# Fall 2023 CS543 / ECE549
# Computer Vision

Course webpage URL: http://luthuli.cs.uiuc.edu/~daf

And follow links

# Outline

- Logistics, requirements
- Goal of computer vision and why it is hard
- History of computer vision
- Current state of the art
- Topics covered in class

# Logistics

Look at web page!

# Goal: To extract useful information from pixels

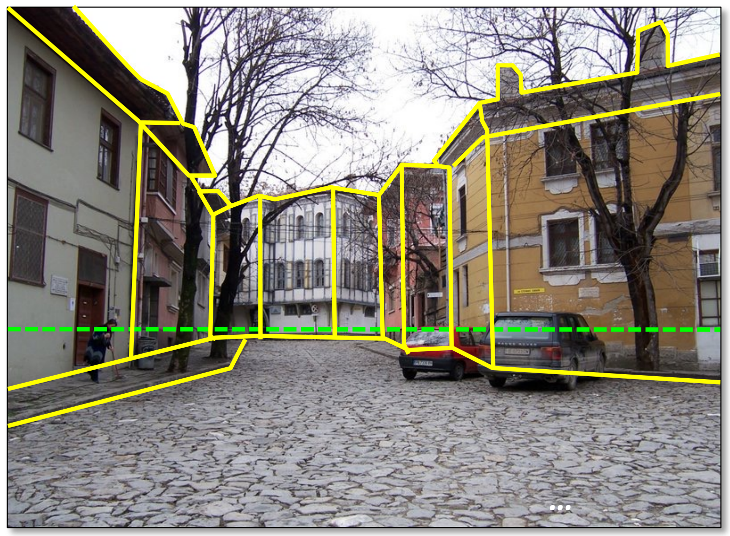
What we see

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0 | 3 | 2 | 5 | 4 | 7 | 6 | 9 | 8 |
| 3 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 2 | 1 | 0 | 3 | 2 | 5 | 4 | 7 | 6 |
| 5 | 2 | 3 | 0 | 1 | 2 | 3 | 4 | 5 |
| 4 | 3 | 2 | 1 | 0 | 3 | 2 | 5 | 4 |
| 7 | 4 | 5 | 2 | 3 | 0 | 1 | 2 | 3 |
| 6 | 5 | 4 | 3 | 2 | 1 | 0 | 3 | 2 |
| 9 | 6 | 7 | 4 | 5 | 2 | 3 | 0 | 1 |
| 8 | 7 | 6 | 5 | 4 | 3 | 2 | 1 | 0 |

What a computer sees

# What kind of information can be extracted from an image?

# What kind of information can be extracted from an image?



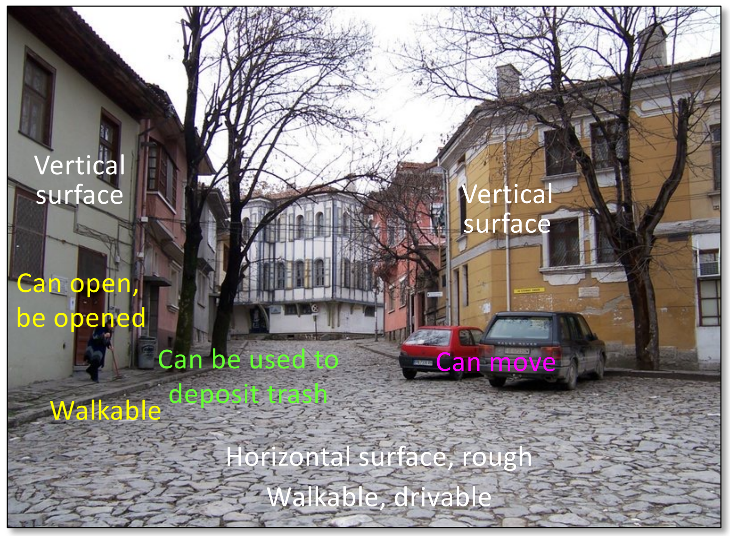
**Geometric** information

# What kind of information can be extracted from an image?


**Geometric** information

**Semantic** information

# What kind of information can be extracted from an image?




**Geometric** information

**Semantic (?)** information – *affordances*

# What kind of information can be extracted from an image?

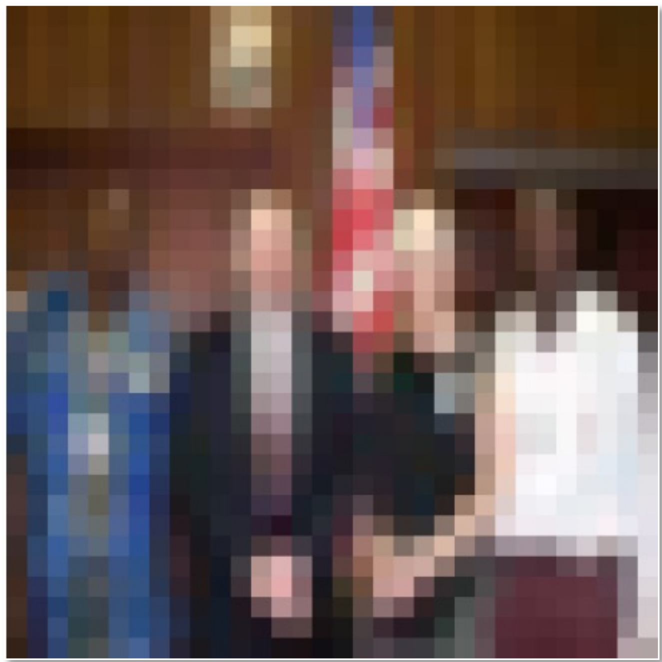
**Geometric** information

**Semantic** information

***Vision for action***

# Images are fundamentally ambiguous!

# Humans are remarkably good at vision…



Source: “80 million tiny images” by Torralba et al.

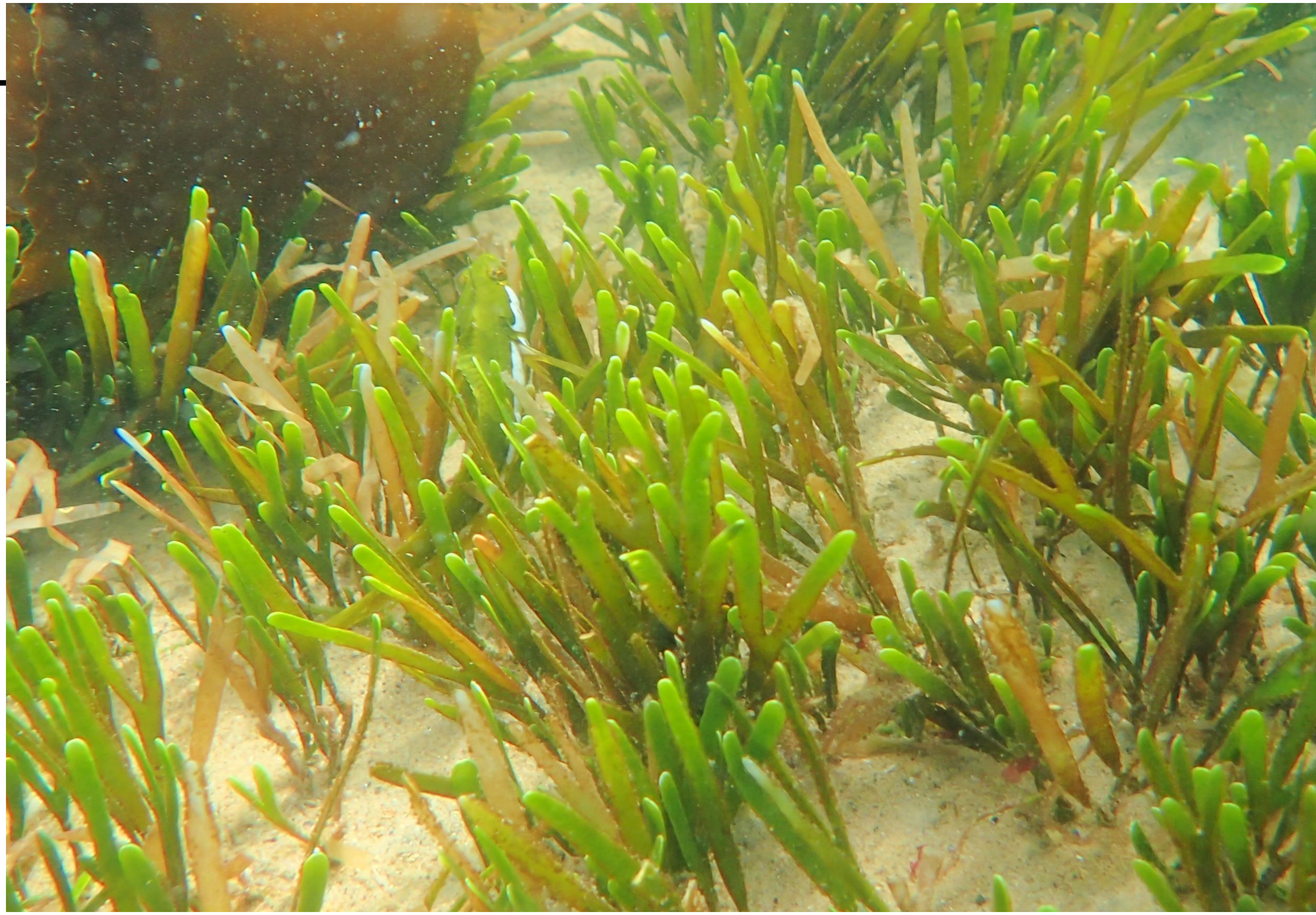
# …still, vision is hard even for humans

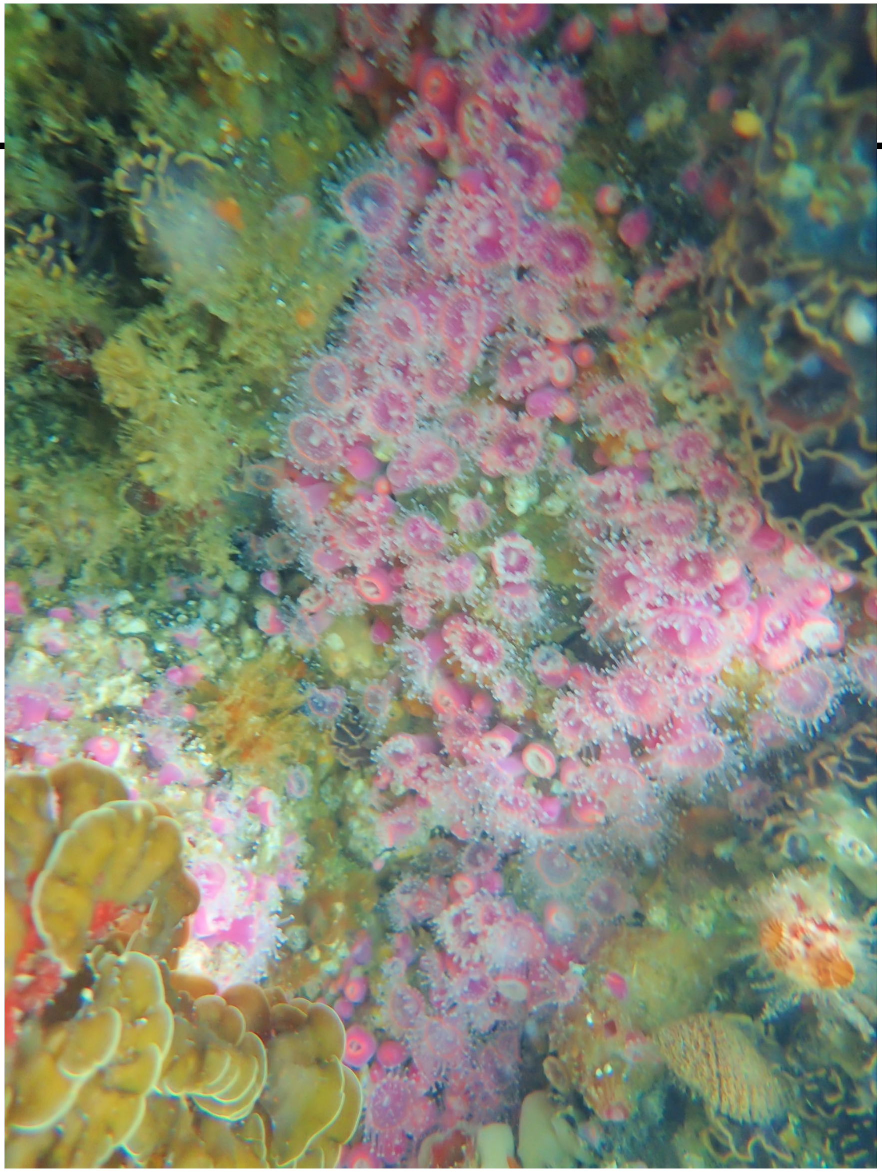
Image source

# …still, vision is hard even for humans

Figure from Marr (1982), attributed to R. C. James

Is





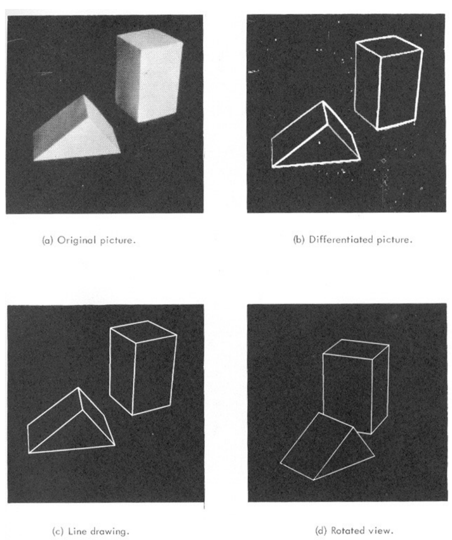
# …still, vision is hard even for humans

[What color is this dress?]

# Outline

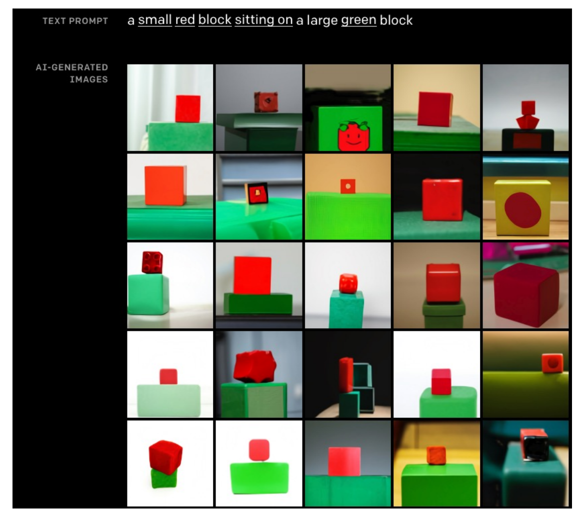
- Logistics, requirements
- Goal of computer vision and why it is hard
- History of computer vision

How it started



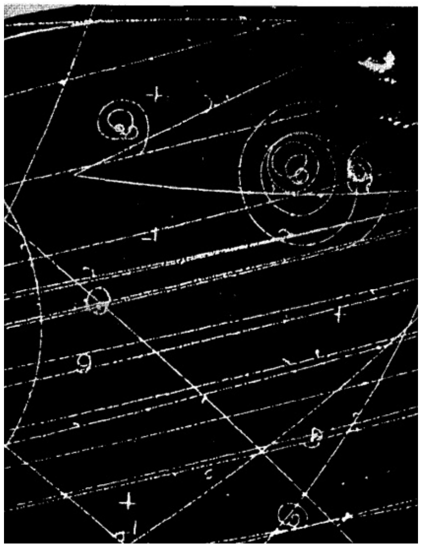

L. G. Roberts, 1963

How it's going

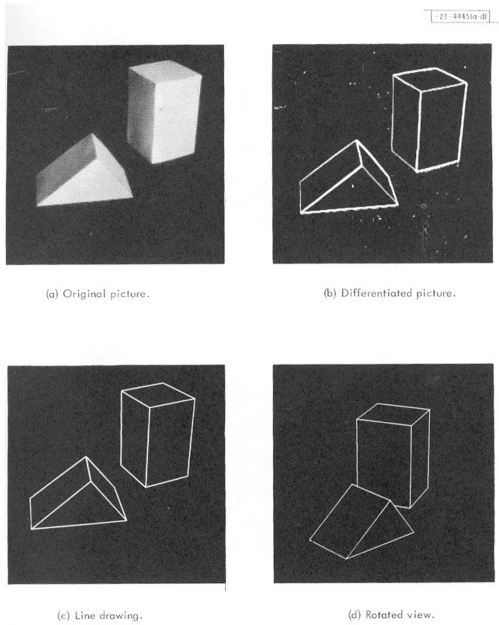



OpenAI DALL-E, 2020

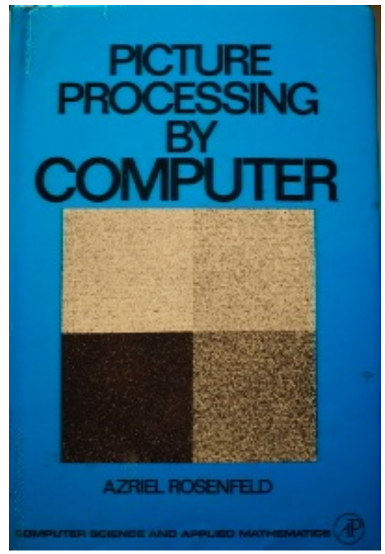
# Origins



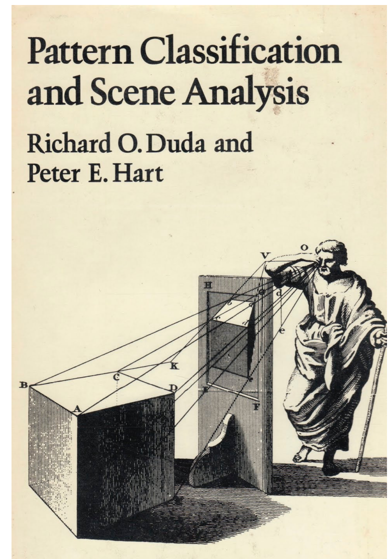
Hough, 1959




Roberts, 1963




Rosenfeld, 1969




Duda & Hart, 1972

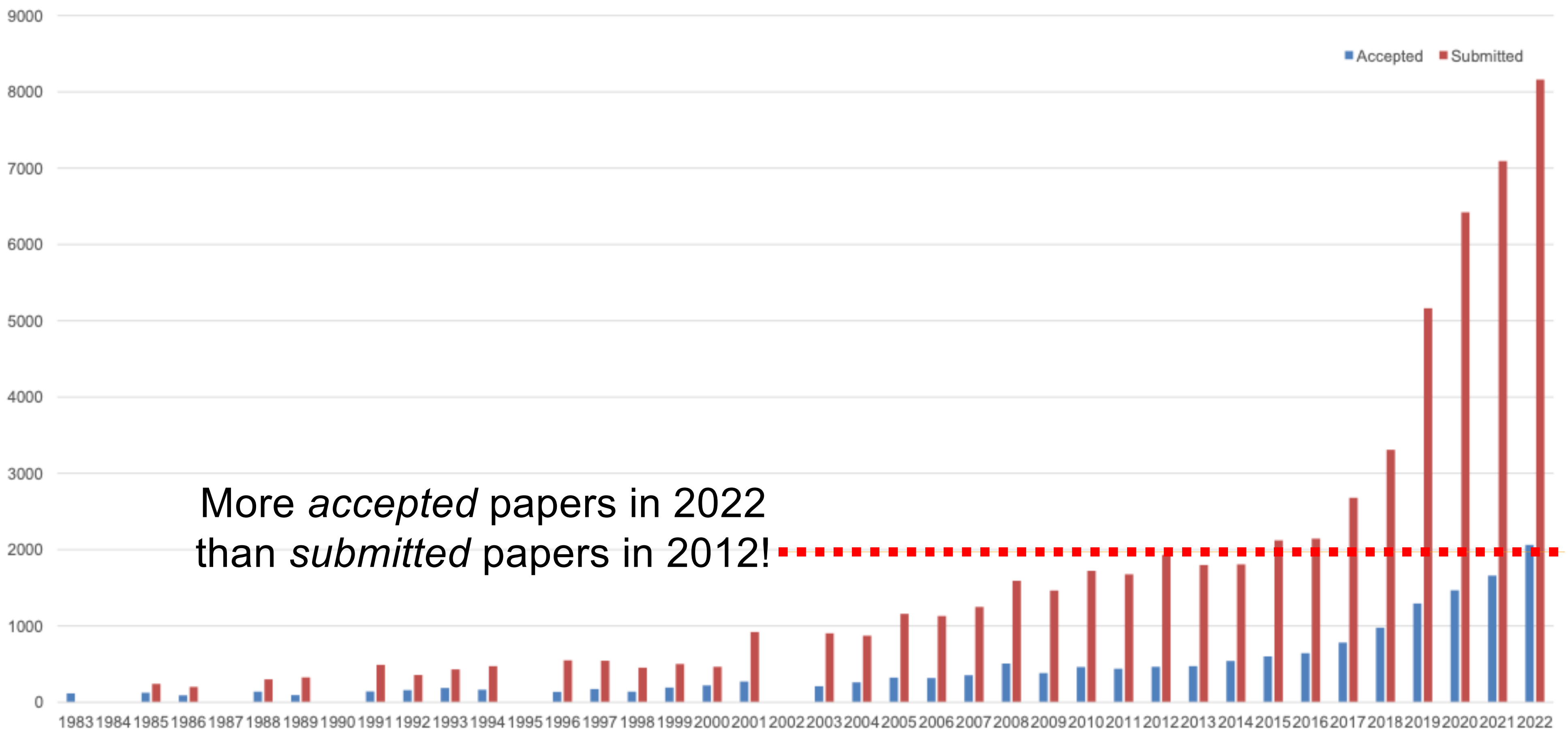
# Decade by decade

- **1960s**: Blocks world, image processing and pattern recognition
- **1970s**: Key recovery problems defined: structure from motion, stereo, shape from shading, color constancy. Attempts at knowledge-based recognition
- **1980s**: Fundamental and essential matrix, multi-scale analysis, corner and edge detection, optical flow, geometric recognition as alignment
- **1990s**: Multi-view geometry, statistical and appearance-based models for recognition, first approaches for (class-specific) object detection
- **2000s**: Local features, generic object recognition and detection
- **2010s**: Deep learning, big data

- For much more detail: see Prof Lazebnik's historical overview

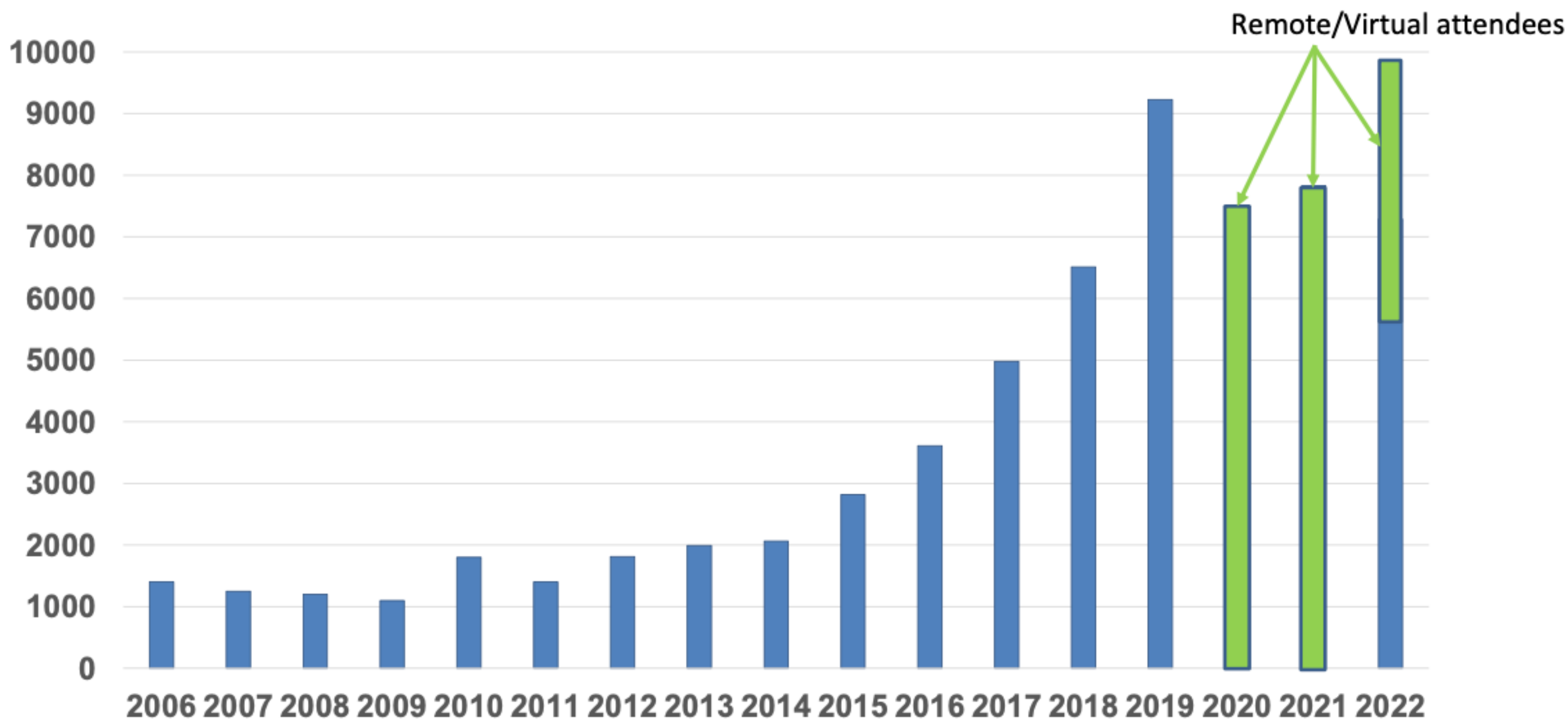
Adapted from J. Malik

# Growth of the field: CVPR papers




Source: [CVPR 2022 opening sides]

# Growth of the field: CVPR attendance




Source: [CVPR 2022 opening sides]

Google Scholar

Top publications

Categories English

| | Publication | h5-index | h5-median |
|---|---|---|---|
| 1. | Nature | 376 | 552 |
| 2. | The New England Journal of Medicine | 365 | 639 |
| 3. | Science | 356 | 526 |
| 4. | The Lancet | 301 | 493 |
| 5. | IEEE/CVF Conference on Computer Vision and Pattern Recognition | 299 | 509 |
| 6. | Advanced Materials | 273 | 369 |
| 7. | Nature Communications | 273 | 366 |
| 8. | Cell | 269 | 417 |
| 9. | Chemical Reviews | 267 | 438 |
| 10. | Chemical Society reviews | 240 | 368 |

Guide2Research

## Top Computer Science Conferences

*Ranking is based on **Conference H5-index>=12** provided by Google Scholar Metrics*

☐ Show **Due** only | All Categories

All Countries | Search by keyword

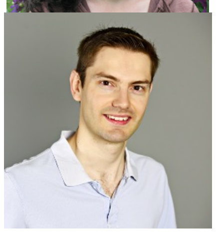
| | Rank | Publisher | Conference Details | H5-index | Impact Score |
|---|---|---|---|---|---|
| Vision | 1 | IEEE | **CVPR : IEEE/CVF Conference on Computer Vision and Pattern Recognition**<br>Jun 21, 2021 - Jun 24, 2021 - Nashville , United States<br>http://cvpr2021.thecvf.com/ | 299 | 51.98 |
| | 2 | | **NeurIPS : Neural Information Processing Systems (NIPS)**<br>Dec 6, 2021 - Dec 14, 2021 - Online , Online<br>https://nips.cc/ | 198 | 33.49 |
| Vision | 3 | IEEE | **ICCV : IEEE/CVF International Conference on Computer Vision**<br>Oct 11, 2021 - Oct 17, 2021 - Montreal , Canada<br>http://iccv2021.thecvf.com/home | 176 | 32.51 |
| Vision | 4 | Springer | **ECCV : European Conference on Computer Vision**<br>Oct 11, 2021 - Oct 17, 2021 - Montreal , Canada<br>http://iccv2021.thecvf.com/ | 144 | 25.91 |
| | 5 | | **AAAI : AAAI Conference on Artificial Intelligence**<br>Feb 2, 2021 - Feb 9, 2021 - Vancouver , Canada<br>https://aaai.org/Conferences/AAAI-21/ | 126 | 25.57 |

# Vision group at Illinois

David Forsyth
- Marr prize, 1993; 2 ex students with Marr prizes; IEEE Tech. Achievement, Fellow; ACM Fellow; EIC IEEE TPAMI

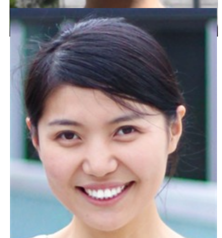
Derek Hoiem
- best paper, CVPR 2006; ACM Doctoral Dissertation honorable mention; Sloan Fellow;PAMI-TC Young Researcher

Lana Lazebnik
- Microsoft Faculty Fellow; Sloan Fellow; Koenderink Prize (2016)



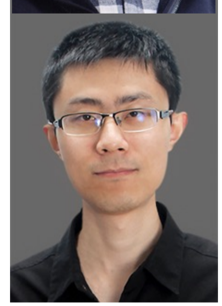
Alex Schwing
- Visual learning, segmentation and GAN models

Saurabh Gupta
- Linking visual sensing to motion



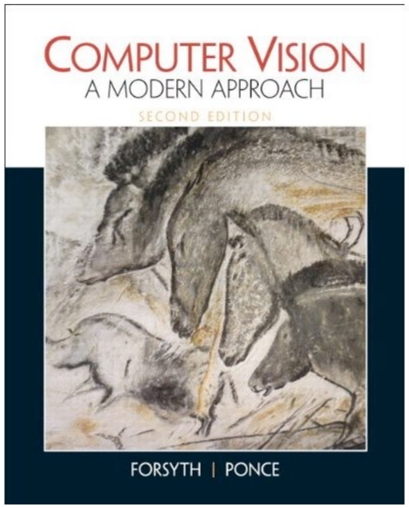
Liangyan Gui
- Understanding human movement

Shenlong Wang
- Simulation and sensing for autonomous vehicles



Yuxiong Wang
- Learning to detect and classify with very little data

# Vision group




**Well-known ex-students:**
**Lana Lazebnik (UIUC)**
**Tamara Berg (UNC)**
**Pinar Duygulu (Hacettepe U.)**
**Ian Endres**
**Ali Farhadi (UW)**
**Varsha Hedau**
**Nazli Ikizler (Hacettepe U.)**
**Brett Jones**
**Kevin Karsch**
**Zicheng Liao**
**Deva Ramanan (CMU)**
**Raj Sodhi**
**Gang Wang (now Alibaba)**
**Amin Sadeghi**
**Zicheng Liao (Zhejiang U.)**

The New Computer Vision

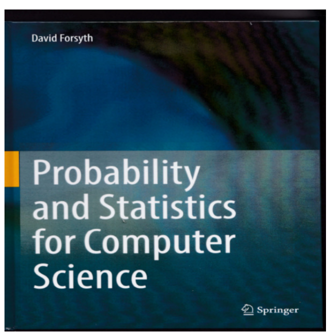
D.A. Forsyth

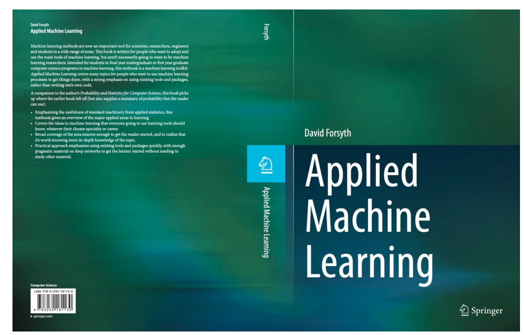
Likely about 2024

Cover design opportunity!

**Startups:**

**Lightform**
**Revery.ai**
**Reconstruct**
**Depix**

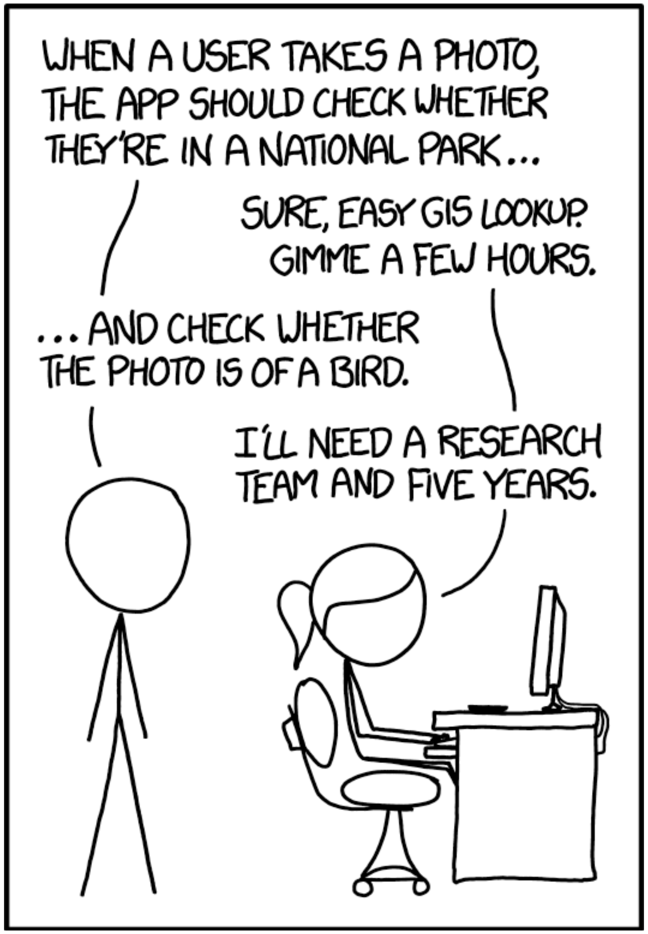


# Introduction: Outline

- Logistics, requirements
- Goal of computer vision and why it is hard
- History of computer vision
- Current state of the art

# What can computer vision do today?



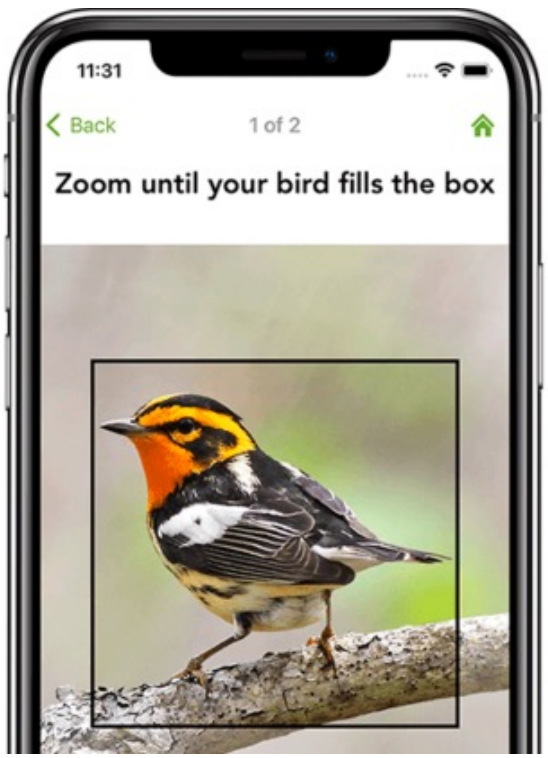

In the 60s, Marvin Minsky assigned a couple of undergrads to spend the summer programming a computer to use a camera to identify objects in a scene. He figured they'd have the problem solved by the end of the summer. Half a century later, we're still working on it.

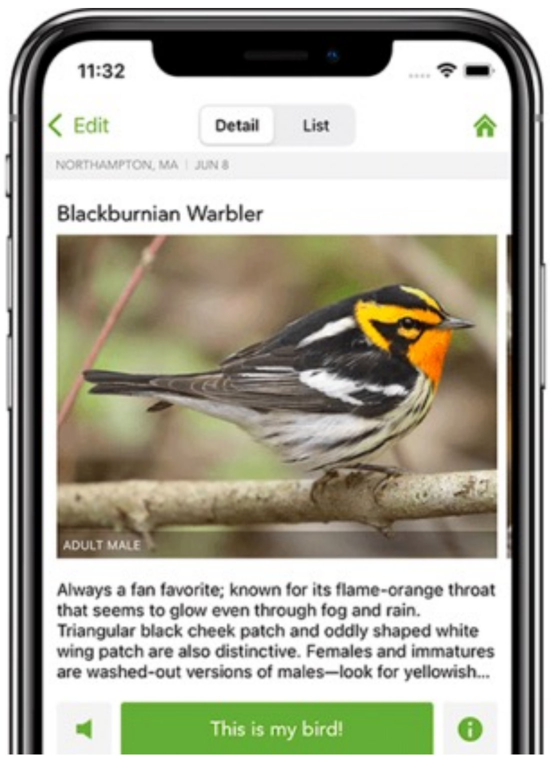
https://xkcd.com/1425/

(September 24, 2014)

# What can computer vision do today?

- It's 2022 now…




TheCornellLab

Merlin®

https://merlin.allaboutbirds.org/

# What can computer vision do today?

- It's 2022 now…

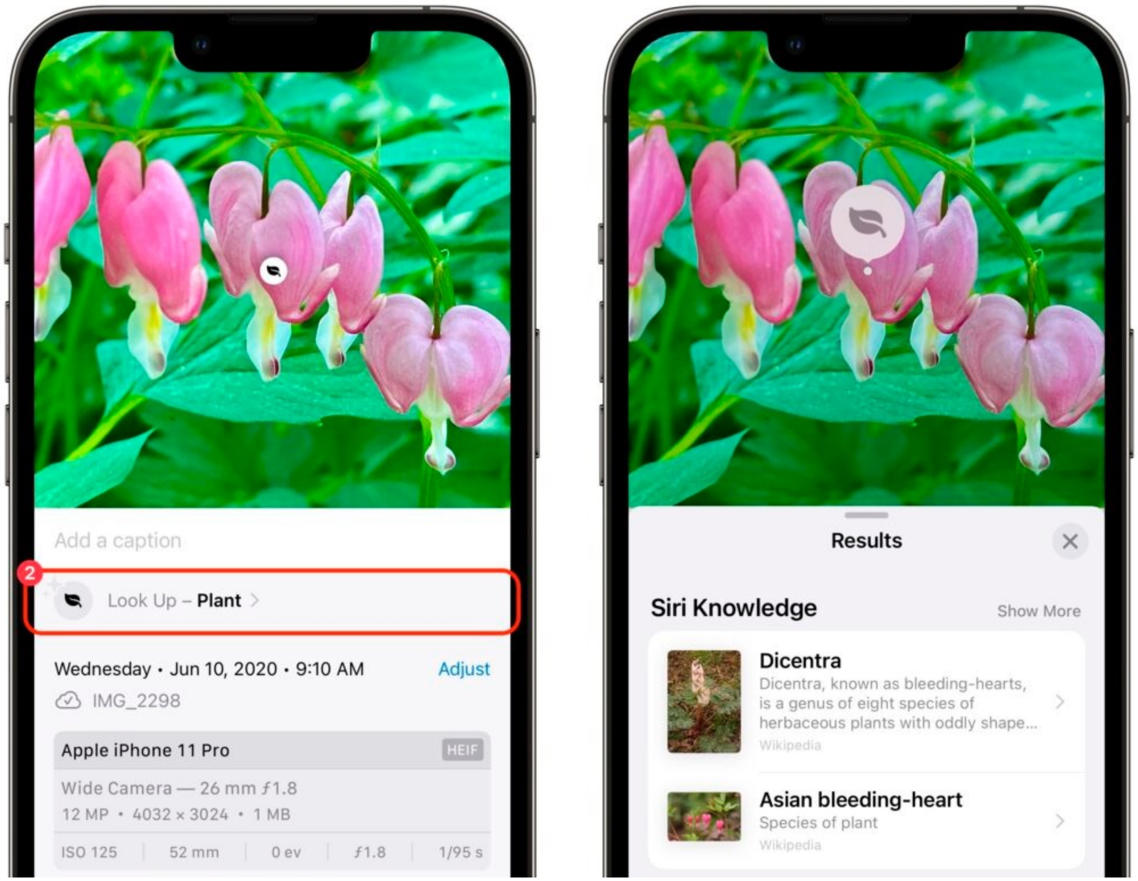



Image source

# What can computer vision do today?

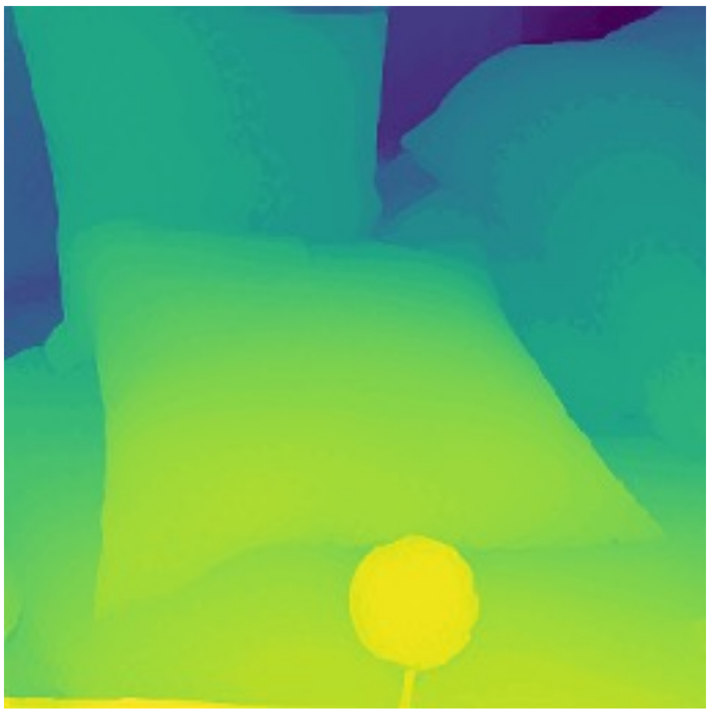
- Reconstruction
- Recognition
- *Reconstruction meets recognition, or 3D scene understanding*
- *Image generation*
- *Vision for action*

## Regression

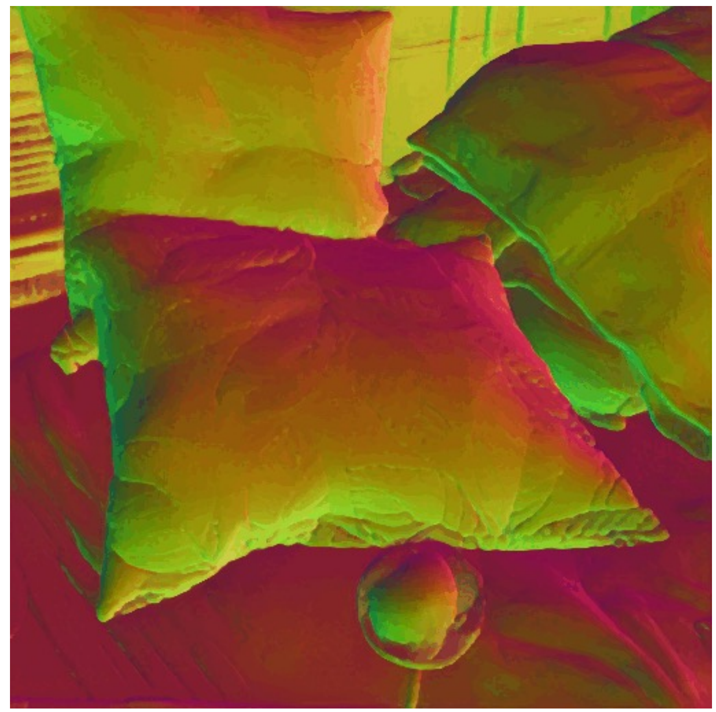
- We must make image-like things from images
- Examples:
  - depth map from image
  - normal map from image
  - derained image from rainy image
  - defogged image from foggy image
- Train with pairs (image, depth)
  - or (image, normal), etc
  - Loss
    - Squared error +abs value of error+other terms as required

# Ex

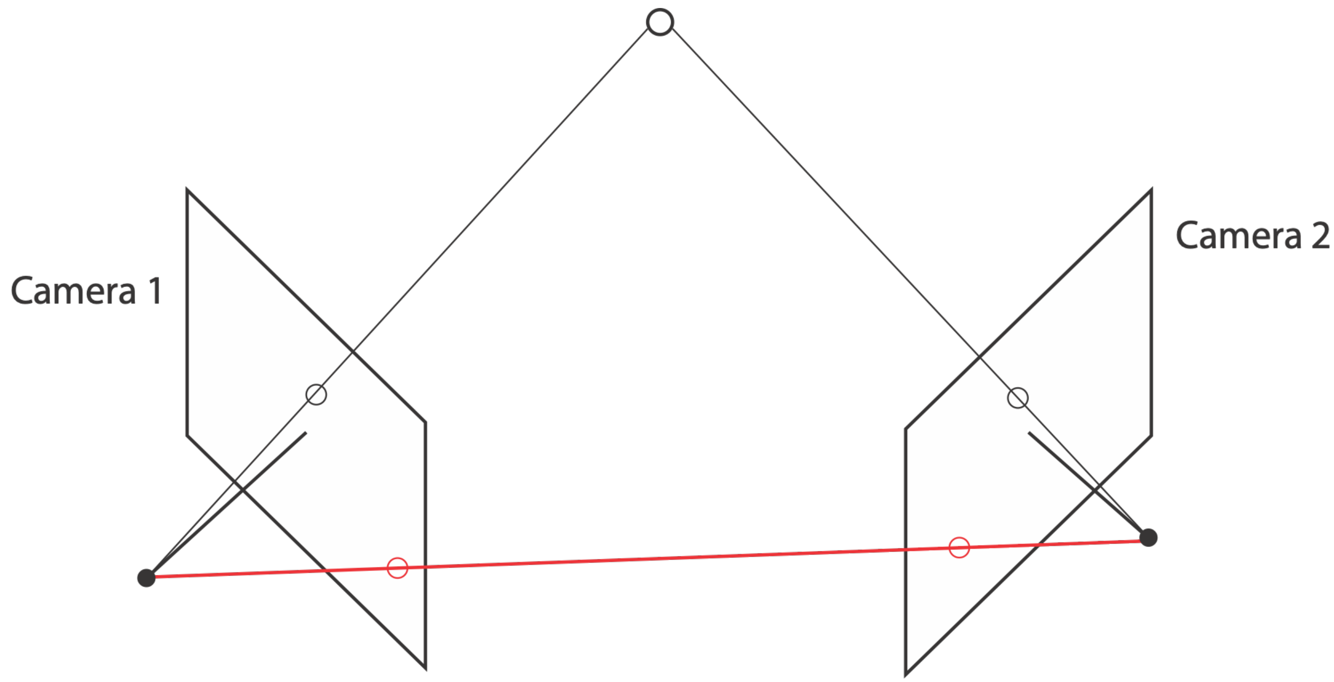
**Depth (omnimap, current best depth est)**



**Normal (omnimap, current best normal est)**

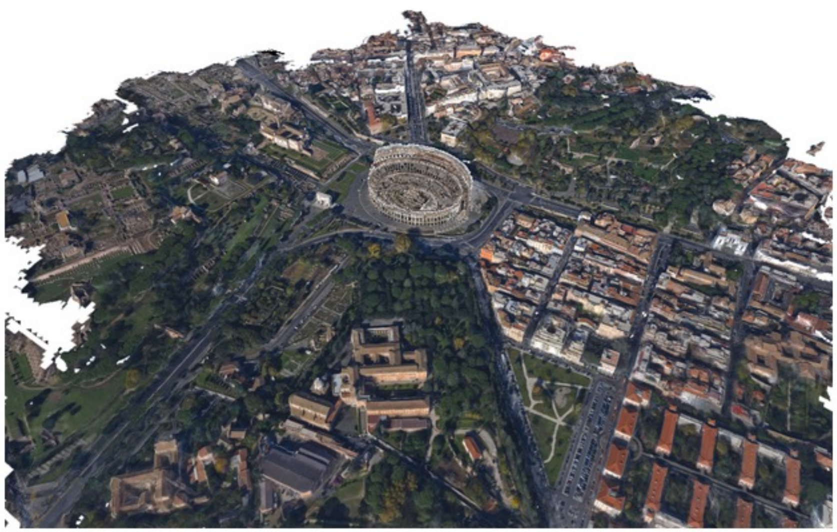


# Correspondence yields 3D configuration



# Reconstruction: 3D from photo collections

Colosseum, Rome, Italy



San Marco Square, Venice, Italy

Q. Shan, R. Adams, B. Curless, Y. Furukawa, and S. Seitz, The Visual Turing Test for Scene Reconstruction, 3DV 2013

YouTube Video

# Reconstruction: 4D from photo collections

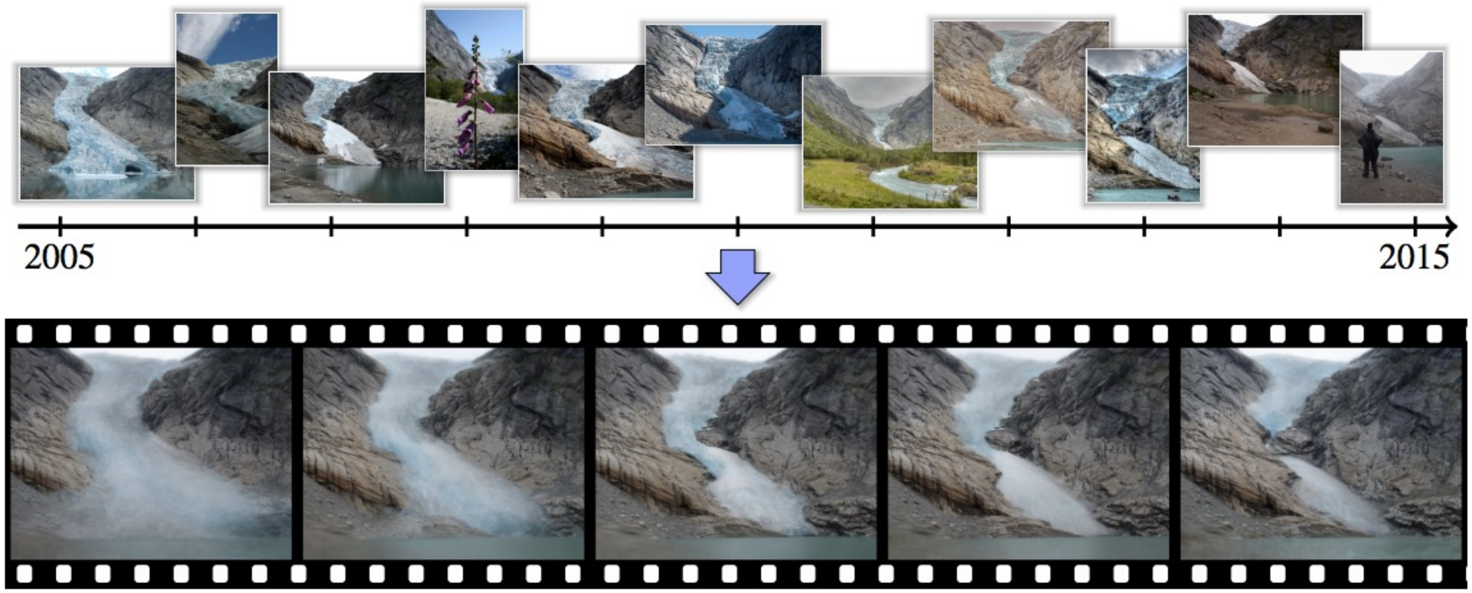



**Figure 1:** *We mine Internet photo collections to generate time-lapse videos of locations all over the world. Our time-lapses visualize a multitude of changes, like the retreat of the Briksdalsbreen Glacier in Norway shown above. The continuous time-lapse (bottom) is computed from hundreds of Internet photos (samples on top). Photo credits: Aliento Más Allá, jirihnidek, mcxurxo, elka_cz, Juan Jesús Orío, Klaus Wißkirchen, Daikrieg, Free the image, dration and Nadav Tobias.*

R. Martin-Brualla, D. Gallup, and S. Seitz, Time-Lapse Mining from Internet Photos, SIGGRAPH 2015

YouTube Video

# Reconstruction: 4D from depth cameras

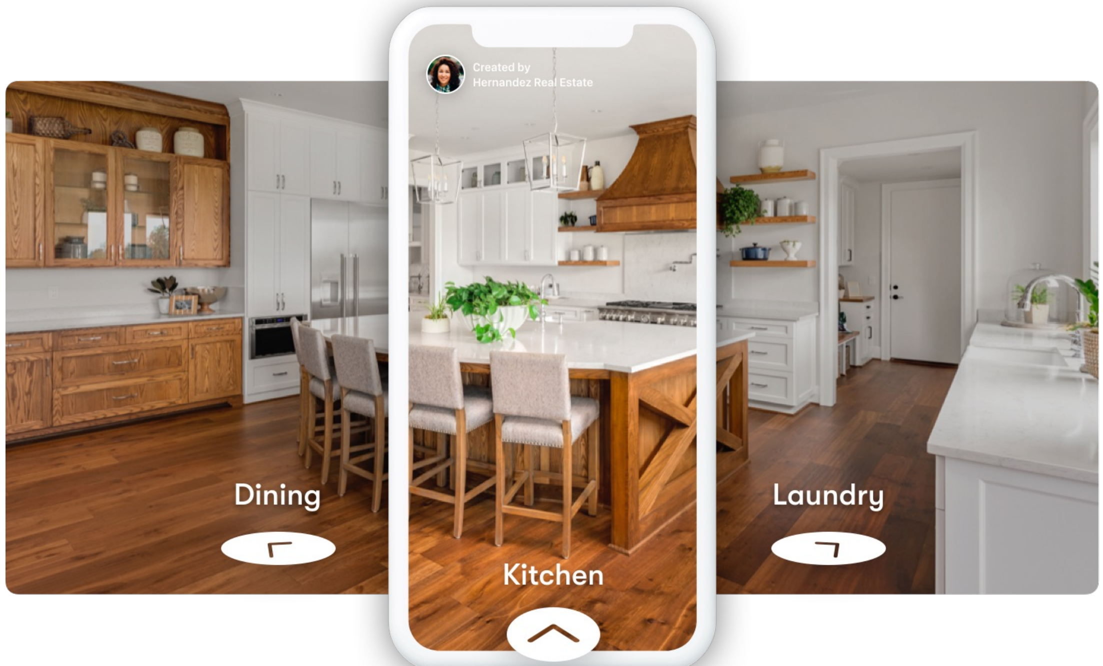

Figure 1: Real-time reconstructions of a moving scene with DynamicFusion; both the person and the camera are moving. The initially noisy and incomplete model is progressively denoised and completed over time (left to right).

R. Newcombe, D. Fox, and S. Seitz, [DynamicFusion: Reconstruction and Tracking of Non-rigid Scenes in Real-Time], CVPR 2015

[YouTube Video]

# Reconstruction: Commercial applications

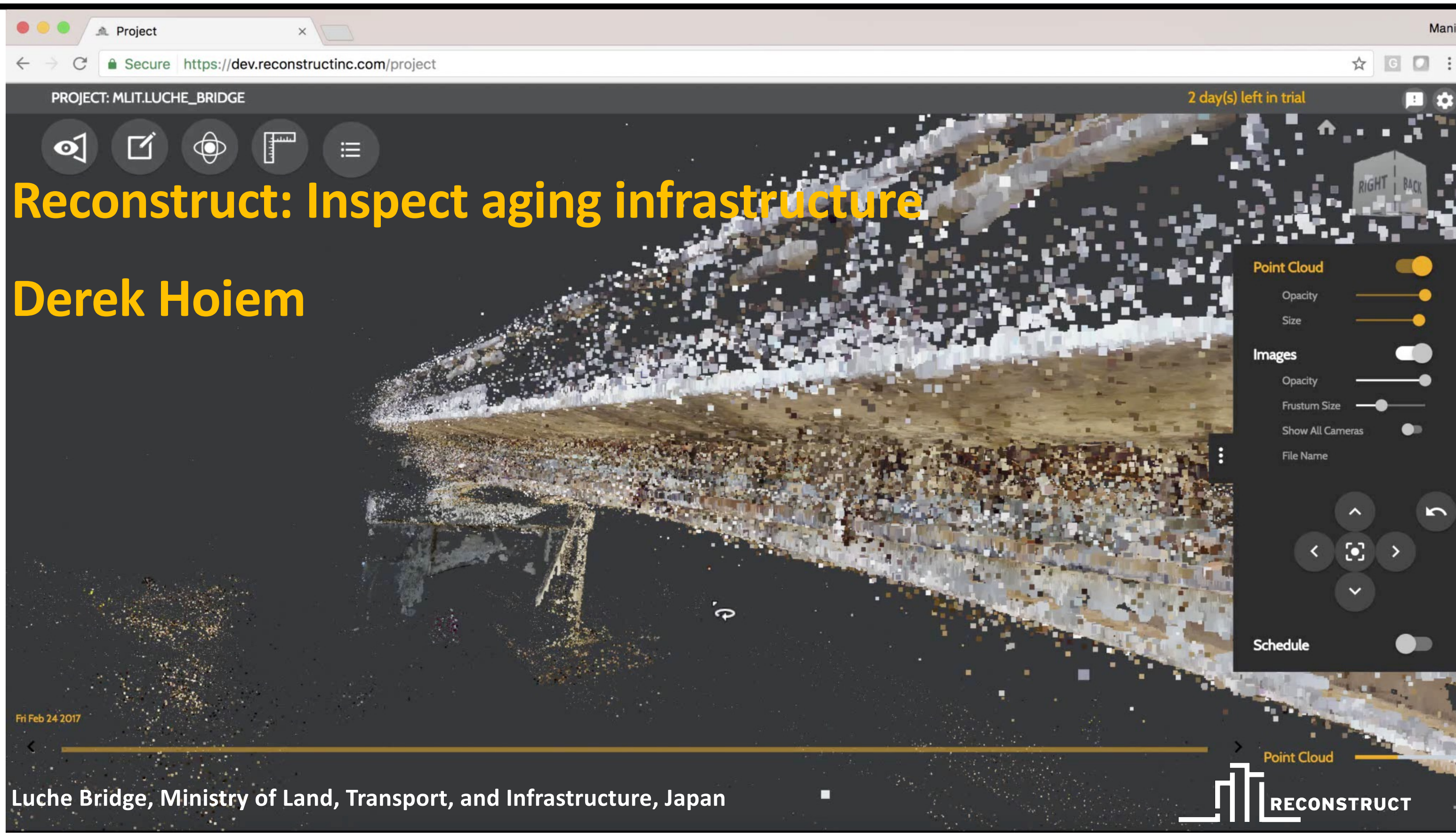
**Make your listing pop with Zillow 3D Home® tours**




https://www.zillow.com/z/3d-home/

# Reconstruct: Inspect aging infrastructure

## Derek Hoiem




Luche Bridge, Ministry of Land, Transport, and Infrastructure, Japan

# Reconstruct: Align reality to plans for construction management

## Derek Hoiem

# Reconstruction: Commercial applications

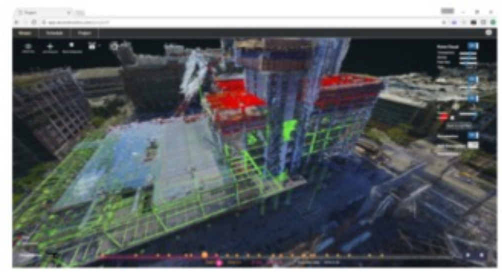
## RECONSTRUCT INTEGRATES REALITY AND PLAN

### Visual Asset Management

Reconstruct 4D point clouds and organize images and videos from smartphones, time-lapse cameras, and drones around the project schedule. View, annotate, and share anywhere with a web interface.

### 4D Visual Production Models

Integrate 4D point clouds with 4D BIM, review "who does what work at what location" on a daily basis and improve coordination and communication among project teams.



### Predictive Visual Data Analytics

Analyze actual progress deviations by comparing Reality and Plan and predict risk with respect to the execution of the look-ahead schedule for each project location, to offer your project team with an opportunity to tap off potential delays before they surface on your jobsite.

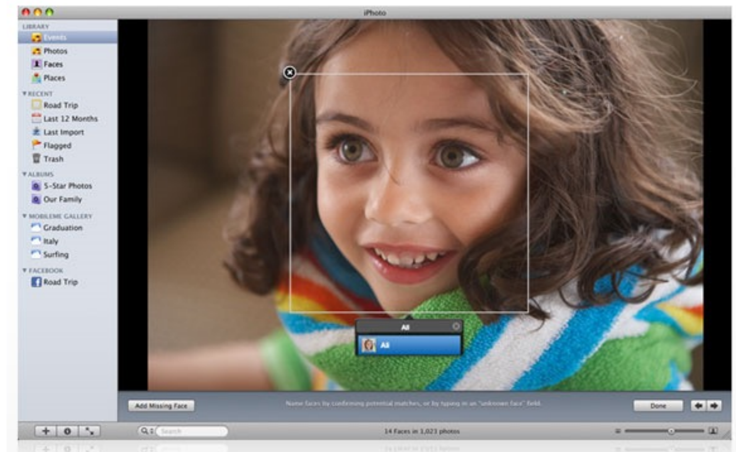
[reconstructinc.com](reconstructinc.com)

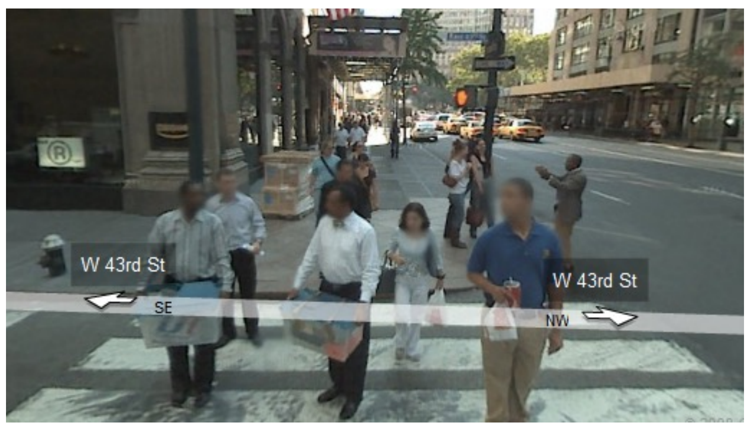
Source: D. Hoiem

# Recognition: “Simple” patterns



# Recognition: Faces

# Recognition: Faces

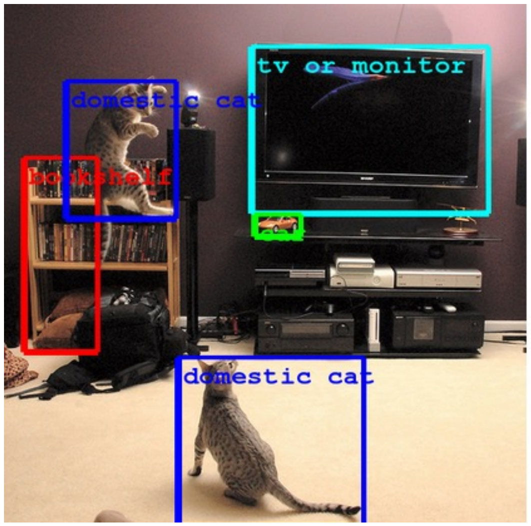

How China Uses High-Tech Surveillance to Subdue Minorities – New York Times, 5/22/2019

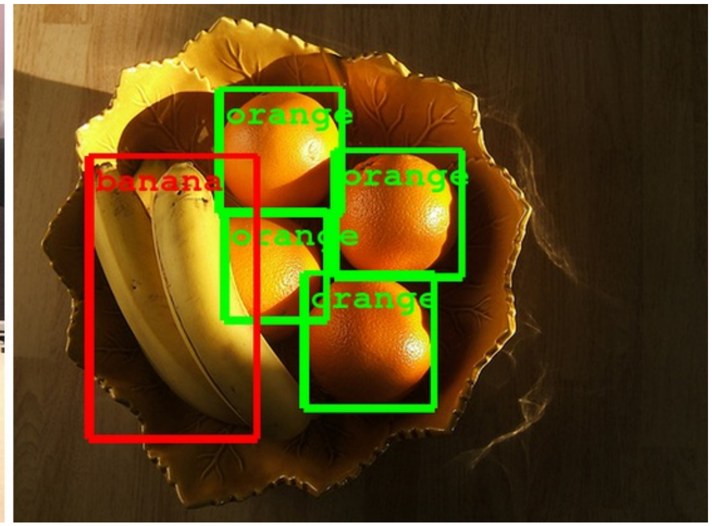
The Secretive Company That Might End Privacy As We Know It – New York Times, 1/18/2020

Wrongfully Accused by an Algorithm – New York Times, 6/24/2020

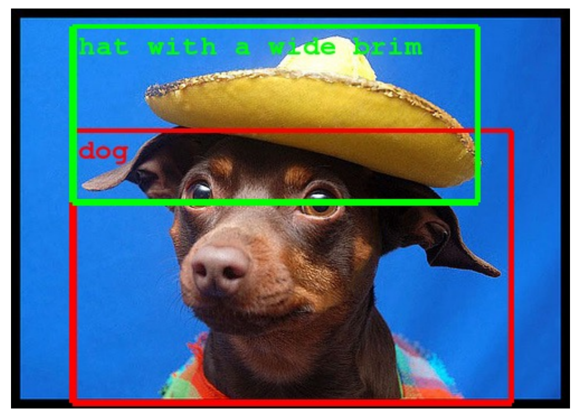
Facial Recognition Goes to War – New York Times, 4/7/2022

# Recognition: General categories



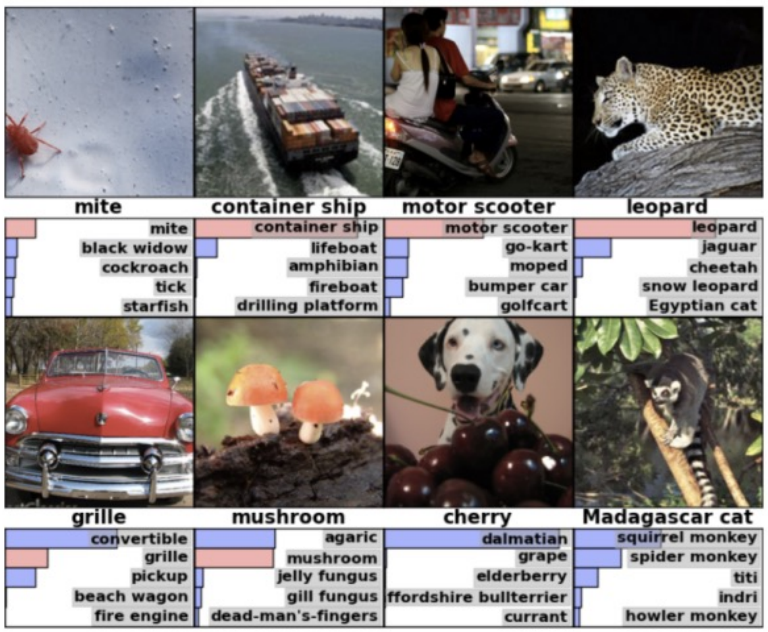



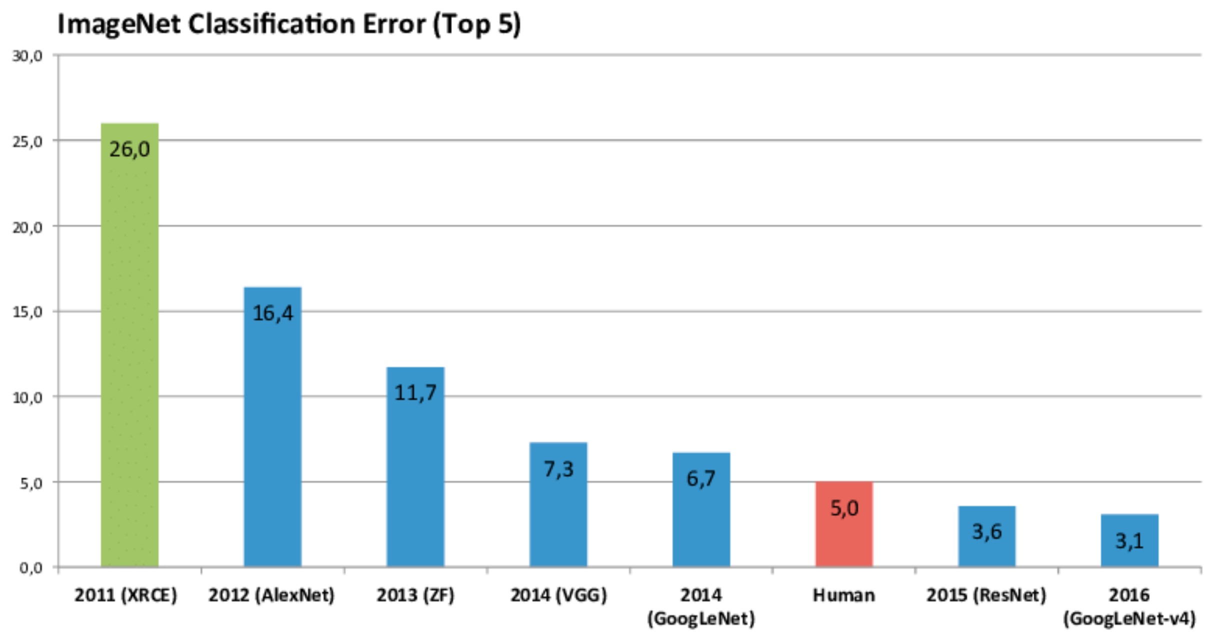

- [Computer Eyesight Gets a Lot More Accurate](), NY Times Bits blog, August 18, 2014
- [Building A Deeper Understanding of Images](), Google Research Blog, September 5, 2014



# Recognition: General categories

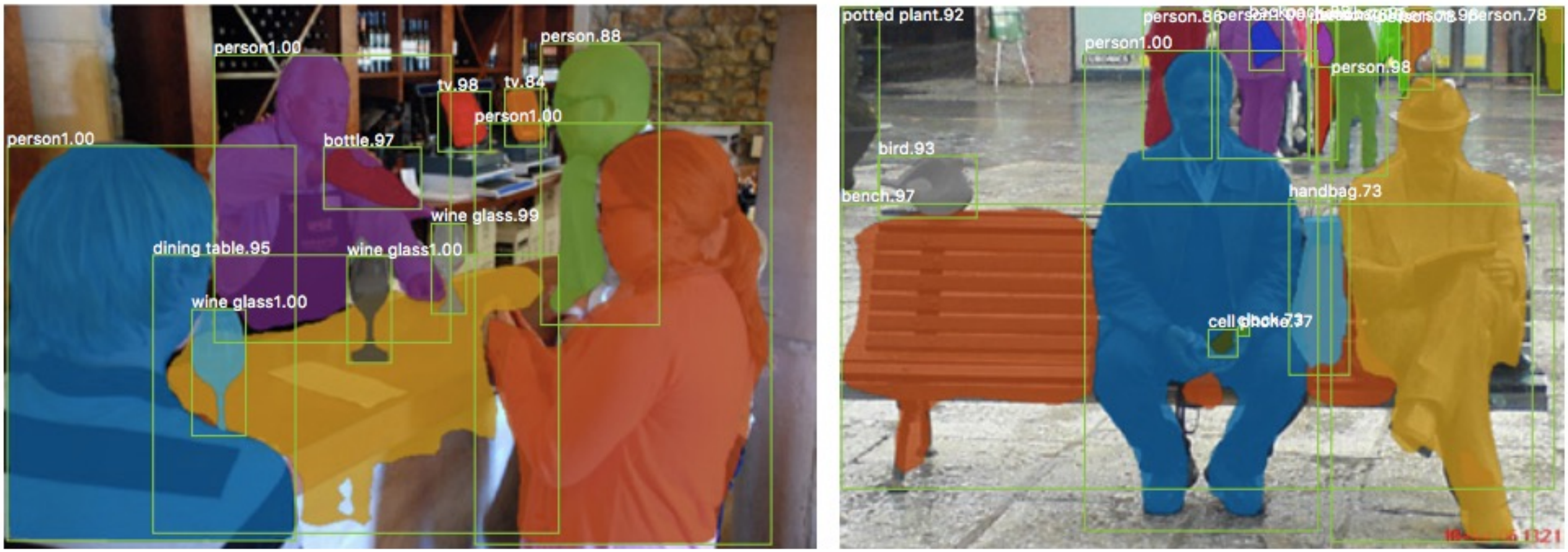
[ILSVRC]



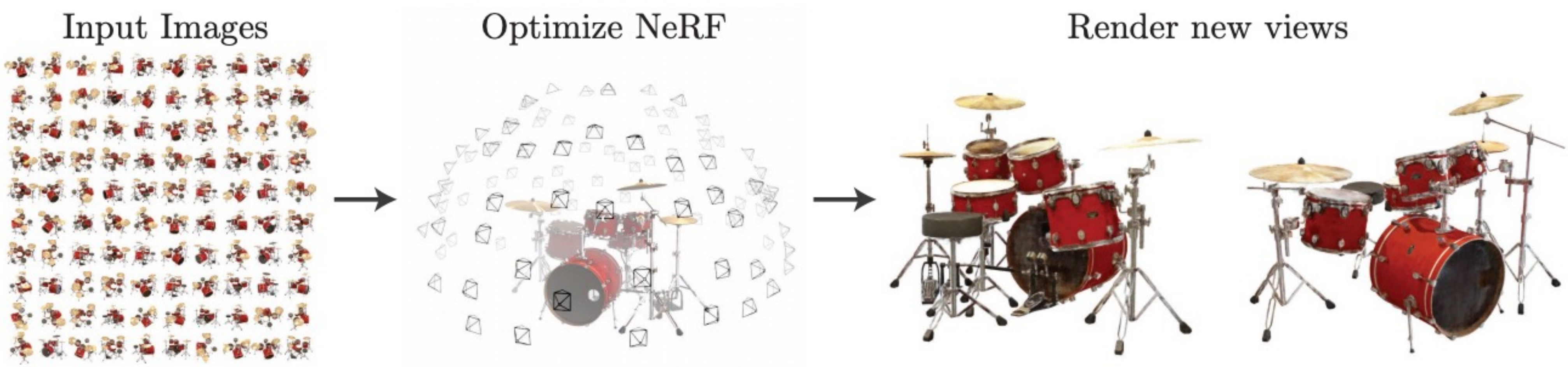

[Figure source]

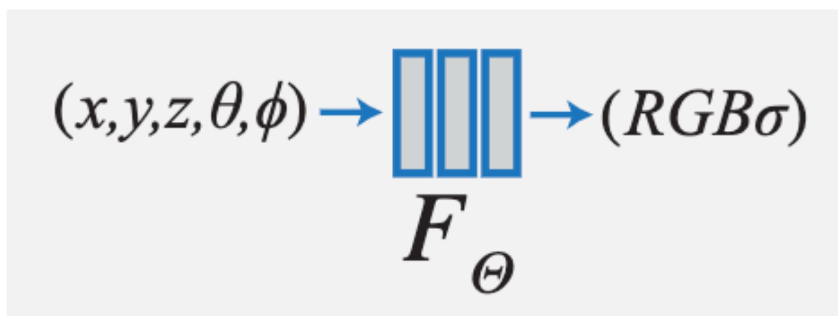
# Object detection, instance segmentation




K. He, G. Gkioxari, P. Dollar, and R. Girshick, [Mask R-CNN](),
ICCV 2017 (Best Paper Award)

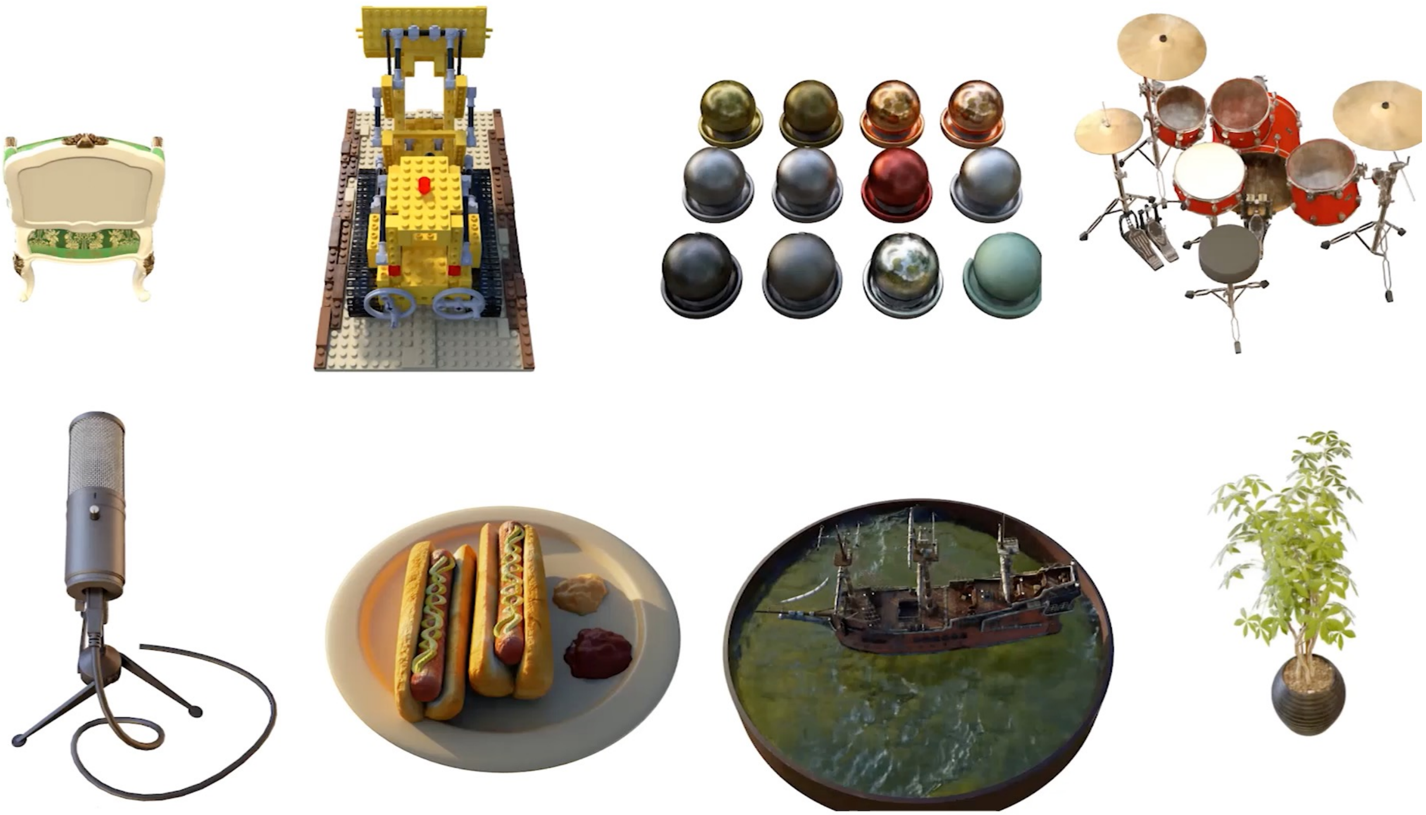
# 3D scene understanding: NERFs




B. Mildenhall et al., Representing Scenes as Neural Radiance Fields for View Synthesis, ECCV 2020

# 3D scene understanding: NERFs



B. Mildenhall et al., [Representing Scenes as Neural Radiance Fields for View Synthesis](), ECCV 2020

# 3D scene understanding: Single-view reconstruction

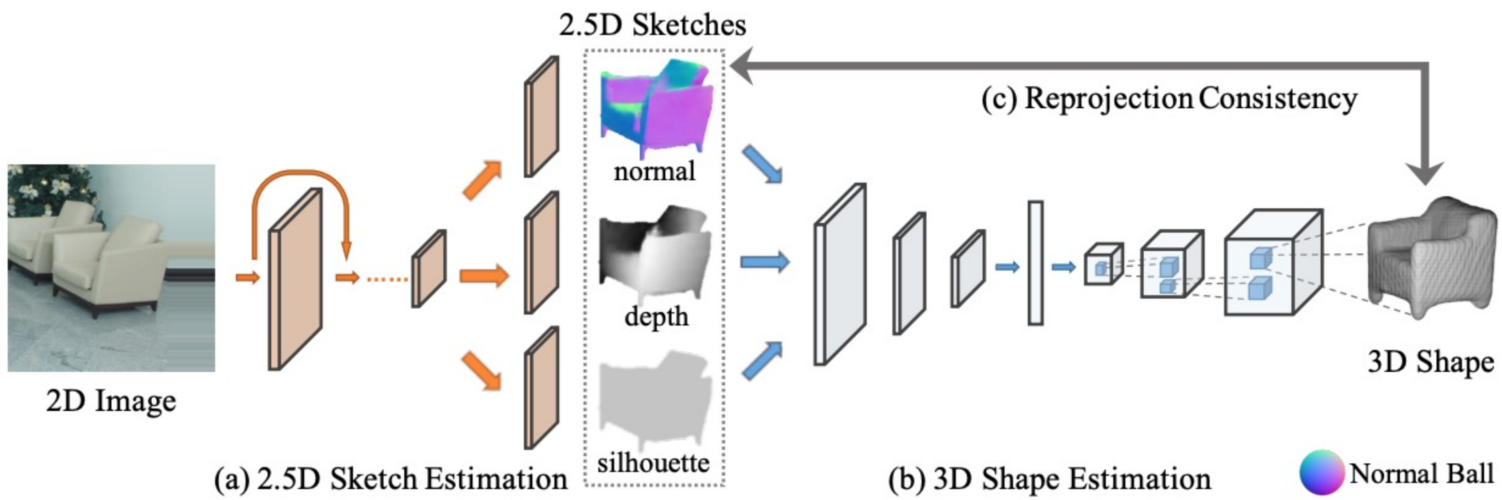



Figure 2: Our model (MarrNet) has three major components: (a) 2.5D sketch estimation, (b) 3D shape estimation, and (c) a loss function for reprojection consistency. MarrNet first recovers object normal, depth, and silhouette images from an RGB image. It then regresses the 3D shape from the 2.5D sketches. In both steps, it uses an encoding-decoding network. It finally employs a reprojection consistency loss to ensure the estimated 3D shape aligns with the 2.5D sketches. The entire framework can be trained end-to-end.

J. Wu, Y. Wang, T. Xue, X. Sun, W. Freeman, J. Tenenbaum, MarrNet: 3D Shape Reconstruction via 2.5D Sketches, NeurIPS 2017

# Image generation: Faces

- 1024x1024 resolution, CelebA-HQ dataset

T. Karras, T. Aila, S. Laine, and J. Lehtinen, Progressive Growing of GANs for Improved Quality, Stability, and Variation, ICLR 2018

Follow-up work

# Image generation: DeepFakes

## Harrison Ford Is Young Han In Solo Deepfake Video

Thanks to deepfake technology, the maligned Solo: A Star Wars Story now stars Harrison Ford instead of Alden Ehrenreich as the young Han.

BY DAN ZINSKI
2 DAYS AGO

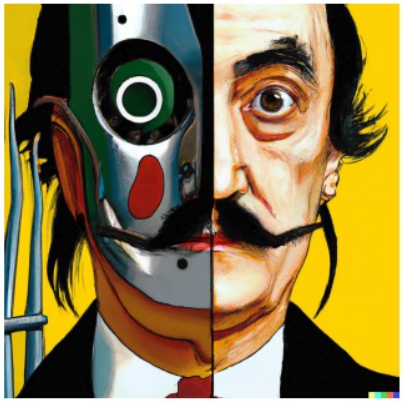
Just a random recent example…

https://screenrant.com/star-wars-han-solo-movie-harrison-ford-video-deepfake/

https://www.youtube.com/watch?v=bC3uH4Xw4Xo

**https://en.wikipedia.org/wiki/Deepfake**

# Image generation: OpenAI DALL-E, DALL-E 2


vibrant portrait painting of Salvador Dalí with a robotic half face


a shiba inu wearing a beret and black turtleneck


a close up of a handpalm with leaves growing from it


an espresso machine that makes coffee from human souls, artstation

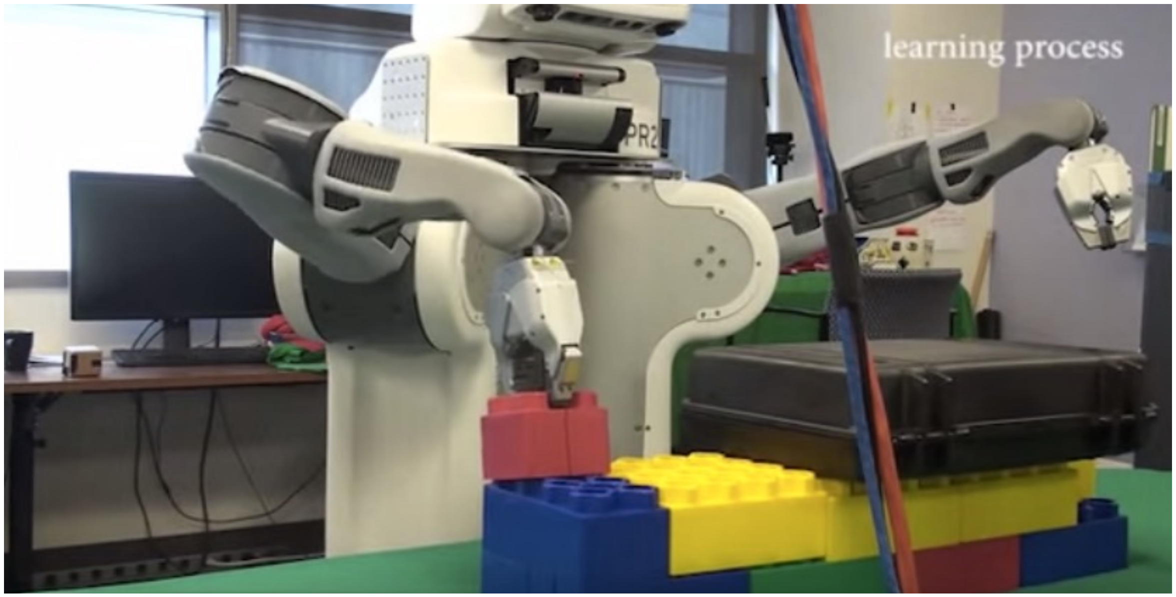

panda mad scientist mixing sparkling chemicals, artstation


a corgi's head depicted as an explosion of a nebula

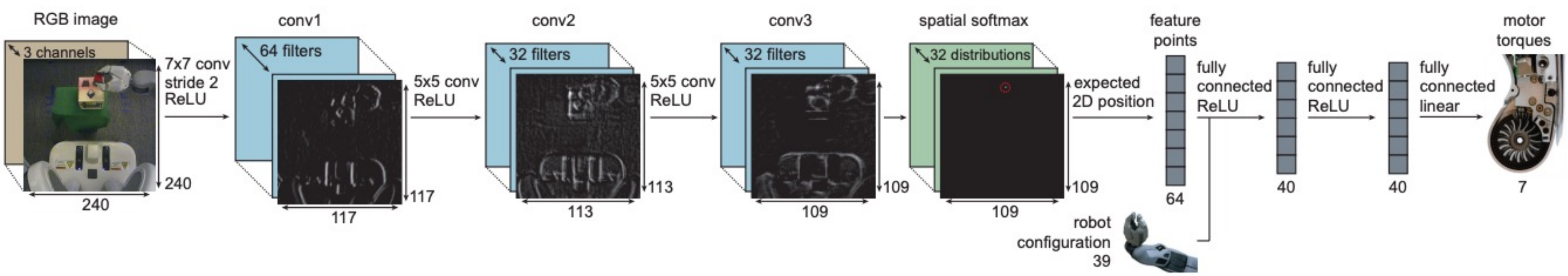
A. Ramesh et al., [Zero-Shot Text-to-Image Generation](), ICML 2021. https://openai.com/blog/dall-e/

A. Ramesh et al., [Hierarchical Text-Conditional Image Generation with CLIP Latents](), arXiv 2022. https://openai.com/dall-e-2/

# Vision for action: Visuomotor learning

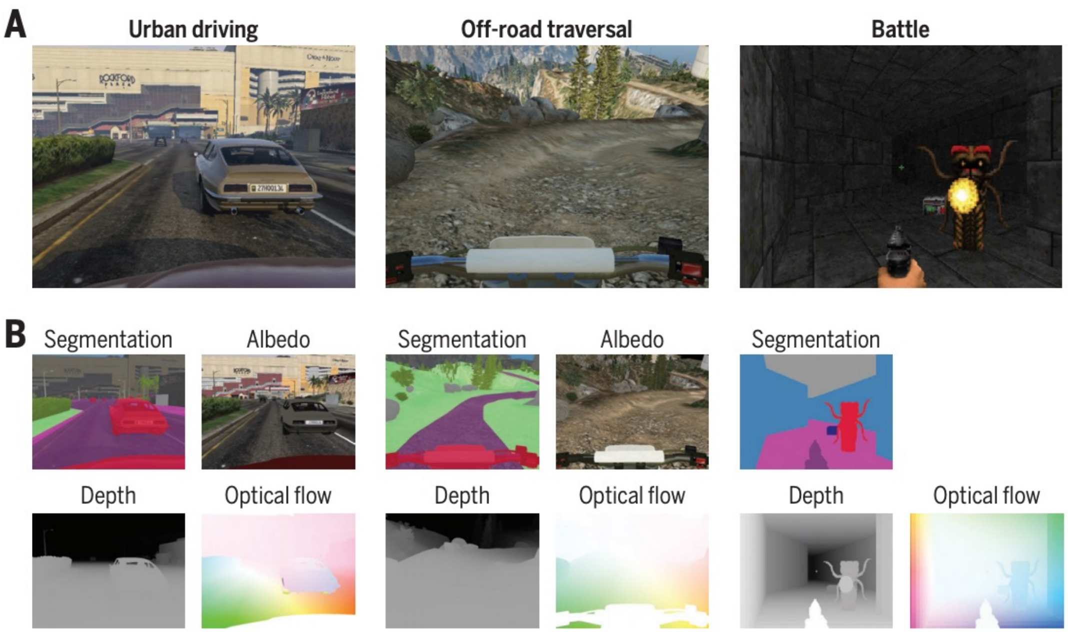


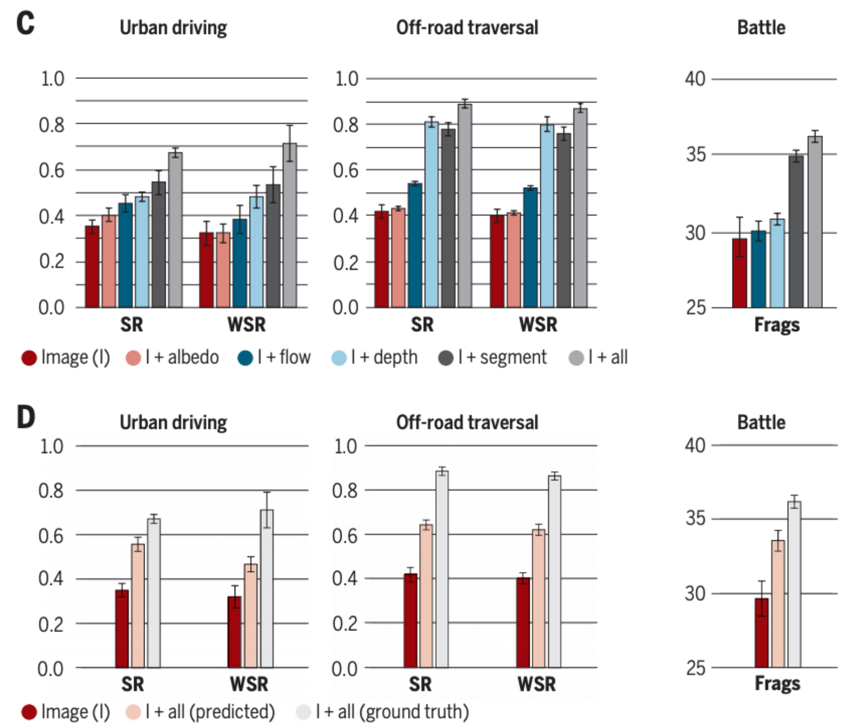

[Overview video](), [training video]()




S. Levine, C. Finn, T. Darrell, P. Abbeel, End-to-end training of deep visuomotor policies, JMLR 2016

# Does computer vision matter for action?




"Our main finding is that computer vision does matter. Models equipped with intermediate representations train faster, achieve higher task performance, and generalize better to previously unseen environments."

B. Zhou, P. Krähenbühl, and V. Koltun, [Does Computer Vision Matter for Action?](#) Science Robotics, 4(30), 2019 ([video](#))

# Vision for action: Learning skills from video

Fig. 1. Simulated characters performing highly dynamic skills learned by imitating video clips of human demonstrations. **Left:** Humanoid performing cartwheel B on irregular terrain. **Right:** Backflip A retargeted to a simulated Atlas robot.

**Video**

X. B. Peng, A. Kanazawa, J. Malik, P. Abbeel, S. Levine, SFV: Reinforcement Learning of Physical Skills from Videos, SIGGRAPH Asia 2018

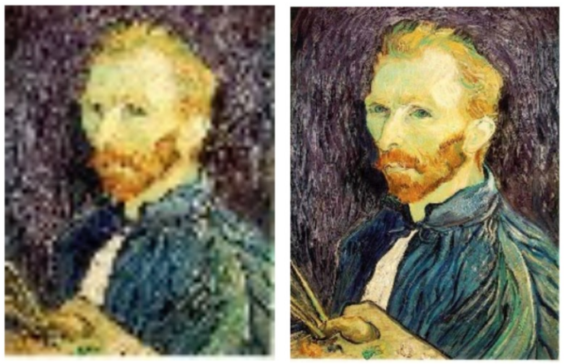
# Outline

- Logistics, requirements
- Goal of computer vision and why it is hard
- History of computer vision
- Current state of the art
- Topics covered in class

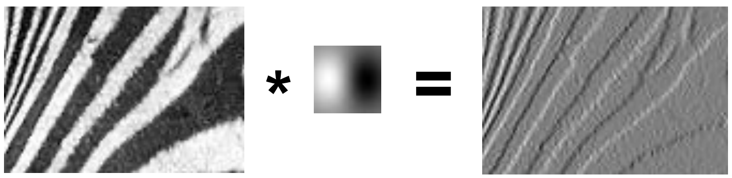
# Topics covered in class

I. Early vision: Image processing and feature extraction
II. Mid-level vision: Grouping and fitting
III. Image formation and geometric vision
IV. Recognition

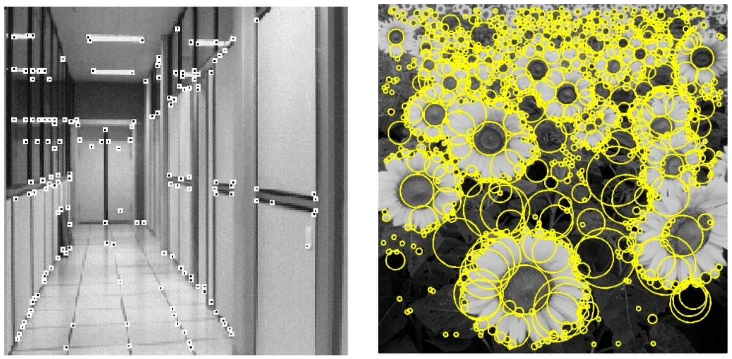
# I. Image processing and feature extraction



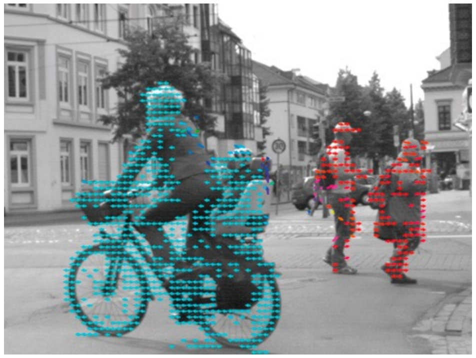
Basic image processing



Linear filtering
Edge detection

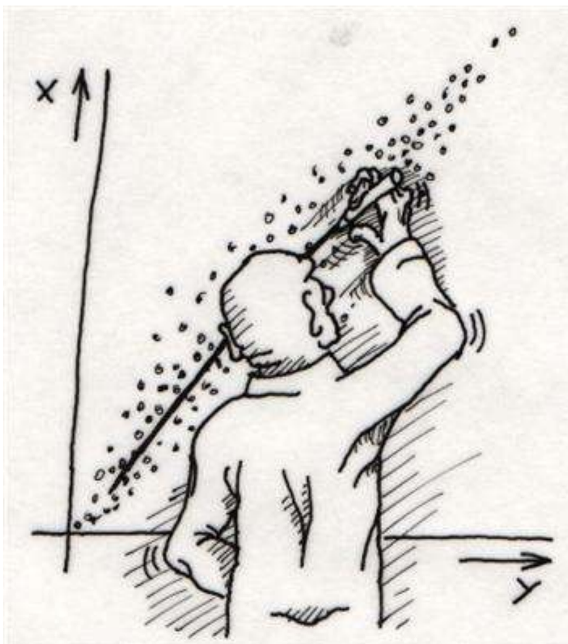


Feature extraction



Optical flow

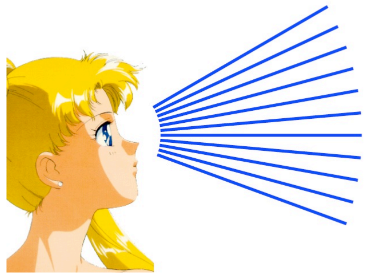
# II. Grouping and fitting



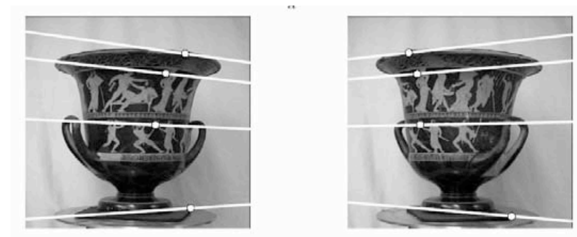

Fitting: Least squares
Voting methods


Alignment

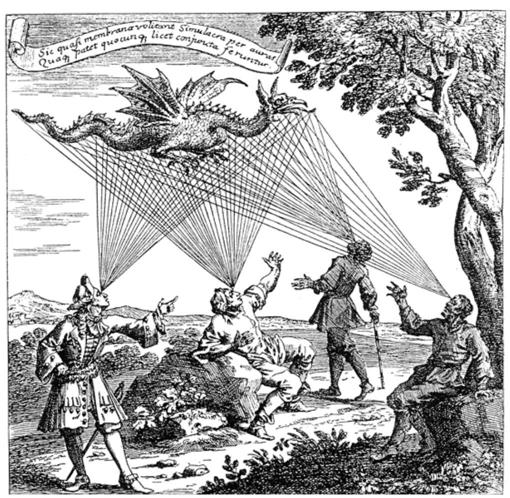
# III. Image formation and geometric vision



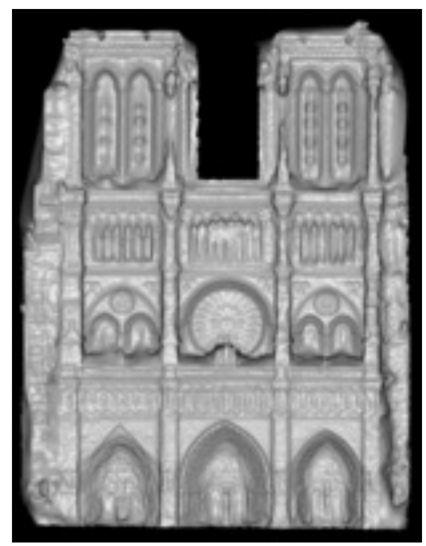
Cameras and sensors
Light and color



Two-view geometry, stereo

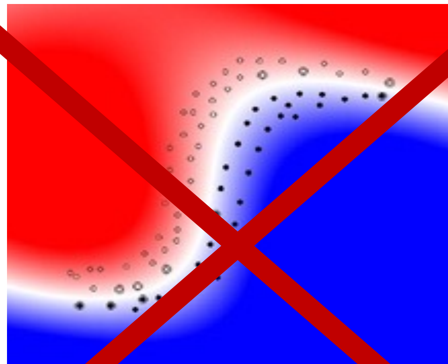


Structure from motion

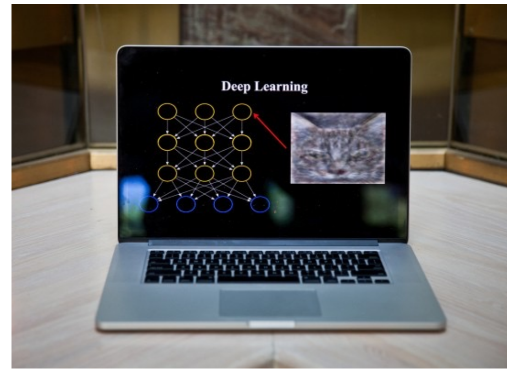


Multi-view stereo

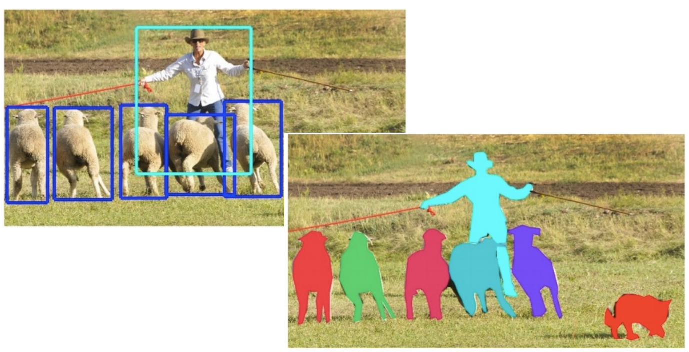
# IV. Recognition



Intro to classification and neural networks




Deep learning architectures for images



Object detection and segmentation

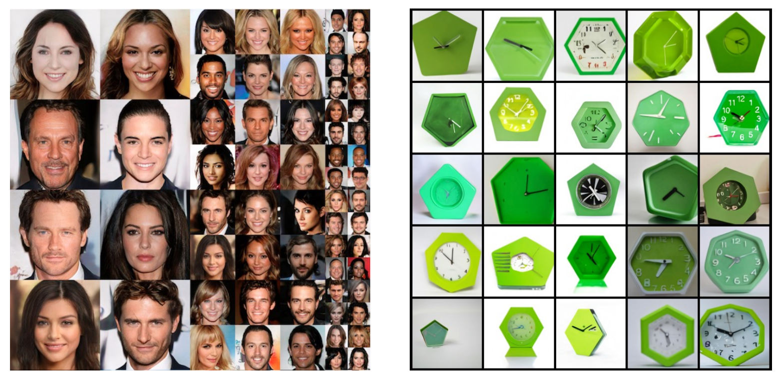


Image generation