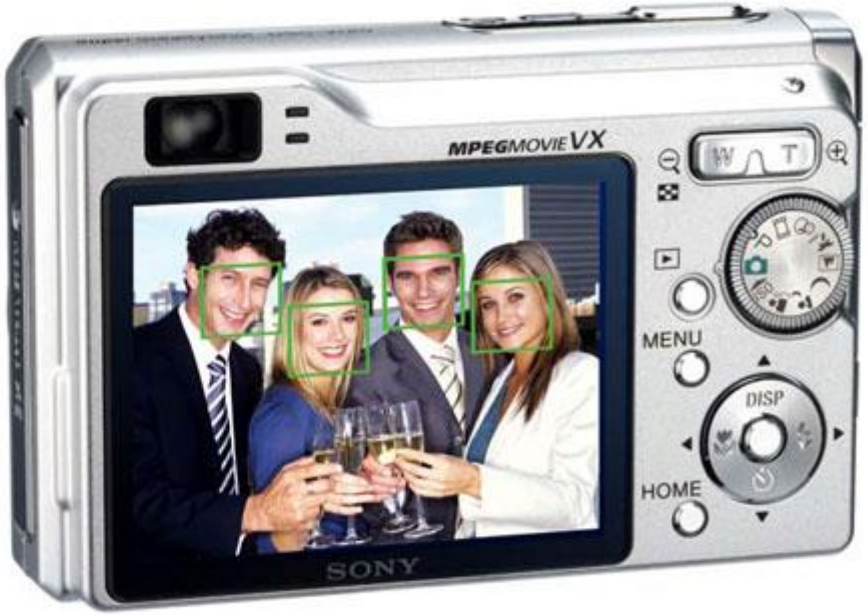
- Most US postal service mail is automatically read.
- In 1997, there were 55 offices reviewing images of 19 billion pieces of mail that OCR failed on.
- Today, there is 1 office, and they only looked at 1.2 billion pieces of mail this year.

How the US Postal Service reads terrible handwriting

3,417,225 views • Aug 8, 2022

https://www.youtube.com/watch?v=XxCha4Kez9c

Face detection



- Digital cameras detect faces

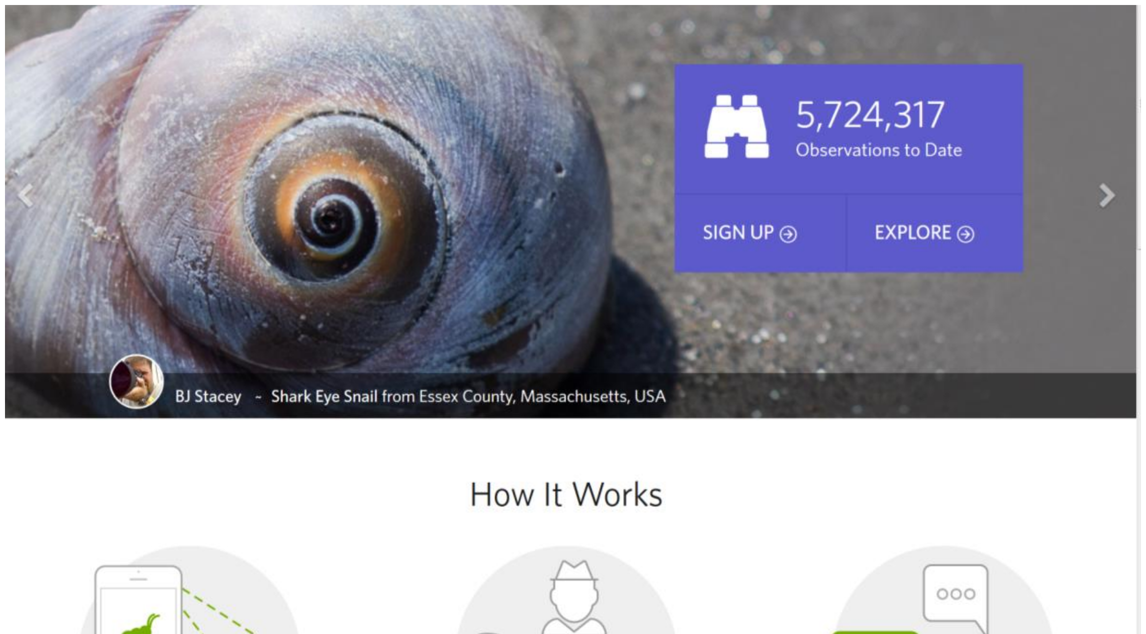
Vision in space

NASA'S Mars Exploration Rover Spirit captured this westward view from atop a low plateau where Spirit spent the closing months of 2007.

Vision systems (JPL) used for several tasks

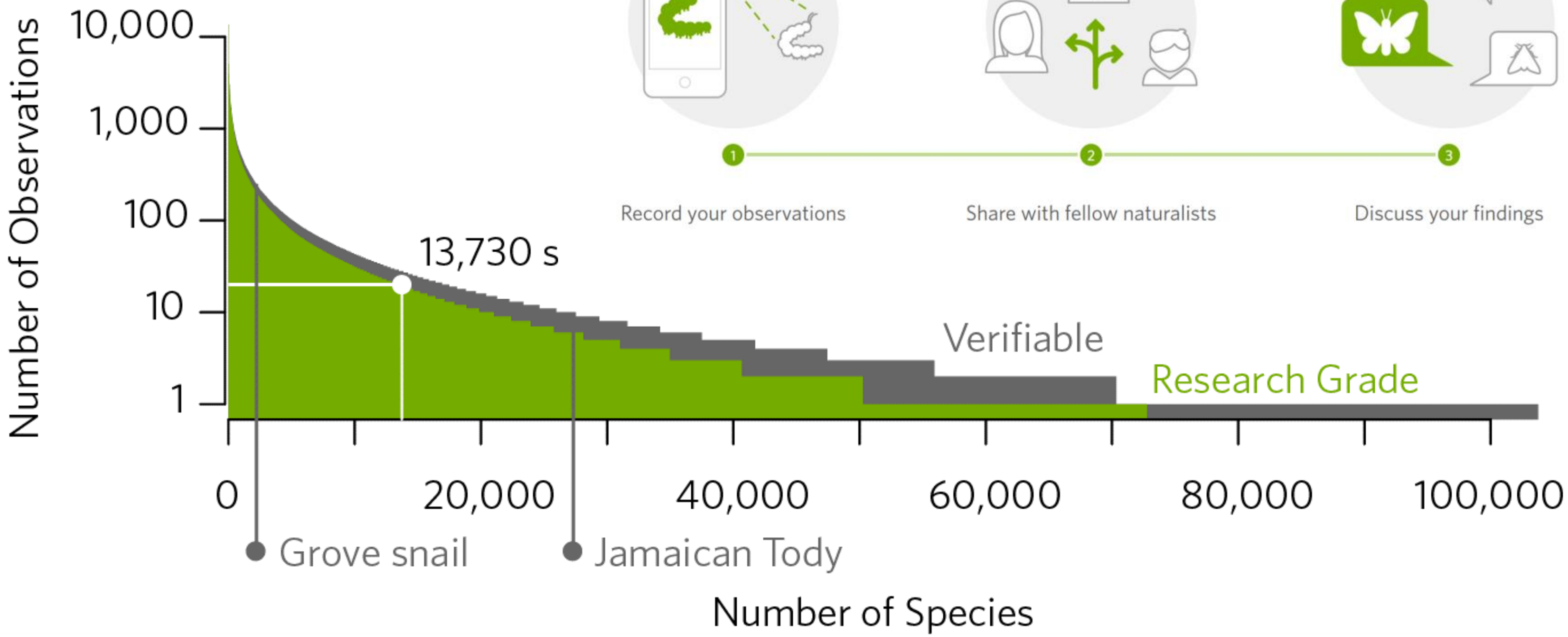
- Panorama stitching
- 3D terrain modeling
- Obstacle detection, position tracking
- For more, read “Computer Vision on Mars” by Matthies et al.

iNaturalist



5,724,317
Observations to Date

SIGN UP
EXPLORE
BJ Stacey - Shark Eye Snail from Essex County, Massachusetts, USA



How It Works

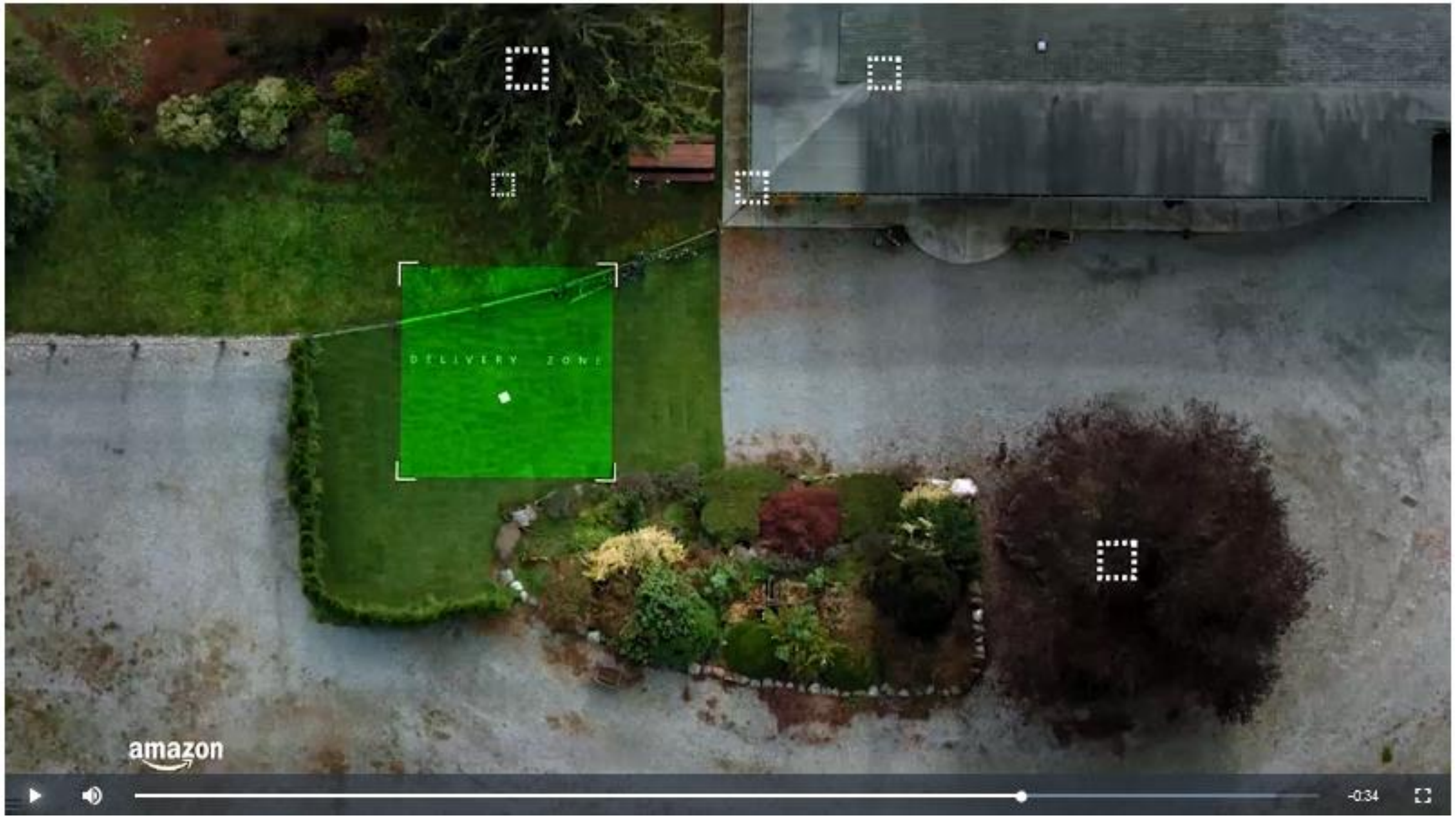
1 Record your observations

2 Share with fellow naturalists

3 Discuss your findings

https://www.inaturalist.org/pages/computer_vision_demo

Amazon Prime Air

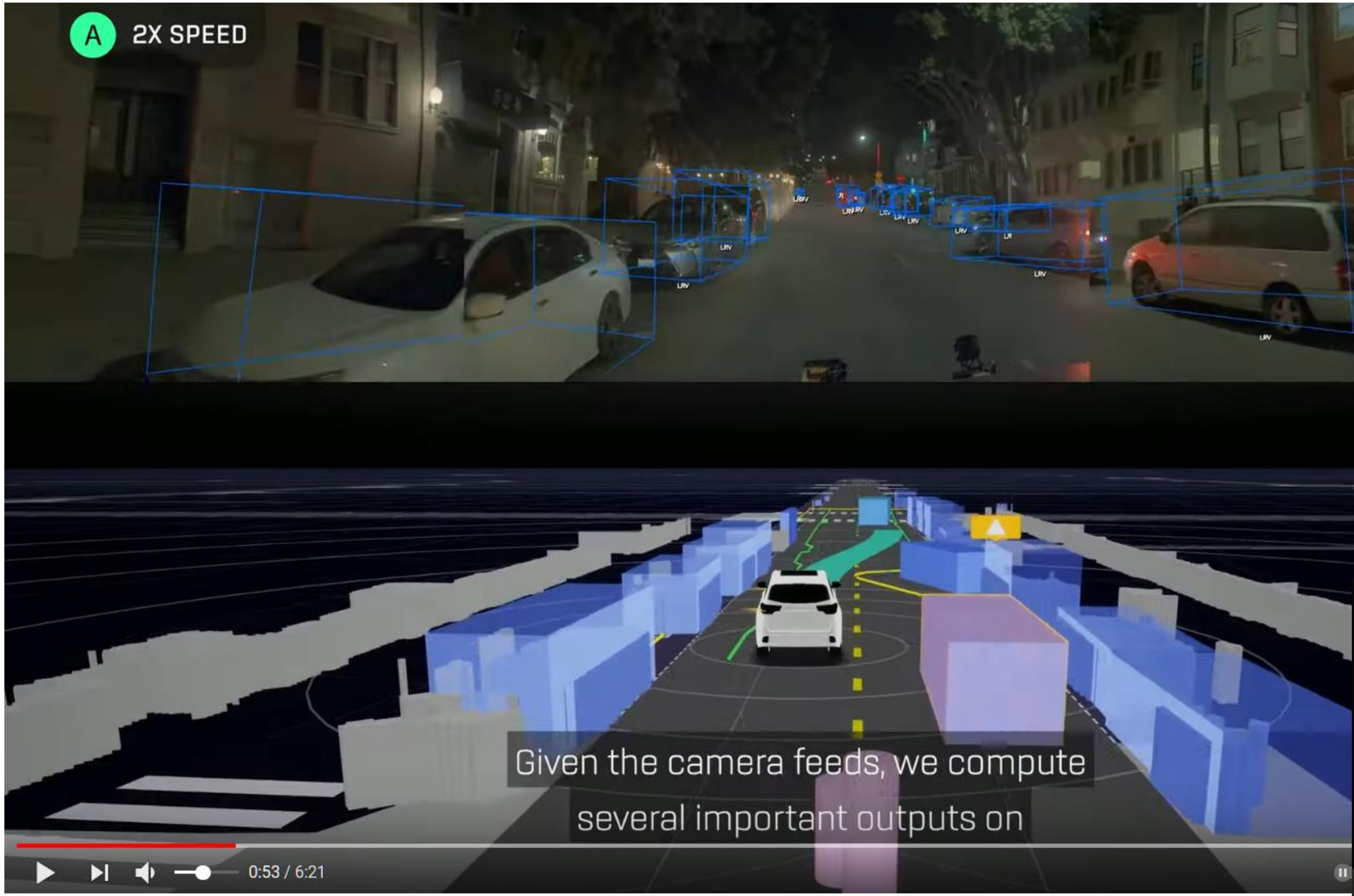


https://www.amazon.com/b?node=8037720011

Skydio

https://www.skydio.com/

Zoox Computer Vision Demo



Given the camera feeds, we compute several important outputs on

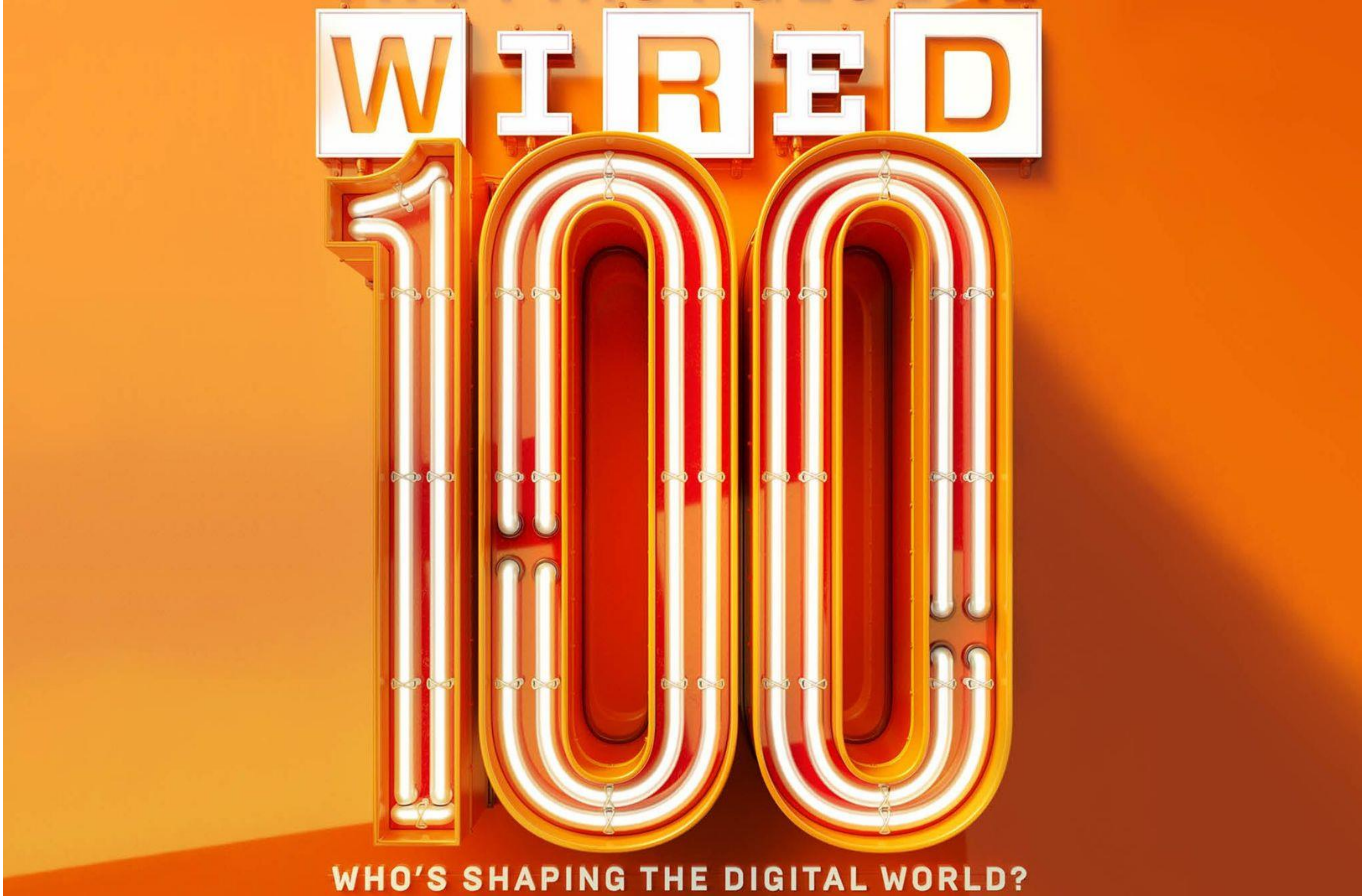
are able to detect and classify.

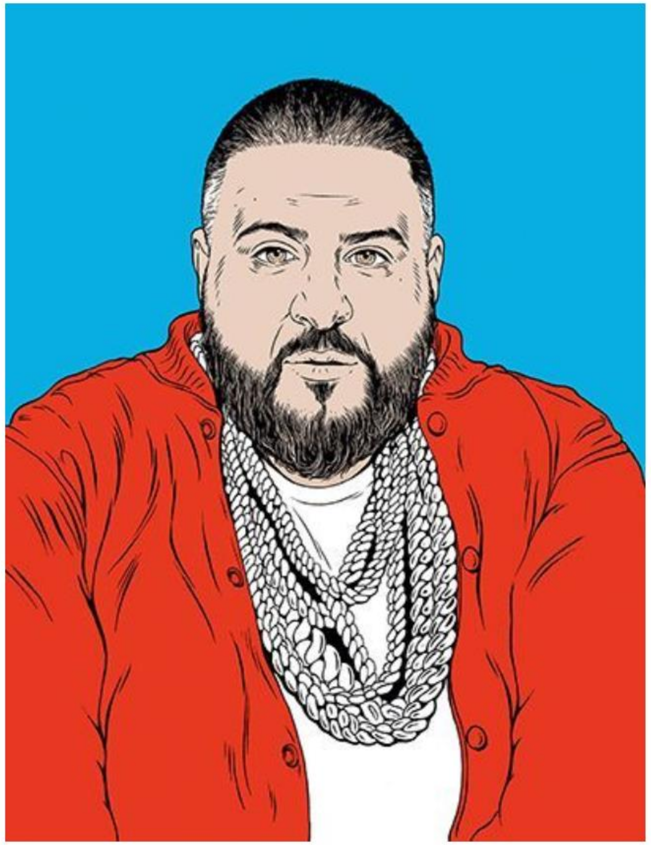
https://www.youtube.com/watch?v=BVRMh9NO9Cs

State of the art today?

With enough training data, computer vision ~~nearly~~ matches human vision at most recognition tasks

Deep learning has been an enormous disruption to the field. More and more techniques are being “deepified”.


WIRED
100
WHO'S SHAPING THE DIGITAL WORLD?



DJ Khaled

Credit **Louise Zergaeng Pomeroy**

73. DJ Khaled

Snapchat icon; DJ and producer

Louisiana-born Khaled Mohamed Khaled, aka DJ Khaled, cut his musical chops in the early 00s as a host for Miami urban music radio WEDR. He proceeded to build a solid if not dazzling career as a mixtape DJ and music producer (he founded his label We The Best Music Group in 2008, and was appointed president of Def Jam South in 2009).

69. Geoffrey Hinton

Psychologist, computer scientist; researcher, Google Toronto

British-born Hinton has been dubbed the ″godfather of deep learning″. The Cambridge-educated cognitive psychologist and computer scientist started being an ardent believer in the potential of neural networks and deep learning in the 80s, when those technologies enjoyed little support in the wider AI community.

But he soldiered on: in 2004, with support from the Canadian Institute for Advanced Research, he launched a University of Toronto programme in neural computation and adaptive perception, where, with a group of researchers, he carried on investigating how to create computers that could behave like brains.

Hinton′s work – in particular his algorithms that train multilayered neural networks – caught the attention of tech giants in Silicon Valley, which realised how deep learning could be applied to voice recognition, predictive search and machine vision.

The spike in interest prompted him to launch a free course on neural networks on e-learning platform Coursera in 2012. Today, 68-year-old Hinton is chair of machine learning at the University of Toronto and moonlights at Google, where he has been using deep learning to help build internet tools since 2013.

63. Yann Lecun

Director of AI research, Facebook, Menlo Park

LeCun is a leading expert in deep learning and heads up what, for Facebook, could be a hugely significant source of revenue: understanding its user's intentions.

62. Richard Branson

Founder, Virgin Group, London

Branson saw his personal fortune grow £550 million when Alaska Air bought Virgin America for $2.6 billion in April. He is pressing on with civilian space travel with Virgin Galactic.

61. Taylor Swift

Entertainer, Los Angeles

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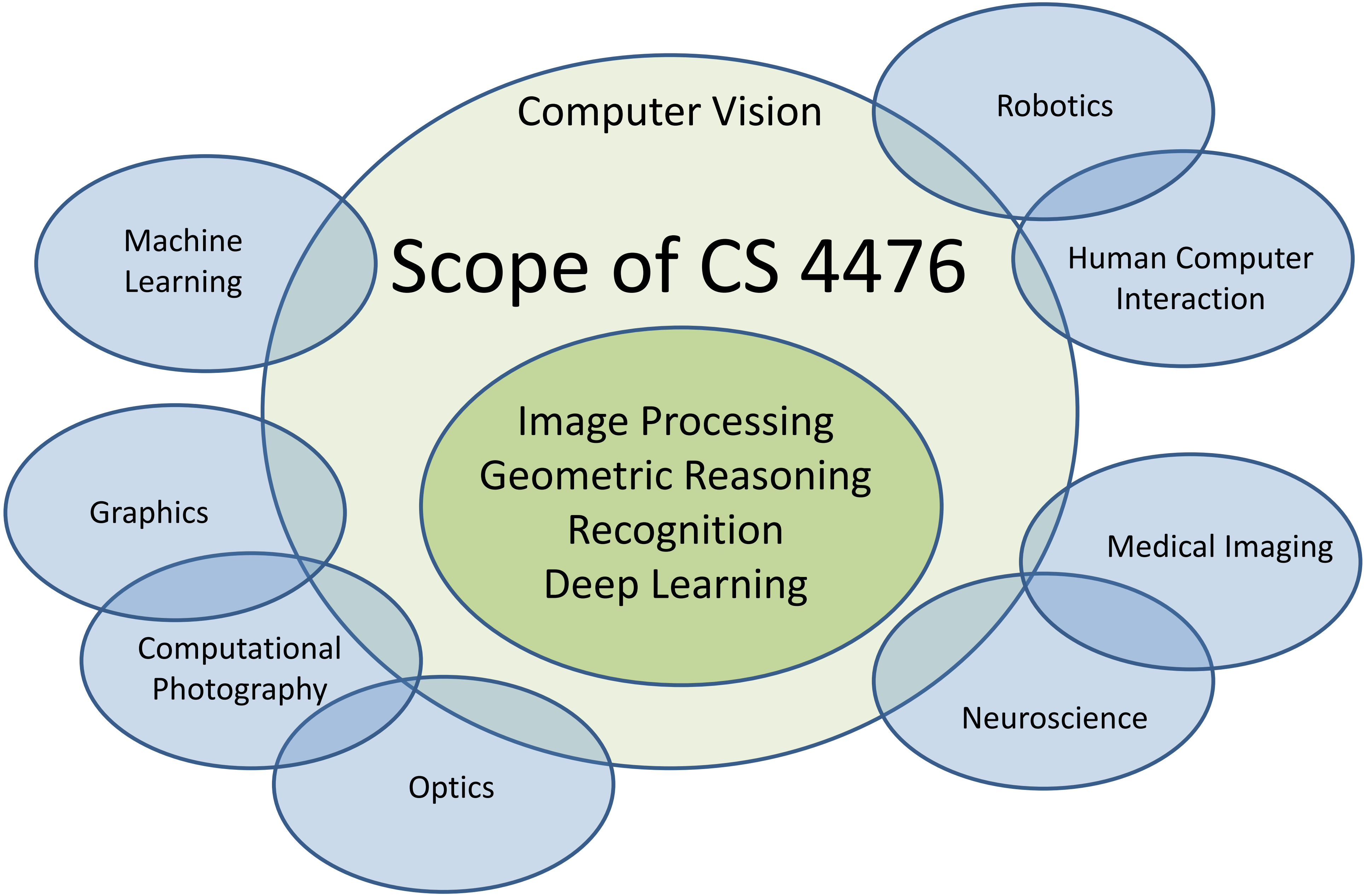
Grading

- 80% programming projects (5 total + 1 extra credit, maybe)
- 20% Quizzes or Problem sets

- Students in 6476 will have to do more for each project.

- We will have no final exam. The last project might extend into the final exam period.



Scope of CS 4476

Computer Vision

Image Processing
Geometric Reasoning
Recognition
Deep Learning

Machine Learning

Graphics

Computational Photography

Optics

Robotics

Human Computer Interaction

Medical Imaging

Neuroscience

Textbook

Computer Vision: Algorithms and Applications, 2nd ed.

© 2020 Richard Szeliski, Facebook

http://szeliski.org/Book/

Prerequisites

- **Linear algebra**, basic calculus, and probability
- Experience with image processing will help but is not necessary
- Experience with Python or Python-like languages will help

You need a decent computer

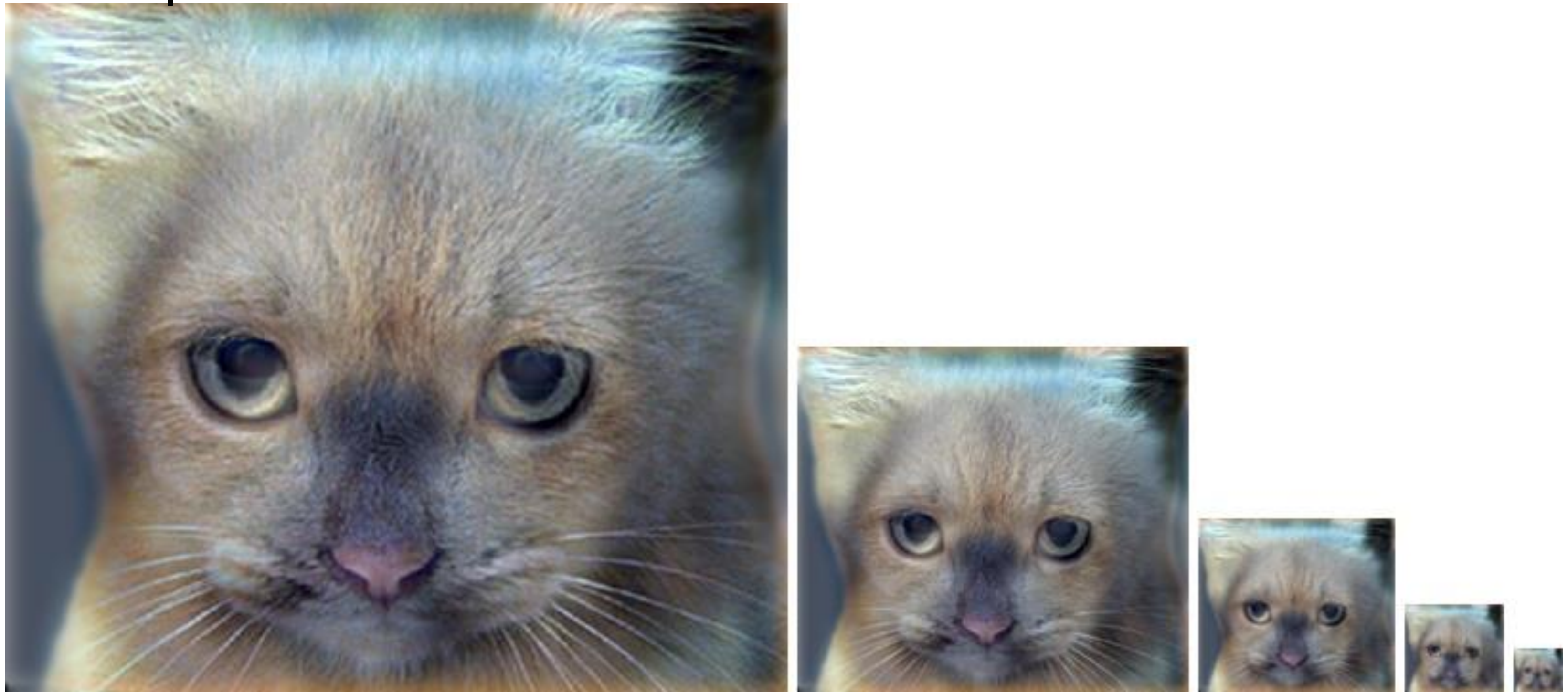
You may want to buy a month of Google Colab Pro near the end of the semester

Projects

- (project 0 to test environment setup and handin)
- Image Filtering and Hybrid Images
- Local Feature Matching
- Camera Calibration and Fundamental Matrix Estimation with RANSAC
- Image Classification with Deep Learning
- Semantic Segmentation with Deep Learning
- Possibly a new extra credit project

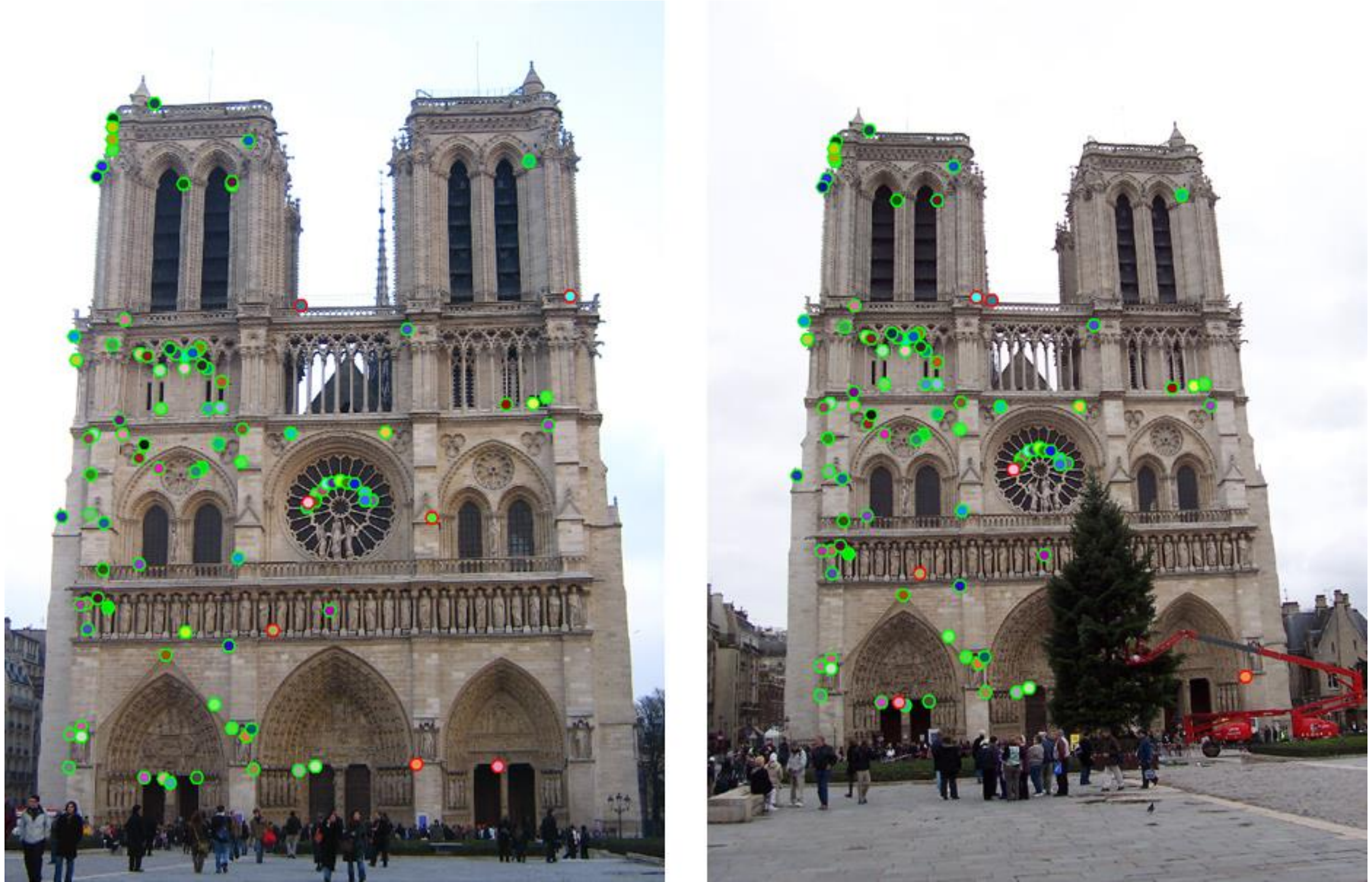
Proj1: Image Filtering and Hybrid Images

- Implement image filtering to separate high and low frequencies
- Combine high frequencies and low frequencies from different images to create an image with scale-dependent interpretation



Proj2: Local Feature Matching

- Implement interest point detector, SIFT-like local feature descriptor, and simple matching algorithm.



Course Syllabus (tentative)

https://faculty.cc.gatech.edu/~hays/compvision/

Code of Conduct

Your work must be your own. We’ll look for cheating. Don’t talk at the level of code with other students.

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Cuisinart
WÓDKA
[VODKA]
VISIONS of JAPAN TOMATSU Shomei
SNOW CRYSTALS
MYSTERIES OF MIND SPACE & TIME
FOTOGRAFIE UND DAS UNSICHTBARE
DER KLEINE STOWASSER
MATHEMATICS
MAN AND SPACE
DRUGS
STACK-ON

Cuisinart
WÓDKA
SNOW CRYSTALS
FOTOGRAFIE UND DAS UNSIC
NE STOWASSER
MATHEMATICS
MAN AND SPACE
DRUGS
STACK-ON

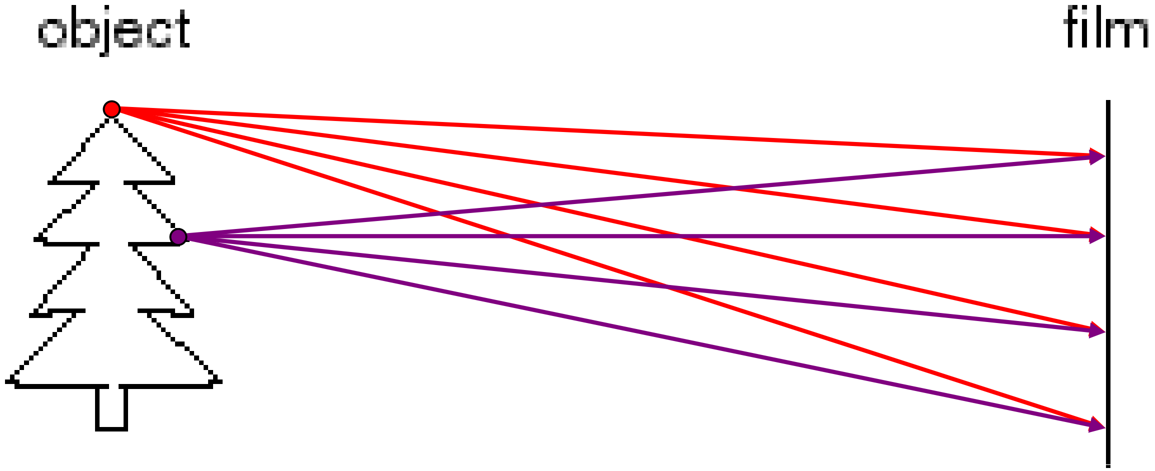
The Geometry of Image Formation

Mapping between image and world coordinates

- Pinhole camera model
- Projective geometry
    - Vanishing points and lines
- Projection matrix

What do you need to make a camera from scratch?

Image formation

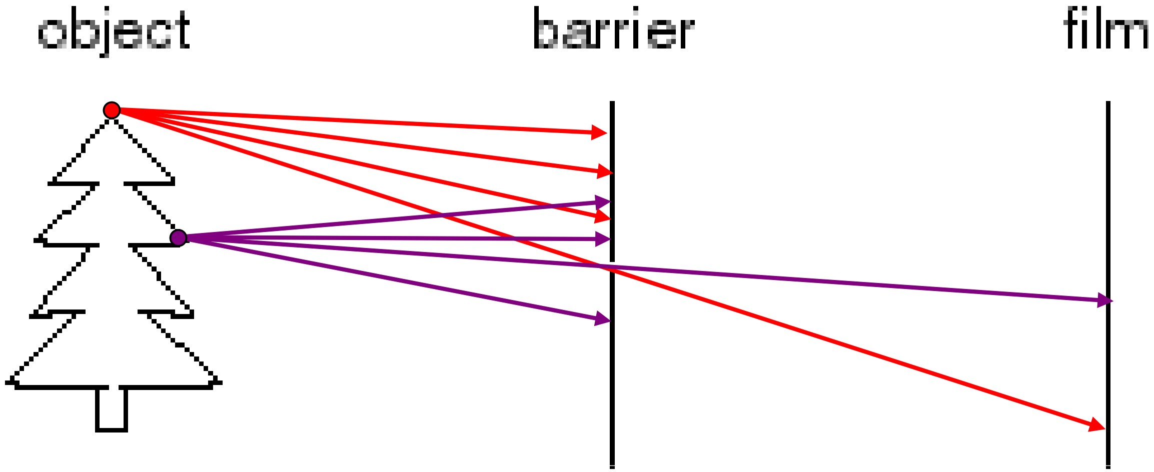


Let’s design a camera

- Idea 1: put a piece of film in front of an object
- Do we get a reasonable image?

Slide source: Seitz

Pinhole camera

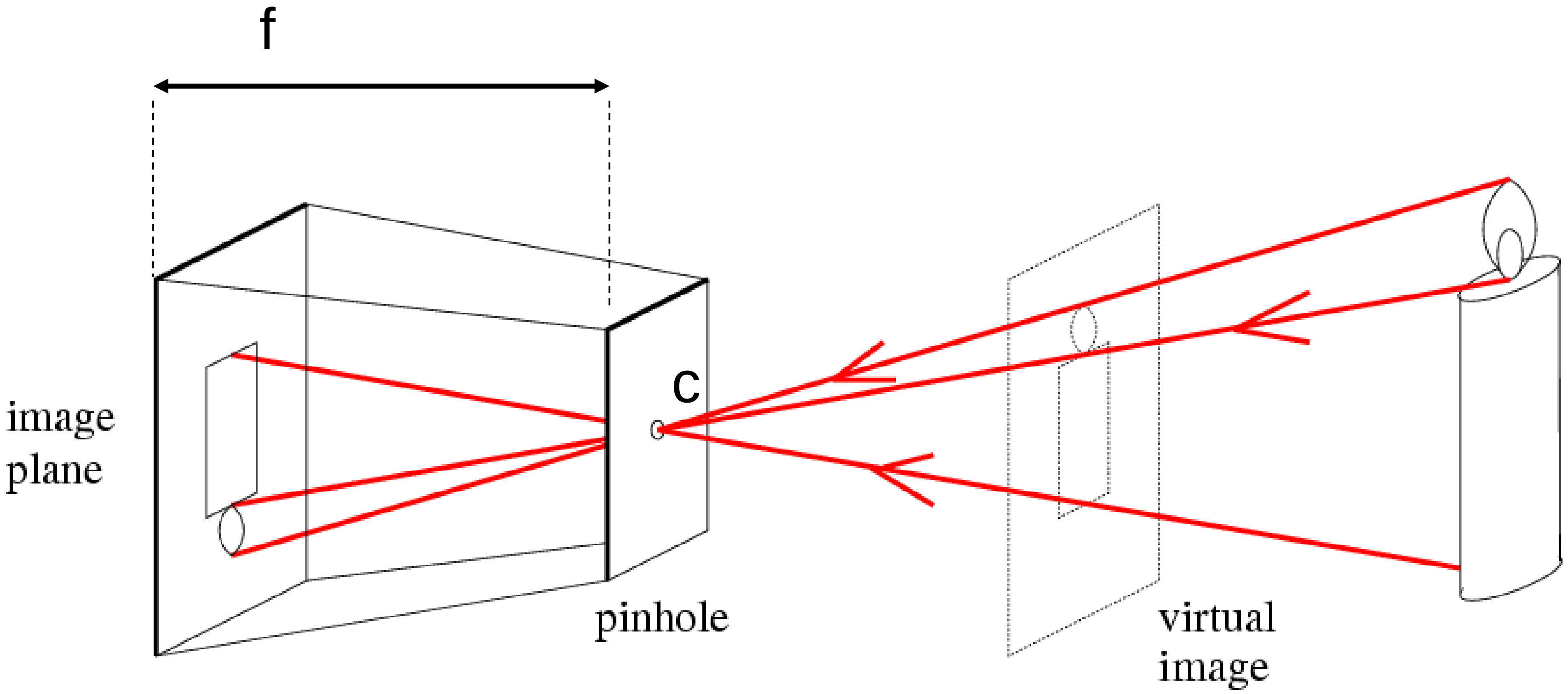


Idea 2: add a barrier to block off most of the rays

- This reduces blurring
- The opening known as the **aperture**

Slide source: Seitz

Pinhole camera



f = focal length

c = center of the camera

Figure from Forsyth

Camera obscura: the pre-camera

- Known during classical period in China and Greece (e.g. Mo-Ti, China, 470BC to 390BC)

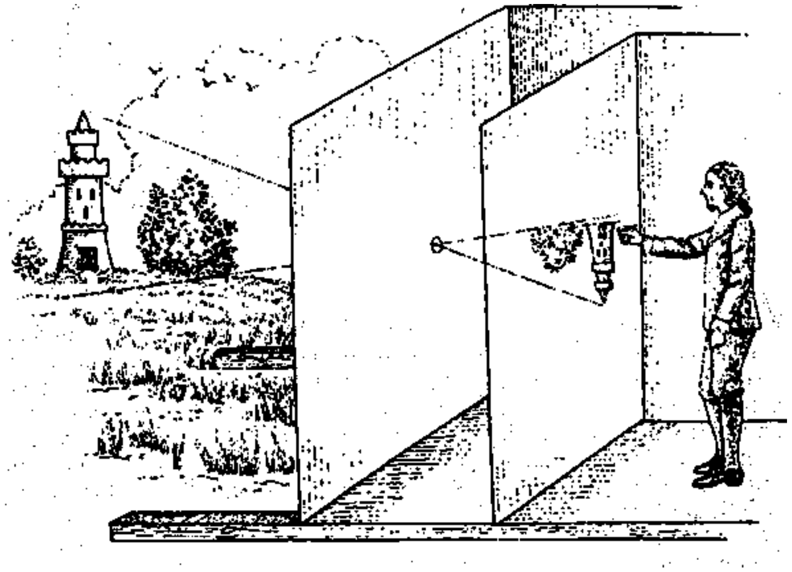
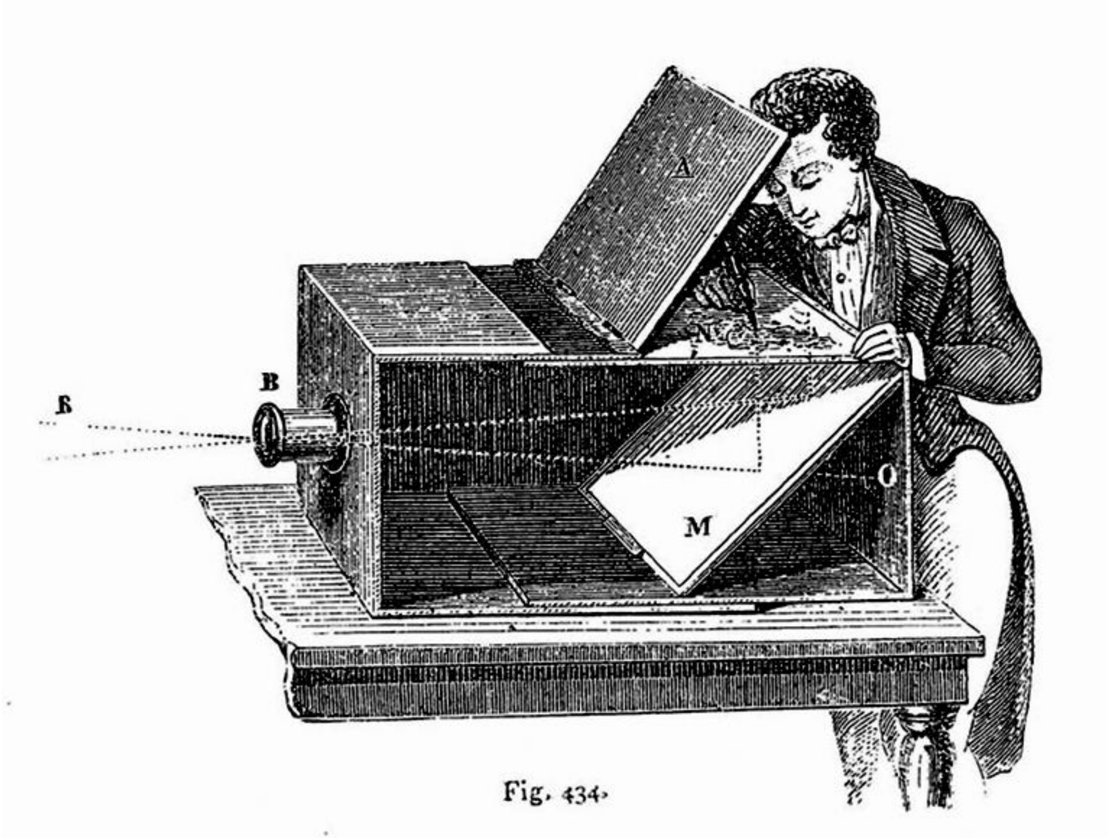


Illustration of Camera Obscura

Freestanding camera obscura at UNC Chapel Hill

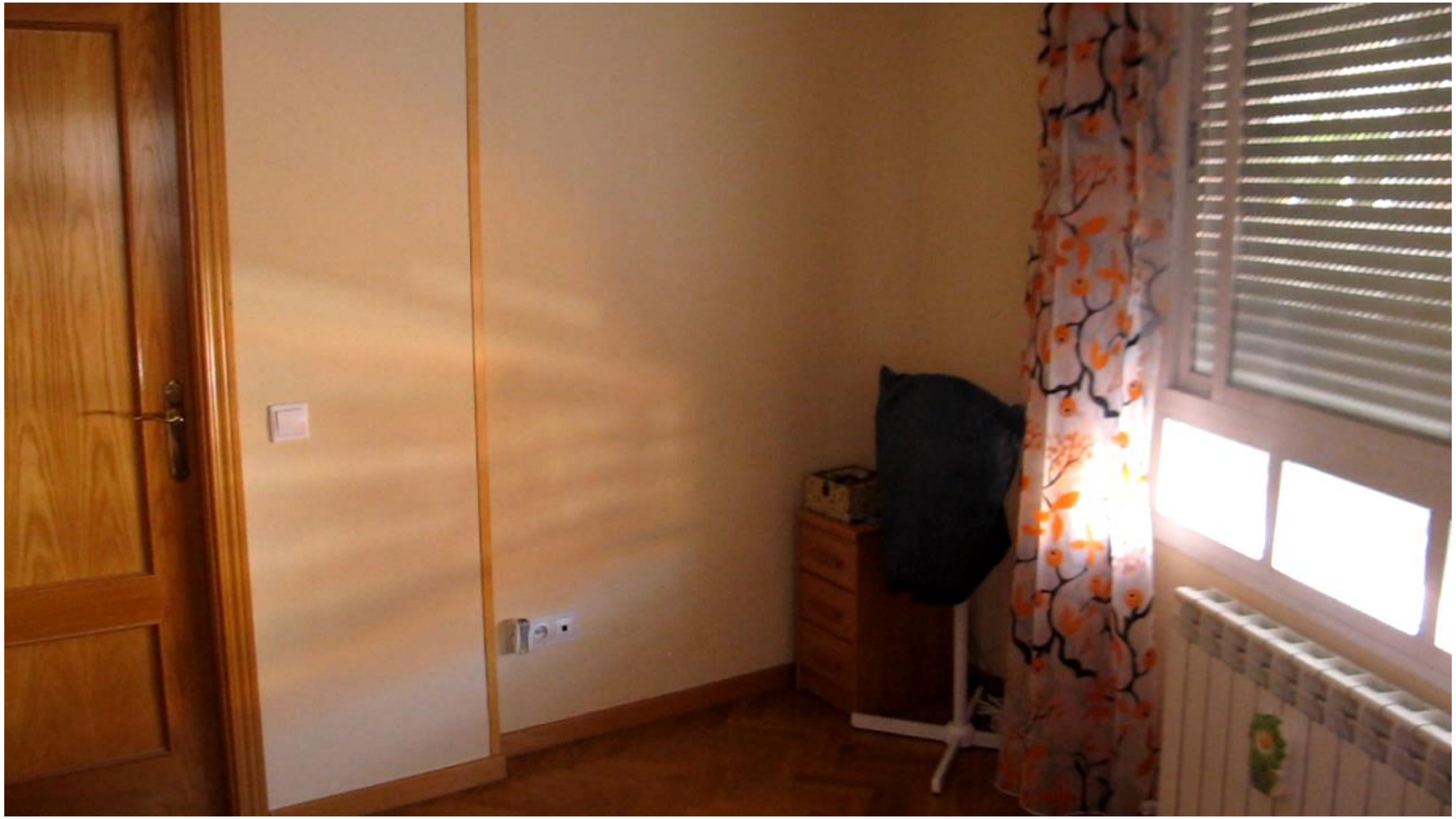
Photo by Seth Ilys

Camera Obscura used for Tracing



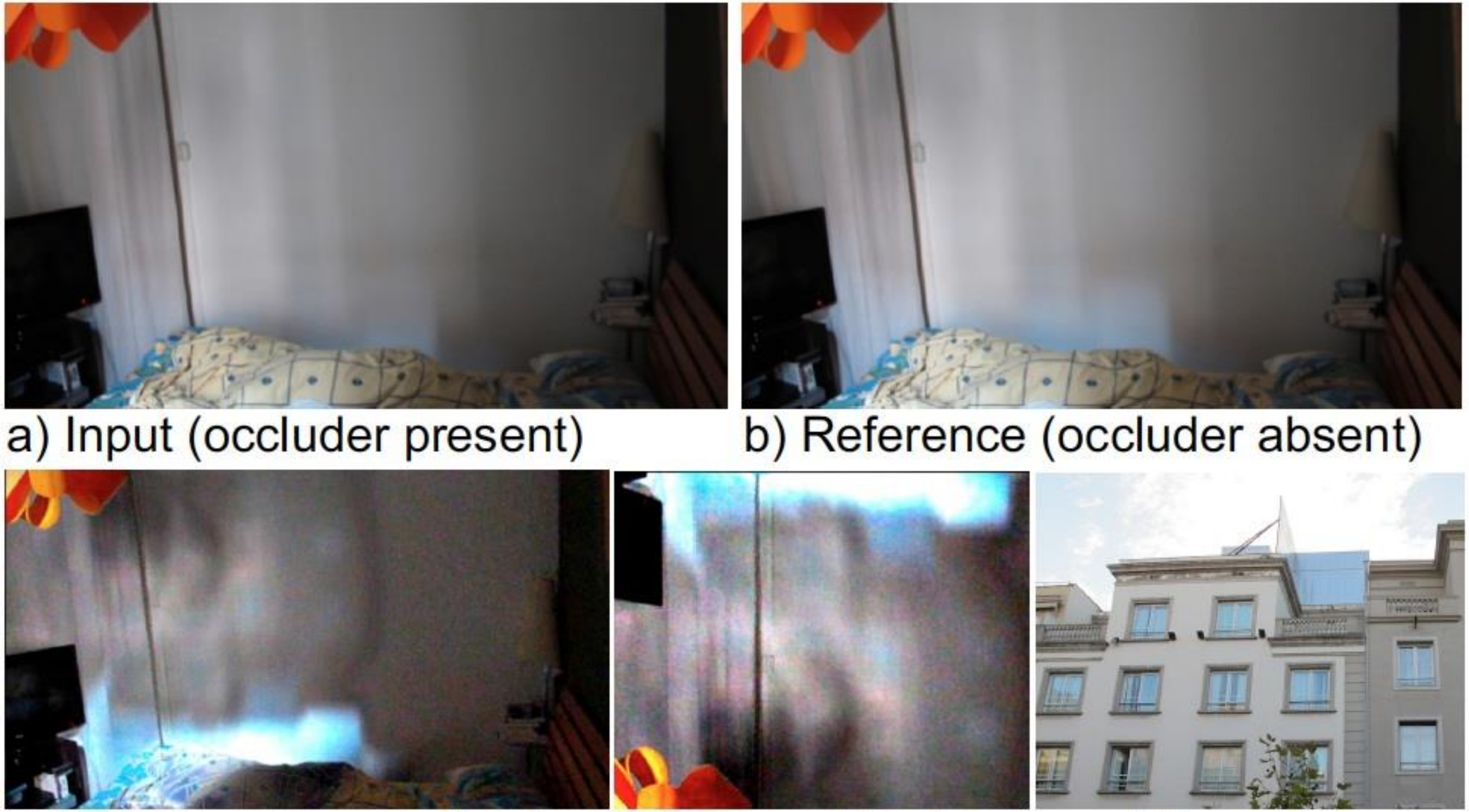
Lens Based Camera Obscura, 1568

Accidental Cameras



Accidental Pinhole and Pinspeck Cameras
Revealing the scene outside the picture.
Antonio Torralba, William T. Freeman

Accidental Cameras



a) Input (occluder present)

b) Reference (occluder absent)

c) Difference image (b-a)

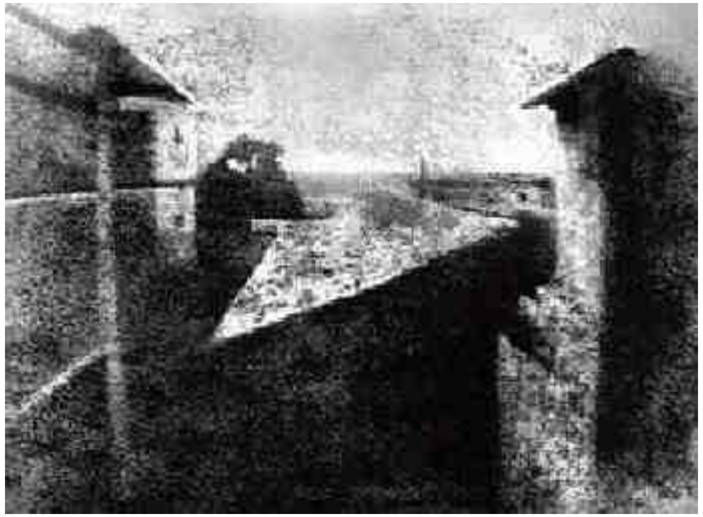
d) Crop upside down

e) True view

First Photograph

Oldest surviving photograph

- Took 8 hours on pewter plate

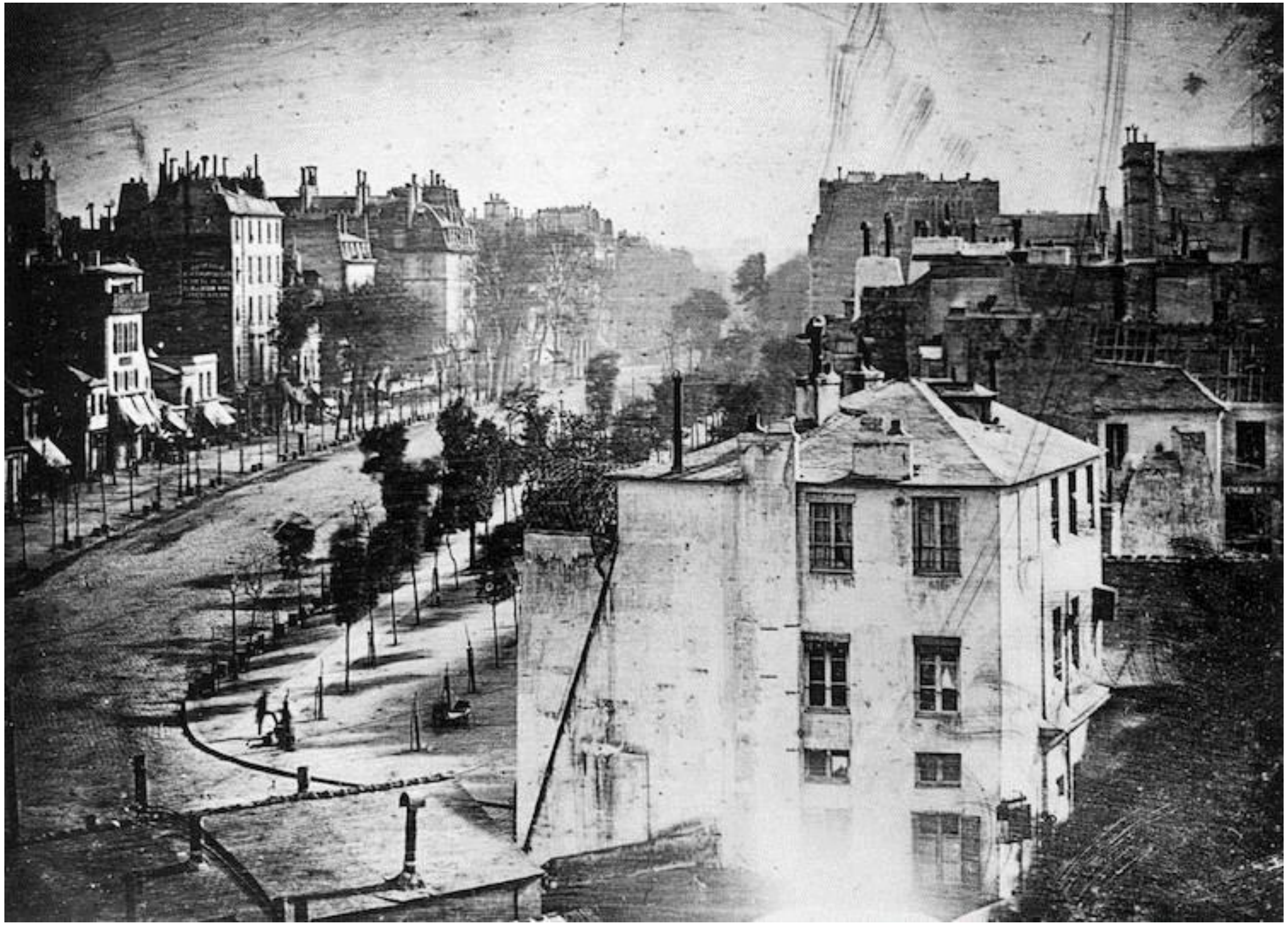


Joseph Niepce, 1826

Photograph of the first photograph

Stored at UT Austin

Niepce later teamed up with Daguerre, who eventually created Daguerrotypes



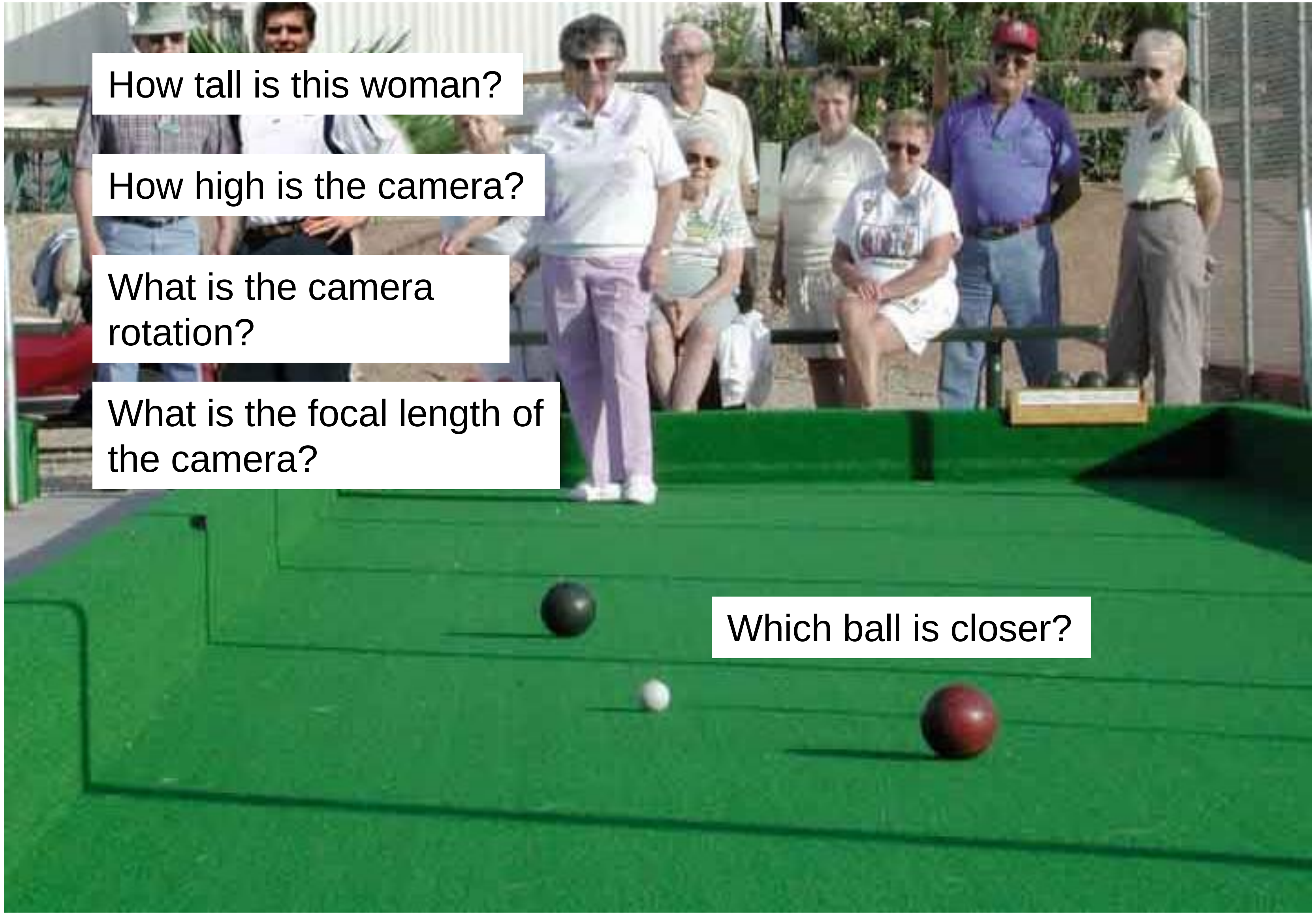
“Louis Daguerre—the inventor of daguerreotype—shot what is not only the world's oldest photograph of Paris, but also the first photo with humans. The 10-minute long exposure was taken in 1839 in Place de la République and it's just possible to make out two blurry figures in the left-hand corner.”

Source

Great history lesson on the chemistry and engineering challenges of early photography from the “Technology Connections” YouTube channel.

https://www.youtube.com/watch?v=wbbH77rYaa8&list=PLv0jwu7G_DFV6yW240e6CbiwCLaZ0Z6PV

Camera and World Geometry



How tall is this woman?

How high is the camera?

What is the camera rotation?

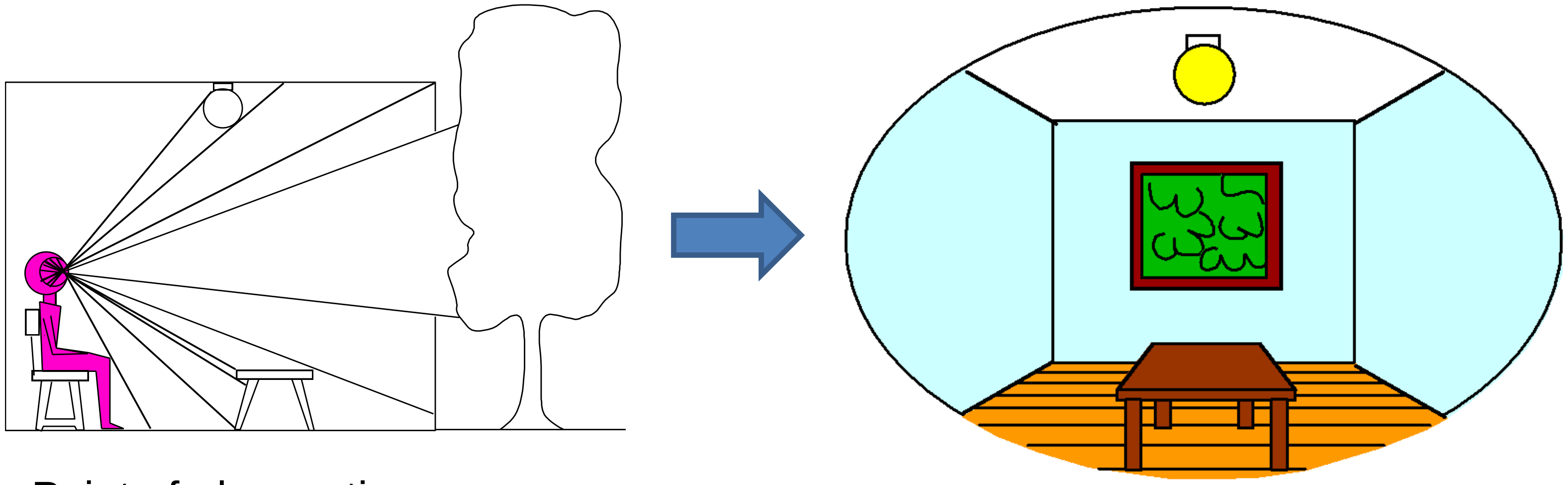
What is the focal length of the camera?

Which ball is closer?

Dimensionality Reduction Machine (3D to 2D)

3D world

2D image

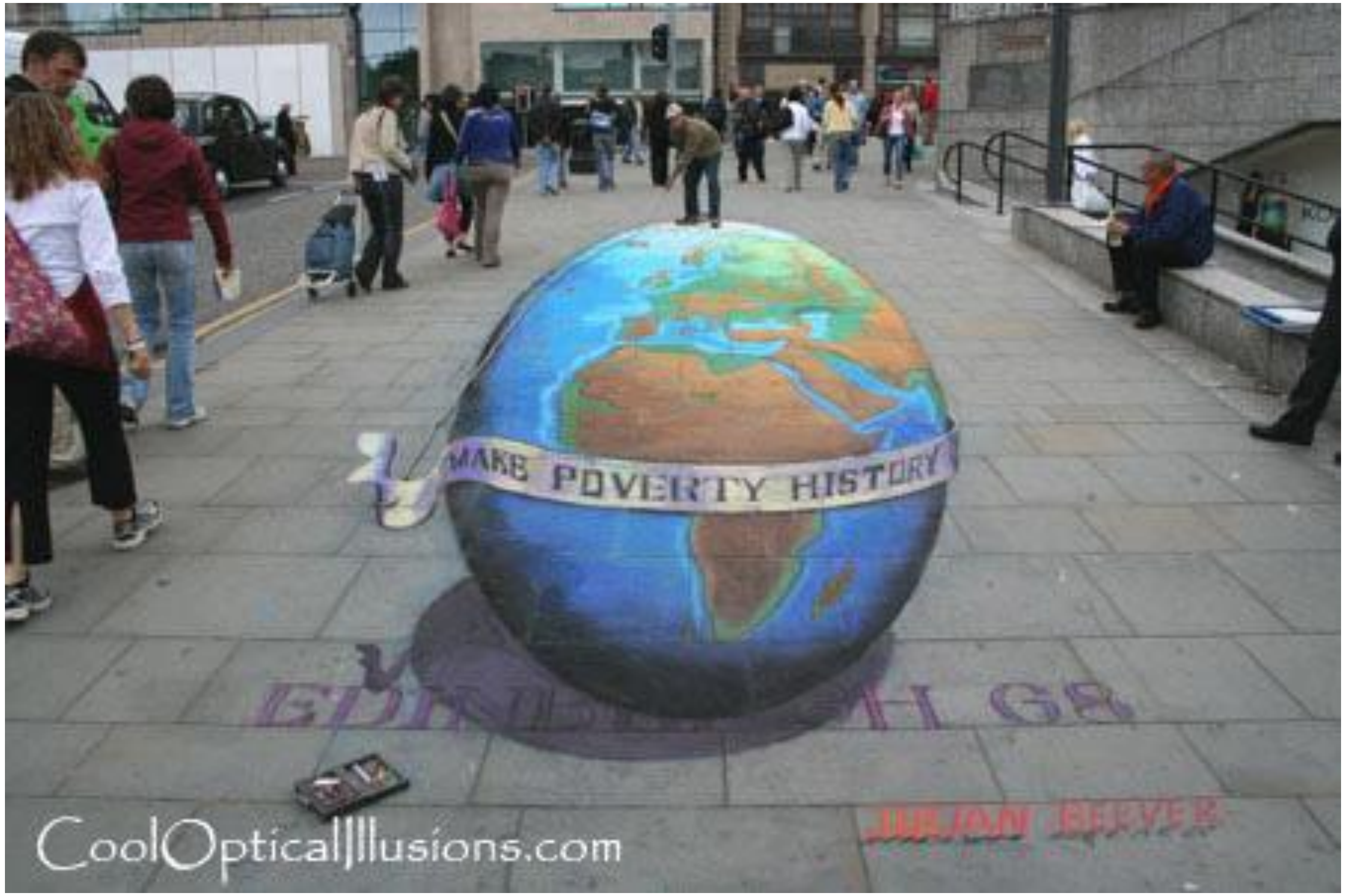


Point of observation

Figures © Stephen E. Palmer, 2002

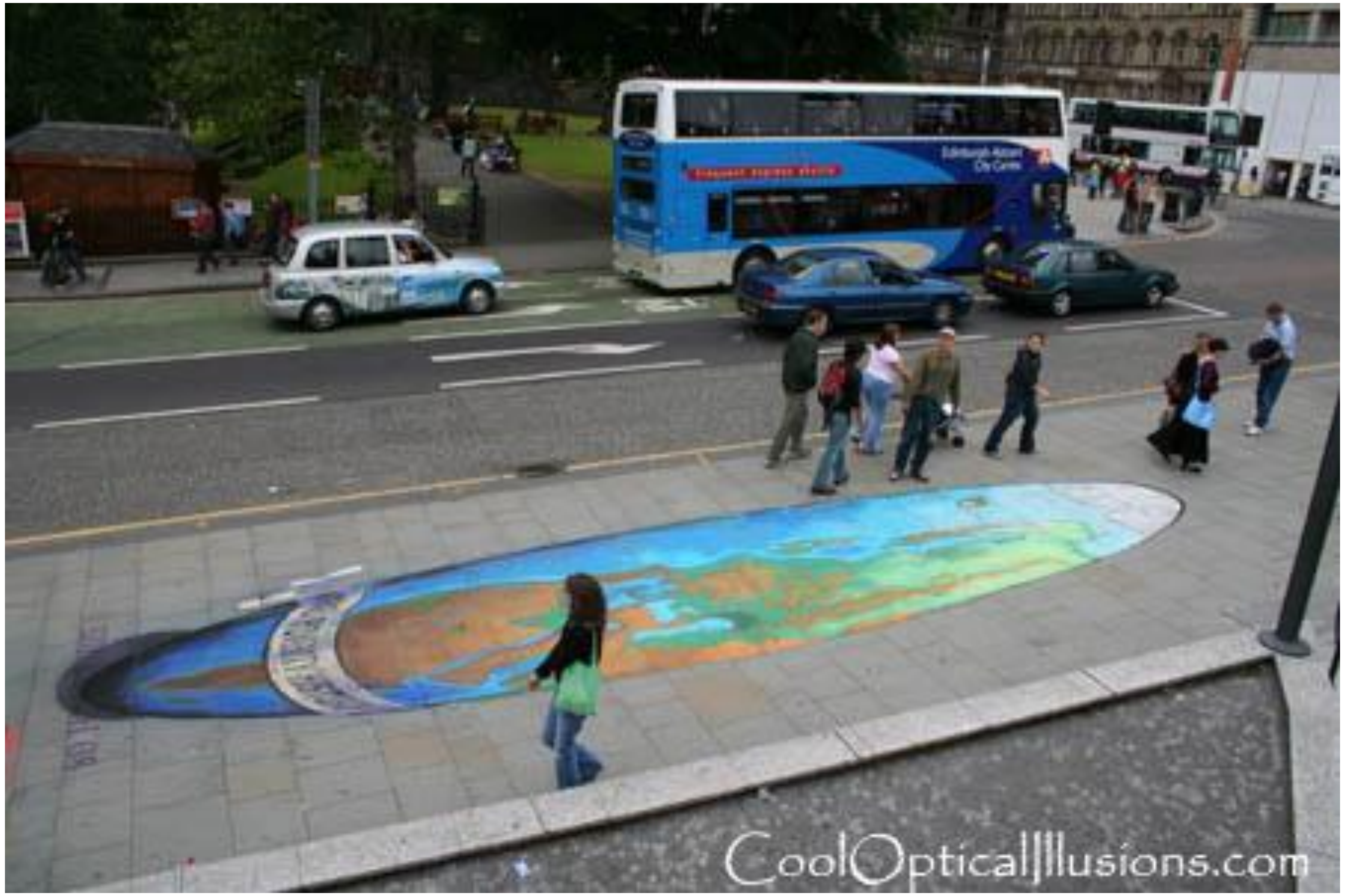
Slide source: Seitz

Projection can be tricky…



Slide source: Seitz

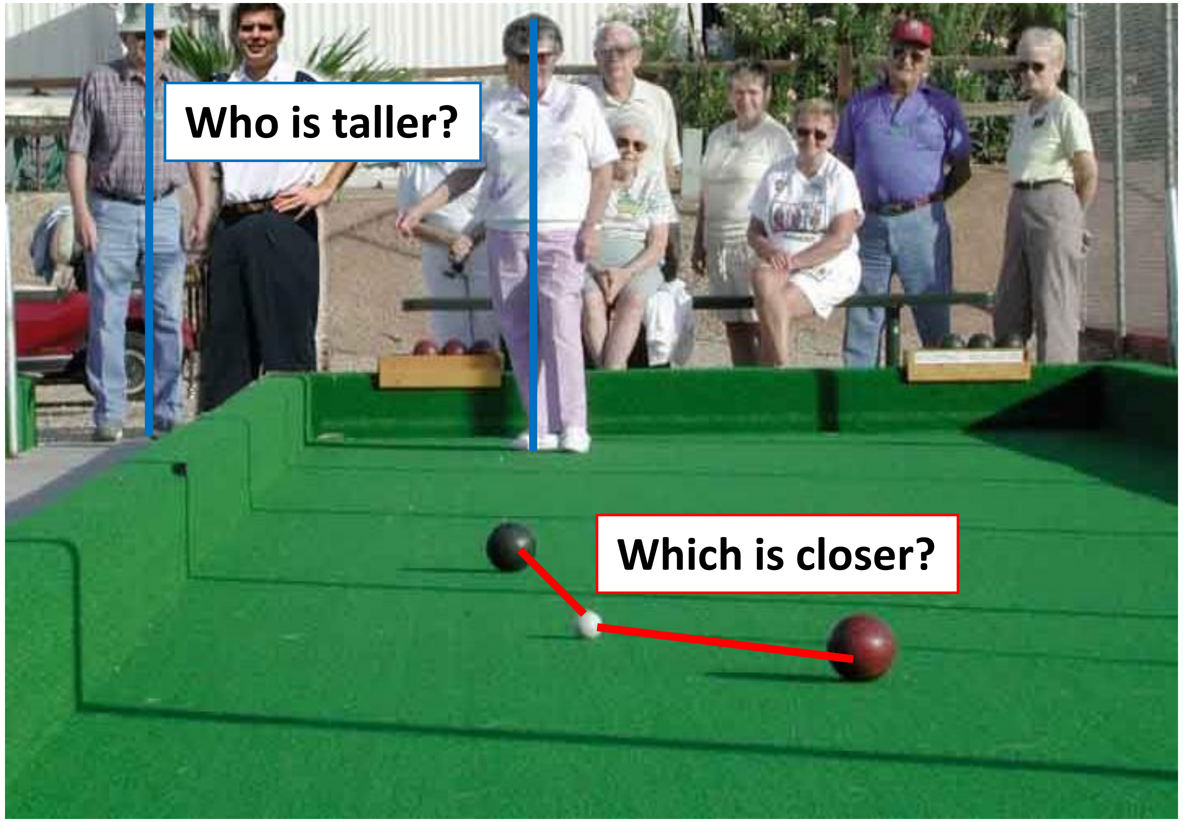
Projection can be tricky…



Projective Geometry

What is lost?

- Length



Length and area are not preserved

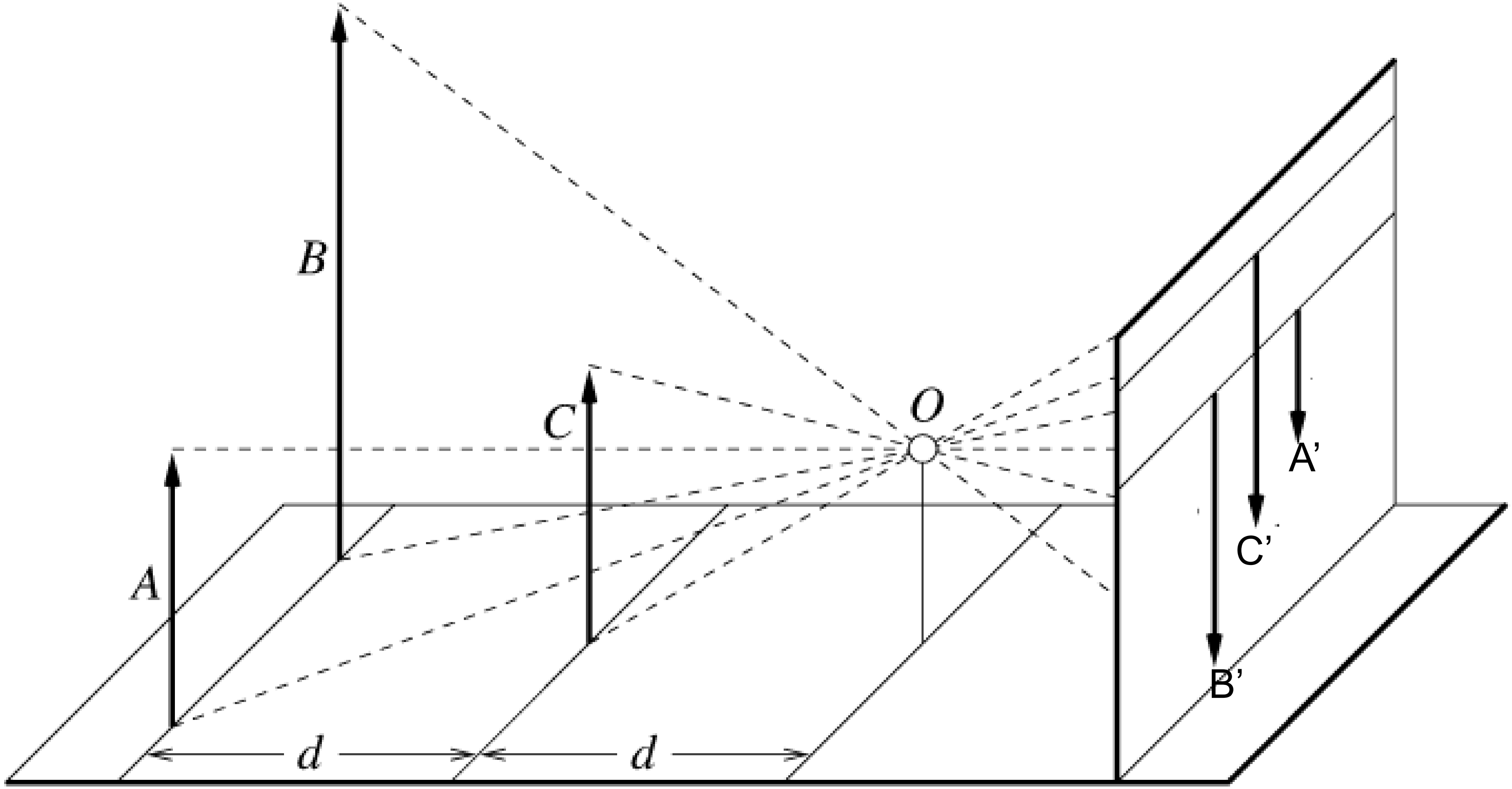
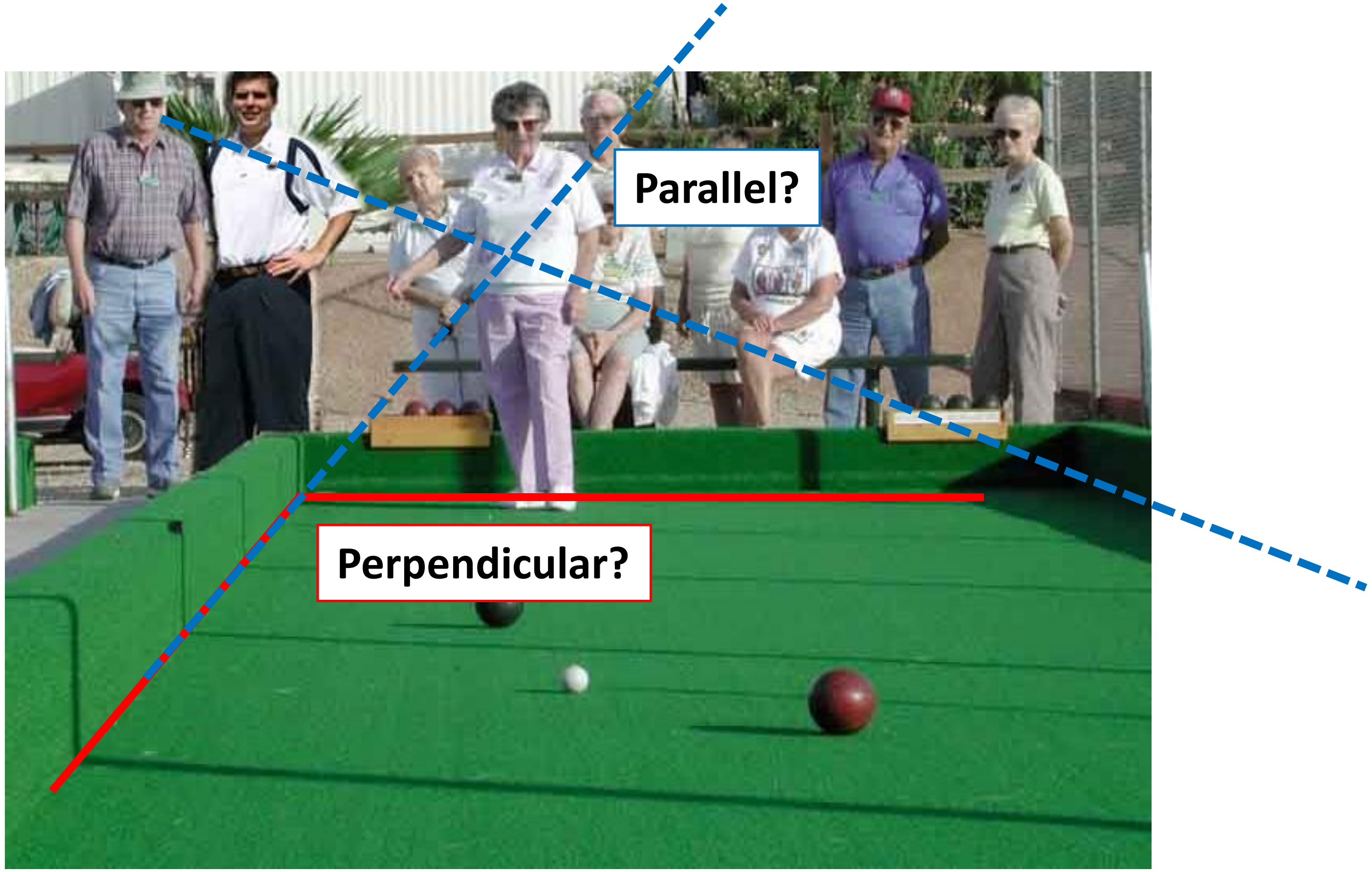


Figure by David Forsyth

Projective Geometry

What is lost?

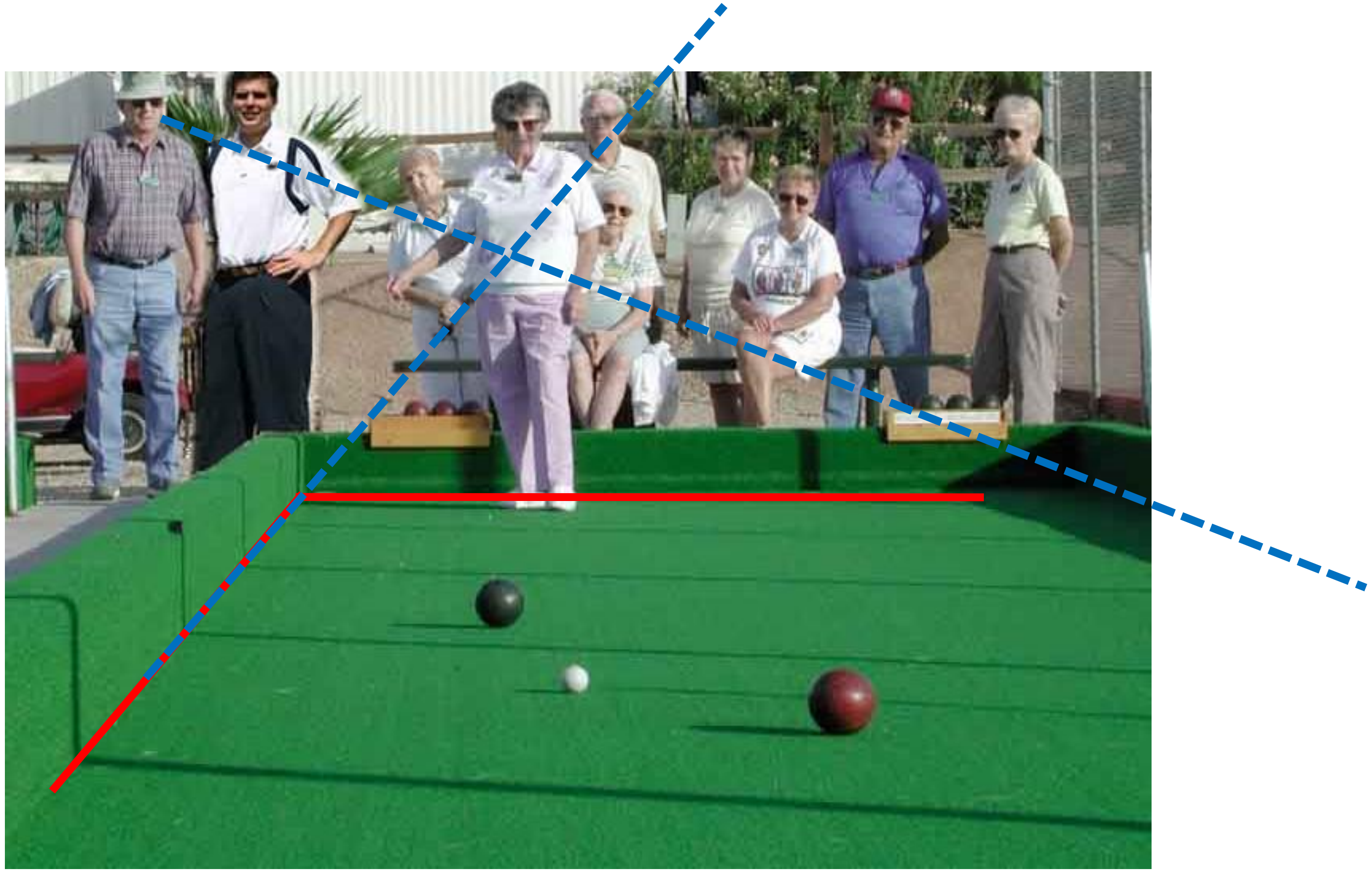
- Length
- Angles



Projective Geometry

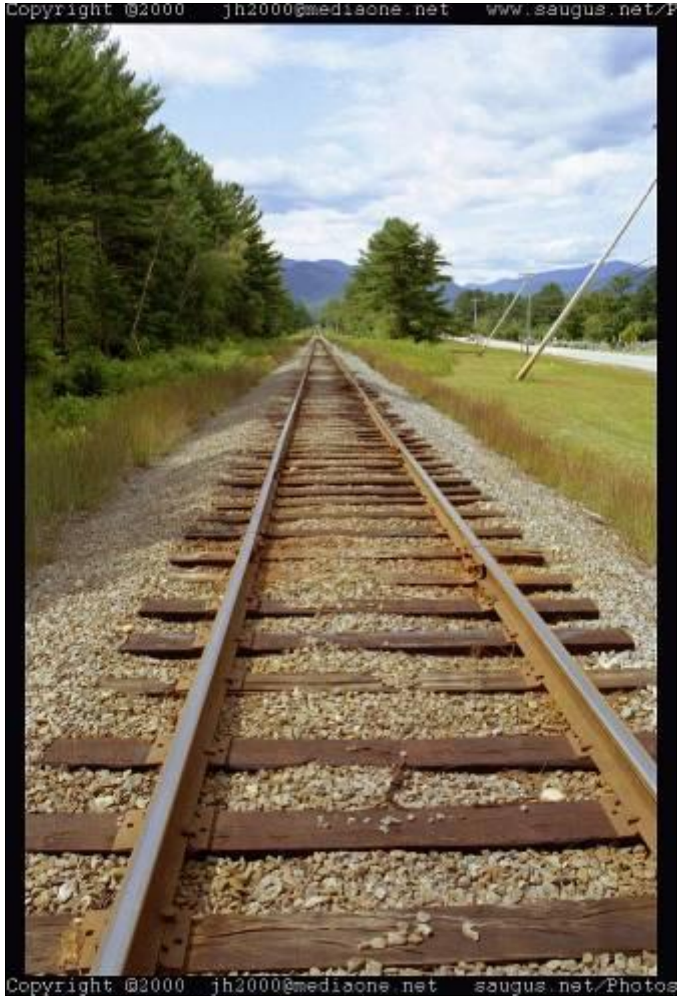
What is preserved?

- Straight lines are still straight



Vanishing points and lines

Parallel lines in the world intersect in the image at a “vanishing point”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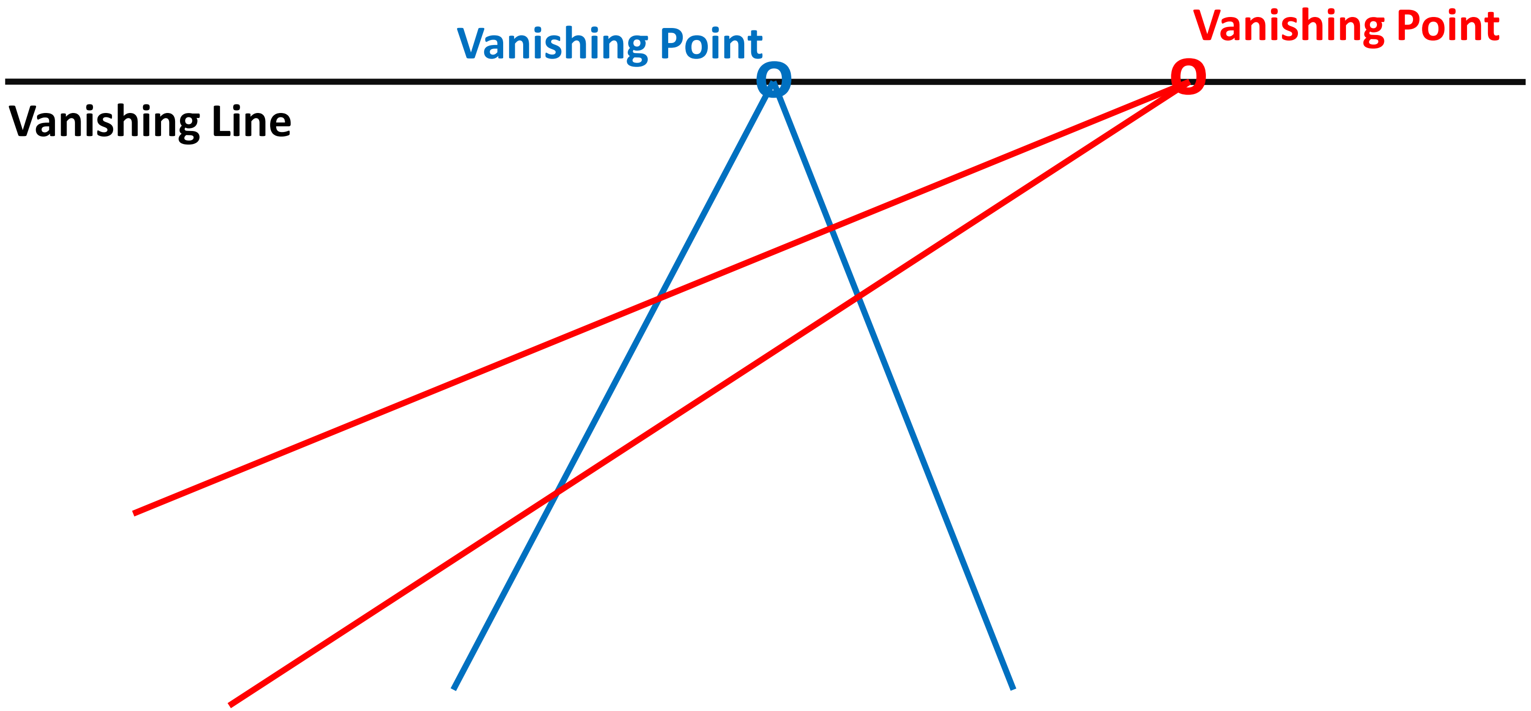
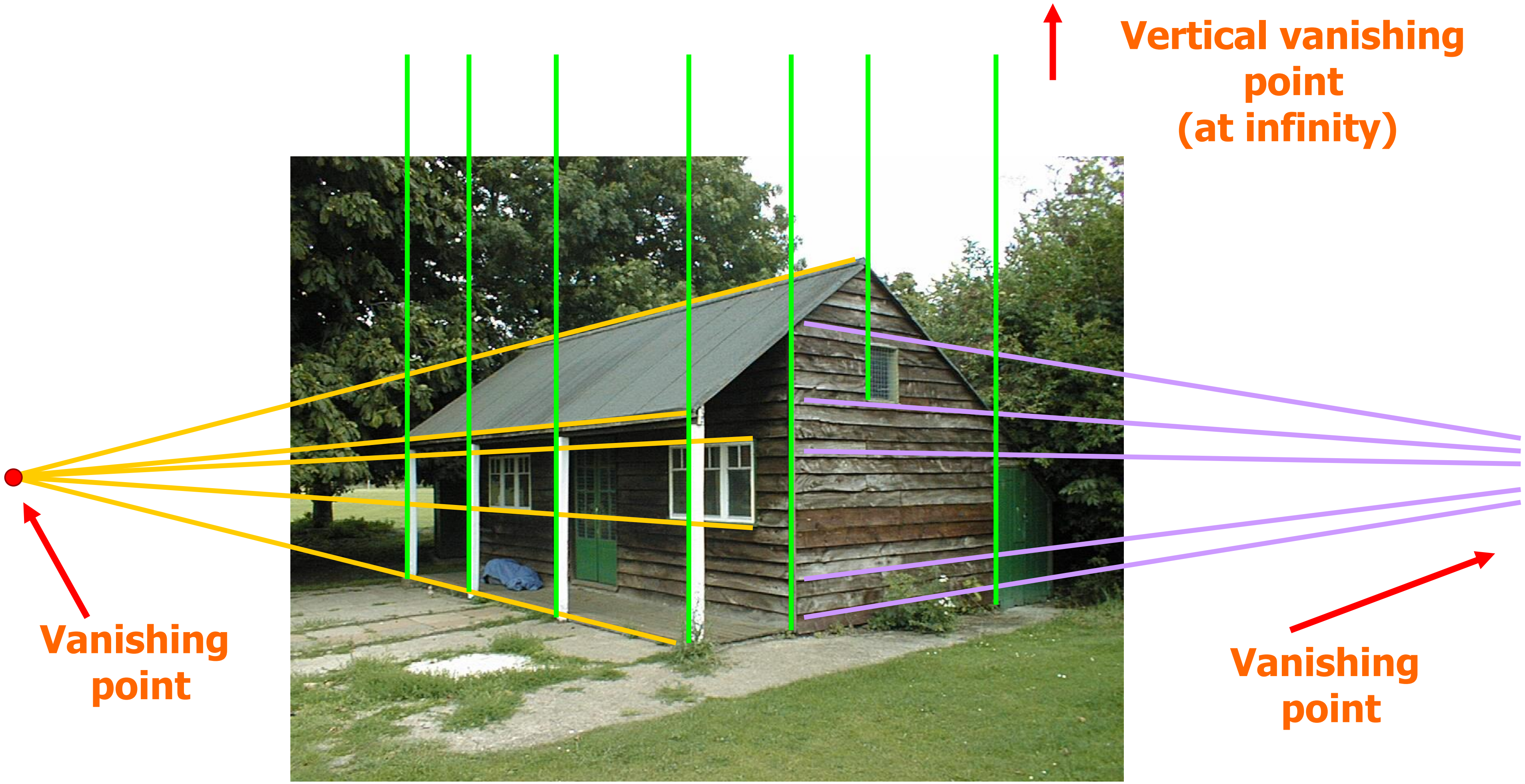
Vanishing points and lines



Vanishing points and lines



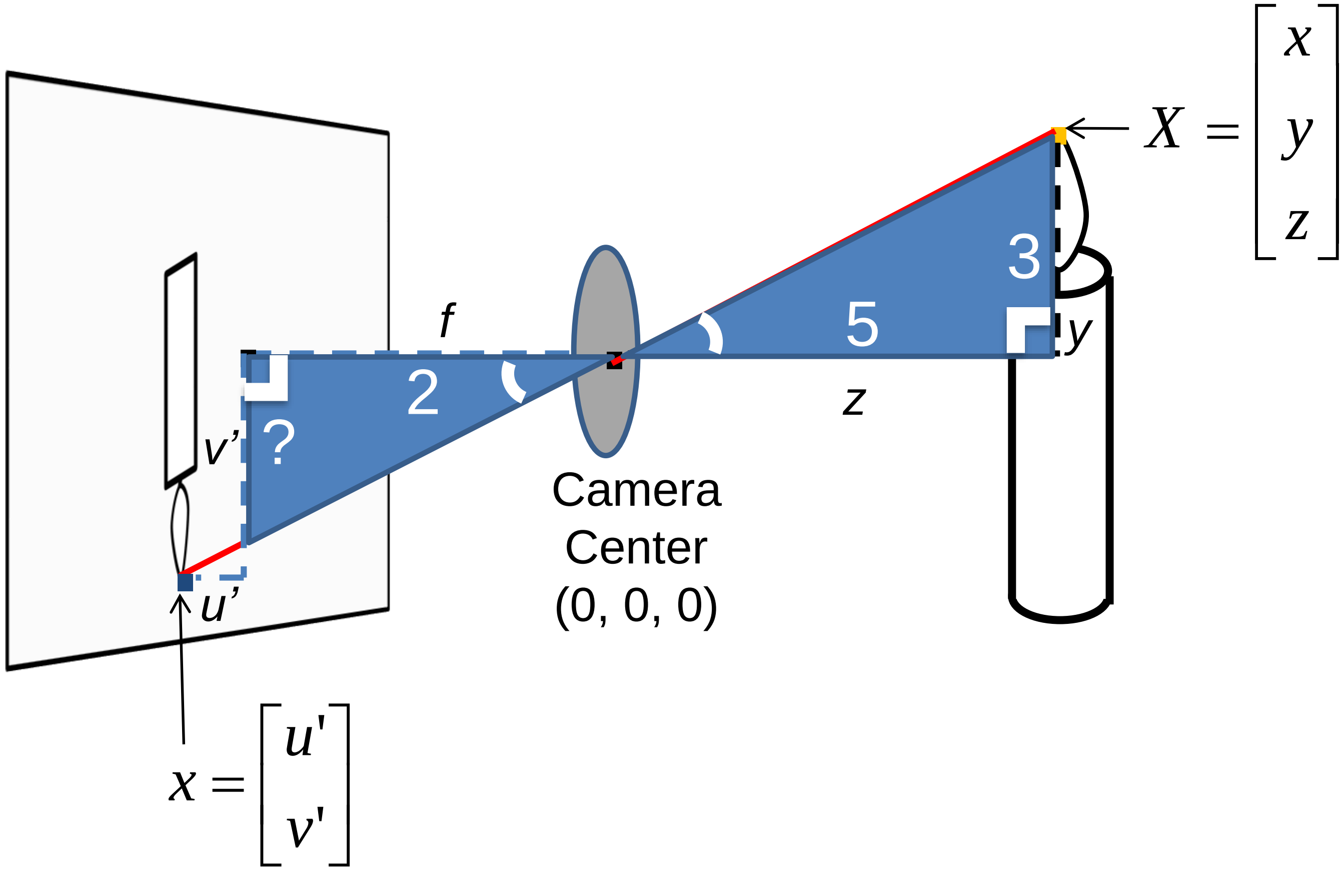
Vertical vanishing point (at infinity)

Vanishing point

Vanishing point

Slide from Efros, Photo from Criminisi

Projection: world coordinates→image coordinates



$X = \begin{bmatrix} x \\ y \\ z \end{bmatrix}$
f
2
?
v'
u'
3
5
y
z
Camera
Center
(0, 0, 0)
$x = \begin{bmatrix} u' \\ v' \end{bmatrix}$

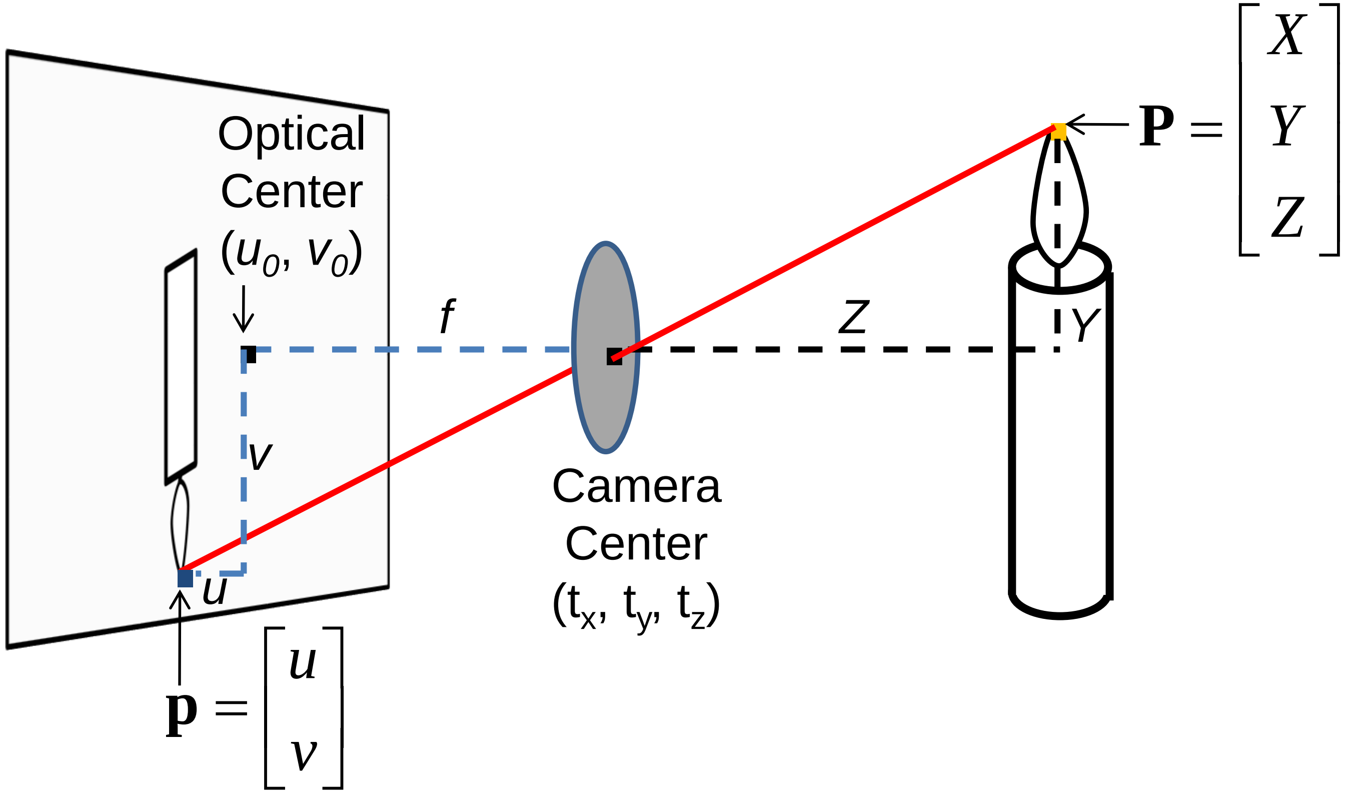
If x = 2, y = 3,
z = 5, and f = 2
What are u and v?

$$\frac{v'}{-f} = \frac{y}{z}$$

$$u' = -x * \frac{f}{z} \qquad u' = -2 * \frac{2}{5}$$

$$v' = -y * \frac{f}{z} \qquad v' = -3 * \frac{2}{5}$$

Projection: world coordinates→image coordinates


Optical Center
(u_0, v_0)
f
v
u
$\mathbf{p} = \begin{bmatrix} u \\ v \end{bmatrix}$
Camera Center
(t_x, t_y, t_z)
Z
Y
$\mathbf{P} = \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$

How do we handle the general case?