THE UNIVERSITY OF BRITISH COLUMBIA

# CPSC 425: Computer Vision

**Image Credit**: Devi Parikh

**Lecture 1:** Introduction and Course Logistics

# Course **logistics**

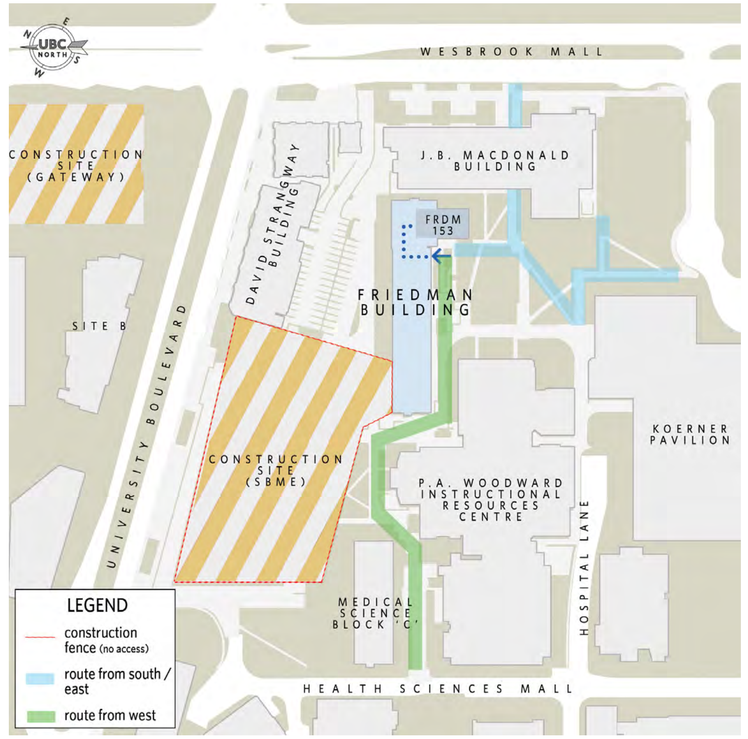
**Times:** Mon, Wed 3:30-5:00pm

**Locations:** Friedman (FRDM), Room 153


**Instructor:** Kwang Moo **YI**

**E-mail:** kmyi@cs.ubc.ca

**Office:** ICICS 115

# About **me …**

I have been working in **Computer Vision** for the last 15+ years

**Assistant Professor**
2020–present


THE UNIVERSITY OF BRITISH COLUMBIA

**Assistant Professor**
2017–2020


**Postdoctoral Researcher**
2014–2017

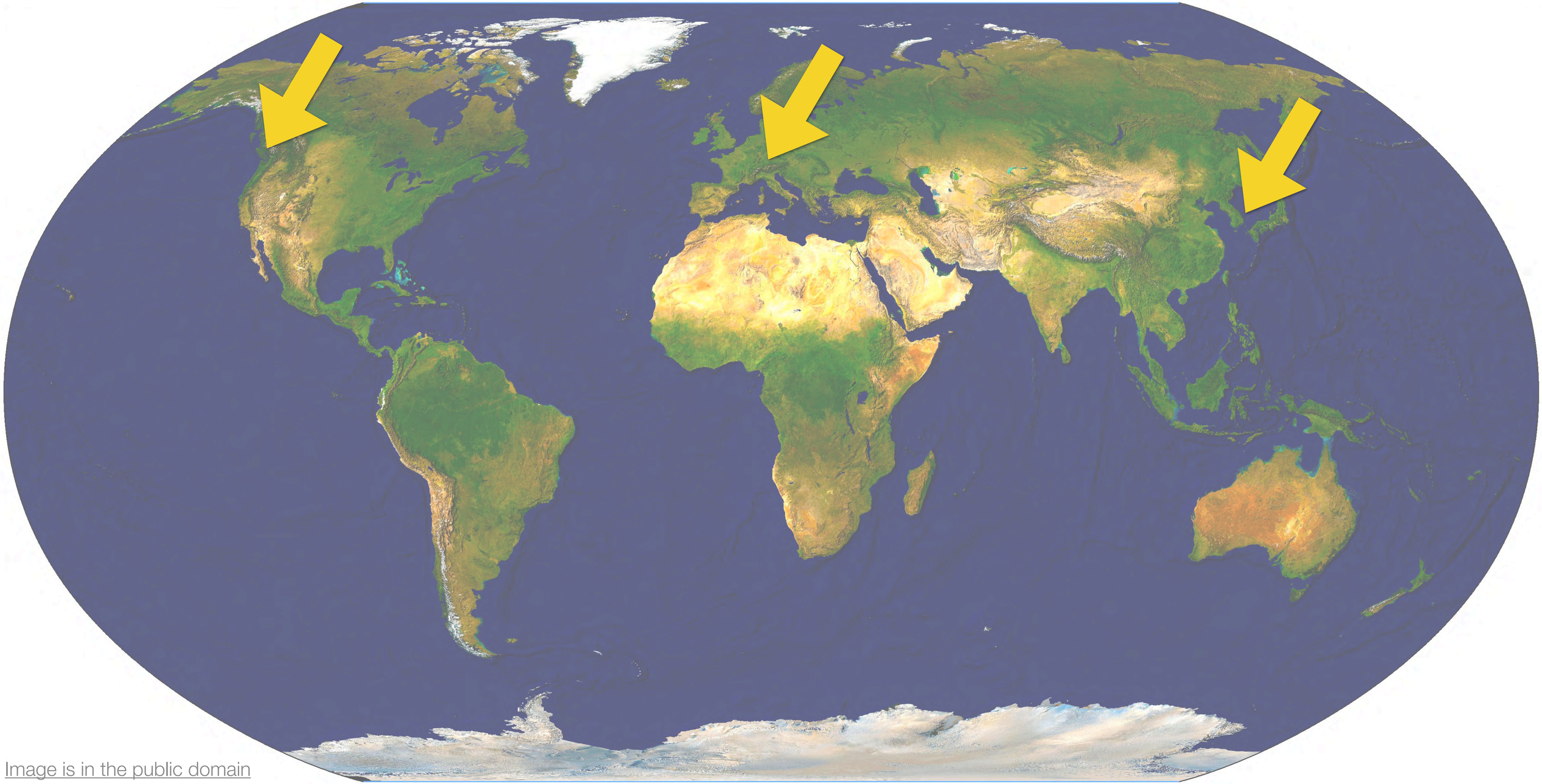

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

EPFL

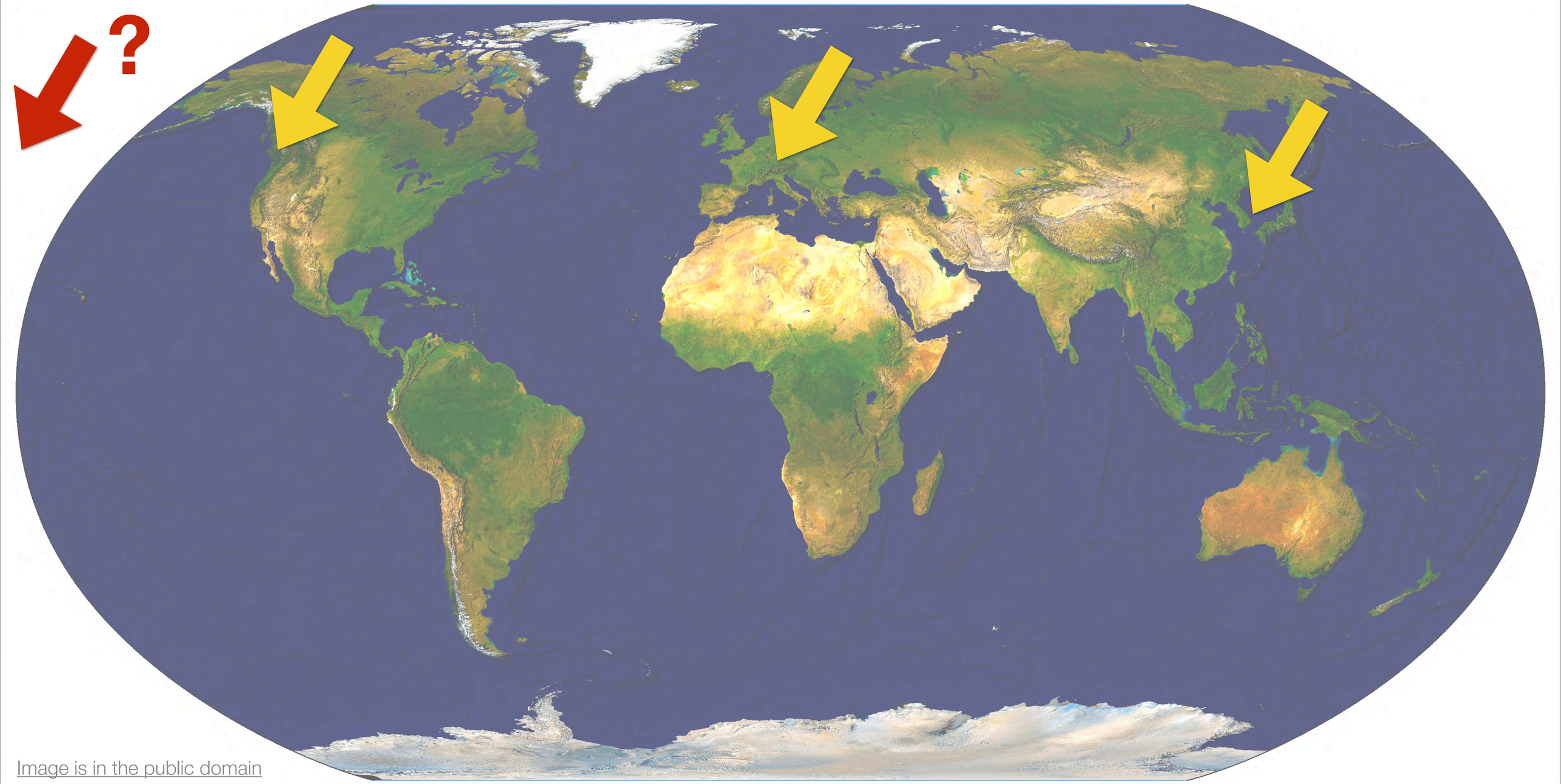
**PhD**
2007–2014


Seoul National University

# About **me ...**



# About **me ...**



# Course **logistics**

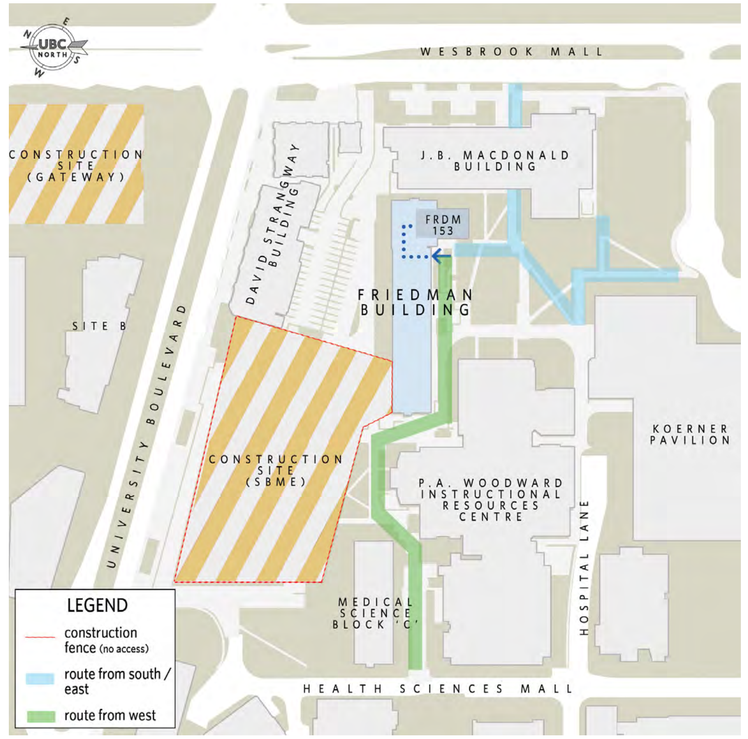
**Times:** Mon, Wed 3:30-5:00pm

**Locations:** Friedman (FRDM), Room 153


**Instructor:** Kwang Moo **YI**

**E-mail:** kmyi@cs.ubc.ca

**Office:** ICICS 115

# Course **logistics**

**Times:** Mon, Wed 3:30-5:00pm

**Locations:** Friedman (FRDM), Room 153


**Instructor:** Kwang Moo **YI**

**E-mail:** kmyi@cs.ubc.ca

**Office:** ICICS 115


## Teaching Assistants

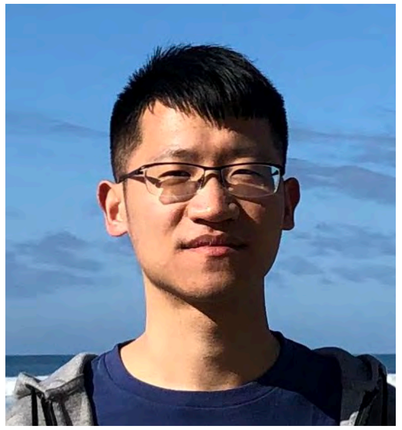

Fred Xie

ztxie@cs.ubc.ca

Ramin Nakhli

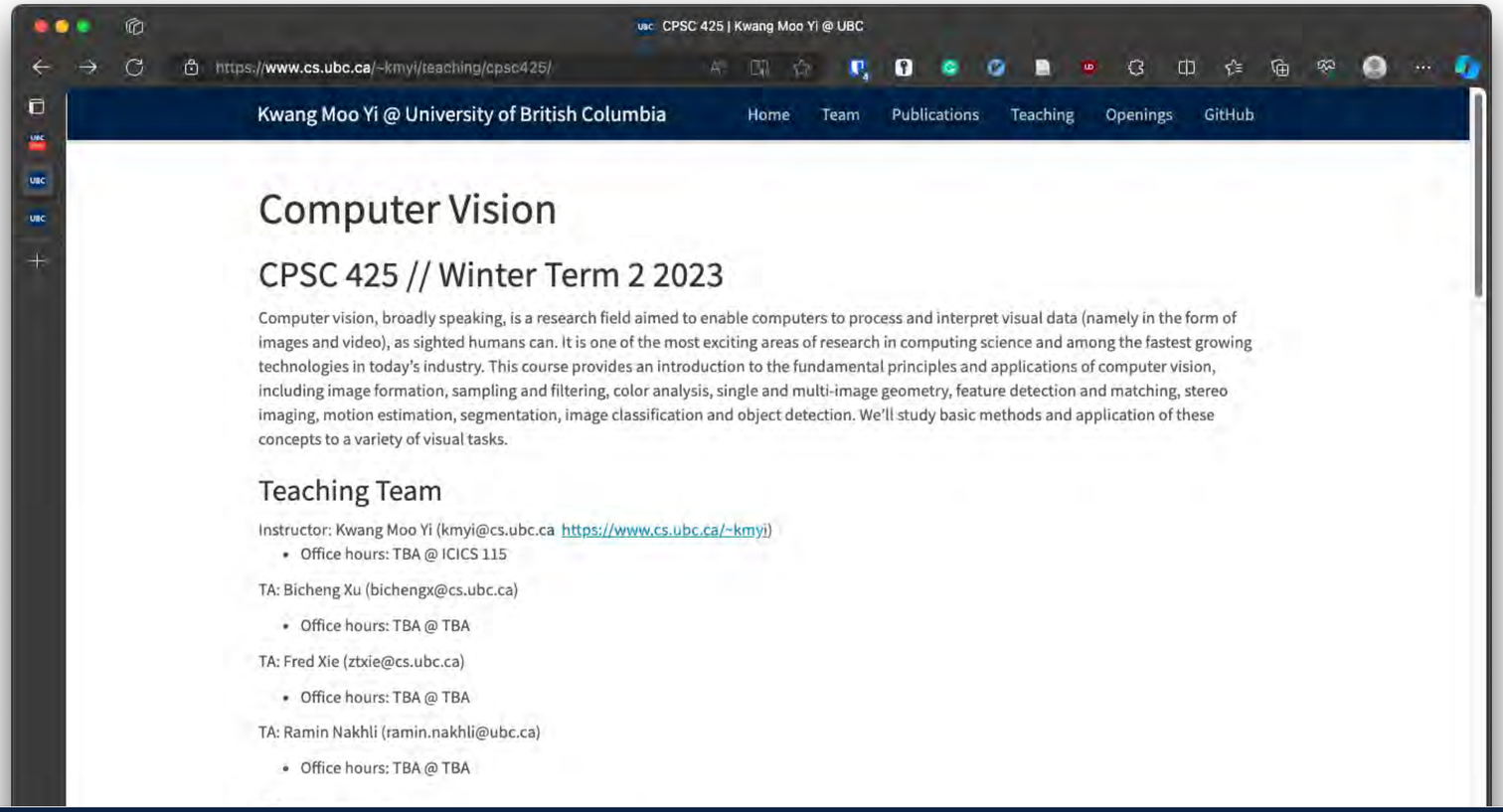
ramin.nakhli@ubc.ca

Bicheng Xu



bichengx@cs.ubc.ca

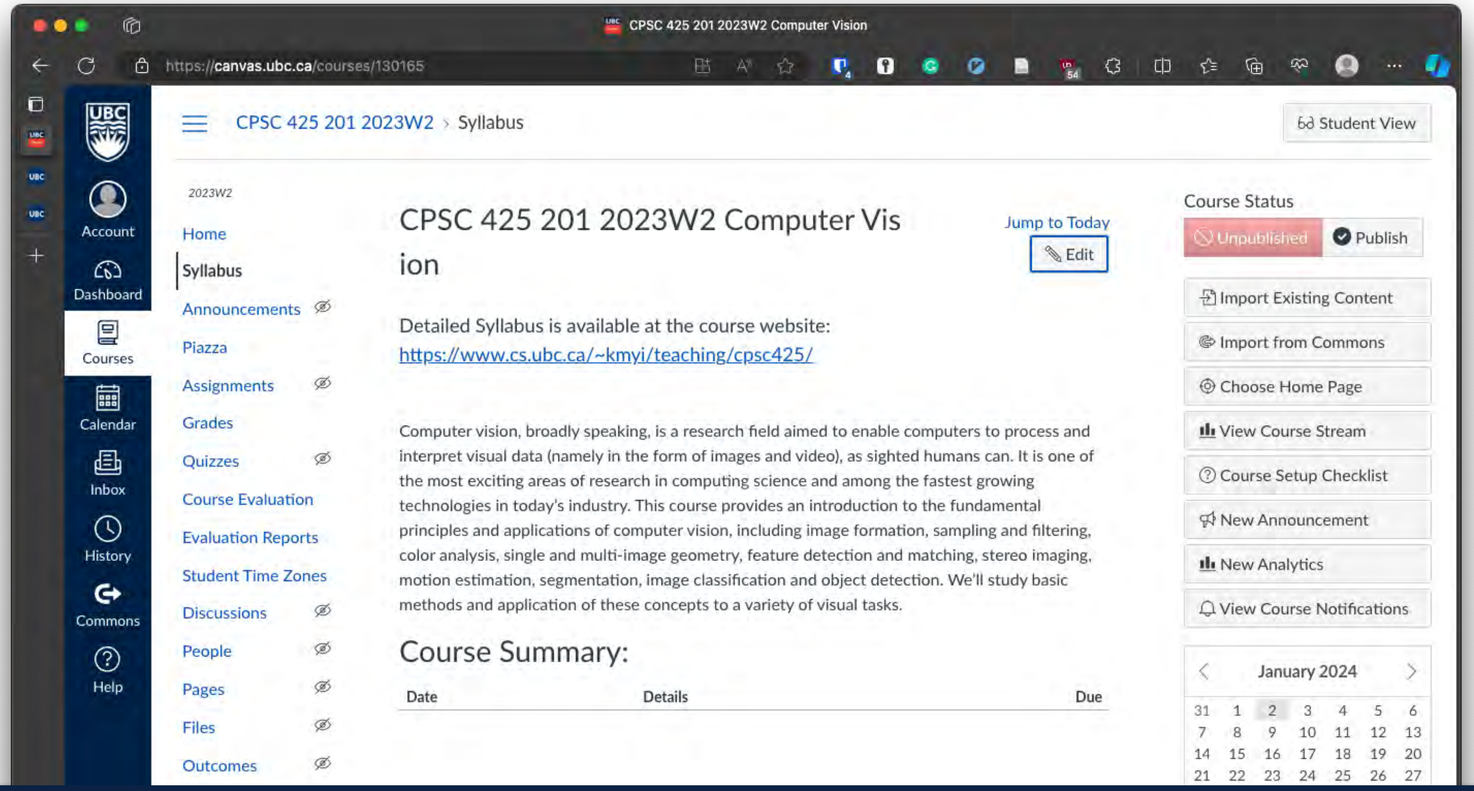
# Course Webpage




- Schedule, Assignments
- Lecture Slides and Notes
- Course Information (public)

https://www.cs.ubc.ca/~kmyi/teaching/cpsc425

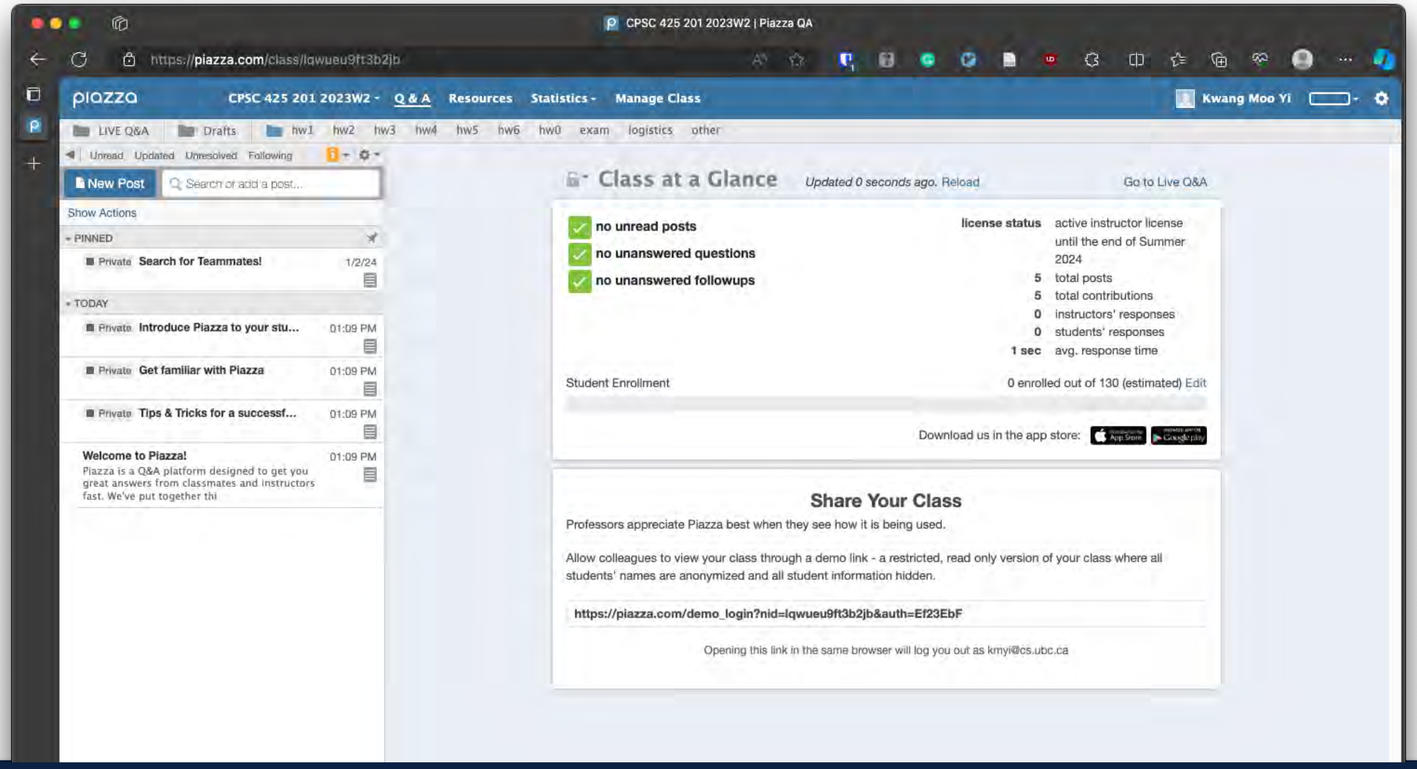
# Canvas




- Assignment hand-in
- Course Information (private)
- Gradescope linke (assignments)
- Piazza link

https://canvas.ubc.ca/courses/130165

# Piazza




- Discussions and Q+A
- Confused? Likely someone else has the same question as you!
- Lectures, Technical Issues, Assignments …
- Instructor/TA will answer only between **9am—6pm, weekdays**

Link in Canvas and the course website

# Office Hours

Starts next week (Week of Jan 15th)

**Instructor:** Kwang Moo **YI**

Fri. (ICICS/CS 115)
1 — 2 pm

## Teaching Assistants

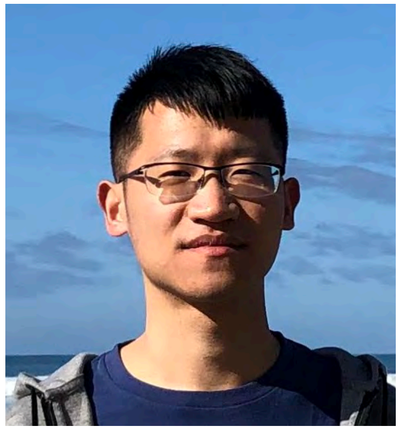
Fred Xie

Mon. (Room TBA)
5 — 6 pm

Ramin Nakhli

Tues. (Room TBA)
5 — 6 pm

Bicheng Xu



Wed. (Room TBA)
5 — 6 pm

See Course website for Links and Locations
(announced next week)

# What is **Computer Vision**?


Image Credit: https://www.deviantart.com/infinitecreations/art/BioMech-Eye-168367549

# What is **Computer Vision**?

Compute vision, broadly speaking, is a research field aimed to enable computers to **process and interpret visual data**, as sighted humans can.

**Image** (or video)

**Sensing** Device

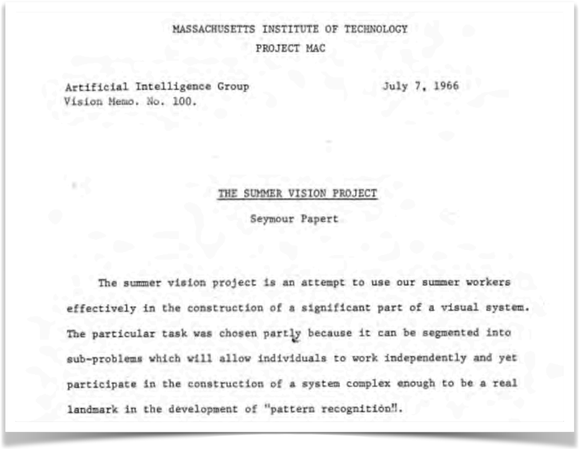
**Interpreting** Device

**Image Credit:** https://www.flickr.com/photos/flamephoenix1991/8376271918

**Interpretation**

blue sky,
trees,
fountains,
UBC, …

# **Computer vision** … the beginning …



MASSACHUSETTS INSTITUTE OF TECHNOLOGY
PROJECT MAC

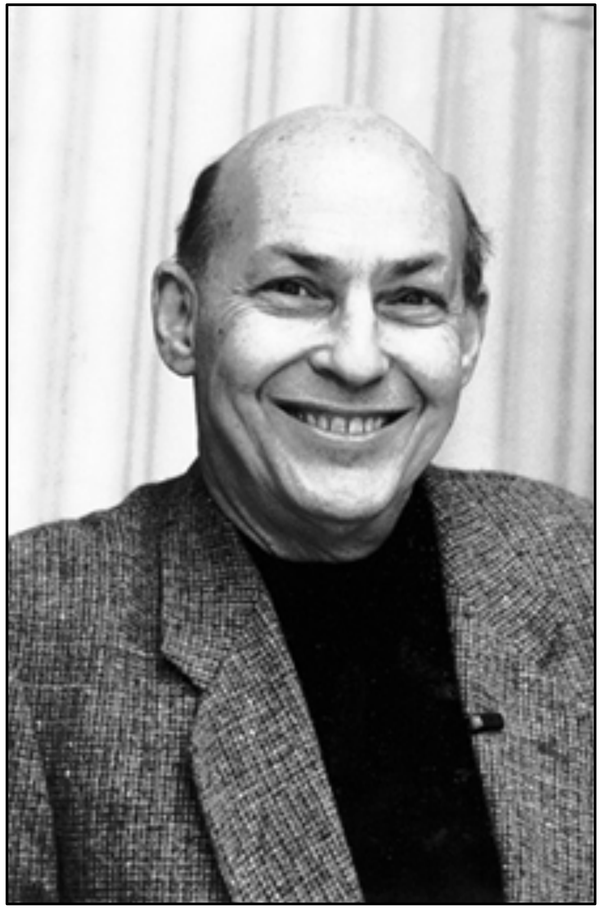
Artificial Intelligence Group
Vision Memo. No. 100.

July 7, 1966

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".



**The Summer Vision Project**

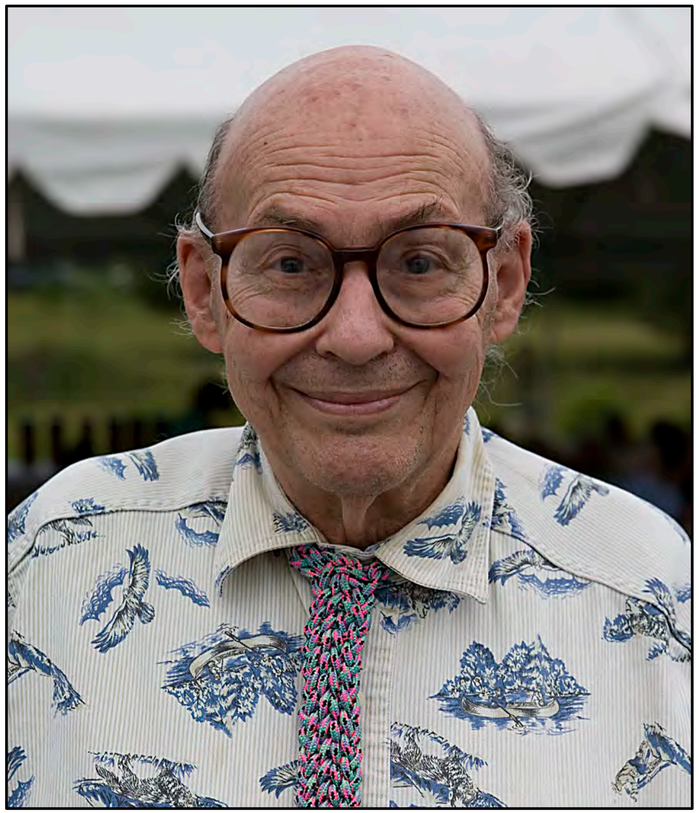
"spend the summer linking a camera to a computer and getting the computer to describe what it saw"

- Marvin Minsky (1966), MIT
  Turing Award (1969)

… >50 years later

**Slide Credit**: Devi Parikh (GA Tech)

# **Computer vision** … the beginning …



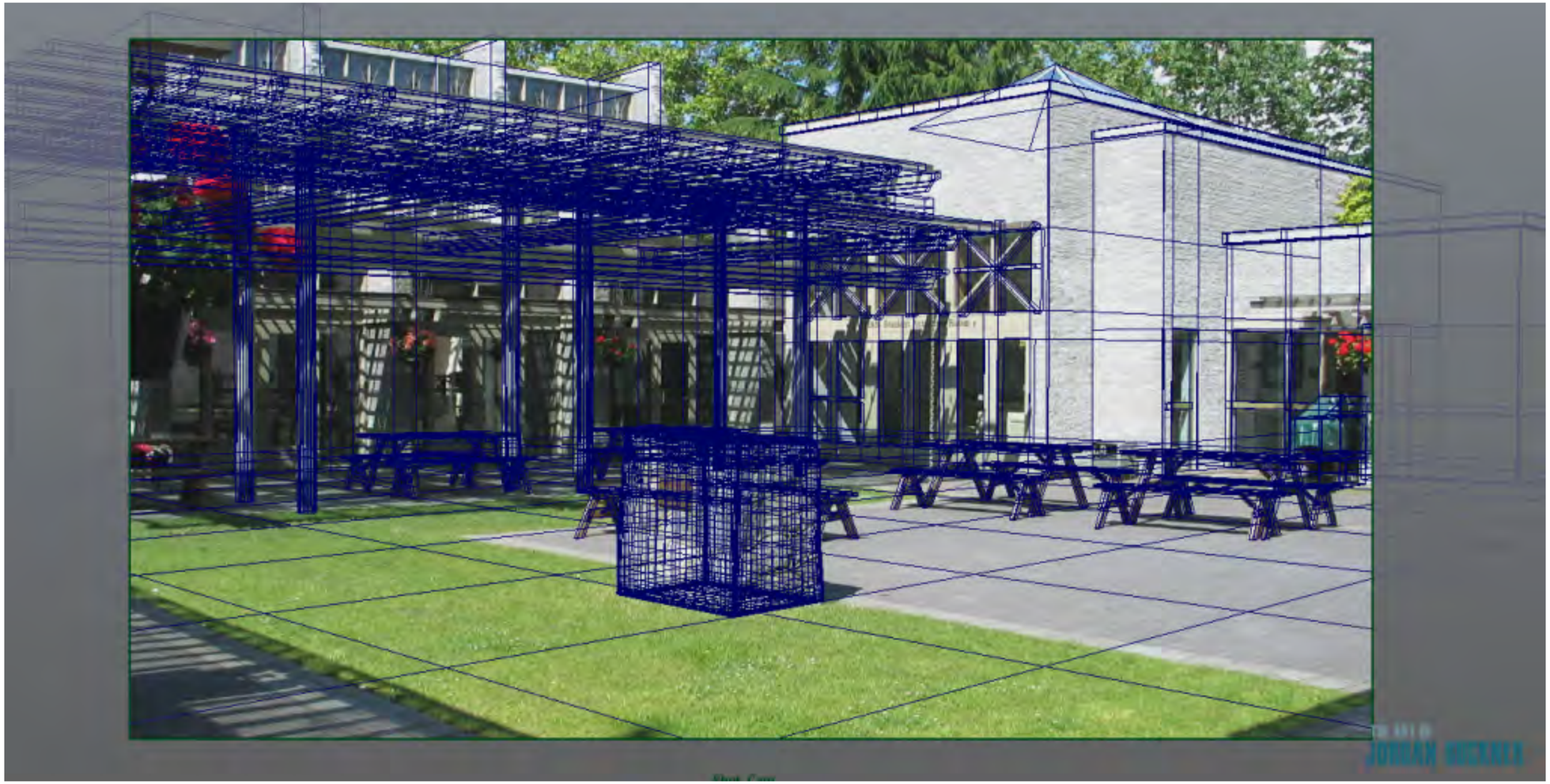
Gerald Sussman, MIT

"You'll notice that **Sussman** never worked in vision again!" – Berthold Horn

**Slide Credit**: Devi Parikh (GA Tech)

# Definitions of Computer Vision #1

**“Inverse Computer Graphics”**



[ J. Buckner ]

# Definitions of Computer Vision #1

**“Inverse Computer Graphics”**

Graphics

Vision

# Definitions of Computer Vision #2

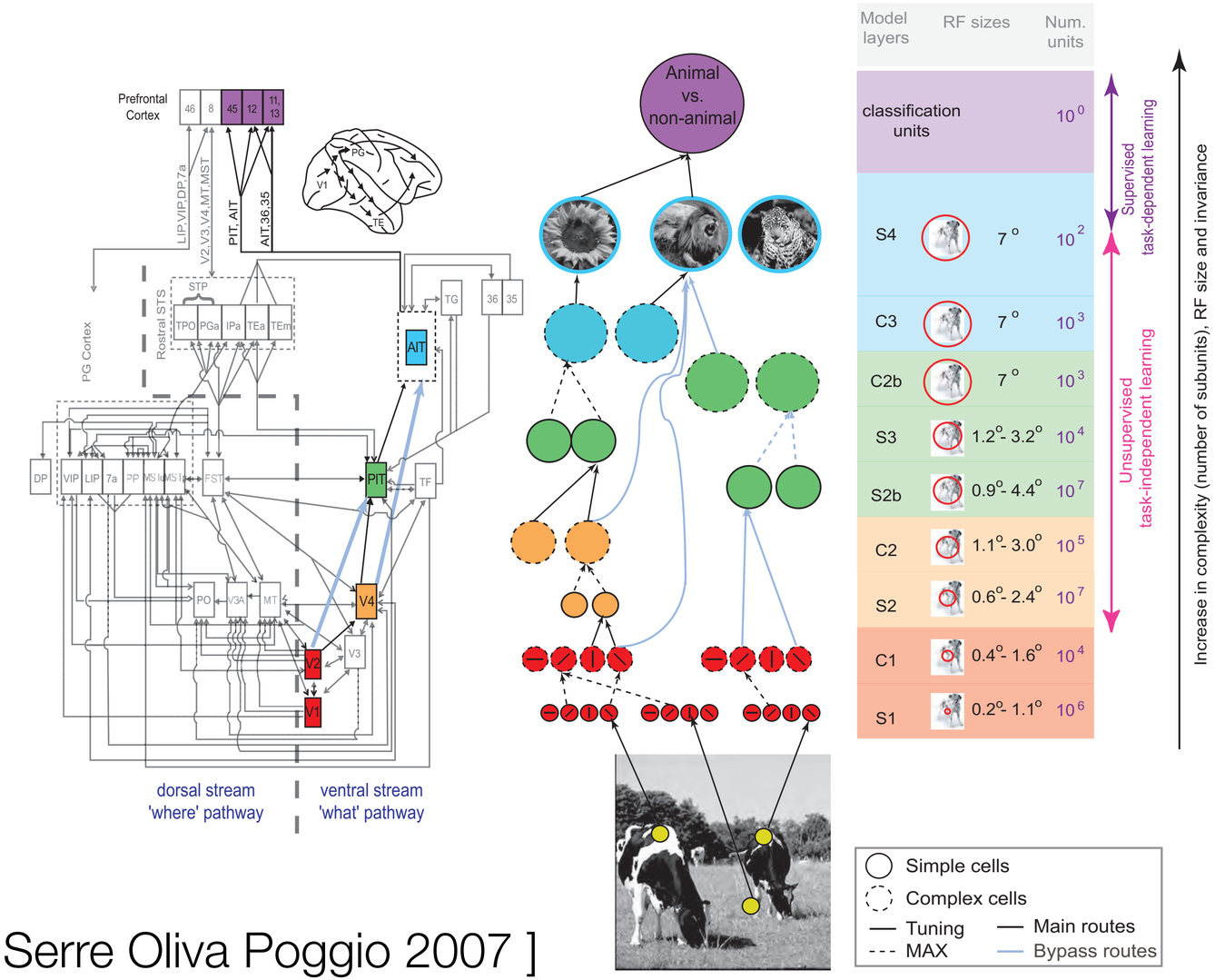
**“Replicate Human Vision”**

=


=

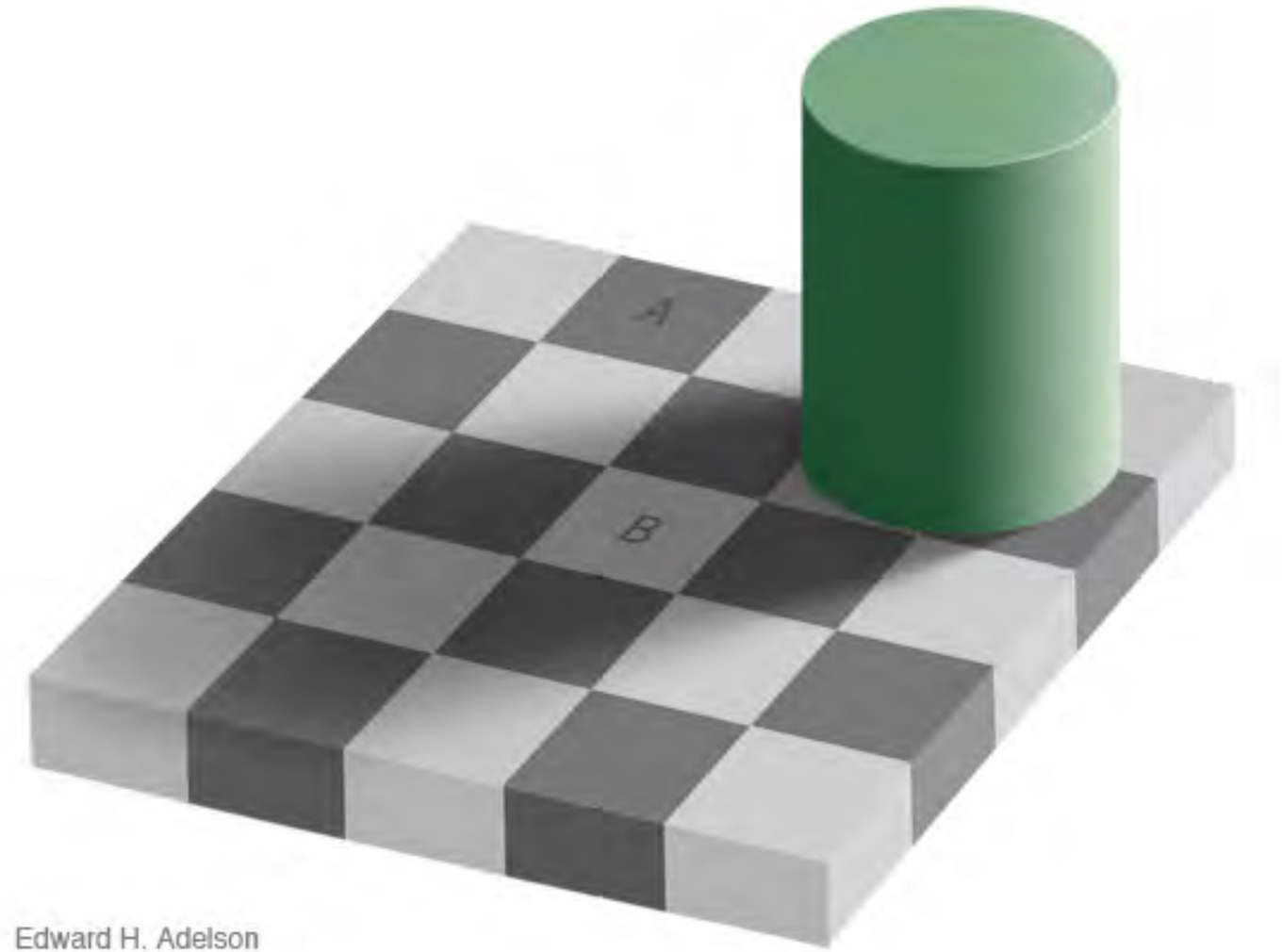
# Definitions of Computer Vision #2

## “Replicate Human Vision”



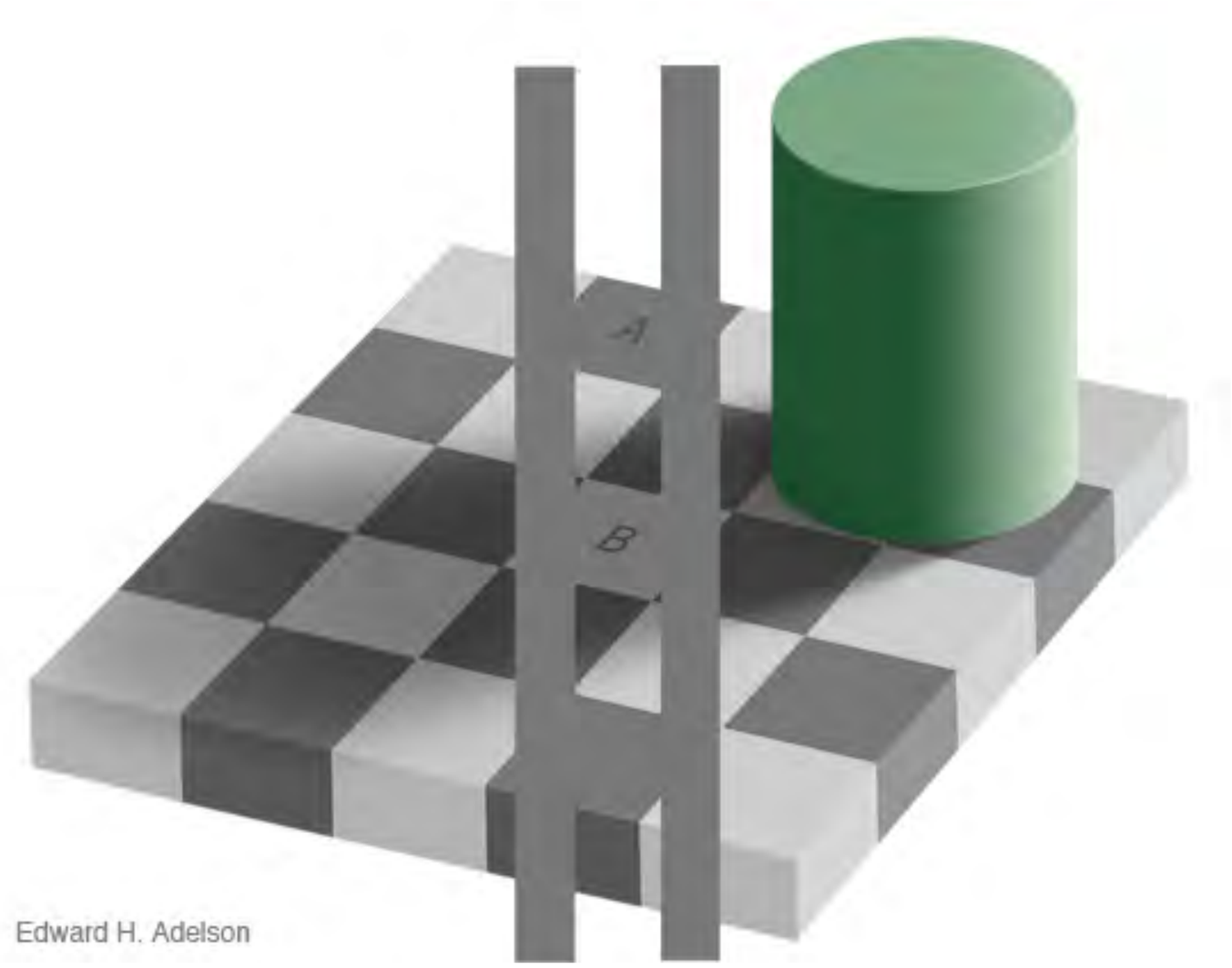

[ Serre Oliva Poggio 2007 ]

# Can computers **match (or beat)** human vision?




Edward H. Adelson

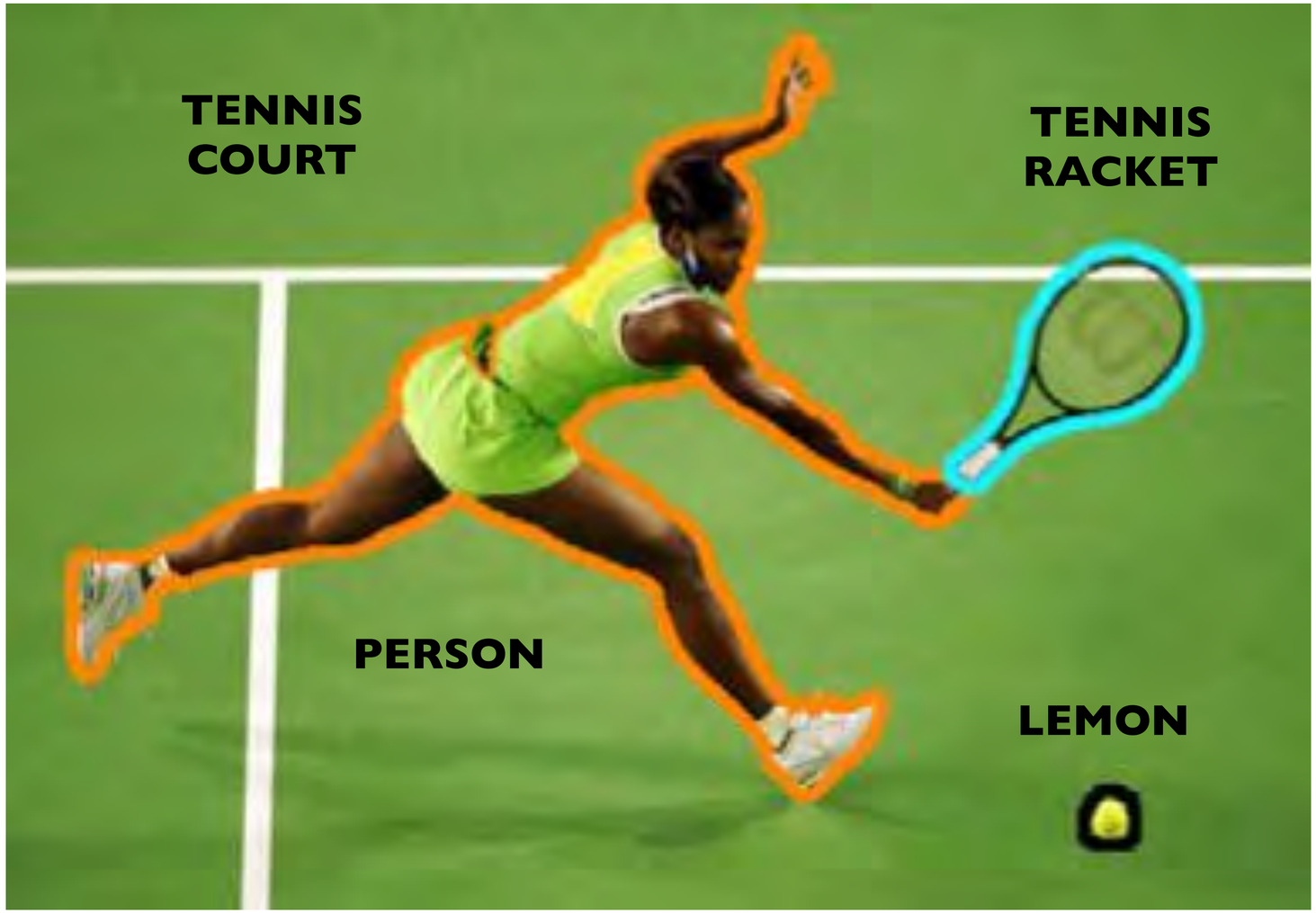
# Can computers **match (or beat)** human vision?




Edward H. Adelson

# Definitions of Computer Vision #3

**“Image/Video Understanding”**




[ Rabinovich, Galleguillos, Wiewiora, Belongie 2007]

# What do **you** see?

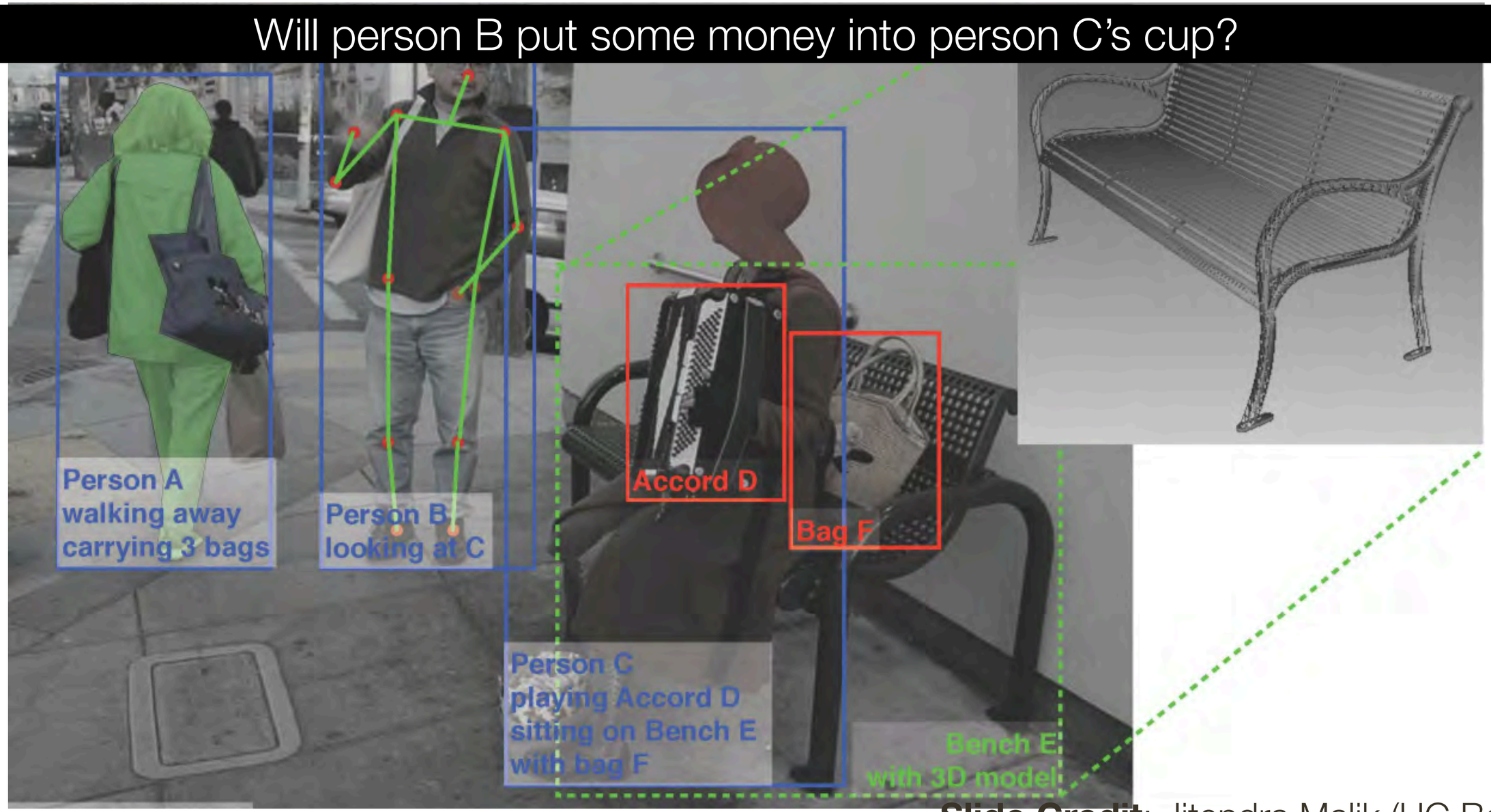
**Slide Credit**: Jitendra Malik (UC Berkeley)

# What we would like **computer to infer**?


**Slide Credit**: Jitendra Malik (UC Berkeley)

# What we would like **computer to infer**?

Will person B put some money into person C's cup?




**Slide Credit**: Jitendra Malik (UC Berkeley)

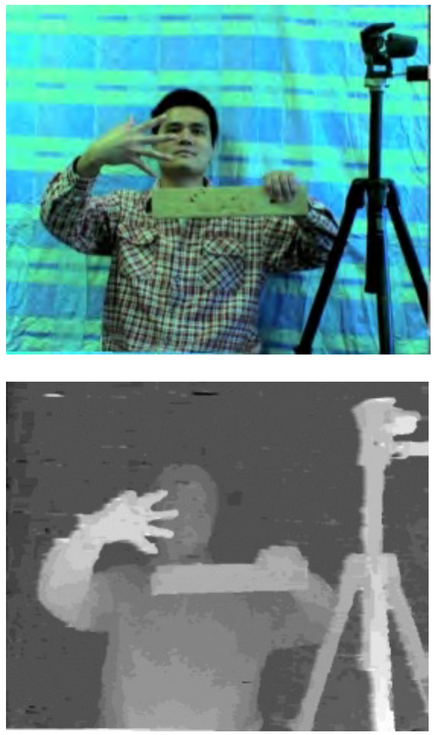
# Computer **Vision Problems**

1. Computing properties of the 3D world from visual data (***measurement***)

**Slide Credit**: Kristen Grauman (UT Austin)

# 1. Vision for **Measurement**

**Real-time stereo**



Wang et al.

**Structure from motion**

Snavely et al.

**Tracking**

Demirdjian et al.

**Slide Credit**: Kristen Grauman (UT Austin)

# Computer **Vision Problems**

1. Computing properties of the 3D world from visual data (***measurement***)

**Ill-posed problem:** real world is much more complex than what we can measure in images: 3D -> 2D

It is (literally) impossible to invert the image formation process

**Slide Credit**: Kristen Grauman (UT Austin)

# Computer **Vision Problems**

1. Computing properties of the 3D world from visual data (***measurement***)

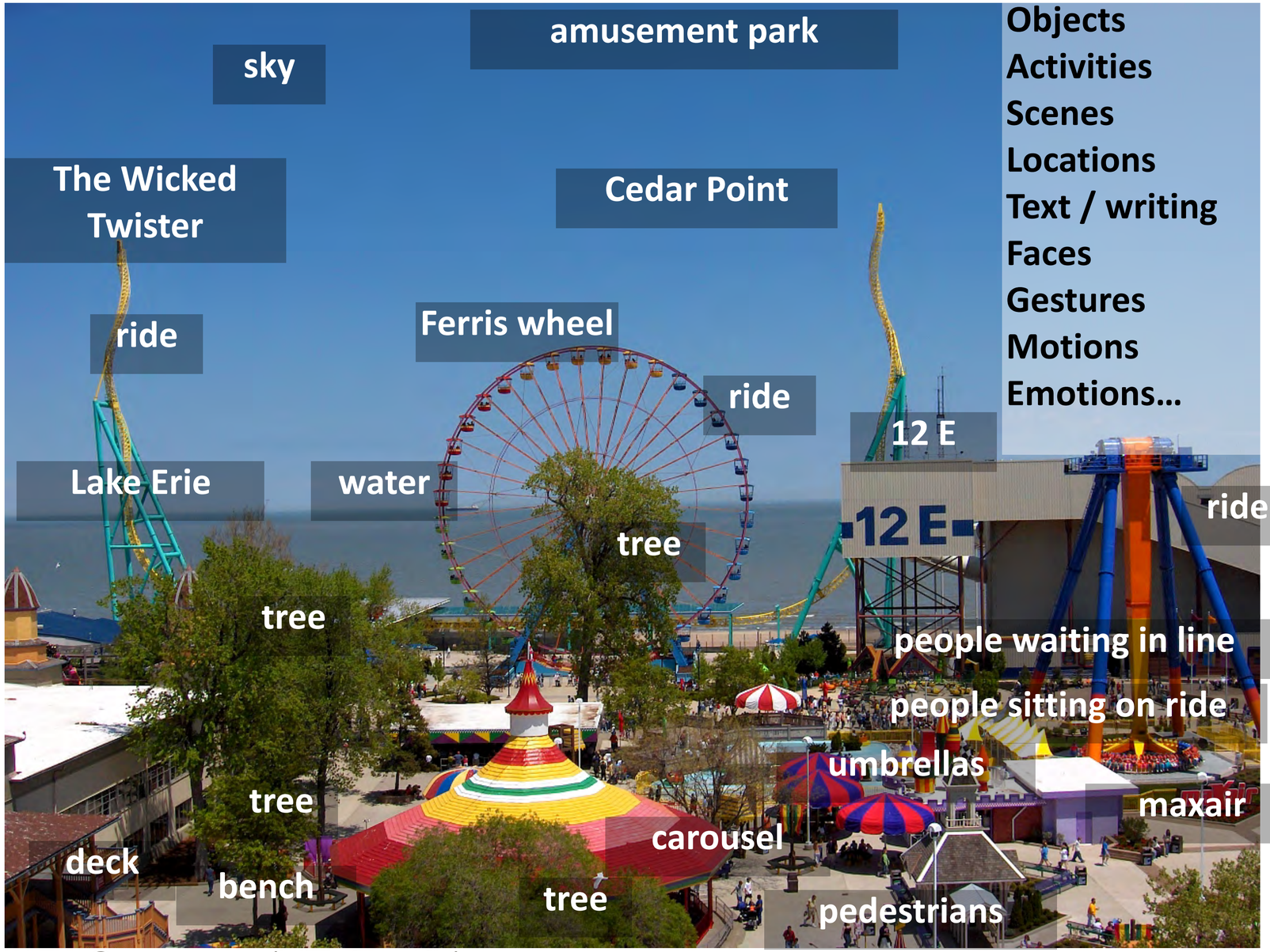
2. Algorithms and representations to allow a machine to recognize objects, people, scenes, and activities (***perception and interpretation***)

**Slide Credit**: Kristen Grauman (UT Austin)

# 2. Vision for **Perception and Interpretation**


**Slide Credit**: Kristen Grauman (UT Austin)

# 2. Vision for **Perception and Interpretation**




**Slide Credit**: Kristen Grauman (UT Austin)

# Computer **Vision Problems**

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***)

It is computationally intensive / expensive

**Slide Credit**: Kristen Grauman (UT Austin)

# 2. Vision for **Perception and Interpretation**

~ 55% of **cerebral cortex** in humans (13 billion neurons) are devoted to vision

more human brain devoted to vision than anything else

# Computer **Vision Problems**

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***)

It is computationally intensive / expensive

We do not (fully) understand the processing mechanisms involved

**Slide Credit**: Kristen Grauman (UT Austin)

# Computer **Vision Problems**

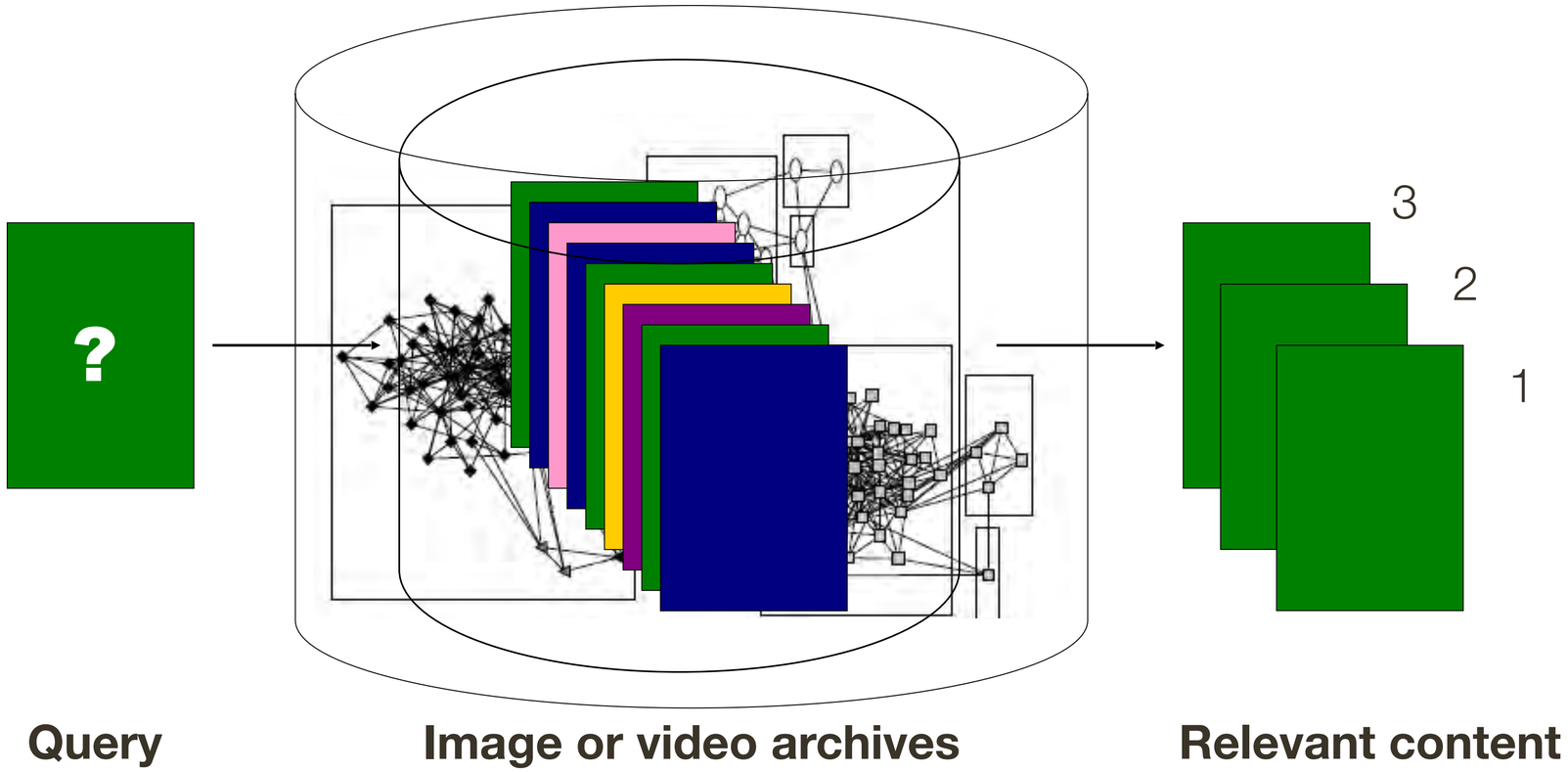
1. Computing properties of the 3D world from visual data (***measurement***)

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 (UT Austin)

# 3. **Search and Organization**




**Slide Credit**: Kristen Grauman (UT Austin)

# Computer **Vision Problems**

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***)

Scale is enormous, explosion of visual content

**Slide Credit**: Kristen Grauman (UT Austin)

# 3. **Search and Organization**

*from iStock by GettyImages

Snapchat

**31.7 Million**
/ hour

WhatsApp

**29.2 Million**
/ hour

Facebook

**14.6 Million**
/ hour

Instagram

**2.9 Million**
/ hour

Flickr

**0.2 Million**
/ hour

YouTube

**18K hours**
/ hour

*based on article by Kimberlee Morrison in Social Times (2015)

# Computer **Vision Problems**

1. Computing properties of the 3D world from visual data (***measurement***)

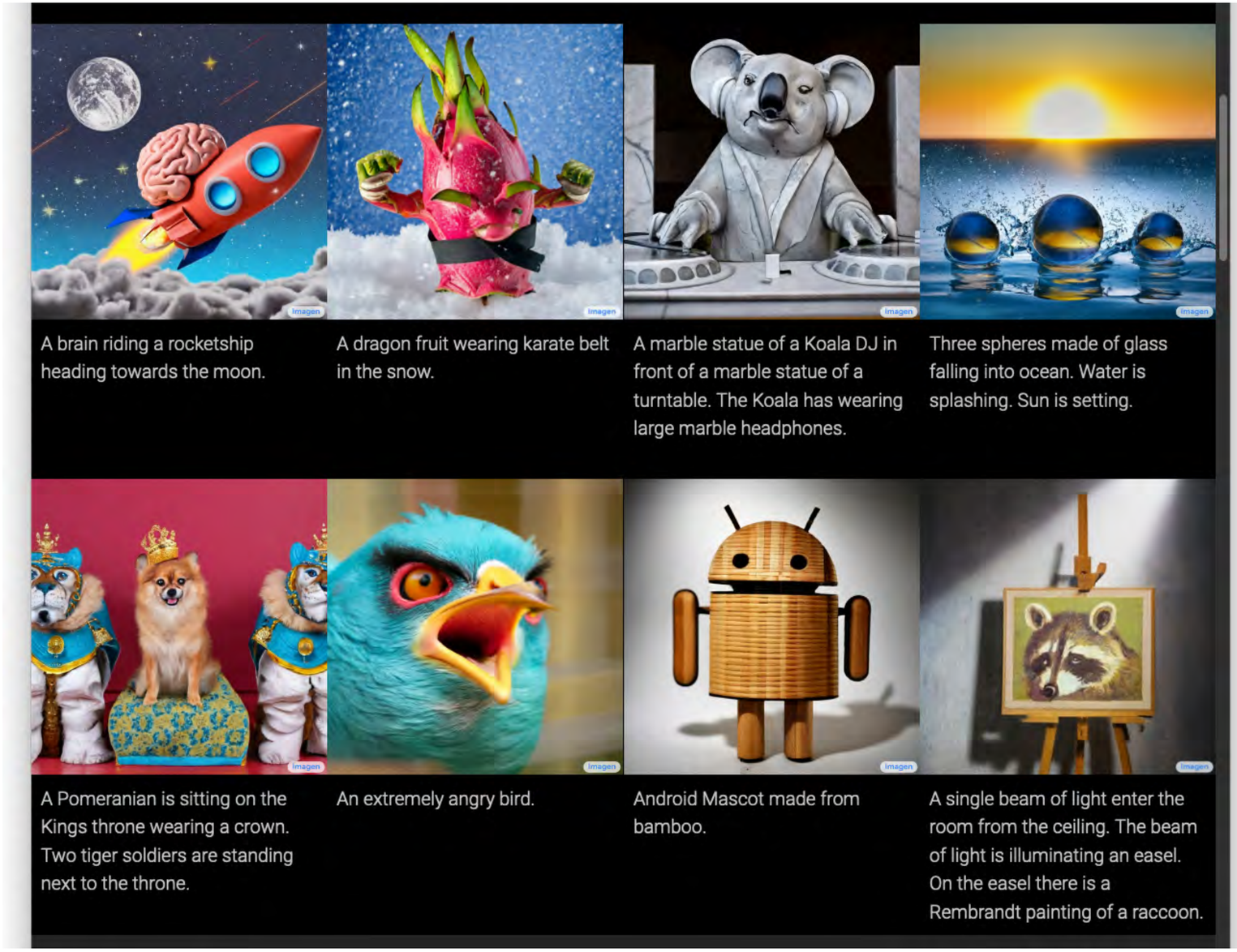
2. Algorithms and representations to allow a machine to recognize objects, people, scenes, and activities (***perception and interpretation***)

3. Algorithms to mine, search, and interact with visual data (***search and organization***)

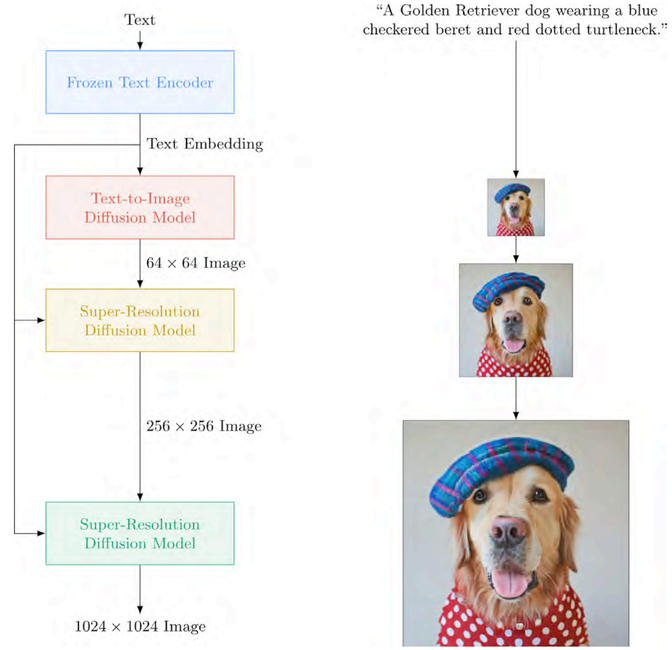
4. Algorithms for manipulation or creation of image or video content (***visual imagination***)

**Slide Credit**: Kristen Grauman (UT Austin)

# 4. Visual **Imagination**




- imagen.research.google
- Text to image generation
- Uses diffusion process, training using large dataset of text (web scale) and image-text (400M) pairs



# Computer **Vision Problems**

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***)

4. Algorithms for manipulation or creation of image or video content (***visual imagination***)

**Slide Credit**: Kristen Grauman (UT Austin)

# **Challenges:** Viewpoint invariance

Optional subtitle

**Michelangelo** 1475-1564

*slide credit Fei-Fei, Fergus & Torralba

# **Challenges:** Lighting

Optional subtitle

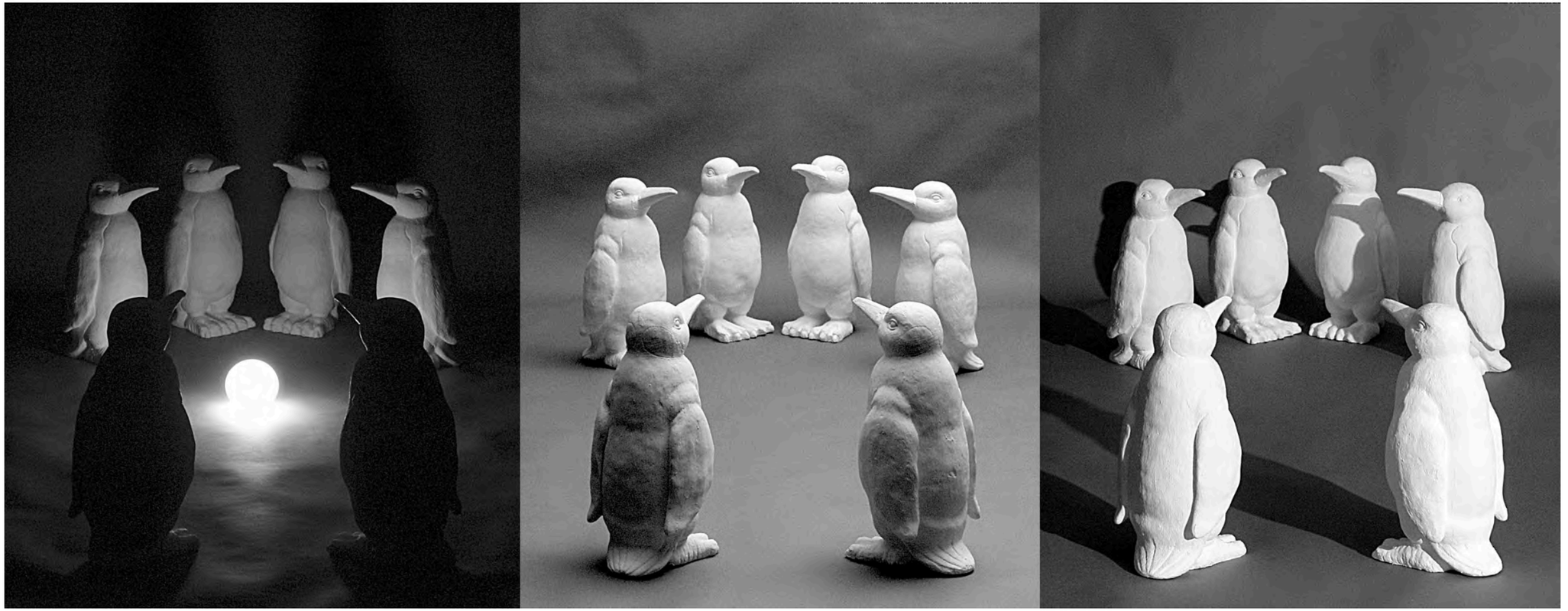


*image credit J. Koenderink

# **Challenges:** Scale

Optional subtitle

*slide credit Fei-Fei, Fergus & Torralba

# **Challenges:** Deformation

Optional subtitle

*image credit Peter Meer

# **Challenges:** Occlusions

Optional subtitle

**Rene Magritte** 1965

# **Challenges:** Background clutter

Optional subtitle

**Kilmeny Niland** 1995

# **Challenges:** Local ambiguity and context

Optional subtitle

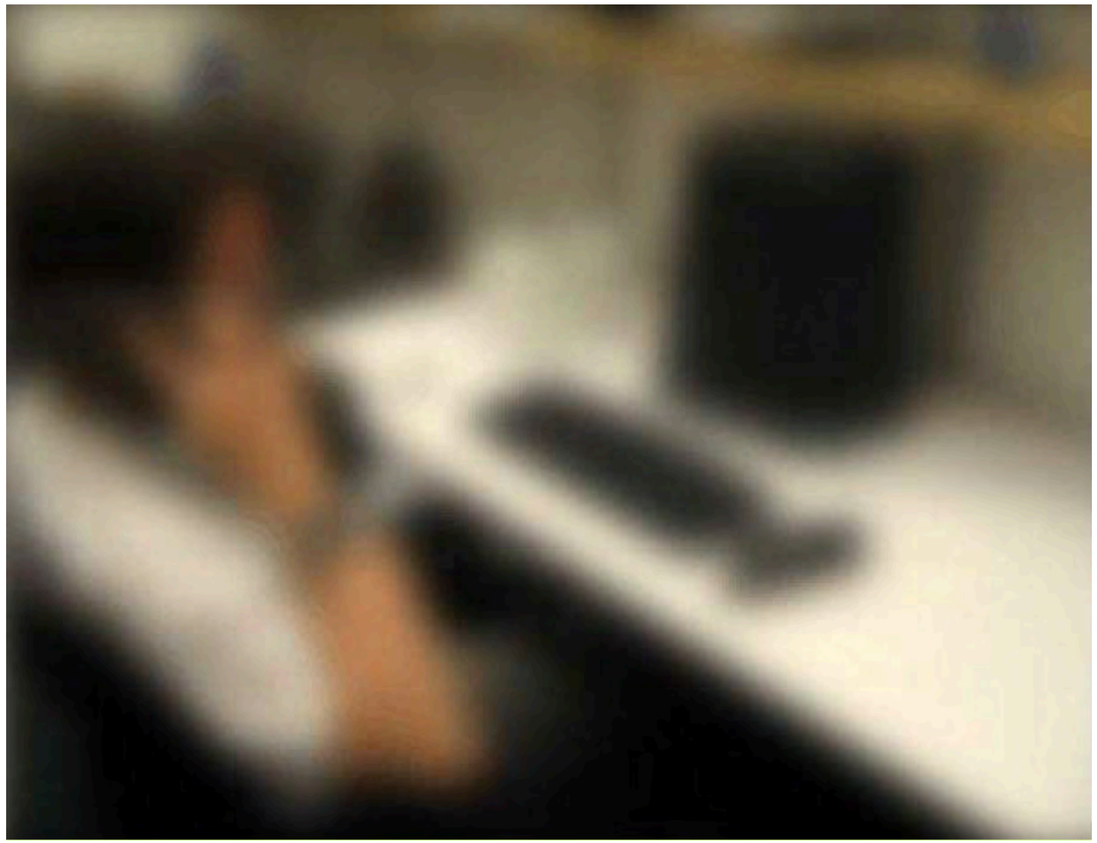


*image credit Fergus & Torralba

# **Challenges:** Local ambiguity and context

Optional subtitle

*image credit Fergus & Torralba

# **Challenges:** Motion

Optional subtitle

*image credit Peter Meer

# **Challenges:** Object inter-class variation

Optional subtitle

*slide credit Fei-Fei, Fergus & Torralba

# Computer Vision **Applications**

- Let’s see some examples of state-of-the-art and where it is used

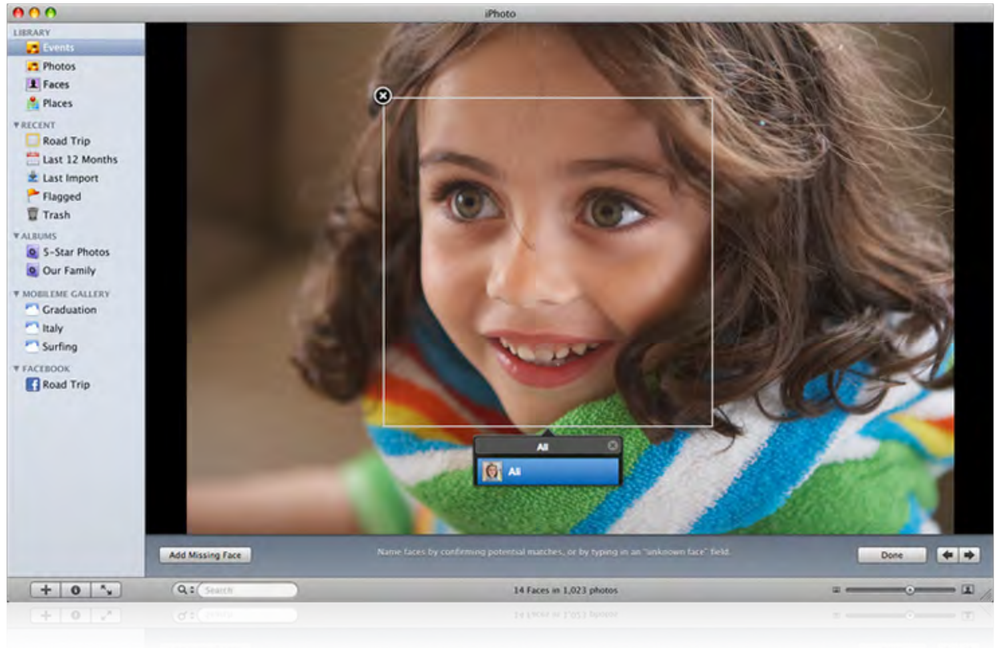
# Face Detection


[ Motorola ]

# Face **Recognition**


Facebook

Apple's iPhoto




http://www.apple.com/ilife/iphoto/

**Slide Credit**: Devi Parikh (GA Tech) and Fei-Fei Li (Stanford)

# Vision for **Biometrics**


Fingerprint scanners on many new laptops, other devices

## iPhone X Face ID


Face recognition systems are not part of widely used technologies

How it works and how to fool it:

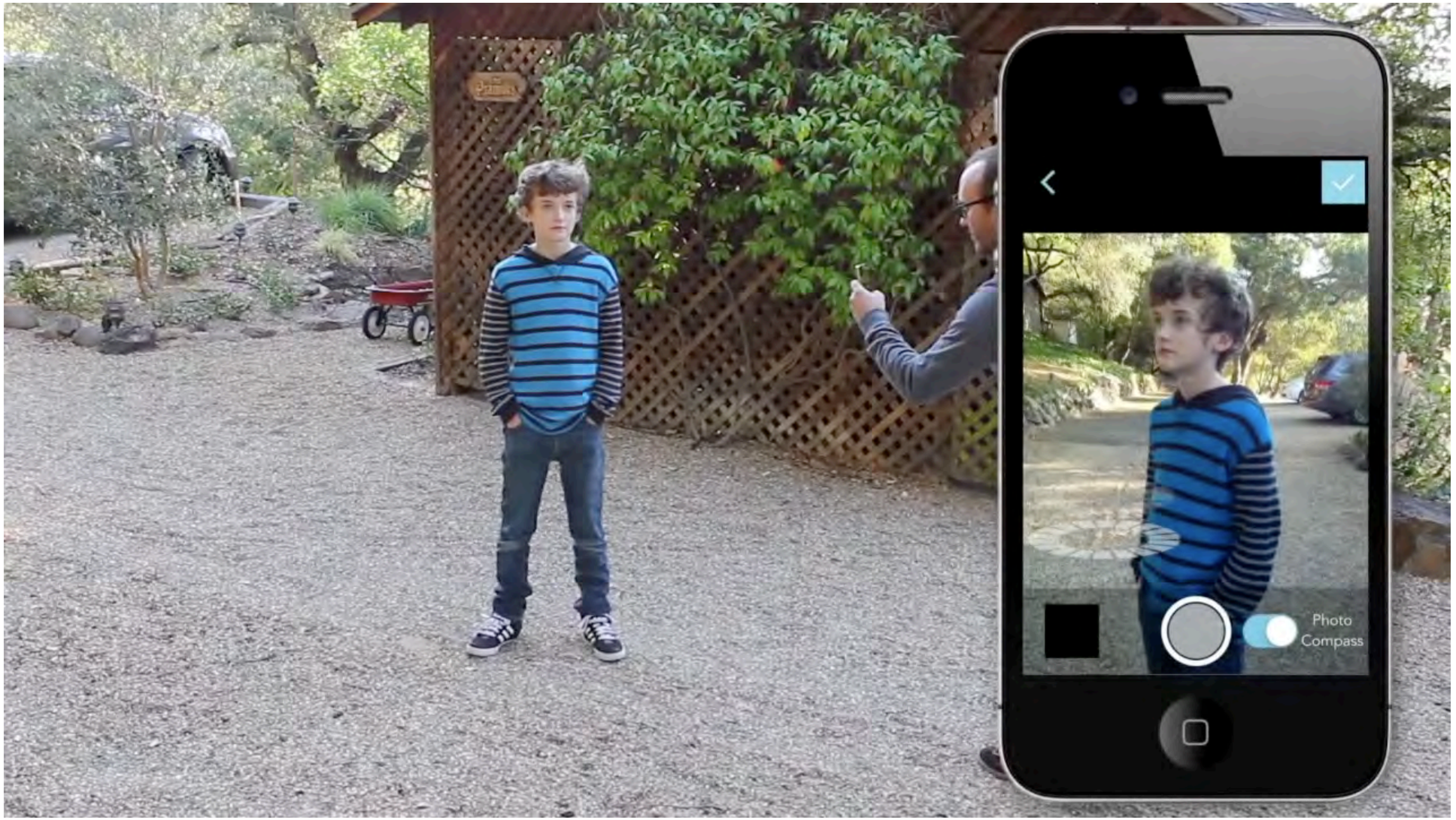
https://www.youtube.com/watch?v=FhbMLmsCax0

**Image Credit**: James Hays (GA Tech)

# Camera Tracking


[ Boujou — Vicon / OMG ]

# 3D Reconstruction

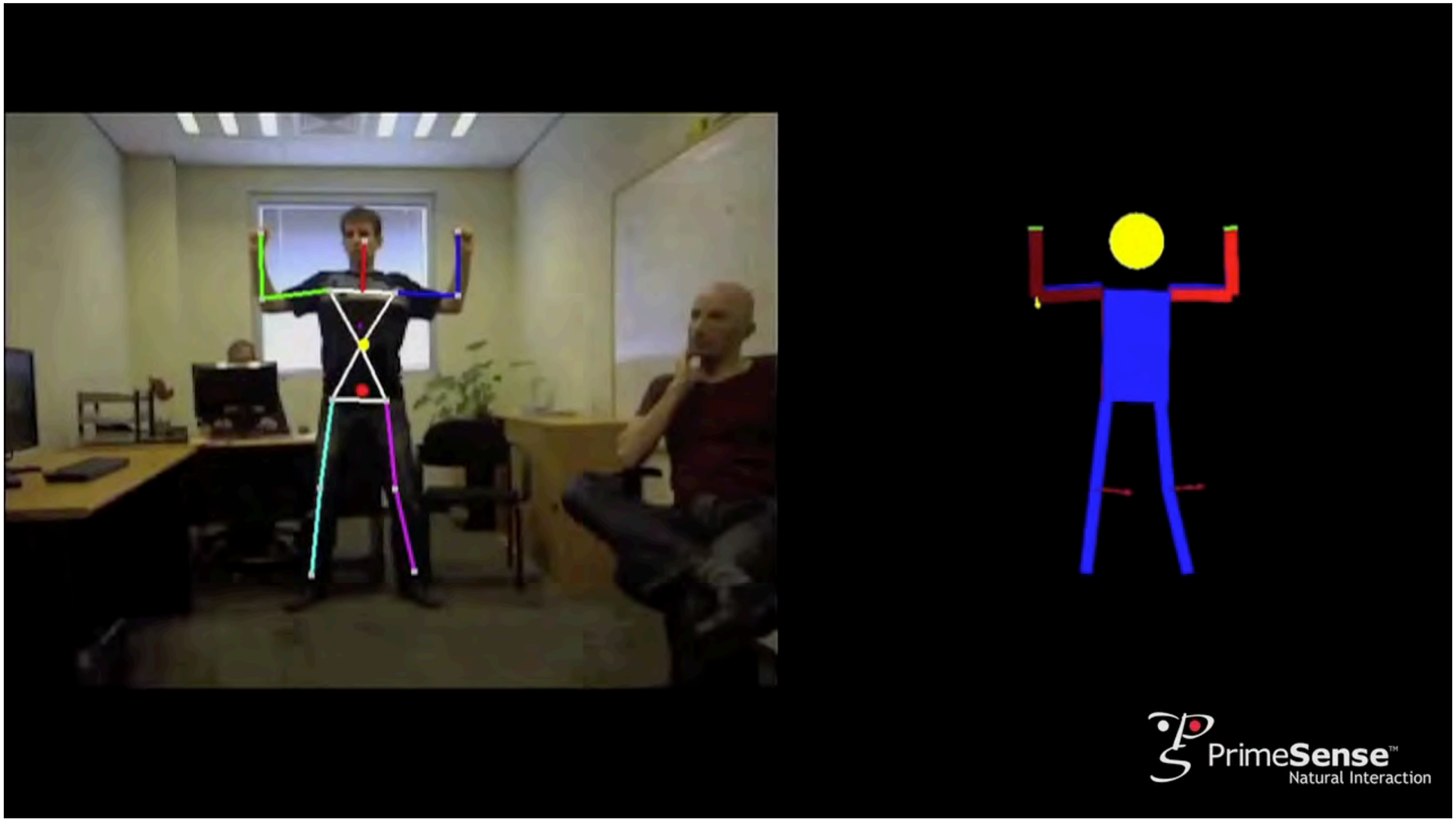



[ Autodesk 123D Catch ]

# Body Pose Tracking

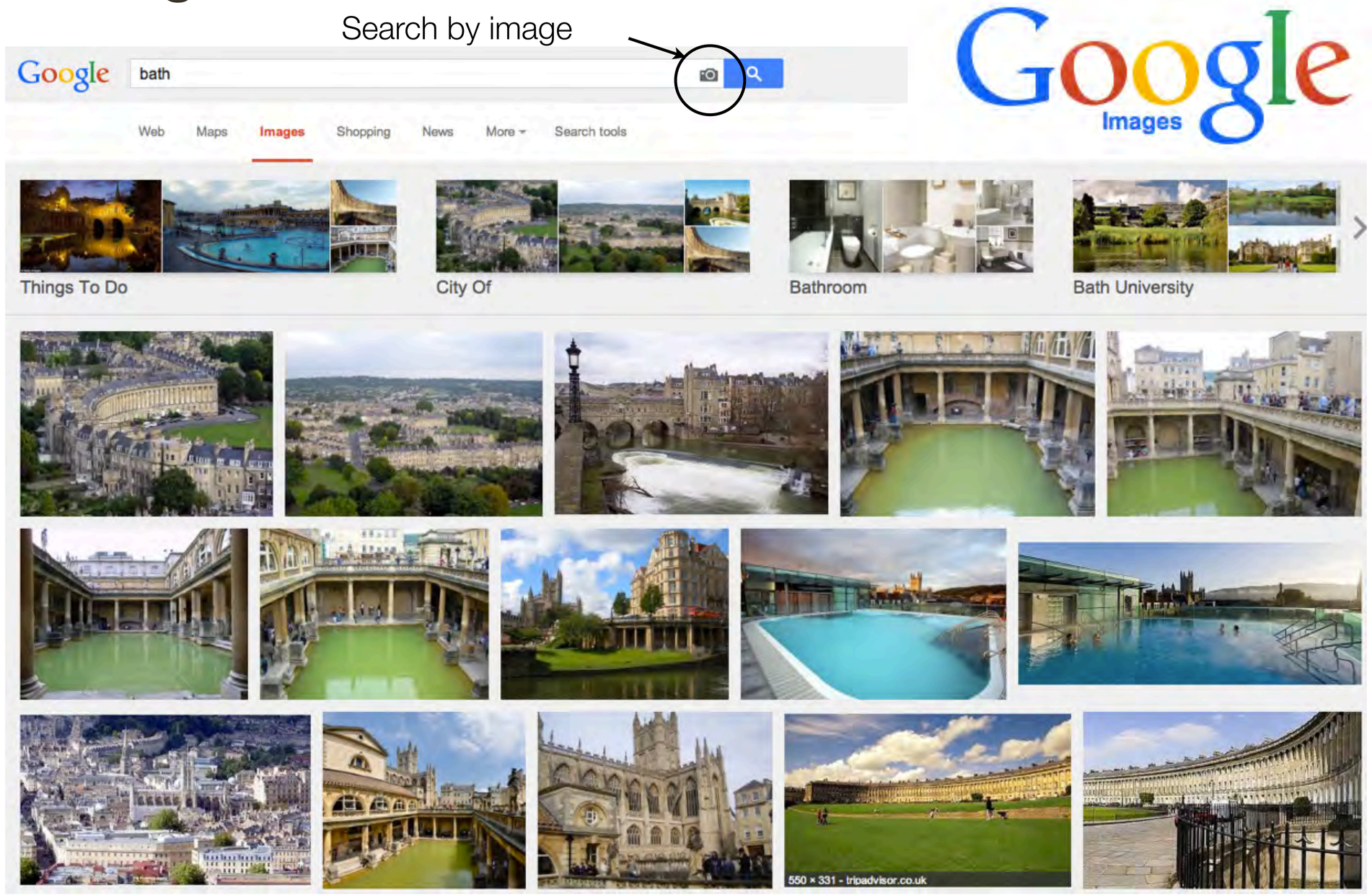
[ Microsoft Xbox Kinect ]

# Body Pose Tracking




[ PrimeSense ]

# Image Recognition and Search



# Self-Driving Cars


[ Google ]

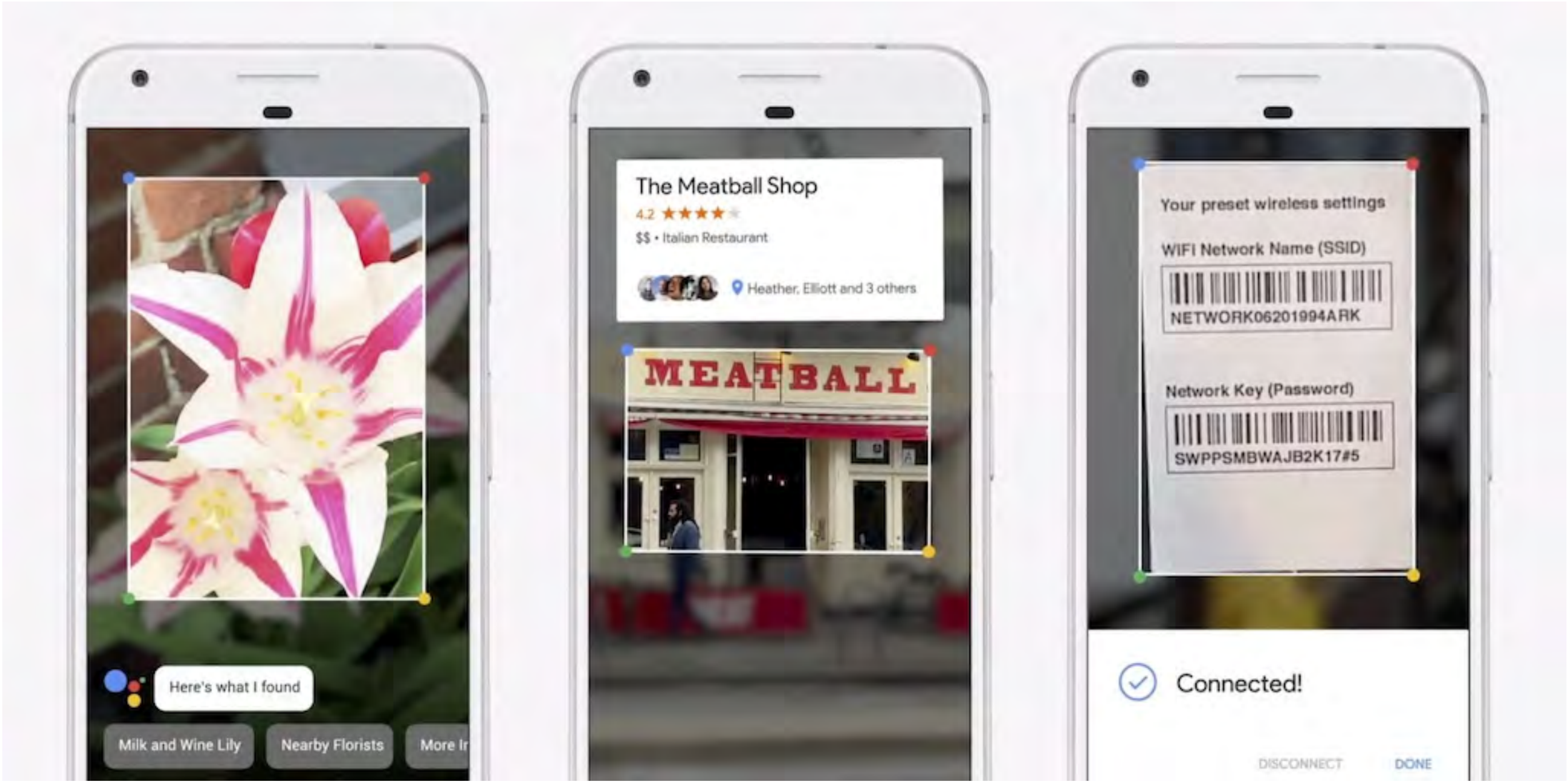
# Flying Vehicles

www.skydio.com

# AR / VR

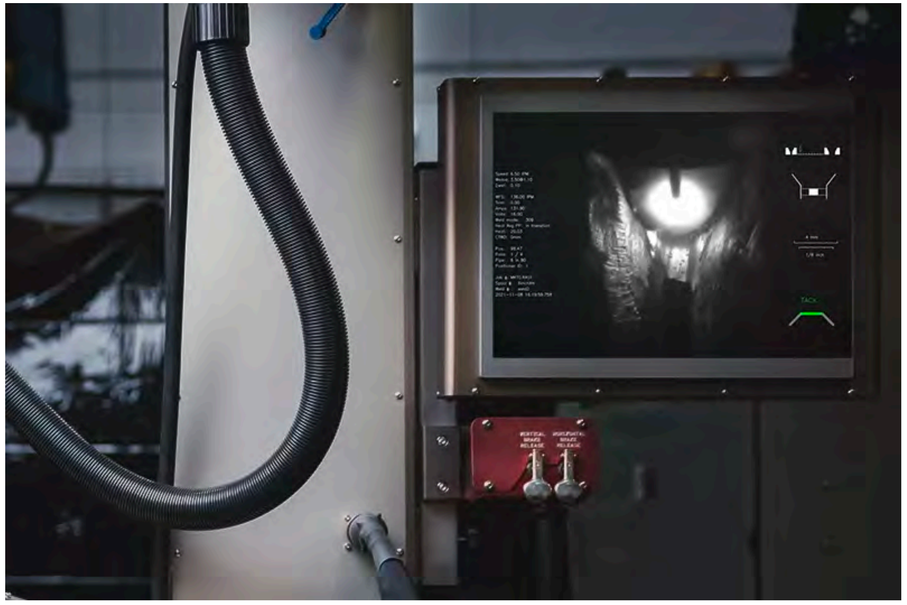
[ Microsoft HoloLens ]

# Mobile Apps




[ Google Lens ]

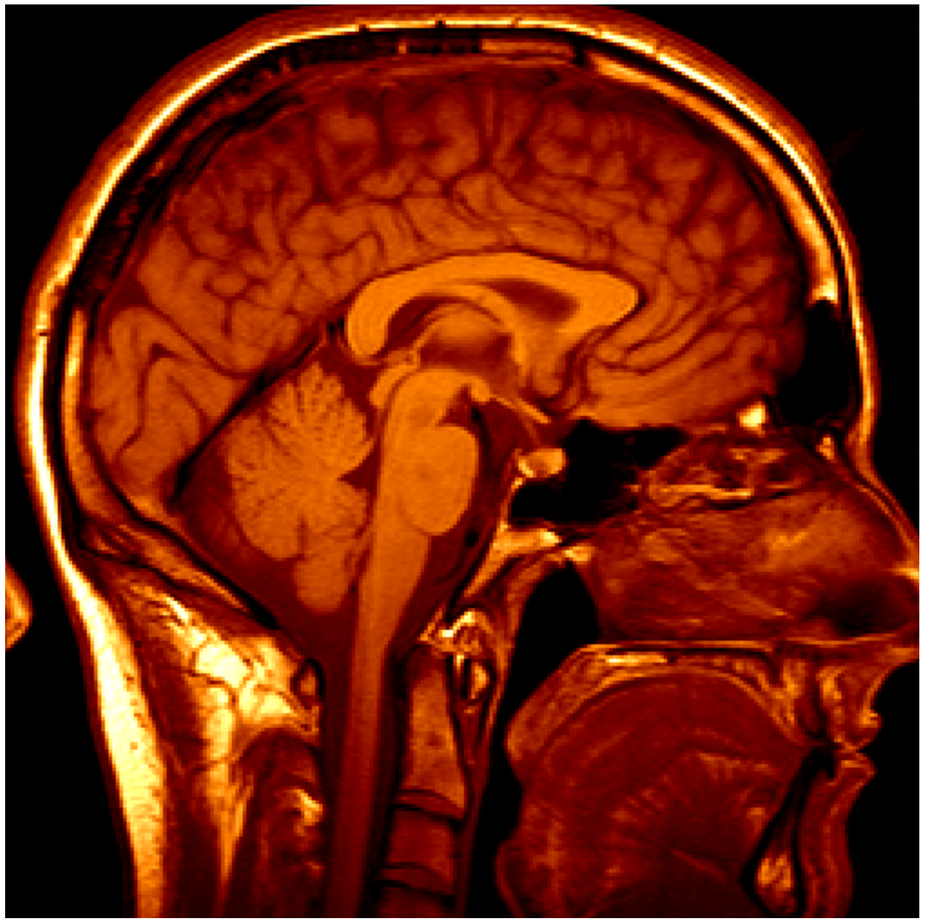
# Industrial




Machine Vision controlled welding robotics

NOVARC
TECHNOLOGIES

# Medicine



3D imaging
MRI, CT

Image guided surgery
Grimson et al., MIT

**Slide Credit**: James Hays (GA Tech)

# Art


[ Gatys, Ecker, Bethge 2015 ]

# Art

TEXT DESCRIPTION

An astronaut Teddy bears A bowl of soup

riding a horse lounging in a tropical resort in space playing basketball with cats in space

in a photorealistic style in the style of Andy Warhol as a pencil drawing

→

DALL·E 2

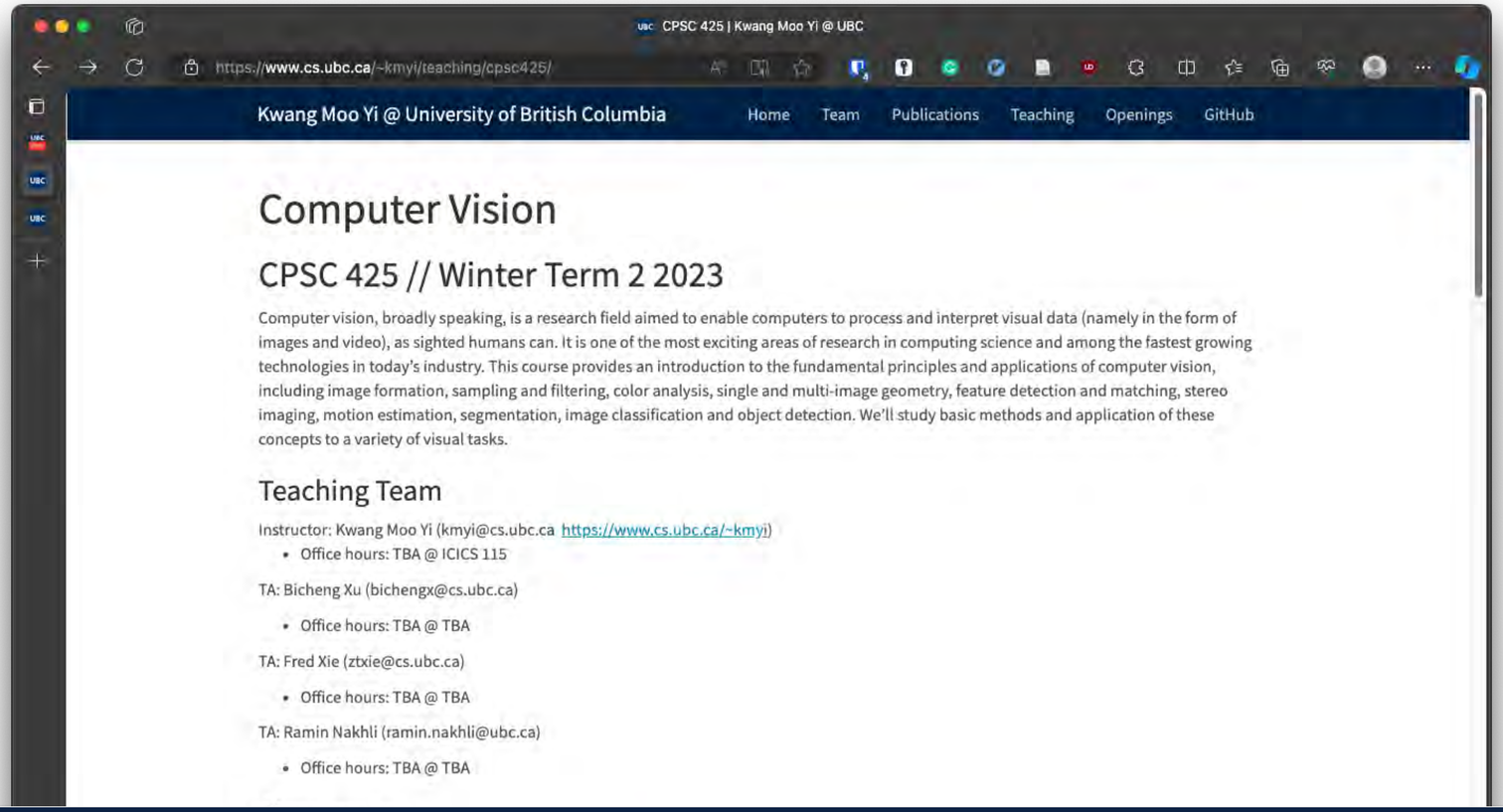
[ Dall-E v2 ]

# **Why** Study Computer Vision?

It is one of the **most exciting areas of research** in computer science

Among the **fastest growing technologies** in the industry today

# Course Schedule




- Schedule, Assignments
- Lecture Slides and Notes
- Course Information (public)

https://www.cs.ubc.ca/~kmyi/teaching/cpsc425

# **Topics** Covered

- Image Processing (Linear Filtering, Convolution)
- Filters as Templates
- Image Feature Detection (Edges & Corners)
- Texture & Colour
- Image Feature Description (SIFT)
- Model Fitting (RANSAC, The Hough Transform)
- Camera Models, Stereo Geometry
- Motion and Optical Flow
- Clustering and Image Segmentation
- Learning and Image Classification
- Deep Learning Introduction

# **Topics** Covered

– Image Processing (Linear Filtering, Convolution)
– Filters as Templates
– Image Feature Detection (Edges & Corners)
– Texture & Color
– Image Feature Description (SIFT)
– Model Fitting (RANSAC, The Hough Transform)
– Camera Models, Stereo Geometry
– Motion and Optical Flow
– Clustering and Image Segmentation
– Learning and Image Classification
– Deep Learning Introduction

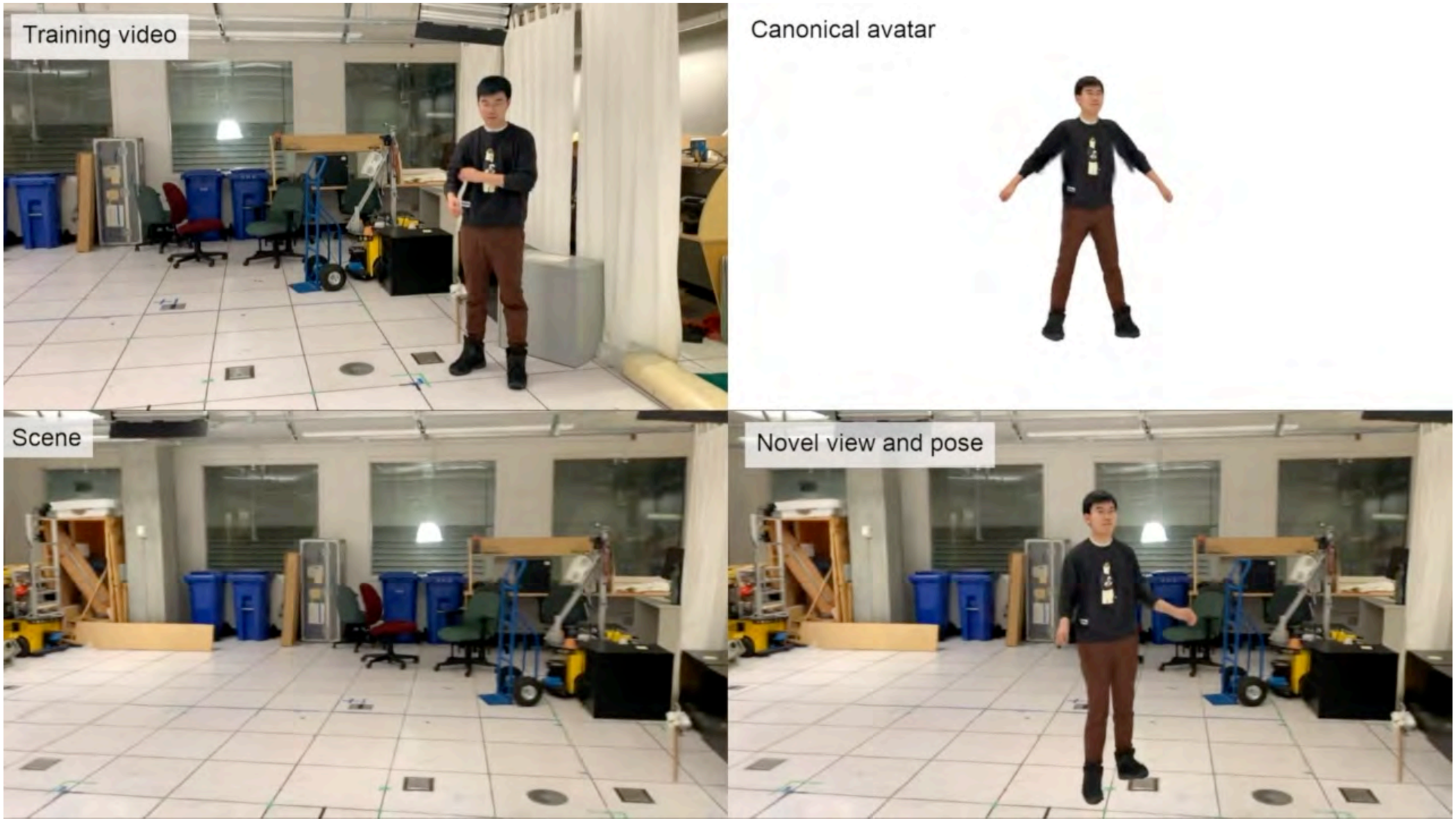
Why learn these?

Aren’t these old?

# A “NeRF” commercial (2023)

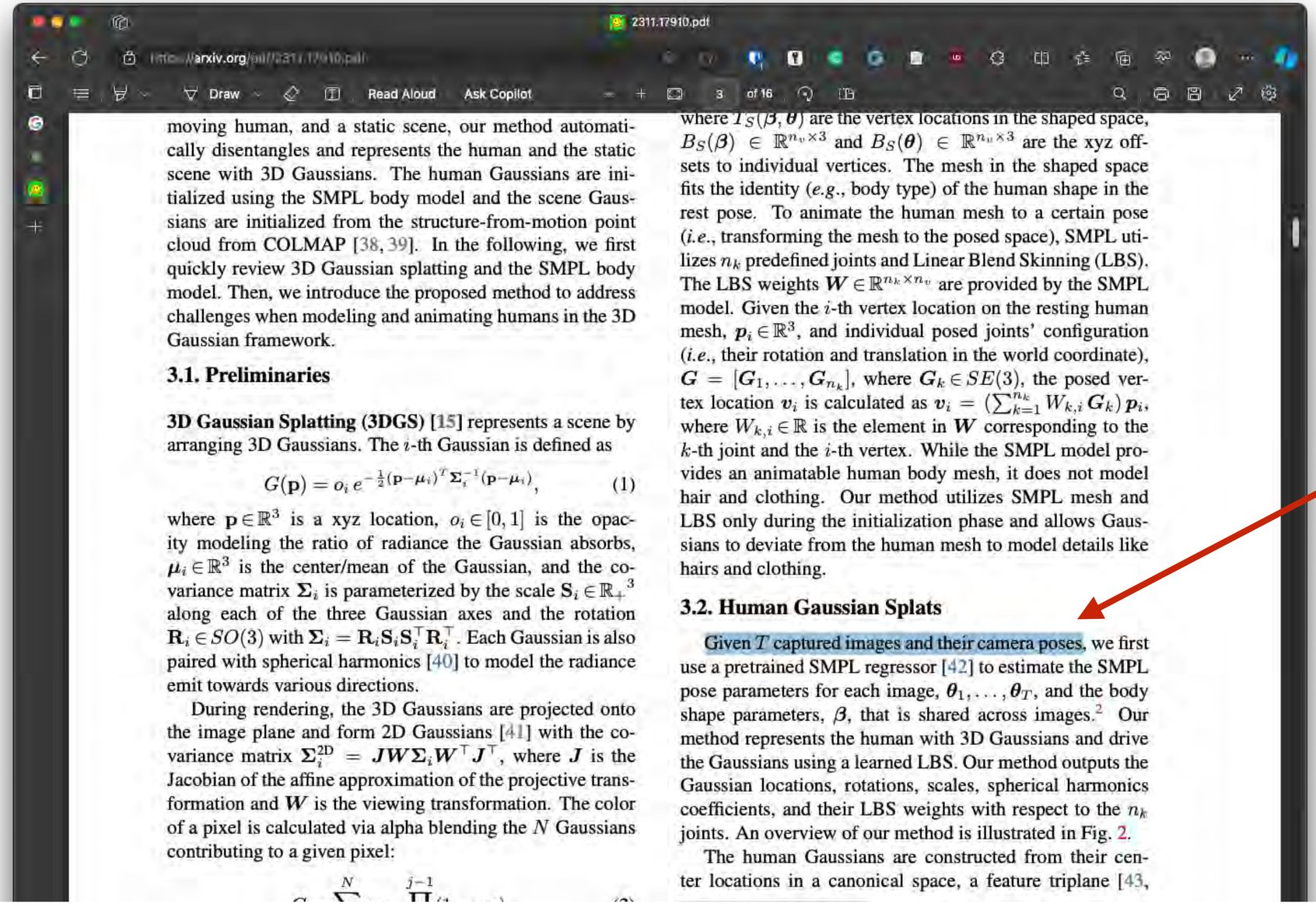
[Video from https://twitter.com/karenxcheng/status/1615404573367361542] reproduced for educational purposes]

# Animatable “avatars” from a video




[Video from https://machinelearning.apple.com/research/hugs reproduced for educational purposes]

# Behind the scenes, they still rely on traditional stuff



moving human, and a static scene, our method automatically disentangles and represents the human and the static scene with 3D Gaussians. The human Gaussians are initialized using the SMPL body model and the scene Gaussians are initialized from the structure-from-motion point cloud from COLMAP [38, 39]. In the following, we first quickly review 3D Gaussian splatting and the SMPL body model. Then, we introduce the proposed method to address challenges when modeling and animating humans in the 3D Gaussian framework.

### 3.1. Preliminaries

**3D Gaussian Splatting (3DGS)** [15] represents a scene by arranging 3D Gaussians. The $i$-th Gaussian is defined as

$$G(\mathbf{p}) = o_i \, e^{-\frac{1}{2}(\mathbf{p}-\boldsymbol{\mu}_i)^T \boldsymbol{\Sigma}_i^{-1}(\mathbf{p}-\boldsymbol{\mu}_i)}, \quad (1)$$

where $\mathbf{p} \in \mathbb{R}^3$ is a xyz location, $o_i \in [0, 1]$ is the opacity modeling the ratio of radiance the Gaussian absorbs, $\boldsymbol{\mu}_i \in \mathbb{R}^3$ is the center/mean of the Gaussian, and the covariance matrix $\boldsymbol{\Sigma}_i$ is parameterized by the scale $\mathbf{S}_i \in \mathbb{R}_+^3$ along each of the three Gaussian axes and the rotation $\mathbf{R}_i \in SO(3)$ with $\boldsymbol{\Sigma}_i = \mathbf{R}_i \mathbf{S}_i \mathbf{S}_i^\top \mathbf{R}_i^\top$. Each Gaussian is also paired with spherical harmonics [40] to model the radiance emit towards various directions.

During rendering, the 3D Gaussians are projected onto the image plane and form 2D Gaussians [41] with the covariance matrix $\boldsymbol{\Sigma}_i^{2D} = \boldsymbol{J}\boldsymbol{W}\boldsymbol{\Sigma}_i\boldsymbol{W}^\top\boldsymbol{J}^\top$, where $\boldsymbol{J}$ is the Jacobian of the affine approximation of the projective transformation and $\boldsymbol{W}$ is the viewing transformation. The color of a pixel is calculated via alpha blending the $N$ Gaussians contributing to a given pixel:

$$C = \sum_{i=1}^{N} \prod_{j=1}^{i-1} (1 - \alpha_j) \, c_i \, \alpha_i \quad (2)$$

where $T_S(\boldsymbol{\beta}, \boldsymbol{\theta})$ are the vertex locations in the shaped space, $B_S(\boldsymbol{\beta}) \in \mathbb{R}^{n_v \times 3}$ and $B_S(\boldsymbol{\theta}) \in \mathbb{R}^{n_v \times 3}$ are the xyz offsets to individual vertices. The mesh in the shaped space fits the identity (*e.g.*, body type) of the human shape in the rest pose. To animate the human mesh to a certain pose (*i.e.*, transforming the mesh to the posed space), SMPL utilizes $n_k$ predefined joints and Linear Blend Skinning (LBS). The LBS weights $\boldsymbol{W} \in \mathbb{R}^{n_k \times n_v}$ are provided by the SMPL model. Given the $i$-th vertex location on the resting human mesh, $\boldsymbol{p}_i \in \mathbb{R}^3$, and individual posed joints' configuration (*i.e.*, their rotation and translation in the world coordinate), $\boldsymbol{G} = [\boldsymbol{G}_1, \ldots, \boldsymbol{G}_{n_k}]$, where $\boldsymbol{G}_k \in SE(3)$, the posed vertex location $\boldsymbol{v}_i$ is calculated as $\boldsymbol{v}_i = (\sum_{k=1}^{n_k} W_{k,i} \boldsymbol{G}_k) \boldsymbol{p}_i$, where $W_{k,i} \in \mathbb{R}$ is the element in $\boldsymbol{W}$ corresponding to the $k$-th joint and the $i$-th vertex. While the SMPL model provides an animatable human body mesh, it does not model hair and clothing. Our method utilizes SMPL mesh and LBS only during the initialization phase and allows Gaussians to deviate from the human mesh to model details like hairs and clothing.

### 3.2. Human Gaussian Splats

Given $T$ captured images and their camera poses, we first use a pretrained SMPL regressor [42] to estimate the SMPL pose parameters for each image, $\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_T$, and the body shape parameters, $\boldsymbol{\beta}$, that is shared across images.[2] Our method represents the human with 3D Gaussians and drive the Gaussians using a learned LBS. Our method outputs the Gaussian locations, rotations, scales, spherical harmonics coefficients, and their LBS weights with respect to the $n_k$ joints. An overview of our method is illustrated in Fig. 2.

The human Gaussians are constructed from their center locations in a canonical space, a feature triplane [43,

- Image Processing (Linear Filtering, Convolution)
- Filters as Templates
- Image Feature Detection (Edges & Corners)
- Texture & Colour
- Image Feature Description (SIFT)
- Model Fitting (RANSAC, The Hough Transform)
- Camera Models, Stereo Geometry
- Motion and Optical Flow
- Clustering and Image Segmentation
- Learning and Image Classification
- Deep Learning Introduction

# **Course** Origins

CPSC 425 was originally developed by **Bob Woodham** and has evolved over the years. Much of the material this year is adapted from material prepared by Bob, as well as extensions developed by others who taught this course

Previously taught by:

— 2023-2024 Term 1 by **Matthew Brown**
— 2022-2023 Term 2 by **Leonid Sigal**
— 2022-2023 Term 1 by **Matthew Brown**
— 2021-2022 Term 1 & 2 by **Jim Little**
— 2020-2021 Term 1 by **Leonid Sigal**
— 2019-2020 Term 2 by **Leonid Sigal**
— 2019-2020 Term 1 by **Jim Little**
— 2018-2019 Term 1 & 2 by **Leonid Sigal**
— 2016-2017 Term 2 by **Jim Little**
— 2015-2016 Term 2 by **Fred Tung**
— 2015-2015 Term 2 by **Jim Little**

# How to **Learn** from the **Course**?

— The course is very **broad**, but relatively **shallow** introduction to a very diverse and complex field that draws material from geometry, statistics, AI, machine learning, computer graphics, psychology and many others.

— It is easy to think that material is easy and course requires no studying

— Part of your job should be going over the slides and carefully analyzing not just what is on them, but the underlying assumptions, algorithmic steps and so on

— Don’t strive for “**template matching**” strive for true “**understanding**”

# **Grading** Criteria

Canvas **quiz**: 10%

**Programming Assignments**: 45%

6 graded and 1 ungraded (optional) assignment

**Midterm** Exam (February 26th): 15%

**Final** Exam (April 16 — 27): 30%

# Assignments

There will be **6+1 assignments** in total (6 marked)

— Approximately 1 every 2 weeks

— You will hand these in by 11:59pm on the due date (read hand in instructions and late policy on course webpage)


You will use the **Python**, with the following libraries: Python Imaging Library (PIL), NumPy, Matplotlib, SciPy, Scikit-Learn

— Assignment 0 (which is ungraded) will introduce you to this.

Assignments contribute 45% to your final score

# **Midterm** Exam

Scheduled for **February 26th**

— Here in class during the lecture period

— Closed book, no notes allowed

Multiple choice, true / false and short answer questions

— Aimed to test your “understanding” of the content of the course

The Midterm exam will contribute 15% to your final score

# **Final** Exam

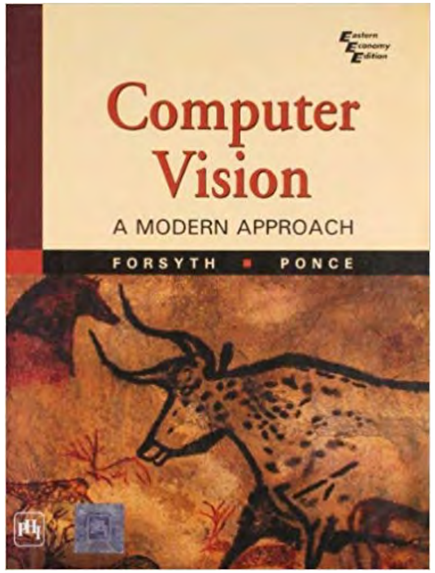
The Final exam is held during the regular examination period, **April 16-27**, and is scheduled by the Registrar's Office

Similar to the midterm but longer and with more extensive short/medium answer questions

The Final exam will contribute 30% to your final score

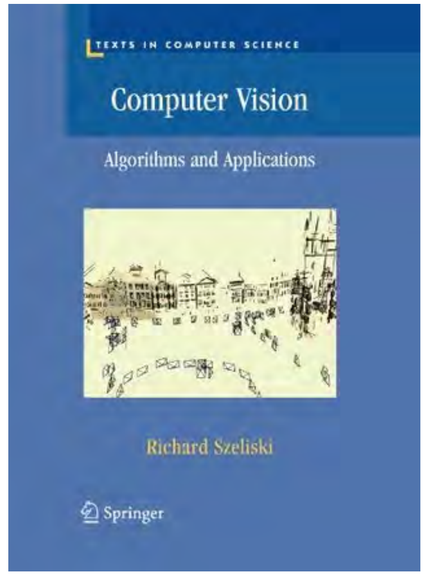
# Textbooks

The course uses the following textbooks, which are recommended (but **not required**):




Computer Vision: A Modern Approach (2nd ed)

**By:** D. Forsyth & J. Ponce
**Publisher:** Pearson 2012



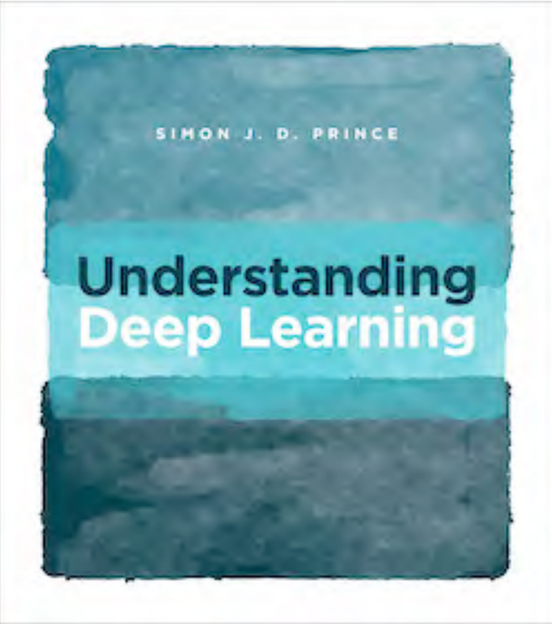

Computer Vision: Algorithms and Applications (2nd ed)

**By:** R. Szeliski
**Publisher:** Springer 2022

https://szeliski.org/Book/

# Text**books**

The course uses the following textbooks, which are recommended (but **not required**):




Understanding Deep Learning

**By:** Simon J.D. Prince
**Publisher:** MIT Press 2023

https://udlbook.github.io/udlbook/

# Readings

You will be assigned **readings**.

— Sometimes you will be assigned readings from other sources

Do the reading **after coming** to the lecture

— Reading assignments will be posted on course webpage

— They will also be mentioned in class