

Introduction to Crowdsourcing for Computer Vision

Danna Gurari

The University of Texas at Austin

Fall 2019



<https://www.ischool.utexas.edu/~dannag/Courses/CrowdsourcingForCV/CourseContent.html>

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Today's Topics

- Class logistics
- Computer vision: past, present, & future
- Computer vision: what makes it hard?
- Introduction to crowdsourcing for computer vision
- Lab: web page creation

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Introductions

Instructor: Danna Gurari

Danna: pronounced like “Donna”

Gurari: rhymes with Ferrari

Pronouns: she/her/hers



Interdisciplinary class:

- introduce yourself
- share about your career aspirations

Q&A: “Do I have the appropriate pre-requisites/background?”

- Yes. There are no pre-requisites.
- You will be expected to further develop skills we cover in class **on your own**; e.g.,
 - Programming; e.g., html, css, javascript, command line tools

Q&A: ““What are required textbooks?”

None.

We will read research papers and online tutorials.

Class Logistics & Overview

- Grading:

	% of Final Class Grade
Class Participation	5%
Reading Assignments	25%
Lab Assignments	30%
Final Project	40%

- Website

- <https://www.ischool.utexas.edu/~dannag/Courses/CrowdsourcingForCV/>

- Objectives, schedule, assignments, and policies

- <https://www.ischool.utexas.edu/~dannag/Courses/CrowdsourcingForCV/Syllabus/Syllabus.pdf>

Class Format

- First half = lecture & group discussions
- Break
- Second half = hands-on lab session

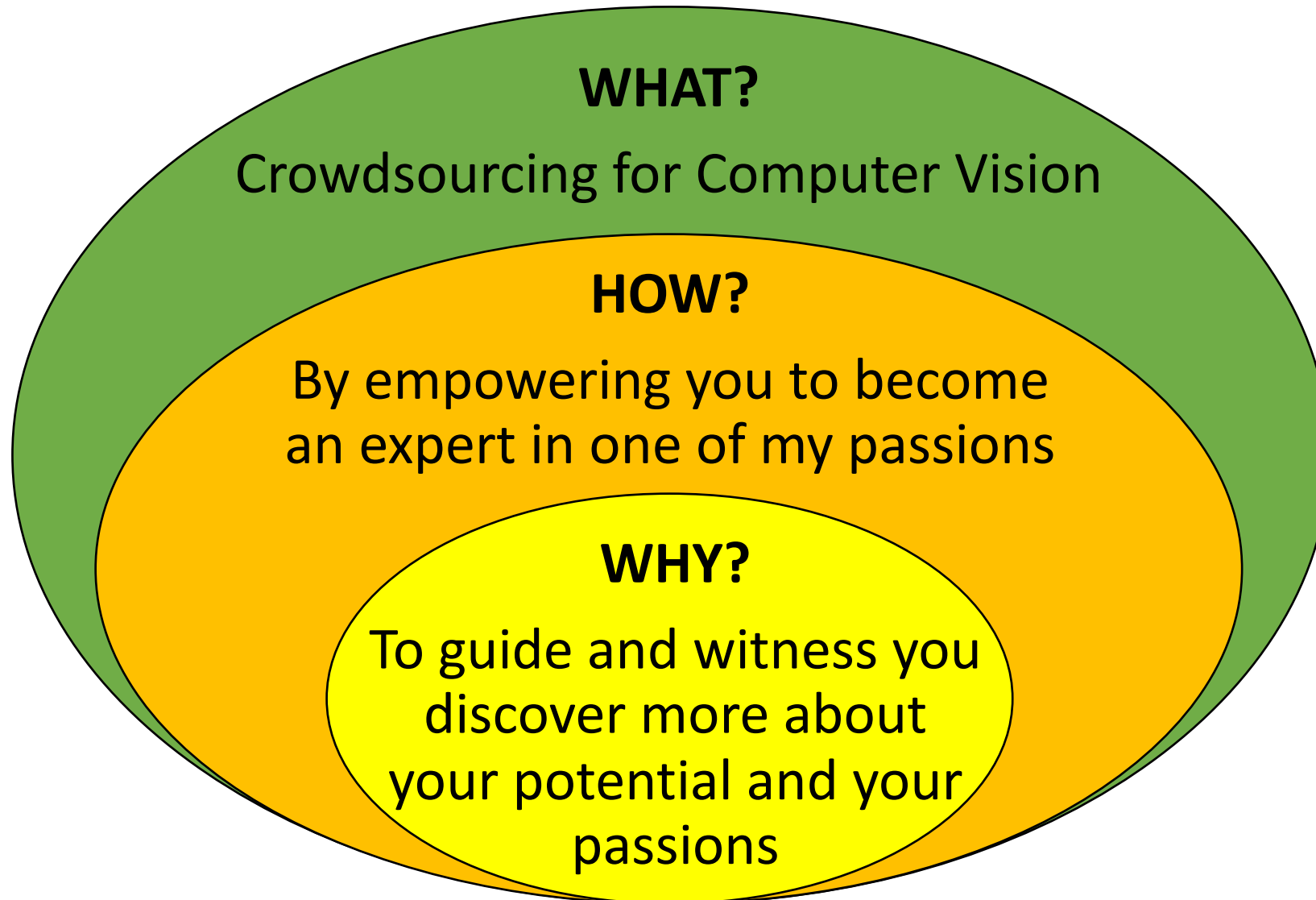
Congratulations!

- By taking this class, you receive a gift of:



- Thanks to: **Microsoft Azure**

What is My “Why” for Teaching You...



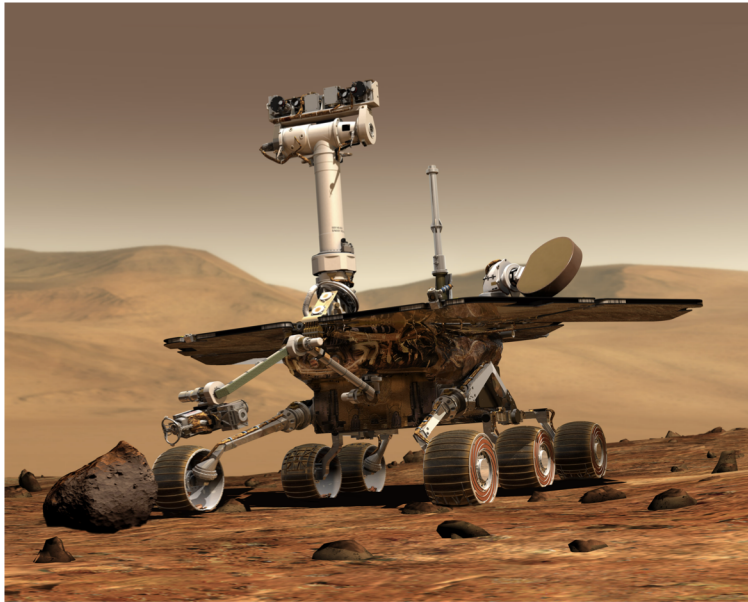
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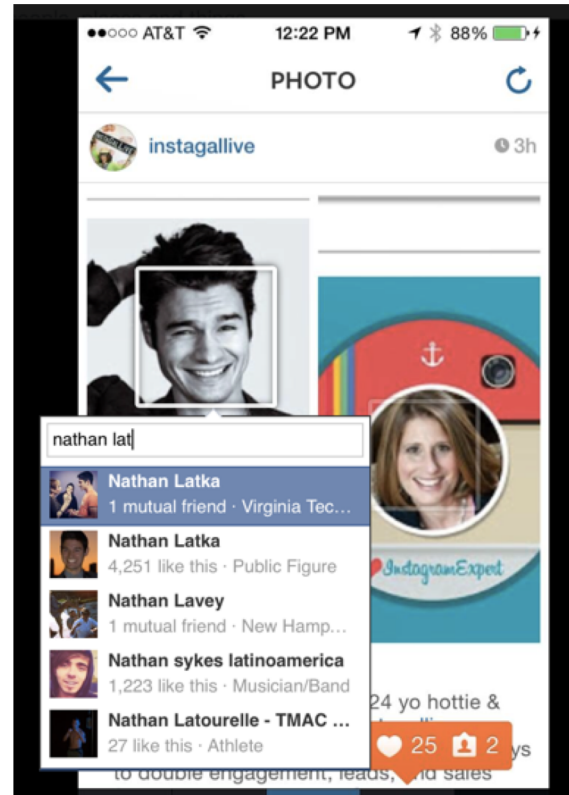
What is Computer Vision?

Algorithms that allow computers to “see”

Modern Examples of Computer Vision



e.g., self-driving vehicle on Mars



e.g., recognizing people



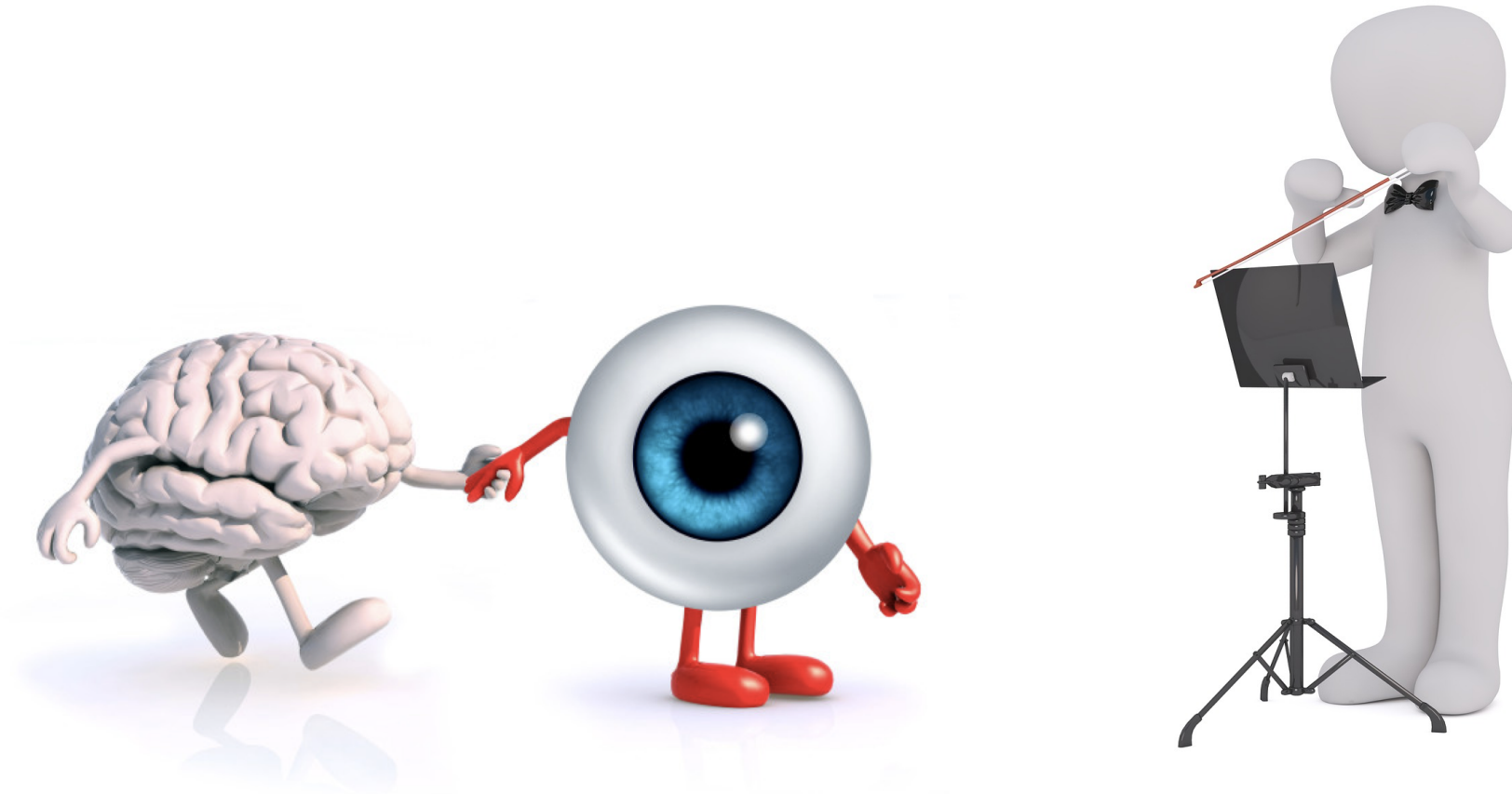
e.g., shopping without a cashier

Modern Examples of Computer Vision

With > 85% of internet data in the form of images and videos, there are many opportunities for computer vision applications!

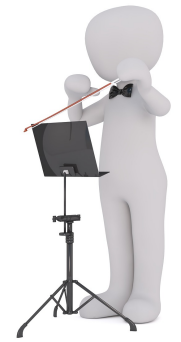
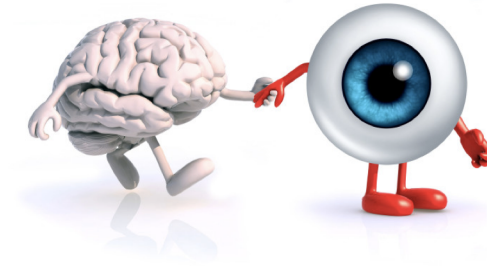
Origins of Computer Vision

- Emulate ingredients that power human sight: brain, eyes, & conductor



Origins of Computer Vision:

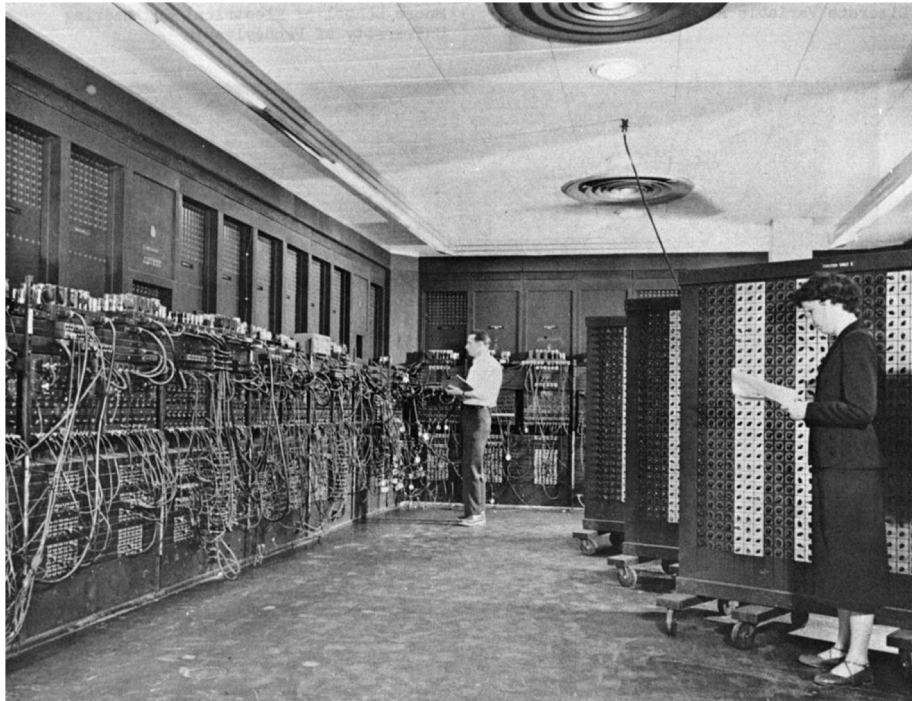
1945



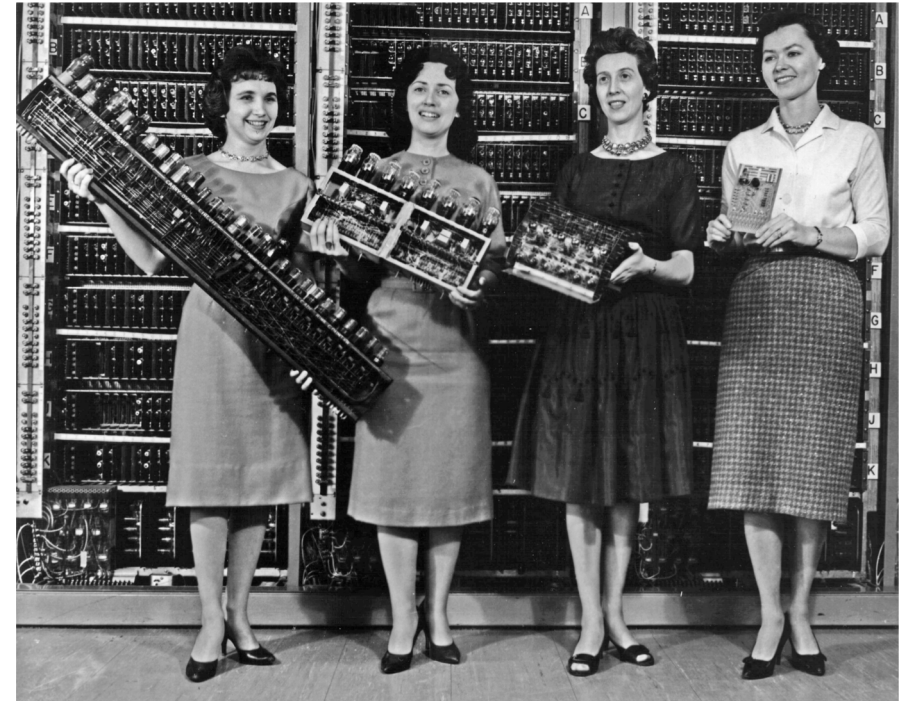
Origins of Computer Vision:



1945



ENIAC (Electronic Numerical Integrator and Computer) created during World War II



First programmers

Origins of Computer Vision:



1945



Origins of Computer Vision:



1945

1957



Origins of Computer Vision:



1945

1957



First digital image (176 x 176 pixels)



Origins of Computer Vision:



1945

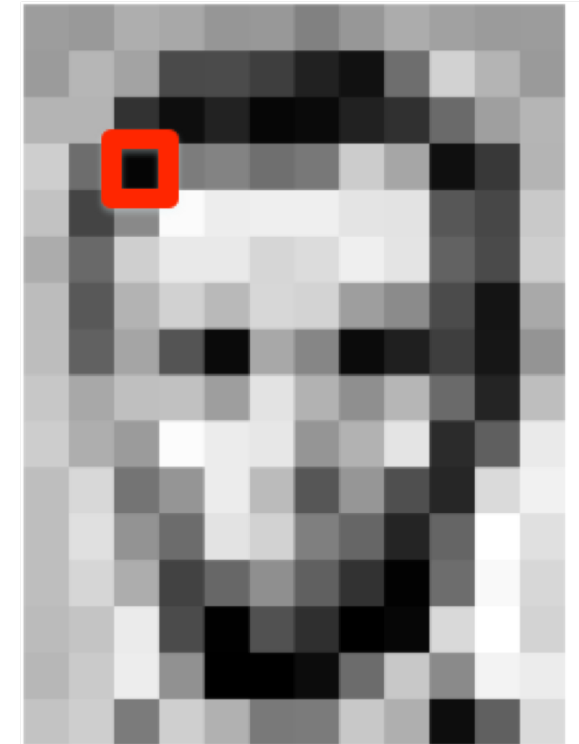
1957



Digital images



157	153	174	168	150	152	129	151	172	161	155	156
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172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
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What a Computer Sees:

Origins of Computer Vision:



1945

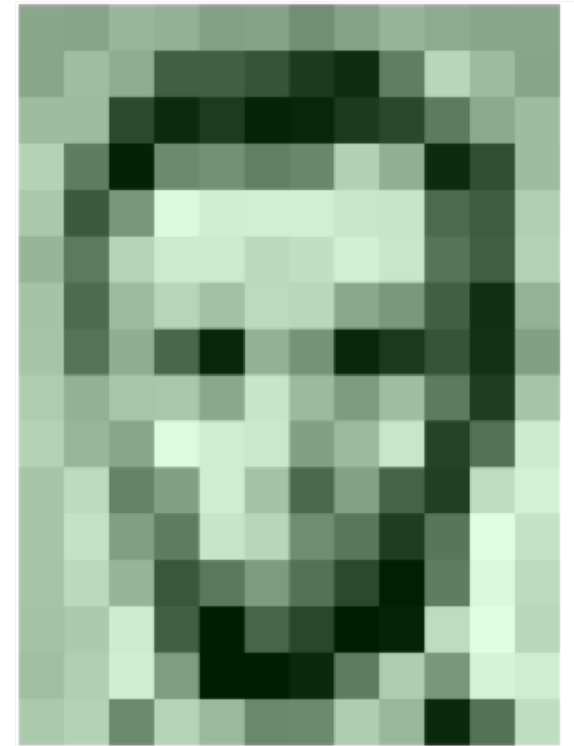
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Origins of Computer Vision:



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What a Computer Sees:

0

255

Origins of Computer Vision:



1945

1957



Digital images



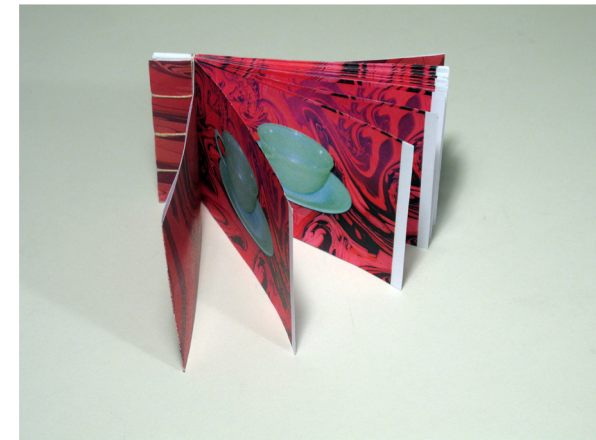
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1 hour

Time 1

Analogous to (for video):



Origins of Computer Vision

1945

1957



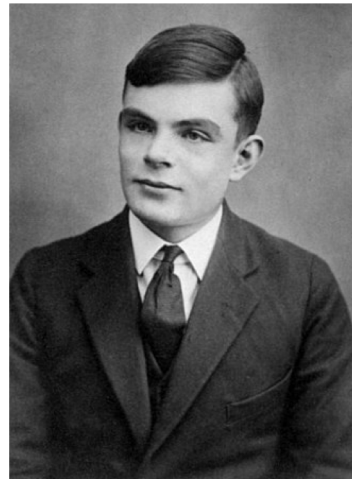
Origins of Computer Vision



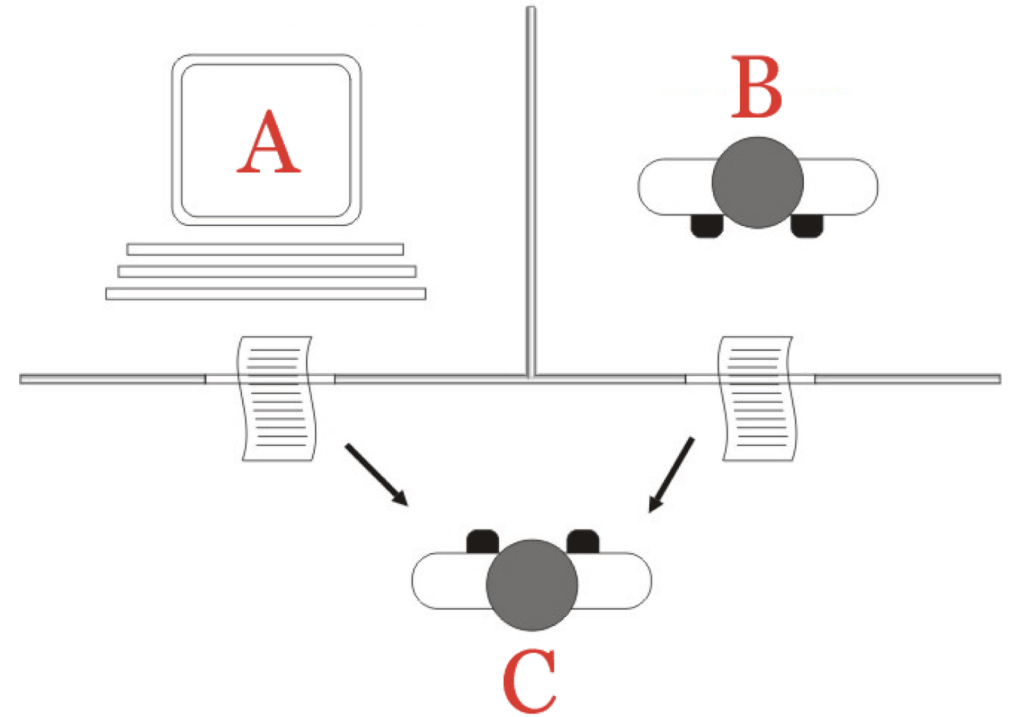
1945 1950 1957



Turing Test

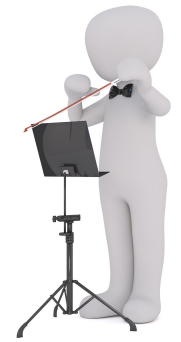


Alan Turing
(1912-1954)



Turing Test: can "C" decide whether text responses come from a machine or human

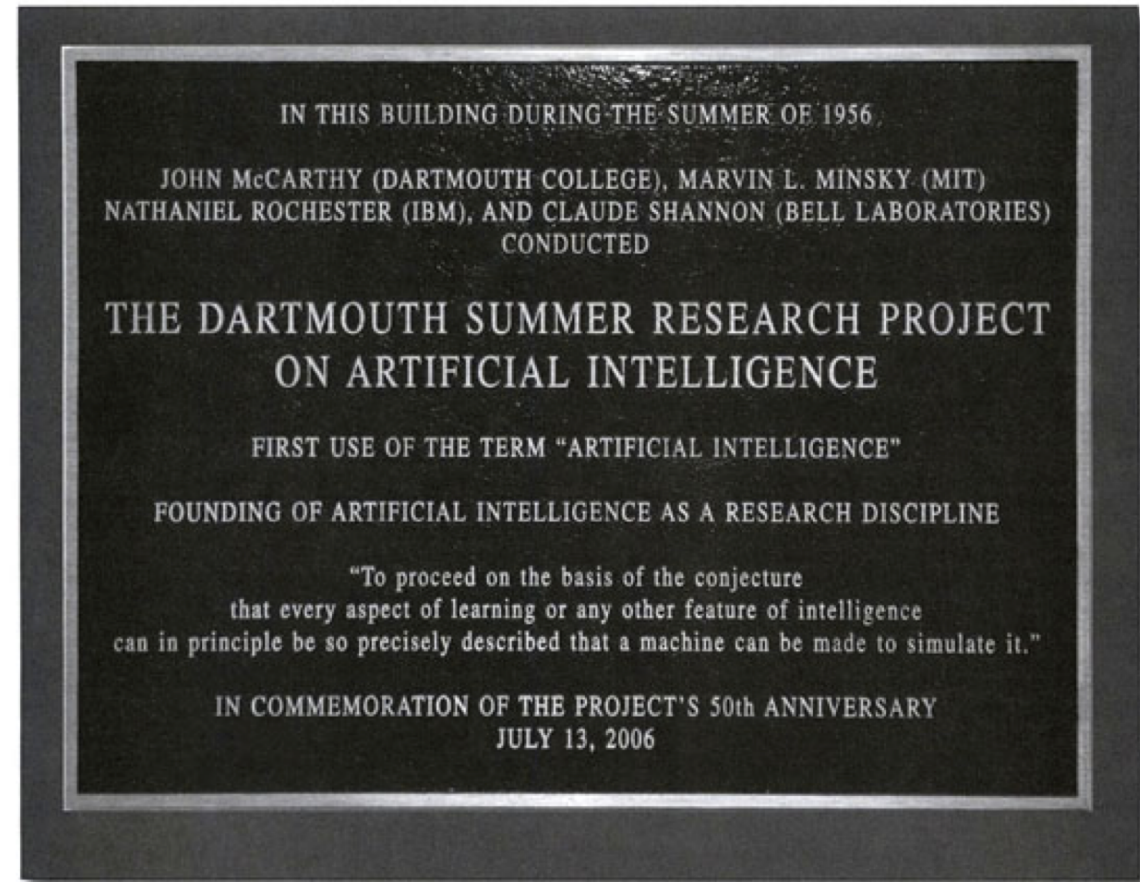
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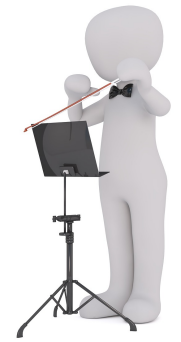
1945 1950 1956



Turing Test **AI Birth**



Origins of Computer Vision



1945 1950 1956

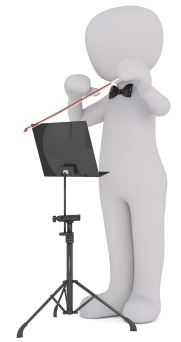


Turing Test AI Birth



Workshop Proposal: "... We propose that **a 2 month, 10 man study of artificial intelligence** be carried out during the summer of 1956 at Dartmouth College in [Hanover, New Hampshire](#). The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of **intelligence can in principle be so precisely described that a machine can be made to simulate it**. An attempt will be made to find how to **make machines** use language, form abstractions and concepts, **solve kinds of problems now reserved for humans**, and improve themselves. **We think that a significant advance can be made** in one or more of these problems **if a carefully selected group of scientists work on it together for a summer...**"

Origins of Computer Vision



1945 1950 1956

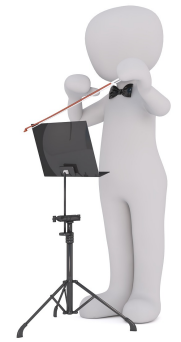


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Origins of Computer Vision



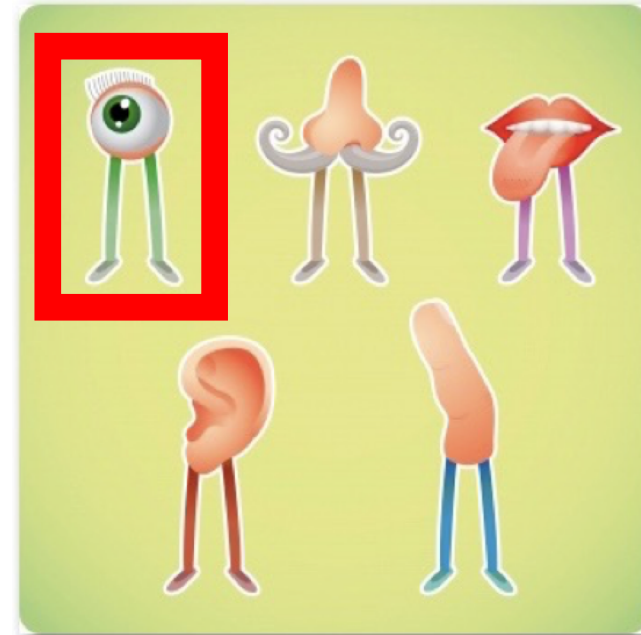
1945 1950 1956



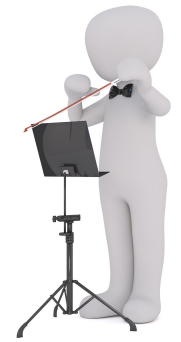
Turing Test AI Birth



What human intelligence
might machines imitate?



Origins of Computer Vision



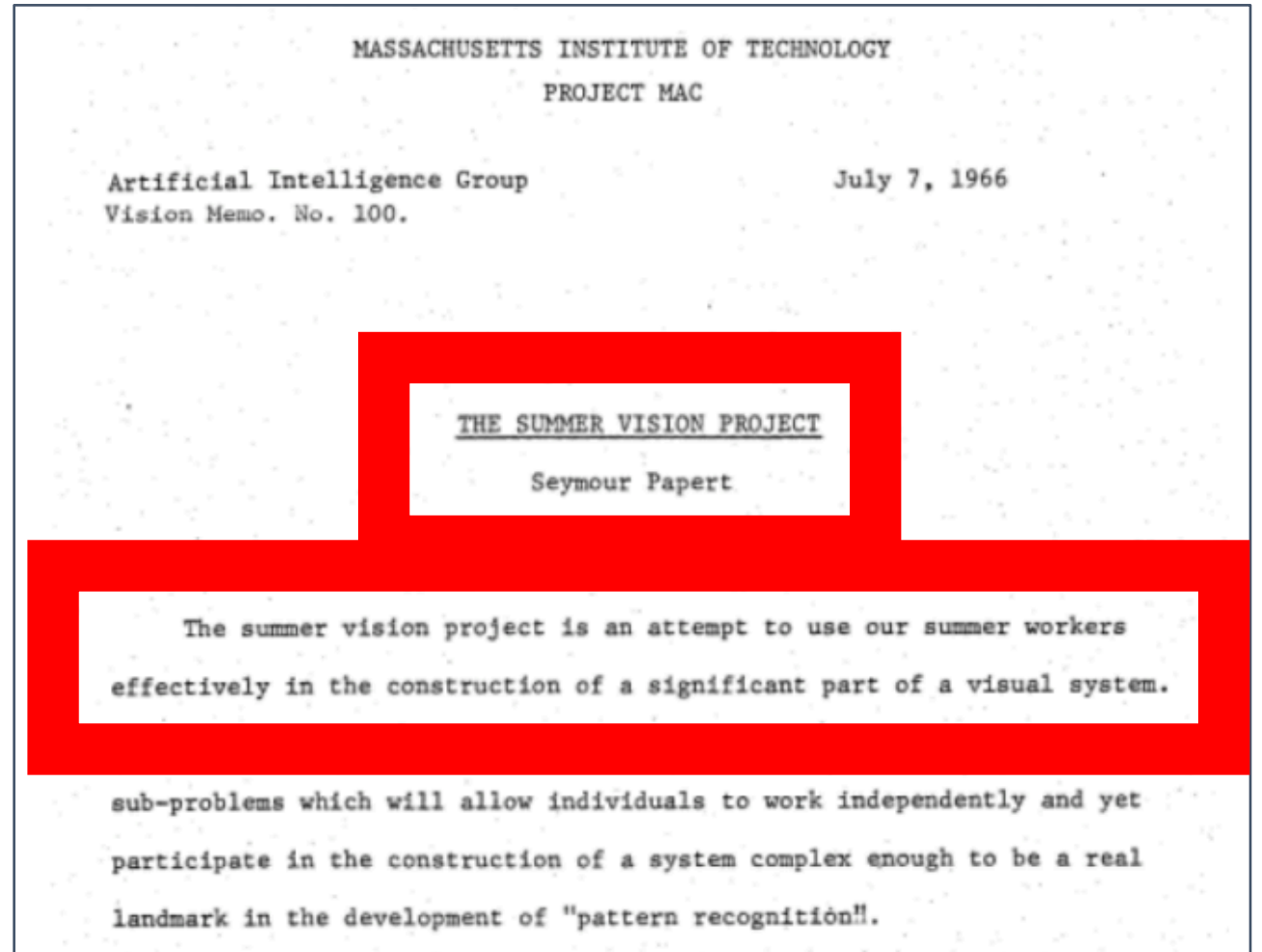
1945 1950 1956 1966



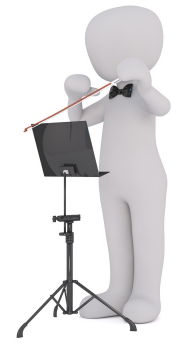
Turing Test

AI Birth

Birth of
Computer Vision



Origins of Computer Vision



1945

1950

1956

1966

Turing Test

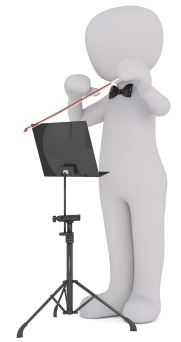
AI Birth

Birth of
Computer Vision

Turing Test: design "computer vision" that is indistinguishable from "human vision"



Origins of Computer Vision



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e.g.,



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What is this?

- A picture of a person

Could you describe this person?

- Long face

- Angular jaw

- Has a beard

Who is this person?

- Abraham Lincoln

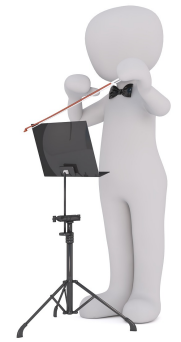
Is this person happy?

- I am not sure.

Is this person attractive?

- ~70% of people would say "yes"

Origins of Computer Vision



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Turing Test

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e.g.,



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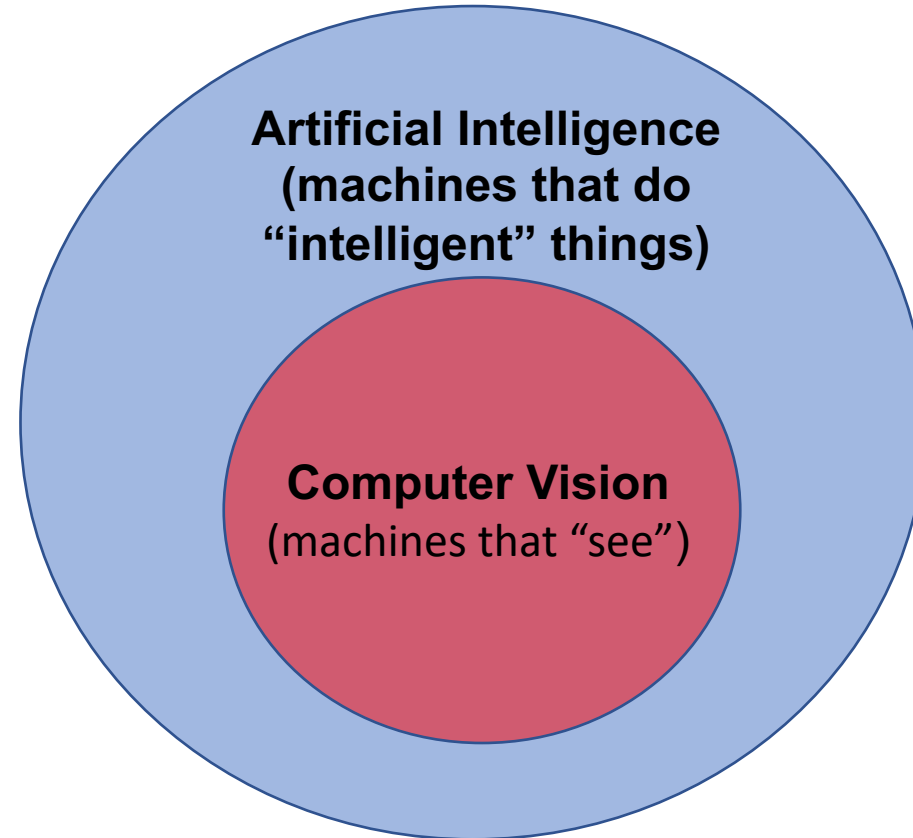
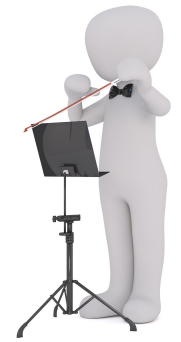
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Origins of Computer Vision

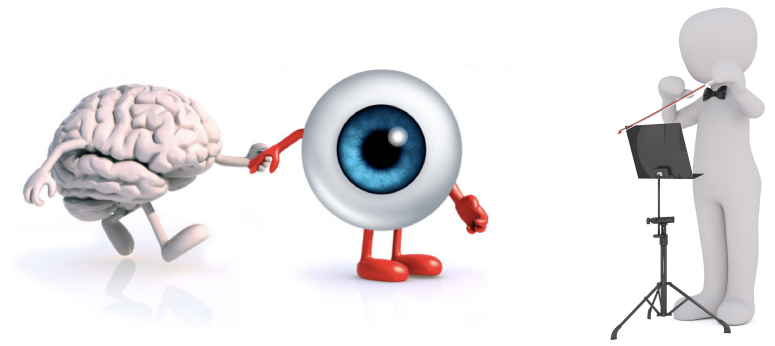


Origins of Computer Vision

1945

1957

1966



Brain, eyes, & conductor needed to emulate human sight were born over ~20 years!

Computer Vision in Research

1945

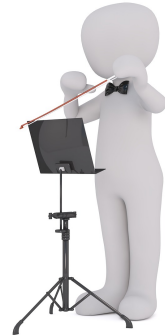
1957

1966

1983

1987

1990



1st Computer Vision and Pattern Recognition (CVPR)
1st International Conference on Computer Vision (ICCV)
1st European Conference on Computer Vision (ECCV)

And more including:

- Asian Conference on Computer Vision (ACCV)
- British Machine Vision Conference (BMVC)
- Winter conference on Applications in Computer Vision (WACV)
- Medical Image Computing and Computer-Assisted Intervention (MICCAI)
- Conference on Automatic Face and Gesture Recognition (IEEE FG)

Computer Vision in Research

1945

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1983

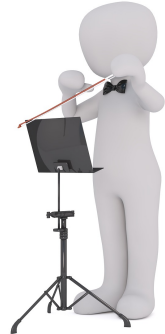
1987

1990

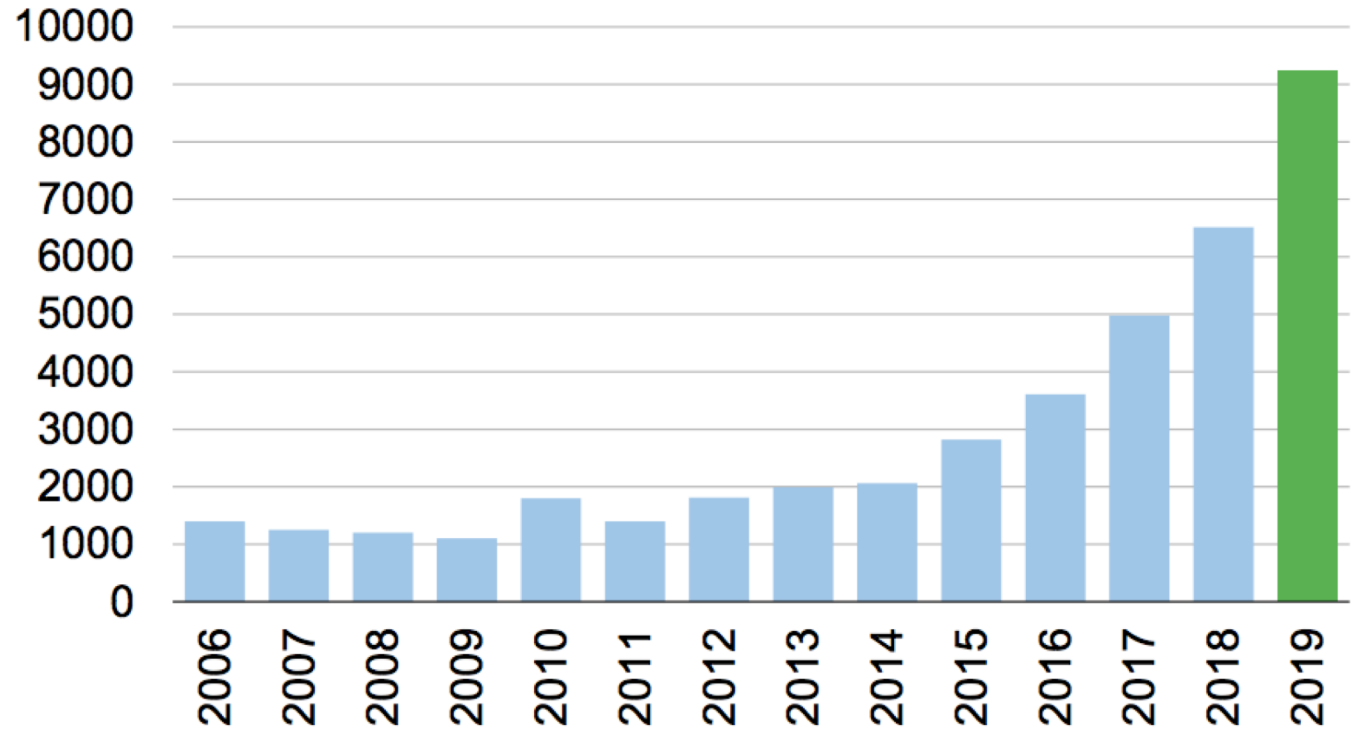
CVPR

ICCV

ECCV

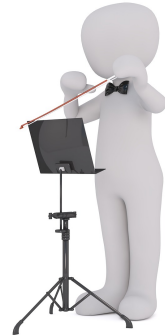
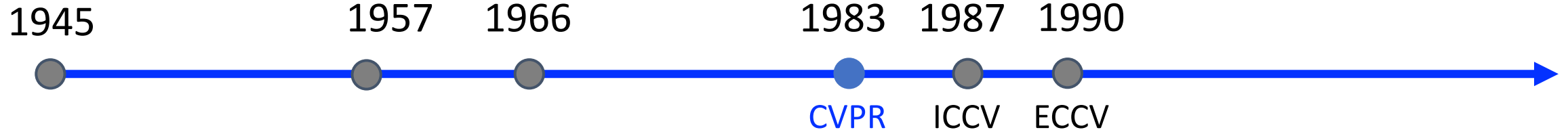


Number of attendees:



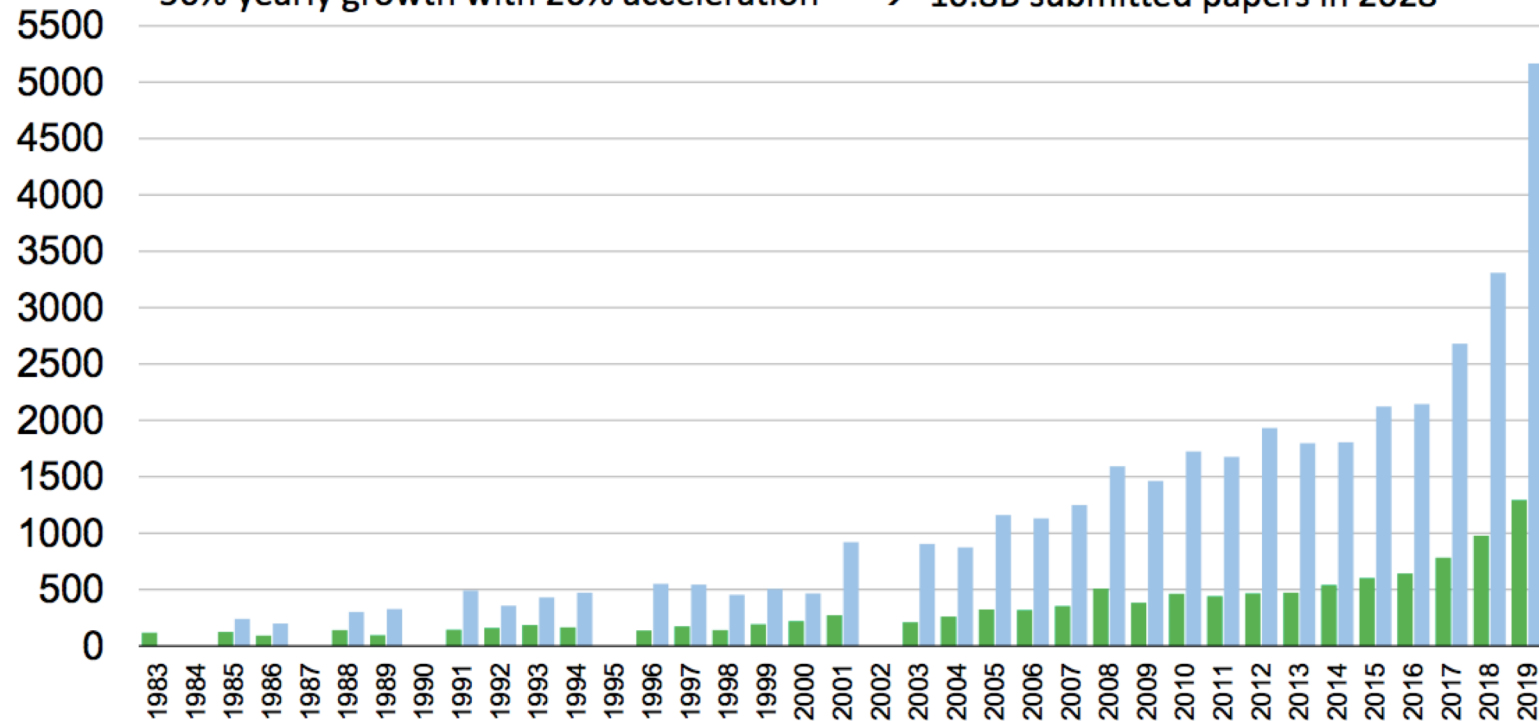
<http://cvpr2019.thecvf.com/>

Computer Vision in Research



Number of submitted and accepted papers:

56% yearly growth with 26% acceleration → 10.8B submitted papers in 2028



<http://cvpr2019.thecvf.com/>

Computer Vision in Industry

1945

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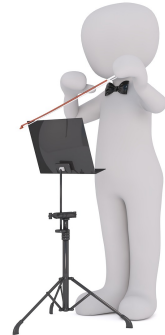
2015

CVPR

ICCV

ECCV

Rapid growth in the
number of applications
that use computer vision



Computer Vision in Industry

1945

1957

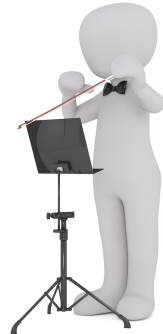
1966

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2015



CVPR

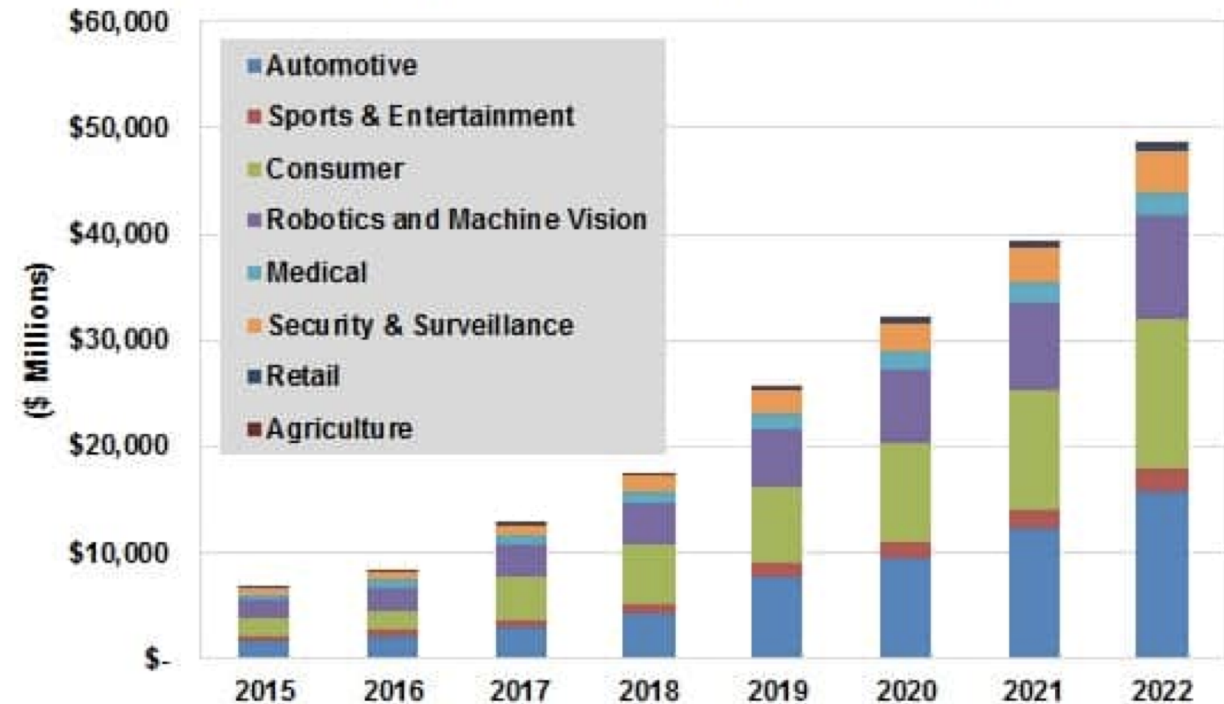
ICCV

ECCV

Rapid growth in the number of applications that use computer vision



Computer Vision Revenue by Application Market, World Markets: 2015-2022

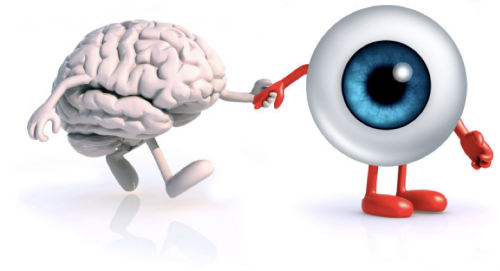


<https://sevenshonestudios.wordpress.com/computer-vision-and-deep-learning/>

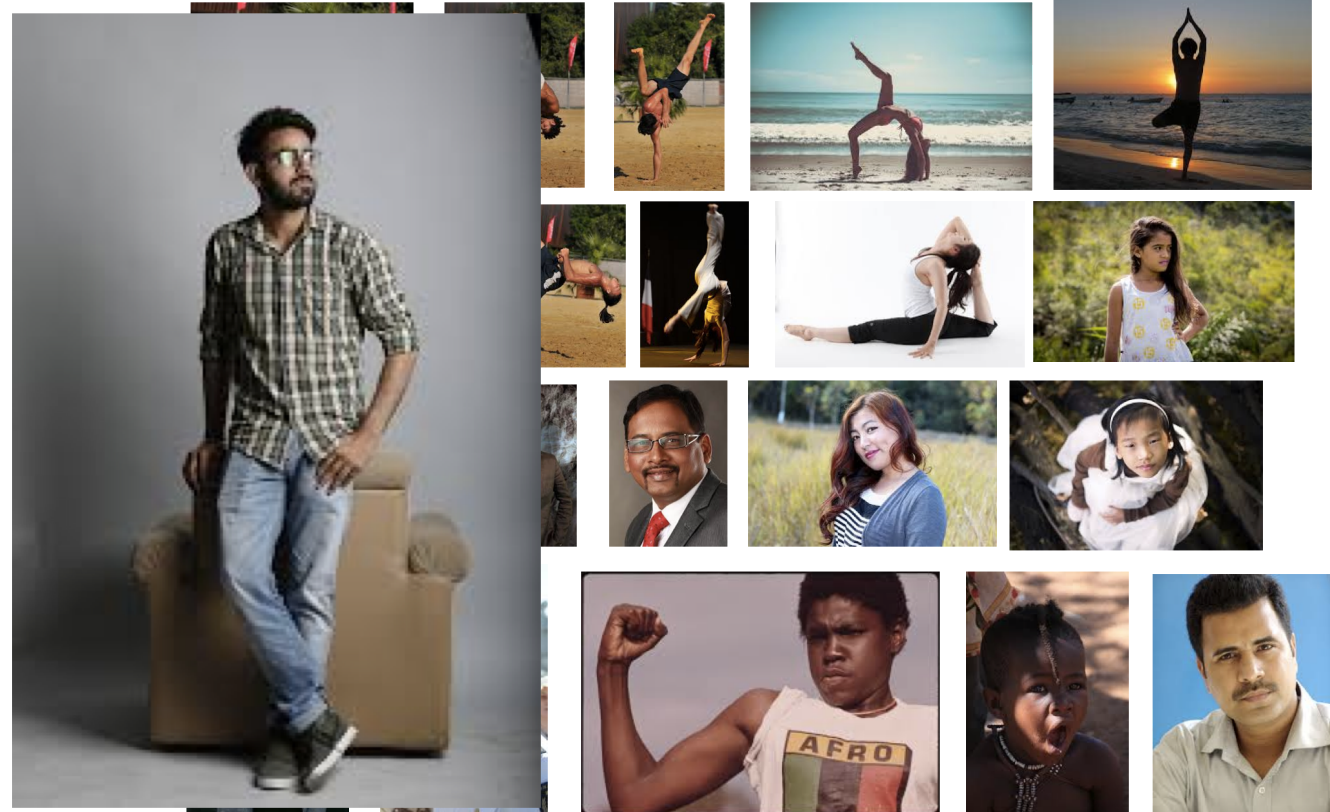
Today's Topics

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- Computer vision: past, present, & future
- **Computer vision: what makes it hard?**
- Introduction to crowdsourcing for computer vision
- Lab: web page creation

Group Discussion



How would you instruct a computer to answer: “Is a person in the image?”



So Much Variation for So Many Tasks!

(List Restricted to Topics We Will Cover in Class)

- Object recognition
- Scene classification
- Attribute labeling
- Segmentation
- Object detection
- Image Captioning
- Activity/Event Recognition
- Object Tracking
- Visual Question Answering
- Subjective Problems
- And more...

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- And more...



e.g., take a picture of an object and find where to buy it

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- Activity/Event Recognition
- Object Tracking
- Visual Question Answering
- Subjective Problems
- And more...



Kitchen



Store

So Much Variation for So Many Tasks!

(List Restricted to Topics We Will Cover in Class)

- Object recognition
- Scene classification
- **Attribute labeling**
- Segmentation
- Object detection
- Image Captioning
- Activity/Event Recognition
- Object Tracking
- Visual Question Answering
- Subjective Problems
- And more...



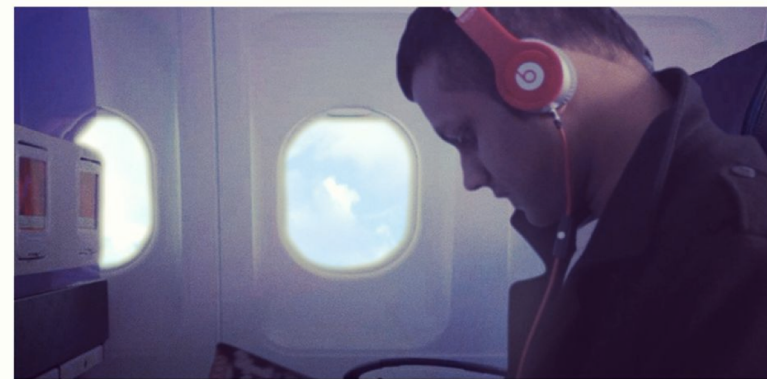
e.g., describe a bird to learn what type it is

Demo: <https://www.youtube.com/watch?v=UPcz9Y17iCc>

So Much Variation for So Many Tasks!

(List Restricted to Topics We Will Cover in Class)

- Object recognition
- Scene classification
- Attribute labeling
- **Segmentation**
- Object detection
- Image Captioning
- Activity/Event Recognition
- Object Tracking
- Visual Question Answering
- Subjective Problems
- And more...

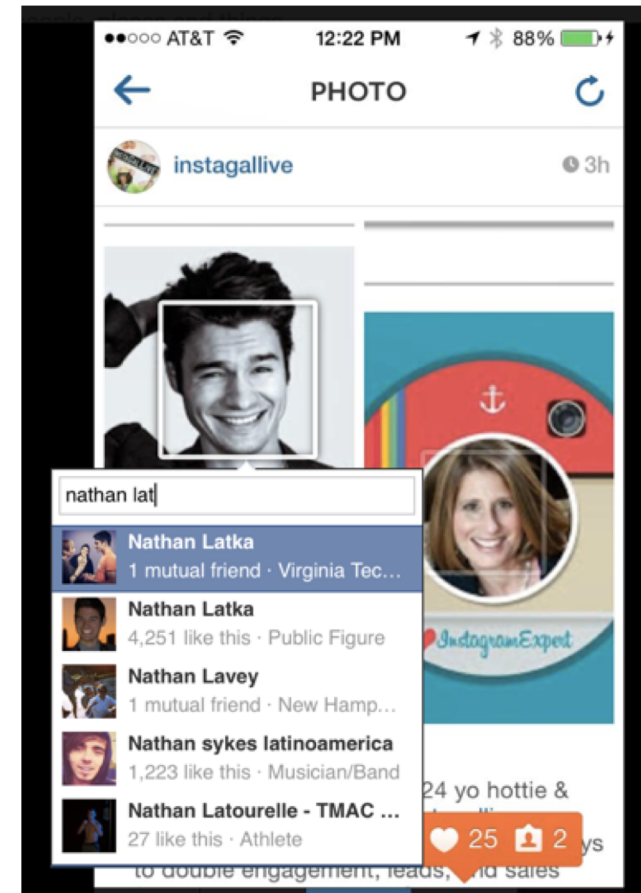


e.g., rotoscoping (more examples on Wiki)
<https://www.starnow.co.uk/ahmedmohammed1/photos/4650871/before-and-after-rotoscopinggreen-screening>

So Much Variation for So Many Tasks!

(List Restricted to Topics We Will Cover in Class)

- Object recognition
- Scene classification
- Attribute labeling
- Segmentation
- **Object detection**
- Image Captioning
- Activity/Event Recognition
- Object Tracking
- Visual Question Answering
- Subjective Problems
- And more...

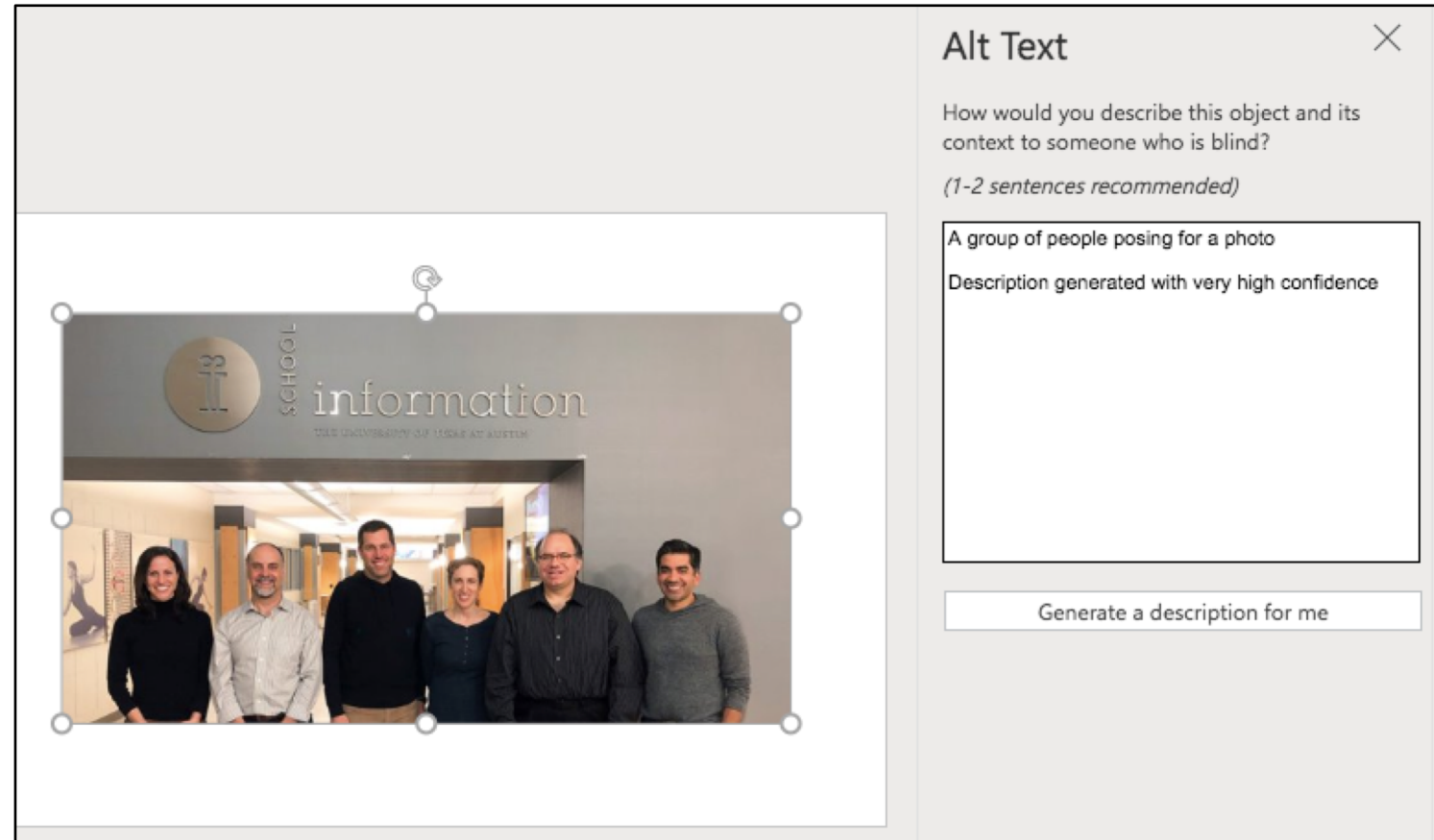


e.g., detect faces to tag

So Much Variation for So Many Tasks!

(List Restricted to Topics We Will Cover in Class)

- Object recognition
- Scene classification
- Attribute labeling
- Segmentation
- Object detection
- **Image Captioning**
- Activity/Event Recognition
- Object Tracking
- Visual Question Answering
- Subjective Problems
- And more...



e.g., Microsoft Power Point (Office 365 demo)

So Much Variation for So Many Tasks!

(List Restricted to Topics We Will Cover in Class)

- Object recognition
- Scene classification
- Attribute labeling
- Segmentation
- Object detection
- Image Captioning
- **Activity/Event Recognition**
- Object Tracking
- Visual Question Answering
- Subjective Problems
- And more...



e.g., shopping without a cashier

So Much Variation for So Many Tasks!

(List Restricted to Topics We Will Cover in Class)

- Object recognition
- Scene classification
- Attribute labeling
- Segmentation
- Object detection
- Image Captioning
- Activity/Event Recognition
- **Object Tracking**
- Visual Question Answering
- Subjective Problems
- And more...



e.g., track bowling ball path



e.g., calculate bat speed

So Much Variation for So Many Tasks!

(List Restricted to Topics We Will Cover in Class)

- Object recognition
- Scene classification
- Attribute labeling
- Segmentation
- Object detection
- Image Captioning
- Activity/Event Recognition
- Object Tracking
- **Visual Question Answering**
- Subjective Problems
- And more...

Result for Visual Question Answering

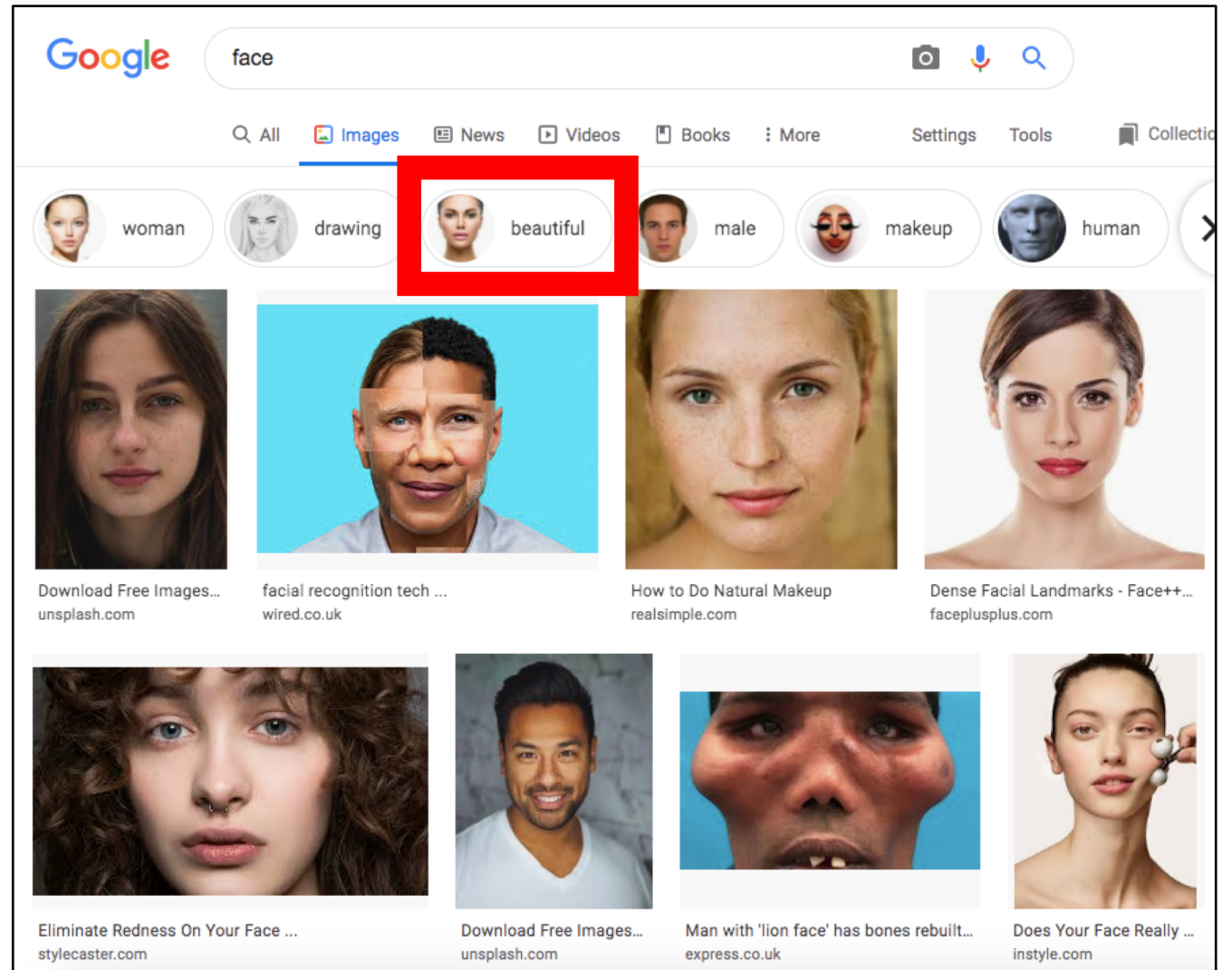
Predicted top-5 answers with confidence:	
no	99.984%
night	0.007%
dusk	0.004%
yes	0.002%
nighttime	0.001%

Demo: <http://vqa.cloudcv.org/>

So Much Variation for So Many Tasks!

(List Restricted to Topics We Will Cover in Class)

- Object recognition
- Scene classification
- Attribute labeling
- Segmentation
- Object detection
- Image Captioning
- Activity/Event Recognition
- Object Tracking
- Visual Question Answering
- Subjective Problems
- And more...



Key Challenge: Replicate Human Vision for So Much Variation for So Many Tasks!

Design computer vision that is indistinguishable from **human** vision



Little Training



Highly Trained

Key Challenge: Replicate Human Vision for So Much Variation for So Many Tasks!

images on hard drive:
(500 GB/2 MB = 250,000)

10^5



images seen during my first 10 years:
(24 images/sec * 60 sec * 60 min * 16 hr * 365 days * 10 yrs = 5,045,760,000)

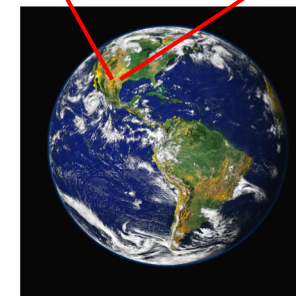
10^9



images seen by all humanity:
(7.5 billion humans¹ * 24 images/sec * 60 * 60 * 16 * 365 * 60 yrs = $2.23 * 10^{20}$)

10^{20}

¹ <http://www.worldometers.info/world-population/>



Computer Vision Beyond Human Vision



e.g., face re-enactment

Demo: <https://www.youtube.com/watch?v=Cx54WPwsG2w>

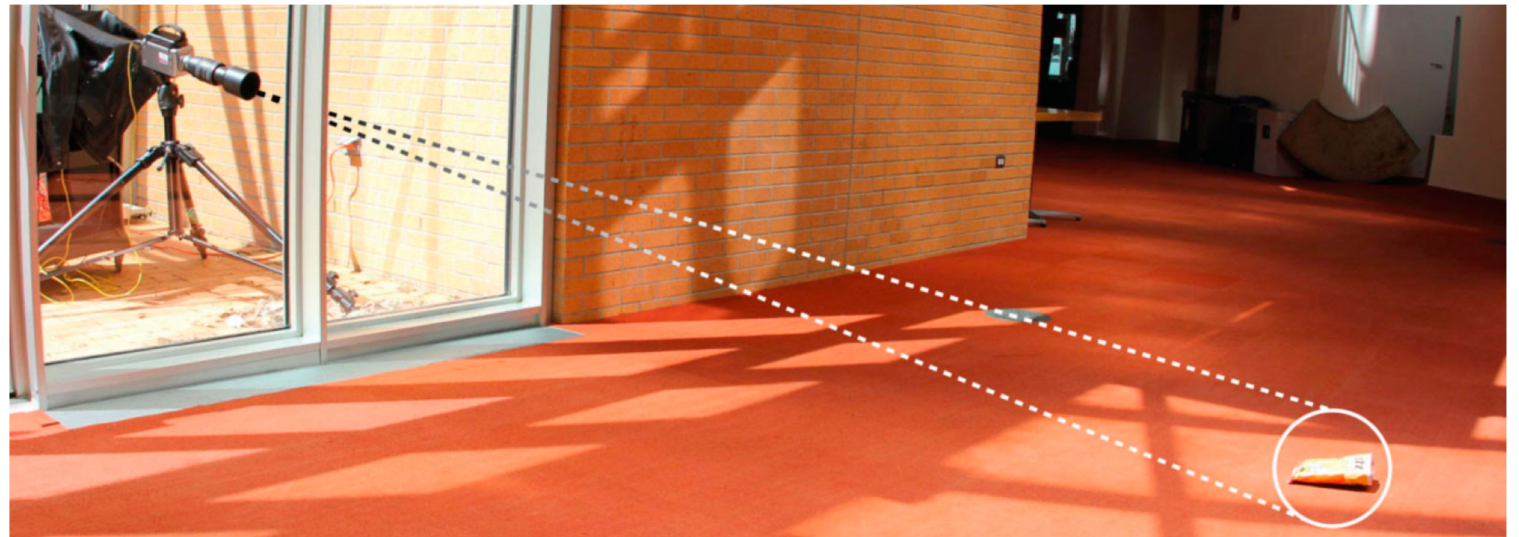
Demo: <https://www.youtube.com/watch?v=ttGUIwfTYvg>

Computer Vision Beyond Human Vision



Detecting Heart Rate

Demo: <https://www.youtube.com/watch?v=9JNkSZJuDJ8>



Recovering Sound

Demo: <https://www.youtube.com/watch?v=npNYP2vzaPo>

Today's Topics

- Class logistics
- Computer vision: past, present, & future
- Computer vision: what makes it hard?
- Introduction to crowdsourcing for computer vision
- Lab: web page creation

Progress Charted By Emulating Human Perception

1945



1957



1966



1983

CVPR

1987

ICCV

1990

ECCV

2015

Progress Charted By Emulating Human Perception

1945



1963



1983

CVPR

1987

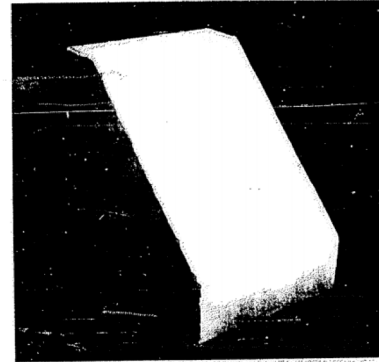
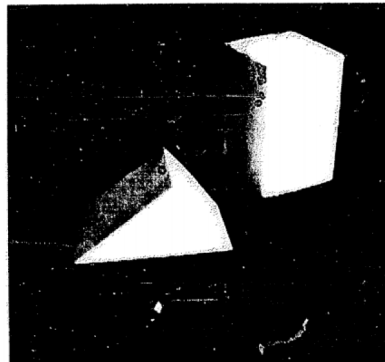
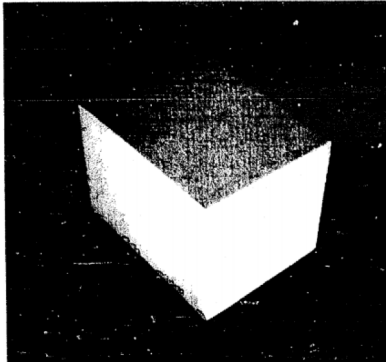
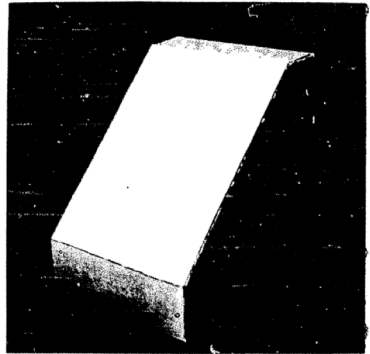
ICCV

1990

ECCV

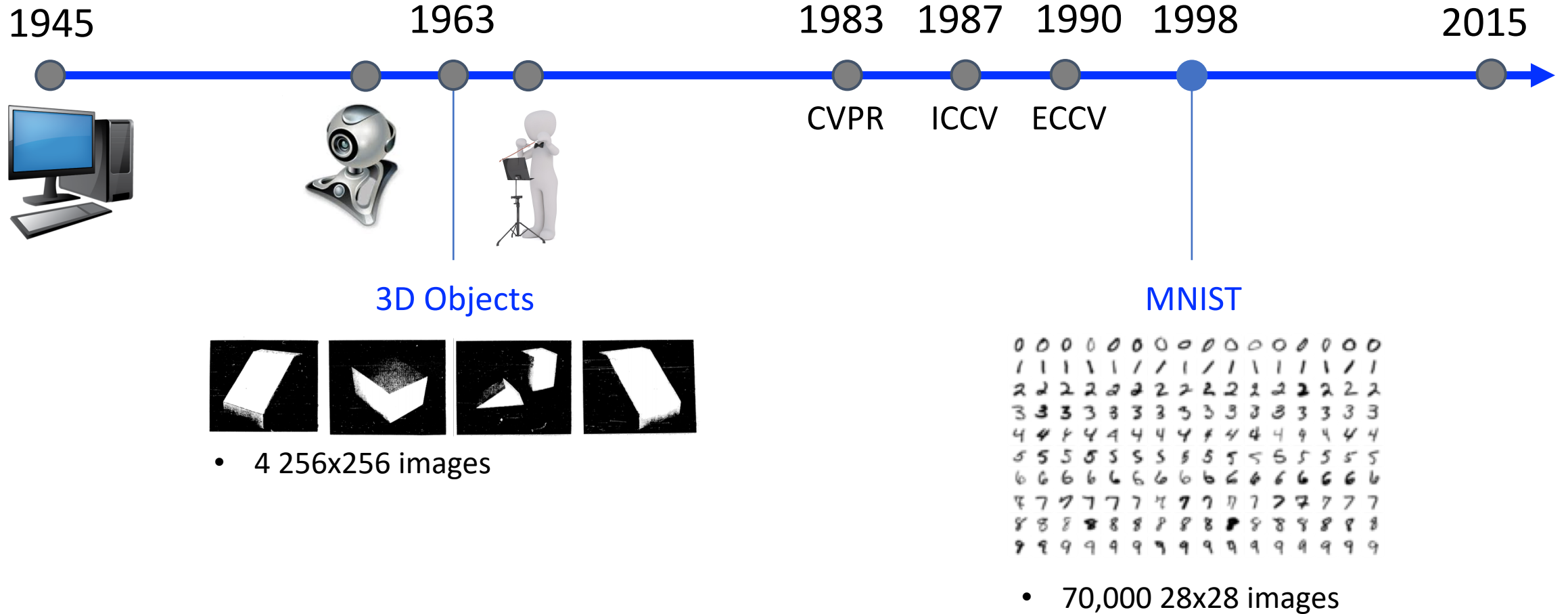
2015

3D Objects

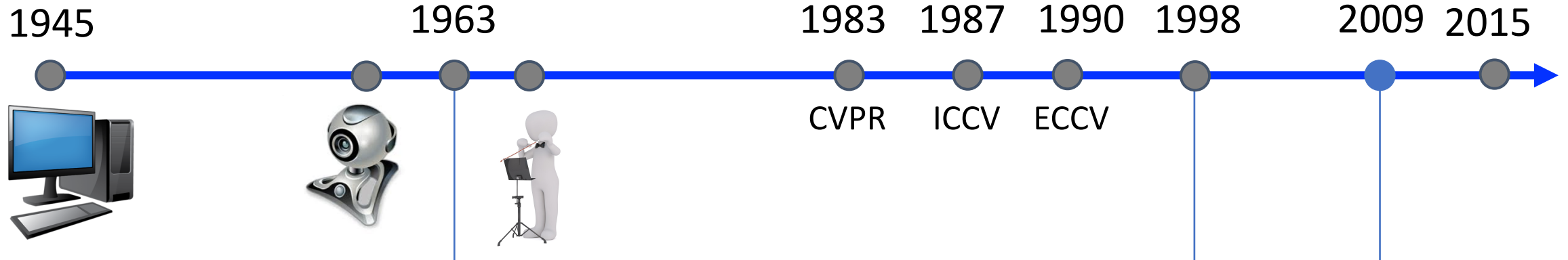


- 4 256x256 images could be stored in the computer memory
- Scanning each image to the computer took ~3 minutes

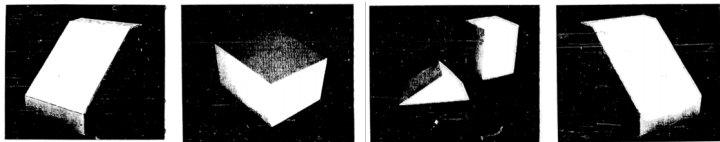
Progress Charted By Emulating Human Perception



Progress Charted By Emulating Human Perception



3D Objects



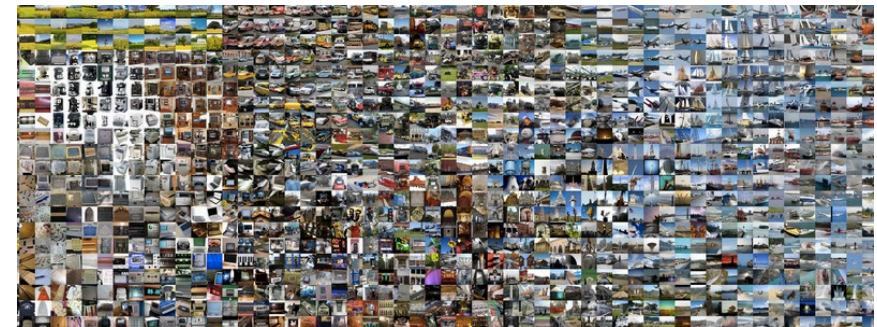
- 4 256x256 images

MNIST

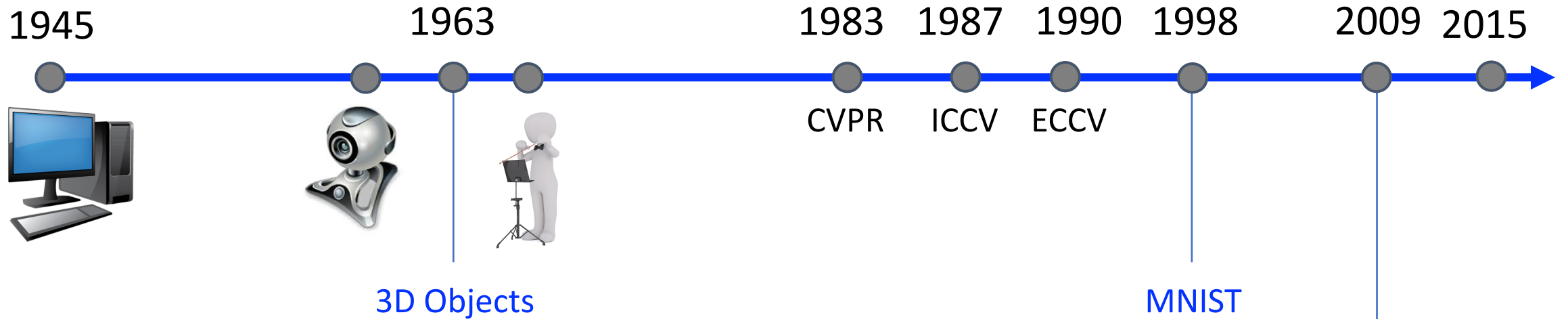


- 70,000 28x28 images [ImageNet](#)

- 3,200,000 images:



Progress Charted By Emulating Human Perception



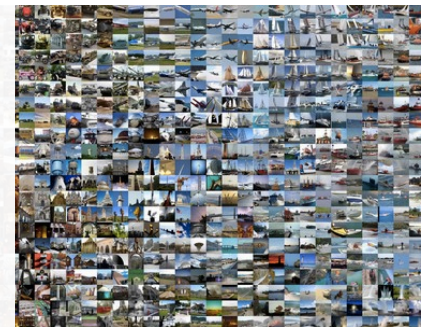
Trend is to build bigger
human-labelled datasets
for many vision tasks!

• 4 256x256 images

• 70,000 28x28 images

• 3200,000 images

ImageNet

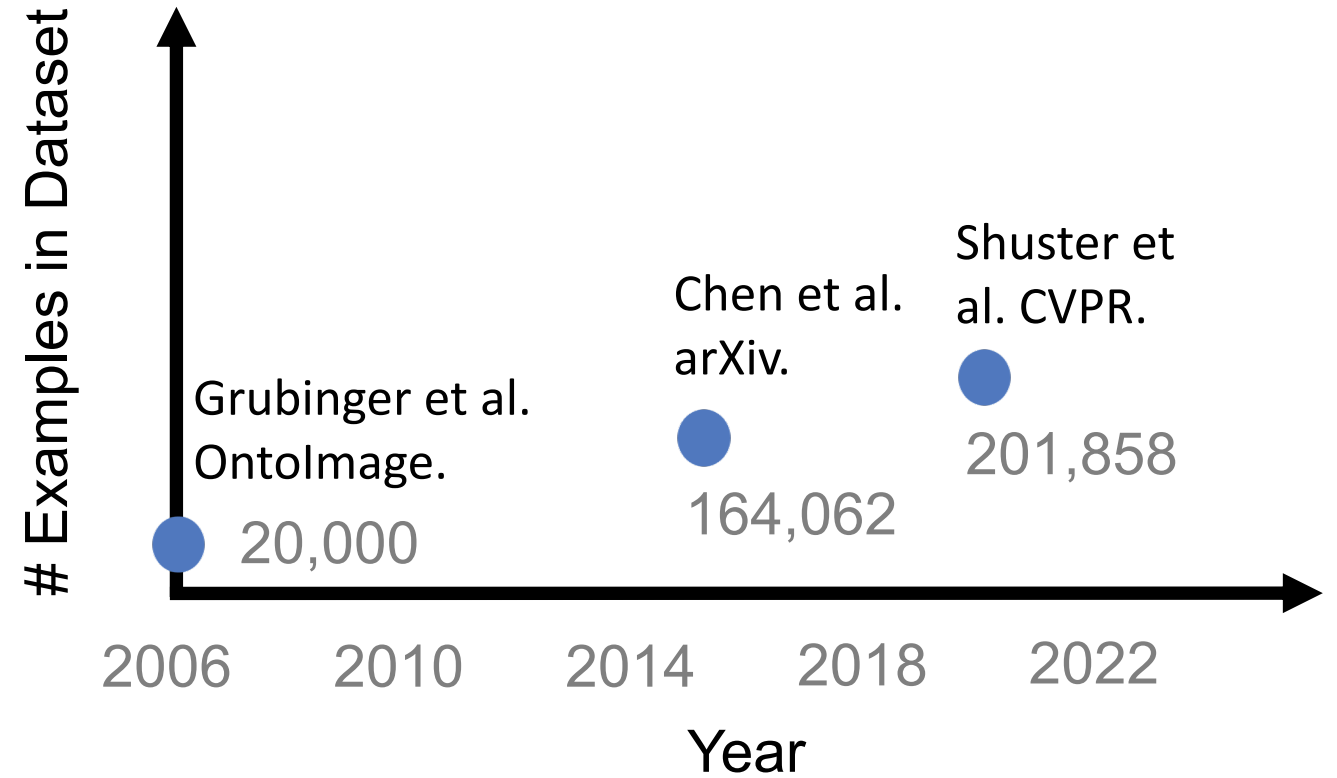


Trend is to Build Bigger Labelled Datasets; e.g.,




Caption:

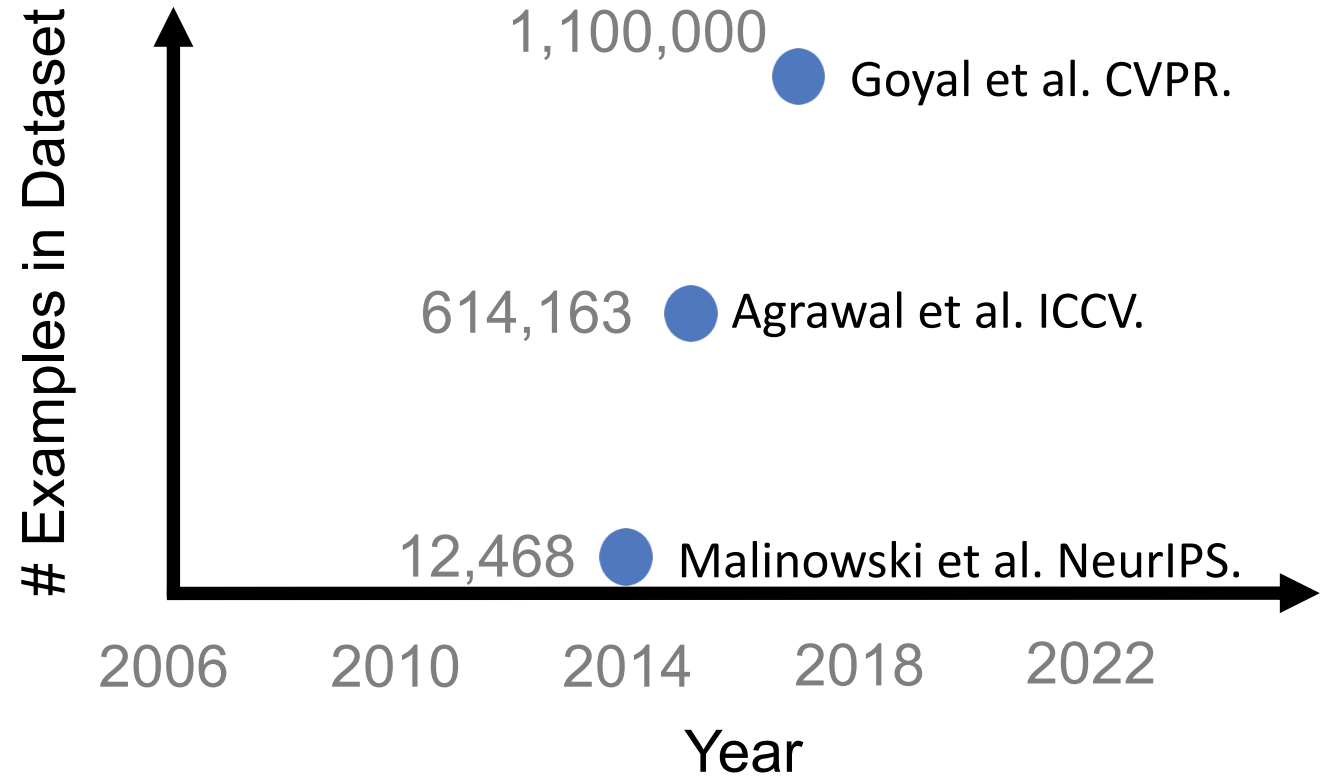
Two tee shirts, one white the other black, hanging in a closet.



Trend is to Build Bigger Labelled Datasets; e.g.,

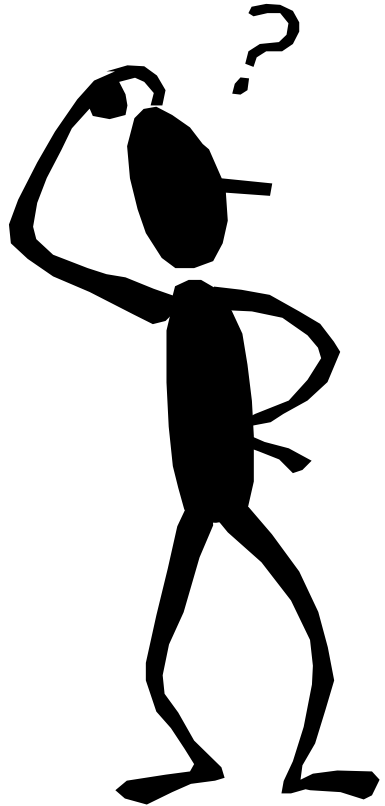


Visual QA
Q: Which shirt is black?
A: Right















Why Bigger Datasets? To Evaluate CV Algorithms

How good is an algorithm?
















e.g., Is a cat in the image?

+	Input:						
	Predicted Label:	Yes	?				?
	True Label:	Yes	?				?

Why Bigger Datasets? To Evaluate CV Algorithms

How good is an algorithm?

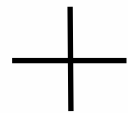
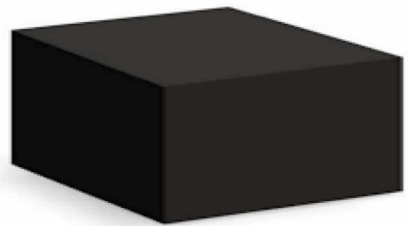
e.g., Is a cat in the image?

Input:						
Predicted Label:	Yes 	?				?
True Label:	Yes	?				?

Why Bigger Datasets? To Evaluate CV Algorithms

How good is an algorithm?

e.g., Is a cat in the image?


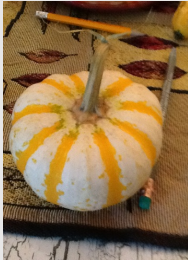













Input:

Prediction Model

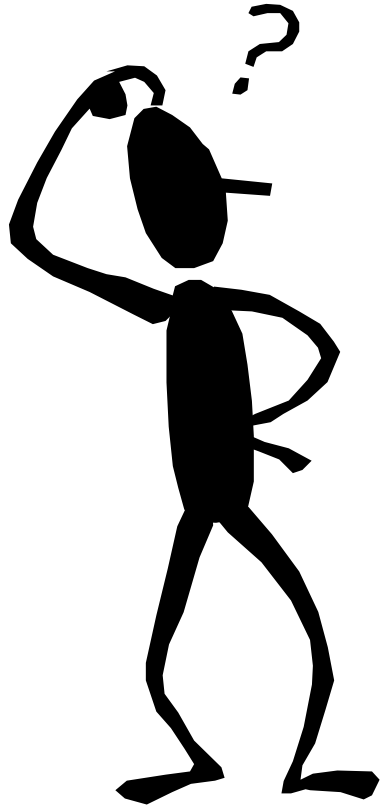
Predicted Label:

True Label:












					
Yes 	Yes				?
Yes	?				?

Why Bigger Datasets? To Evaluate CV Algorithms

How good is an algorithm?

















e.g., Is a cat in the image?

+	Input:						
	Predicted Label:	Yes 	Yes				?
	True Label:	Yes	No				?

Why Bigger Datasets? To Evaluate CV Algorithms

How good is an algorithm?
















e.g., Is a cat in the image?

Input:						
Predicted Label:	Yes 	Yes 				?
True Label:	Yes	No				?

Why Bigger Datasets? To Evaluate CV Algorithms

How good is an algorithm?

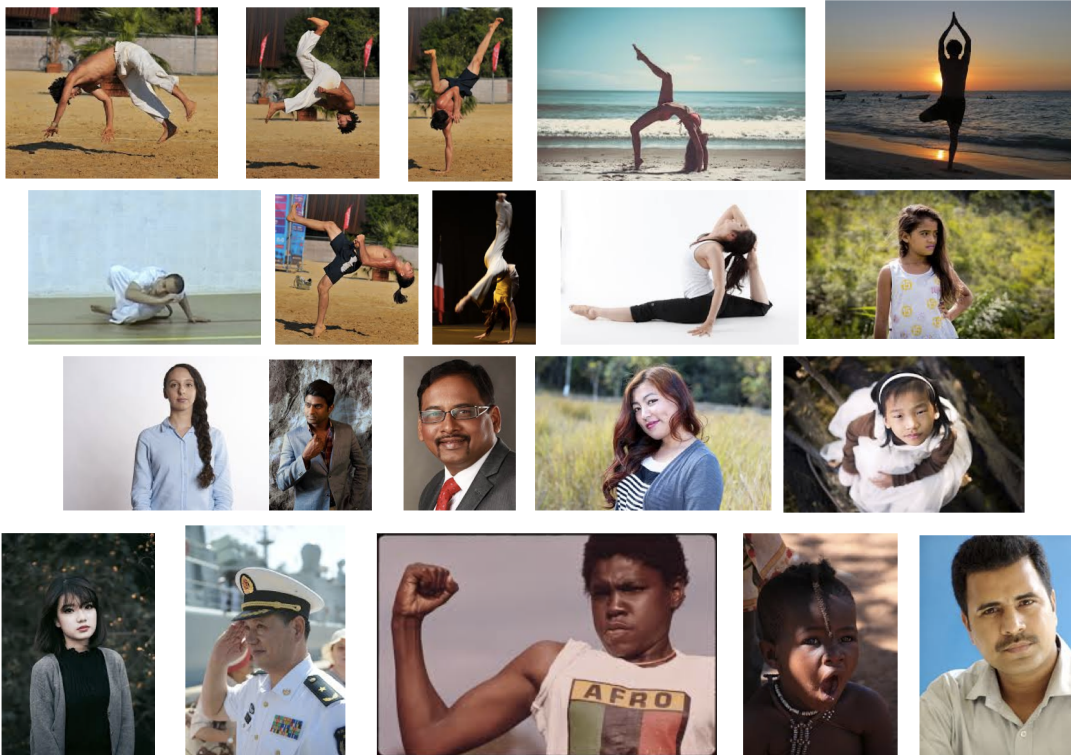
e.g., Is a cat in the image?

Input:						
Predicted Label:	Yes 	Yes 				No 
True Label:	Yes	No				No

Why Bigger Datasets? To Teach CV Algorithms

Typical approach: train using as many labelled examples as possible

e.g., recognize a person



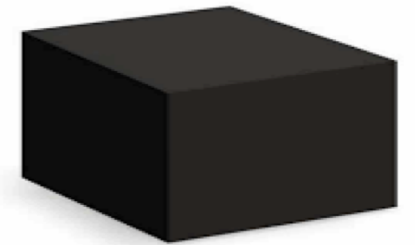
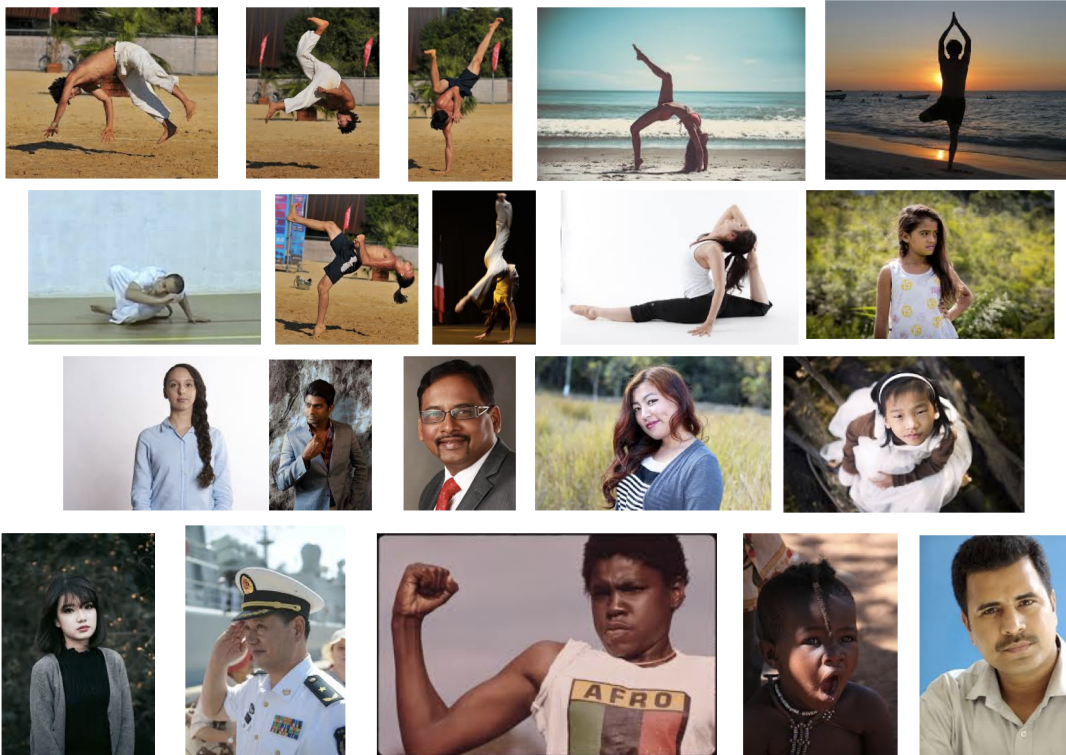
(Intuition: how we teach a person)

Often people perform better when trained on more examples!

Why Bigger Datasets? To Teach CV Algorithms

Typical approach: train using as many labelled examples as possible

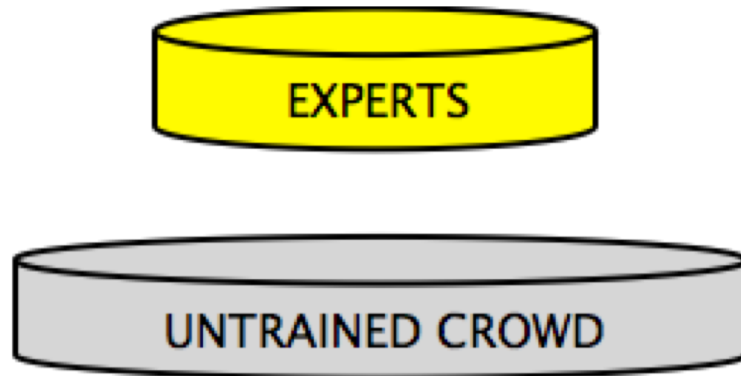
e.g., recognize a person



Algorithms also perform better when trained on more examples!

Why Crowdsourcing?

- Crowds offer a scalable, less expensive alternative to the gold standard of “experts” to generate large human-labelled datasets



Datasets That Have Led to Unethical AI

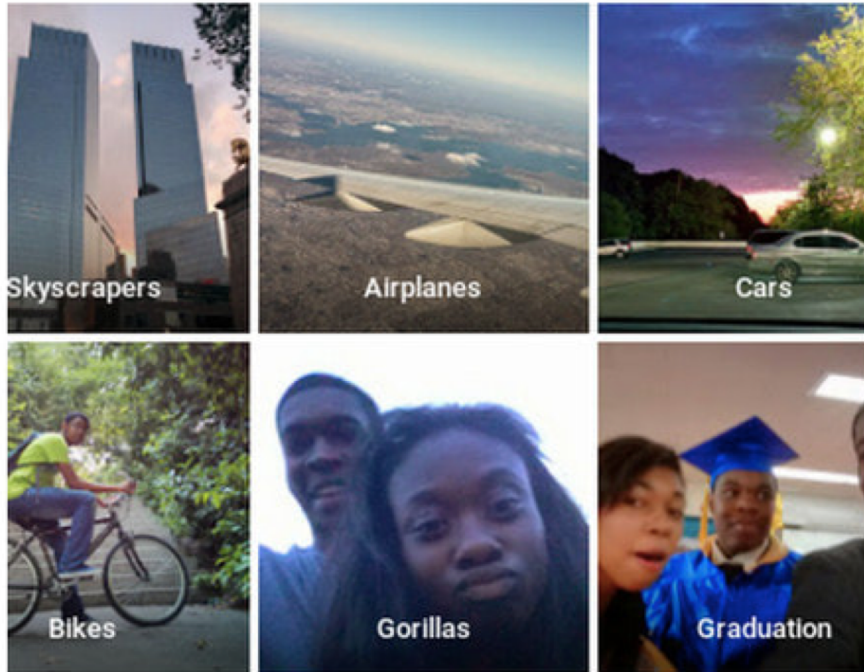


diri noir avec banan
@jackyalcine



+ Follow

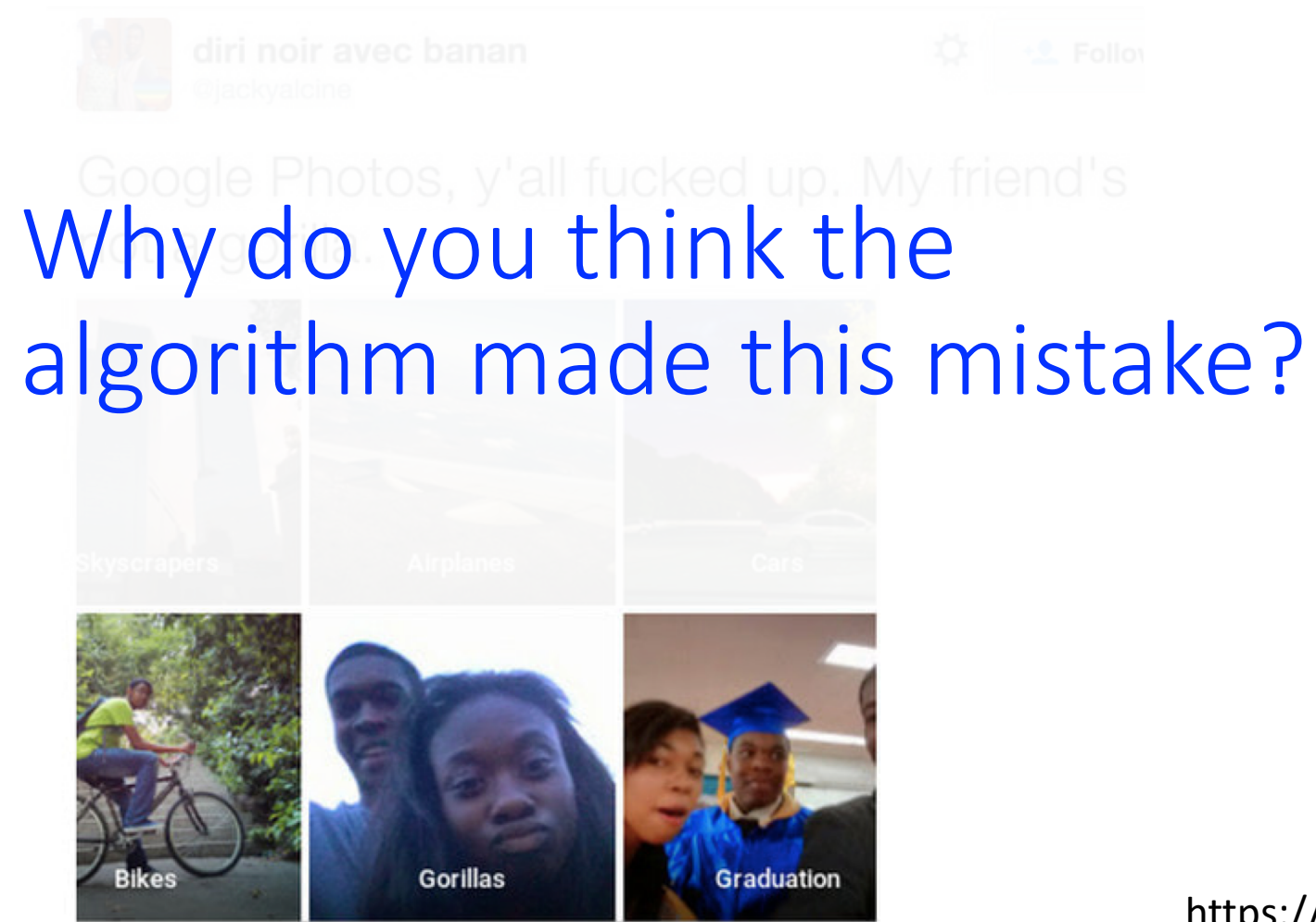
Google Photos, y'all fucked up. My friend's not a gorilla.



Using Twitter to call out Google's algorithmic bias

<https://www.theverge.com/2015/7/1/8880363/google-apologizes-photos-app-tags-two-black-people-gorillas>

Datasets That Have Led to Unethical AI

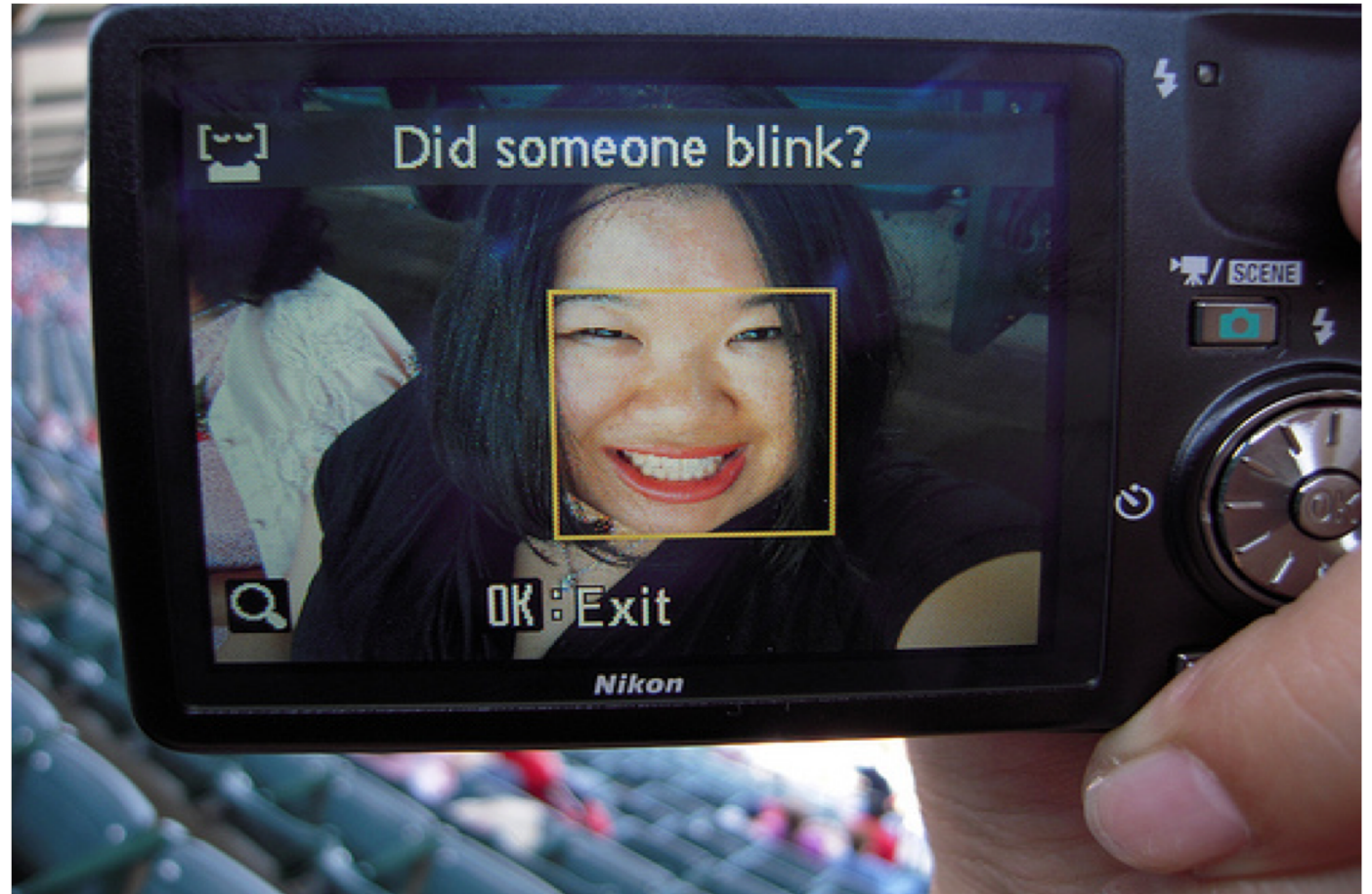


Using Twitter to call out Google's algorithmic bias

<https://www.theverge.com/2015/7/1/8880363/google-apologizes-photos-app-tags-two-black-people-gorillas>

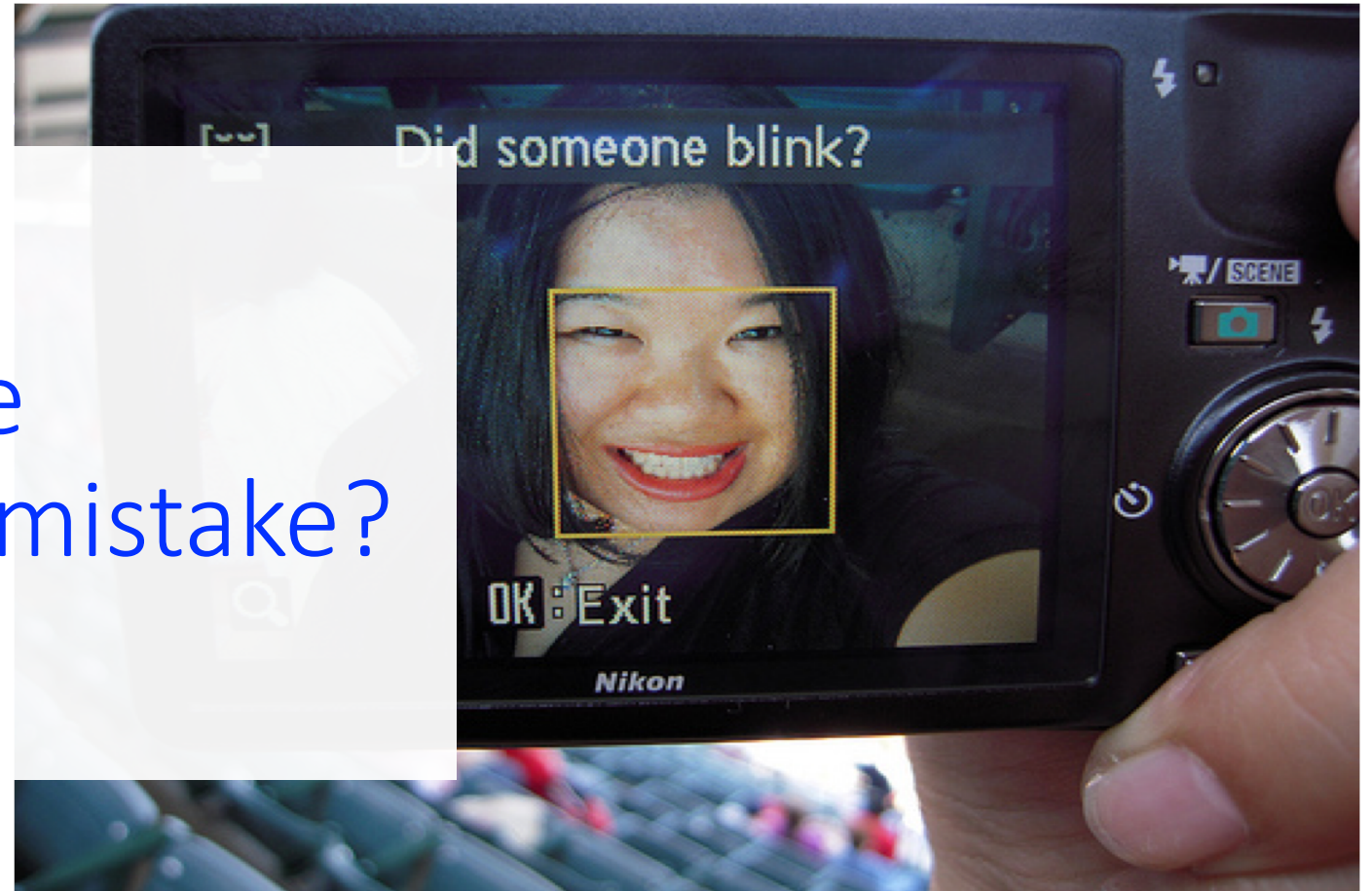
Datasets That Have Led to Unethical AI

Two kids bought their mom a Nikon Coolpix S630 digital camera for Mother's Day... when they took portrait pictures of each other, a message flashed across the screen asking, "Did someone blink?"



Datasets That Have Led to Unethical AI

Why do you think the algorithm made this mistake?



Datasets That Have Led to Unethical AI



COOKING	
ROLE	VALUE
AGENT	WOMAN
FOOD	PASTA
HEAT	STOVE
TOOL	SPATULA
PLACE	KITCHEN



COOKING	
ROLE	VALUE
AGENT	WOMAN
FOOD	FRUIT
HEAT	∅
TOOL	KNIFE
PLACE	KITCHEN



COOKING	
ROLE	VALUE
AGENT	WOMAN
FOOD	MEAT
HEAT	STOVE
TOOL	SPATULA
PLACE	OUTSIDE



COOKING	
ROLE	VALUE
AGENT	WOMAN
FOOD	∅
HEAT	STOVE
TOOL	SPATULA
PLACE	KITCHEN



COOKING	
ROLE	VALUE
AGENT	MAN
FOOD	∅
HEAT	STOVE
TOOL	SPATULA
PLACE	KITCHEN

Algorithm identifies men in kitchens as women. Learned this example from given dataset. (Zhao, Wang, Yatskar, Ordonez, Chang, 2017)

<https://www.wired.com/story/machines-taught-by-photos-learn-a-sexist-view-of-women/>

Datasets That Have Led to Unethical AI

Why do you think the algorithm made this mistake?

The first image shows a woman in a kitchen with a table listing roles like AGENT (WOMAN), FOOD (PASTA), HEAT (STOVE), TOOL (SPATULA), and PLACE (KITCHEN). The second image shows a woman with a table listing AGENT (WOMAN), FOOD (FRUIT), HEAT (empty), TOOL (KNIFE), and PLACE (KITCHEN). The third image shows a woman with a table listing AGENT (WOMAN), FOOD (MEAT), HEAT (STOVE), TOOL (SPATULA), and PLACE (OUTSIDE).

The image shows a man in a kitchen. The table below lists roles: AGENT (WOMAN), FOOD (empty), HEAT (STOVE), TOOL (SPATULA), and PLACE (KITCHEN). The 'AGENT' row is highlighted with a red border.

COOKING	
ROLE	VALUE
AGENT	WOMAN
FOOD	∅
HEAT	STOVE
TOOL	SPATULA
PLACE	KITCHEN

The image shows a man in a kitchen. The table below lists roles: AGENT (MAN), FOOD (empty), HEAT (STOVE), TOOL (SPATULA), and PLACE (KITCHEN).

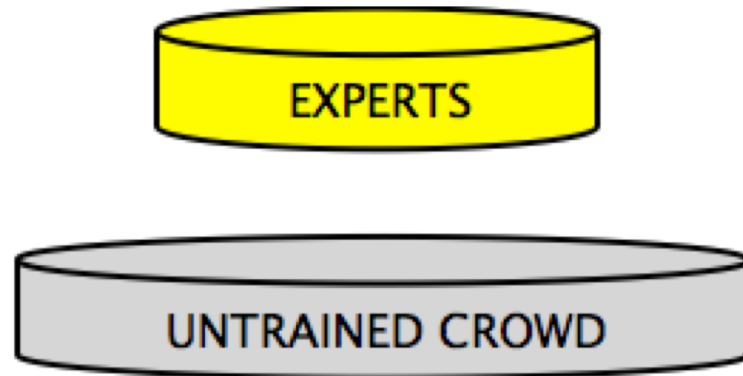
COOKING	
ROLE	VALUE
AGENT	MAN
FOOD	∅
HEAT	STOVE
TOOL	SPATULA
PLACE	KITCHEN

Algorithm identifies men in kitchens as women. Learned this example from given dataset. (Zhao, Wang, Yatskar, Ordonez, Chang, 2017)

<https://www.wired.com/story/machines-taught-by-photos-learn-a-sexist-view-of-women/>

Crowdsourcing for Computer Vision

- Crowds offer a scalable, less expensive alternative to the gold standard of “experts”



- Crowdsourcing challenge: how to **efficiently** collect **high quality** data from an anonymous crowd that leads to **ethical AI**?

Today's Topics

- Class logistics
- Introduction to computer vision
- Introduction to crowdsourcing for computer vision
- Lab: web page creation

References

- Nice summaries of the history of computer vision
 - <https://hackernoon.com/a-brief-history-of-computer-vision-and-convolutional-neural-networks-8fe8aacc79f3>
 - <https://www.epicsysinc.com/blog/machine-vision-history>
 - <https://sevenshonestudios.wordpress.com/computer-vision-and-deep-learning/>
 - <https://cds.cern.ch/record/400313/files/p21.pdf>
- Slide 12: Image Credits
 - <https://www.theverge.com/2018/10/23/18010022/amazon-go-cashier-less-store-san-francisco-location-opens>
 - https://en.wikipedia.org/wiki/File:NASA_Mars_Rover.jpg
- Slide 14-22: Image Credit
 - <http://www.minnesotavisiontherapy.com/what-is-vision-therapy>
- Slide 16: Image Credit
 - <https://en.wikipedia.org/wiki/ENIAC#/media/File:Eniac.jpg>