南京大学
NANJING UNIVERSITY

计算机视觉表征与识别

Chapter 1： Introduction to computer vision

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媒体计算课题组

http://mcg.nju.edu.cn/

Overview

- What is computer vision about?
- Computer vision is useful.
- Computer vision is difficult.
- History and progress of computer vision
- Course overview

Introduction



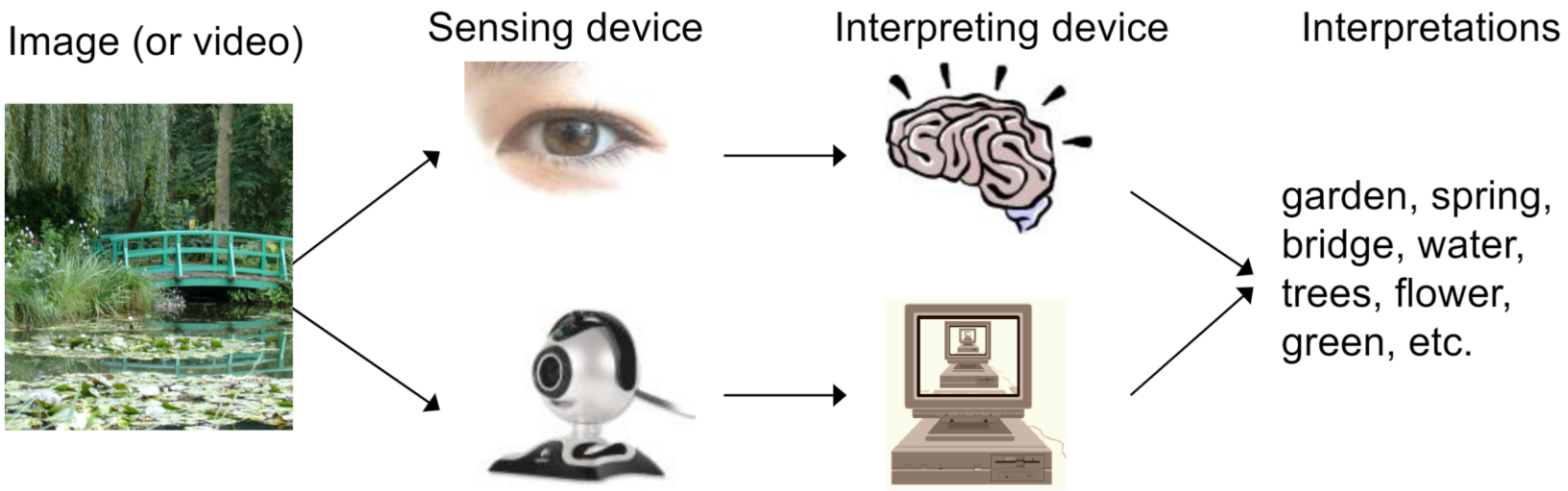


Camera is everywhere






What is computer vision



The goal of computer vision

- To extract “meaning” from pixels

What we see

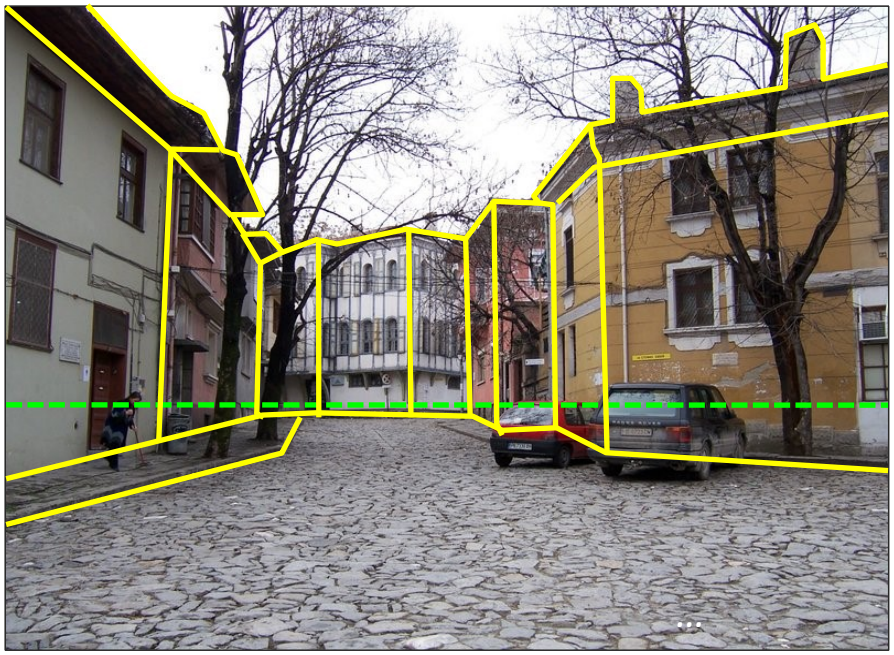
0	3	2	5	4	7	6	9	8
3	0	1	2	3	4	5	6	7
2	1	0	3	2	5	4	7	6
5	2	3	0	1	2	3	4	5
4	3	2	1	0	3	2	5	4
7	4	5	2	3	0	1	2	3
6	5	4	3	2	1	0	3	2
9	6	7	4	5	2	3	0	1
8	7	6	5	4	3	2	1	0

What a computer sees

Source: S. Narasimhan

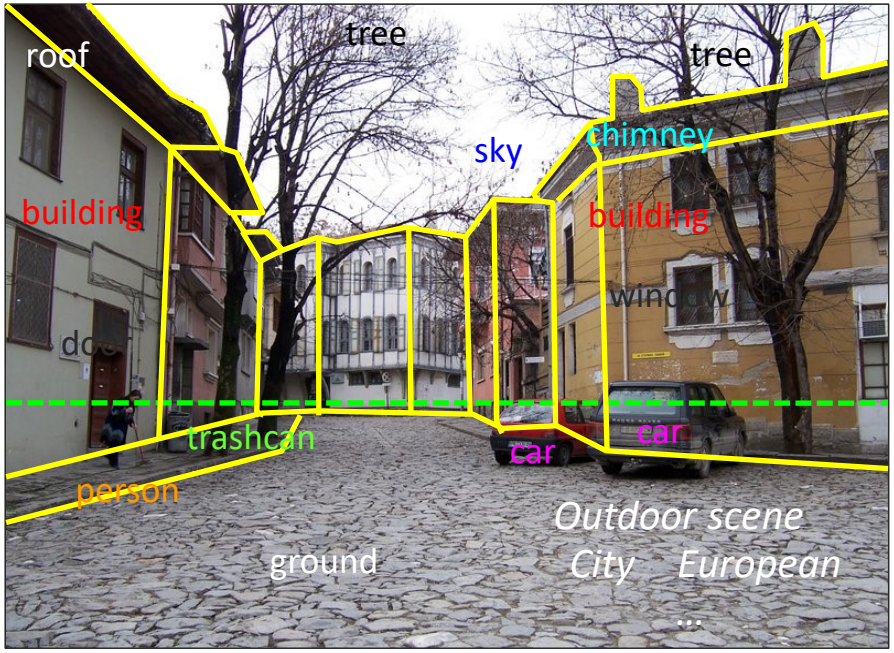
What kind of information

What kind of information



Geometric information

What kind of information



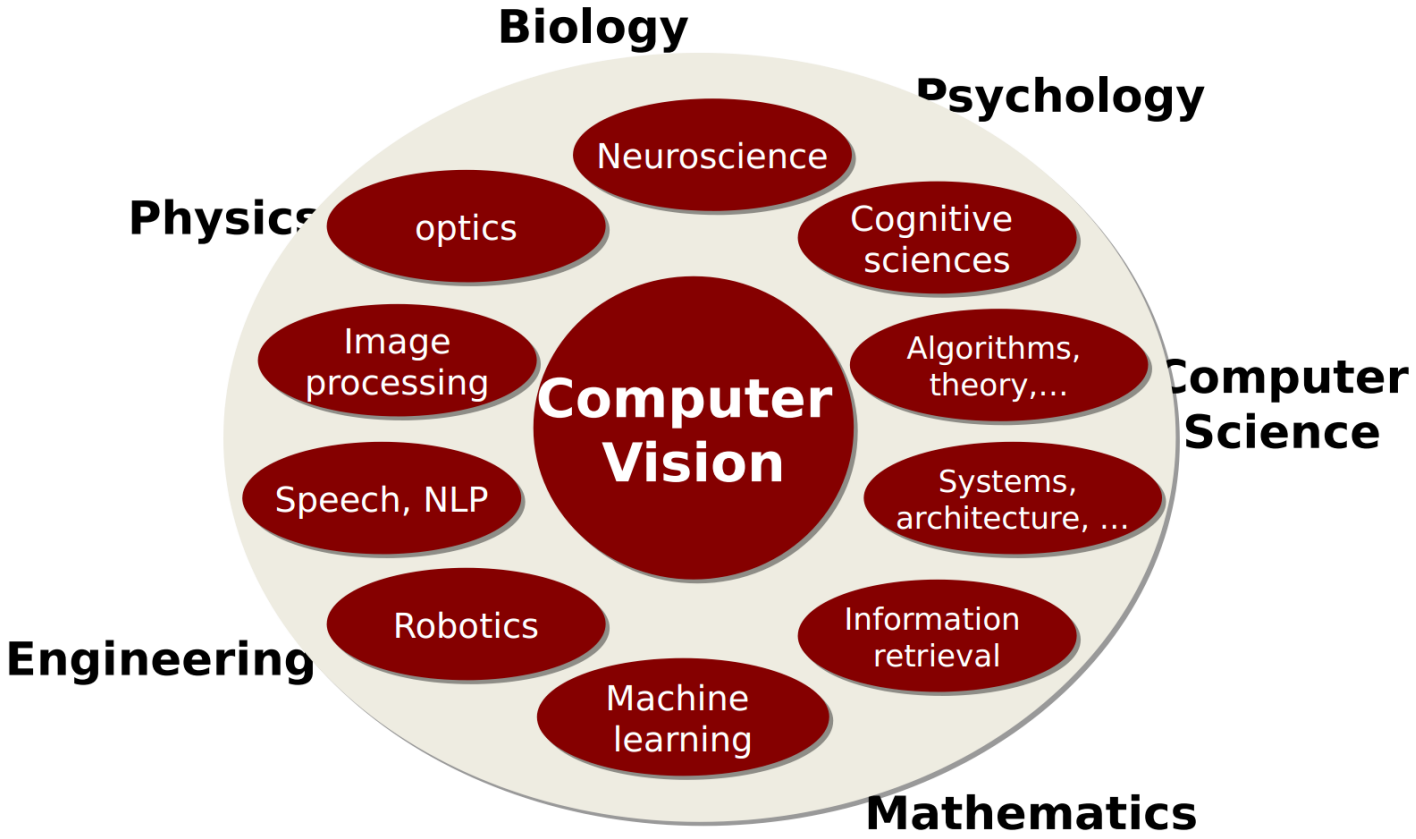
Geometric information

Semantic information

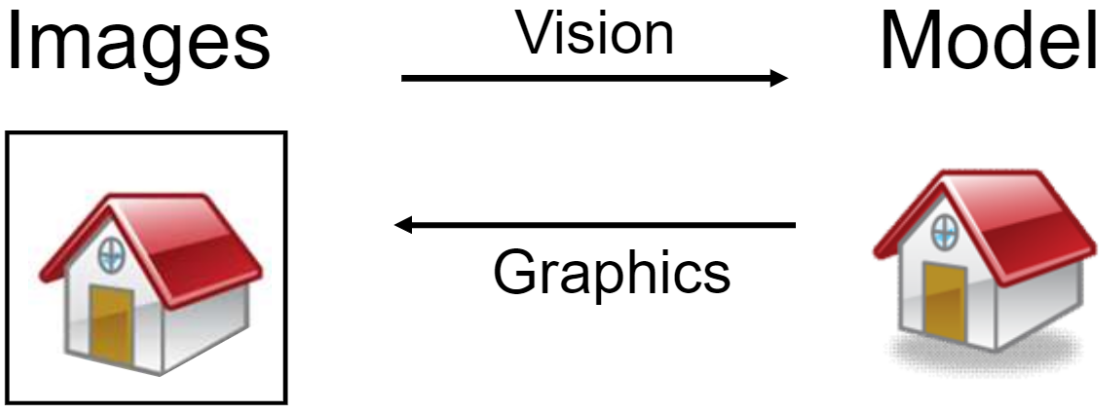
Computer vision

- 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, scene, and people (perception and interpretation)

Related disciplines



Vision and graphics



Inverse problems: analysis and synthesis.

Why study computer vision

- **Computer vision is useful**
- Computer vision is difficult
- Computer vision is fast developing

Vision is useful

- For people vision is their most crucial sense, for good reason:
  - half our brain is devoted to it
  - developed many times during evolution
  - it can be implemented with high resolution
  - yields color, texture, depth, motion, shape

Faces and digital cameras

Camera waits for everyone to smile to take a photo [Canon]

Setting camera focus via face detection


Revision3

MMLAB of CUHK

Deep Learning Face Representation by Joint Identification-Verification Y Sun, X Wang, X Tang arXiv	2251	2014
Deep Learning Face Representation from Predicting 10,000 Classes Y Sun, X Wang, X Tang Computer Vision and Pattern Recognition, 1891-1898	2061	2014
Deep Convolutional Network Cascade for Facial Point Detection Y Sun, X Wang, X Tang Computer Vision and Pattern Recognition, 3476-3483	1477	2013
Deeply learned face representations are sparse, selective, and robust Y Sun, X Wang, X Tang Proceedings of the IEEE conference on computer vision and pattern …	980	2015
Deepid3: Face recognition with very deep neural networks Y Sun, D Liang, X Wang, X Tang arXiv preprint arXiv:1502.00873	970	2015
Hybrid Deep Learning for Face Verification Y Sun, X Wang, X Tang International Conference on Computer Vision, 1489-1496	447	2013
Sparsifying neural network connections for face recognition Y Sun, X Wang, X Tang Proceedings of the IEEE Conference on Computer Vision and Pattern …	133	2016

Pig face recognition

A system made by Yingzi Techology, a small Chinese company, scanning a barn to recognize pig faces.
Yingzi Technology

Video-based interfaces

Human joystick, NewsBreaker Live

Assistive technology systems
Camera Mouse, Boston College

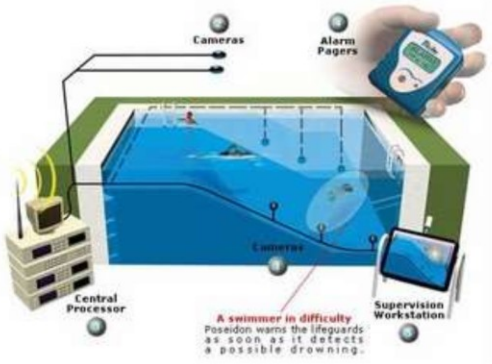
Microsoft Kinect


THE
SOCIAL
MEDIA SHOW


/SUS

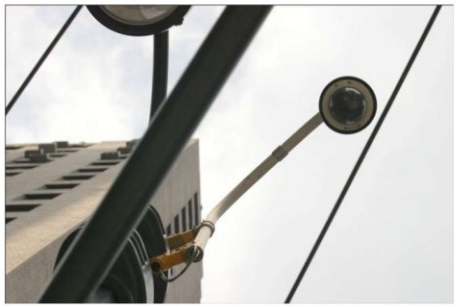
Safety & security

Navigation,
driver safety



Monitoring pool
(Poseidon)

Pedestrian detection
MERL, Viola et al.



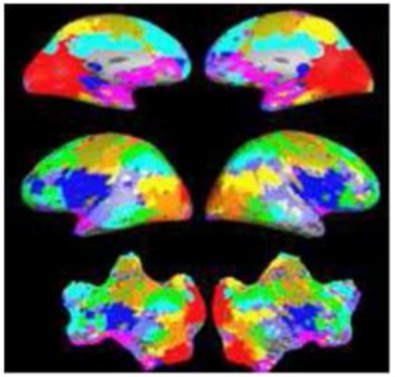
Surveillance

The system converts image data taken by 4 super-wide angle cameras, to display a virtual image of the vehicle from above.


LEARNING
NVIDIA

Vision for medical & neuroimages

Image guided surgery
MIT AI Vision Group



fMRI data
Golland et al.

Overview

- What is computer vision about?
- Computer vision is useful.
- **Computer vision is difficult.**
- History and progress of computer vision
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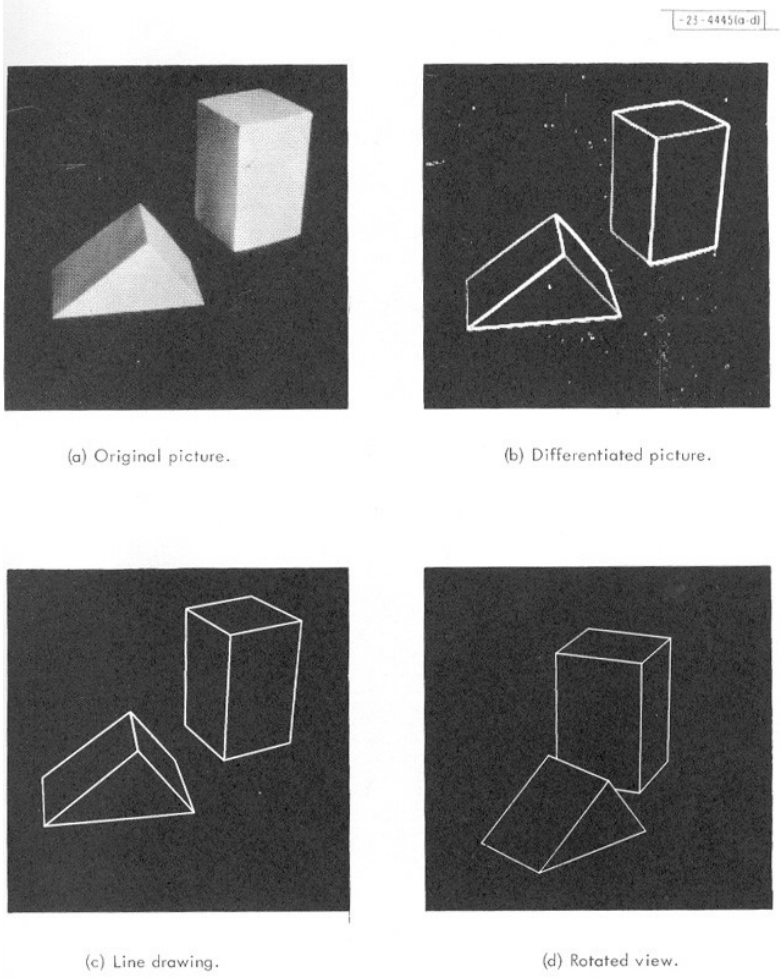
Origins of computer vision



L. G. Roberts *Machine Perception of Three Dimensional Solids*
Ph.D. thesis, MIT Department of Electrical Engineering, 1963.

Origins of computer vision

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

PROJECT MAC

Artificial Intelligence Group — July 7, 1966

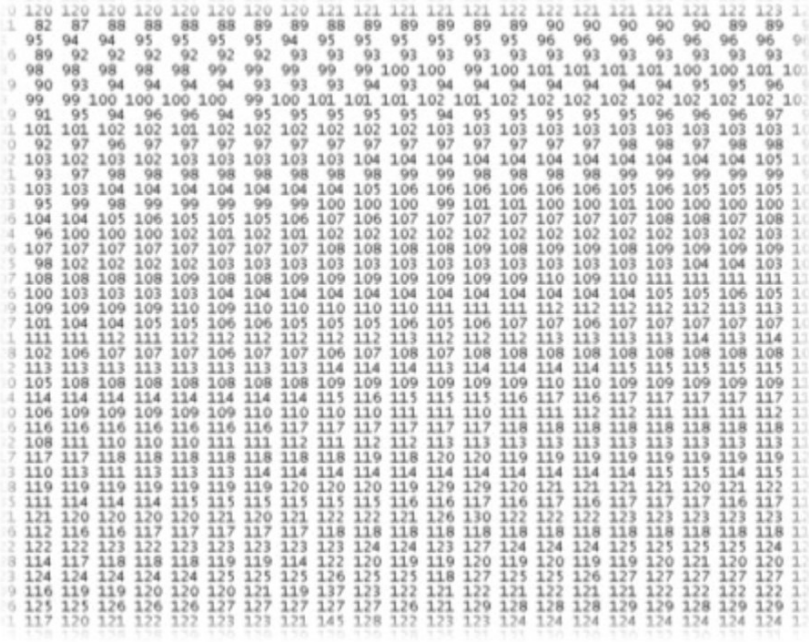
Vision Memo. No. 100.

THE SUMMER VISION PROJECT

Seymour Papert

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

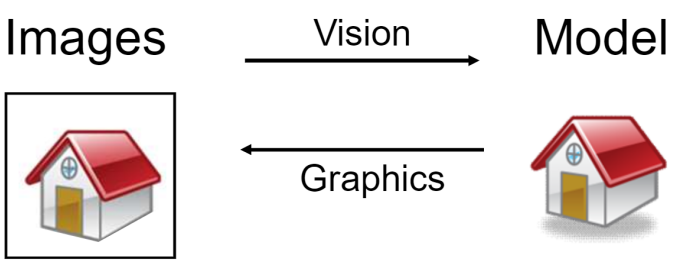
Computer vision is difficult



Gap between low level signal and high level meanings

Challenges: ill posed problem

- Ill-posed problem: real world much more complex than what we can measure in images.
- Impossible to literally “invert” image formation process.



Inverse problems: analysis and synthesis.

Challenges: large variations

Illumination

Object pose

Clutter

Occlusions

Intra-class appearance

Viewpoint

Challenge: intra-class variation

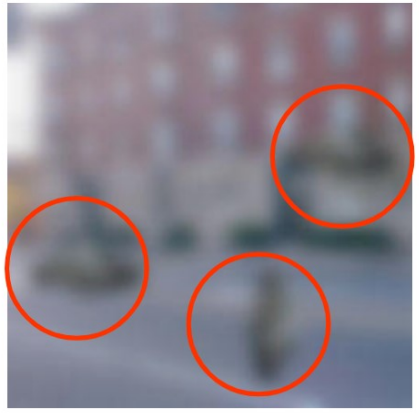





slide credit: Fei-Fei, Fergus & Torralba

Challenge: context

All encircled patterns are identical:



…still, vision is hard even for humans

What color is this dress?

Images are fundamentally ambiguous!

Challenges: complexity

- High dimension of input data
  - Millions of pixels in an image
- Large number of categories
  - 30,000 recognizable object categories
- Large number of visual data
  - Billions of images online
  - 144K hours of new video on YouTube daily
- About half of the cerebral cortex in primates is devoted to processing visual information

Overview

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- **History and progress of computer vision**
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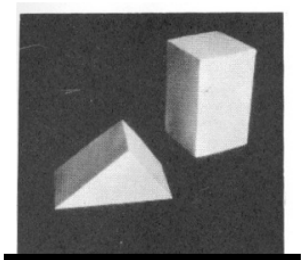
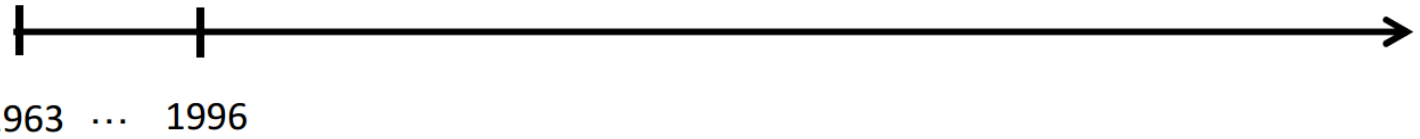
Progress charted by dataset

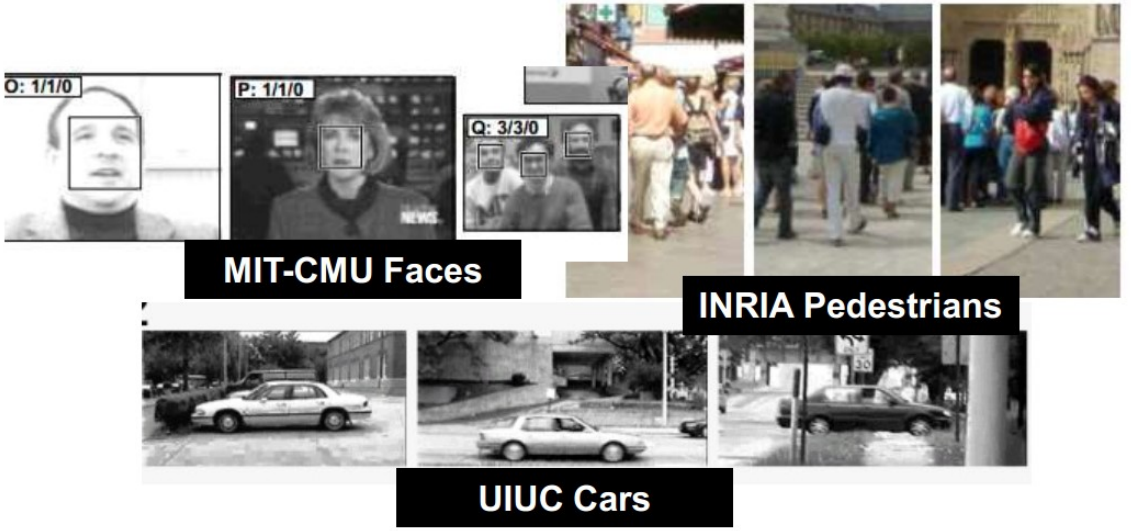


Roberts 1963

COIL



Progress charted by dataset

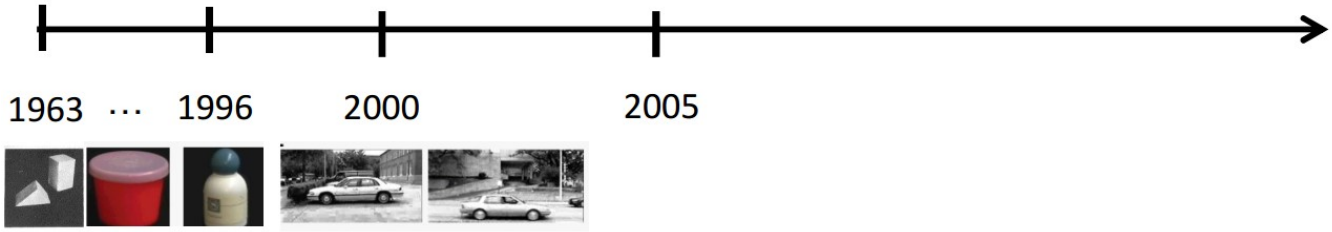


Progress charted by dataset

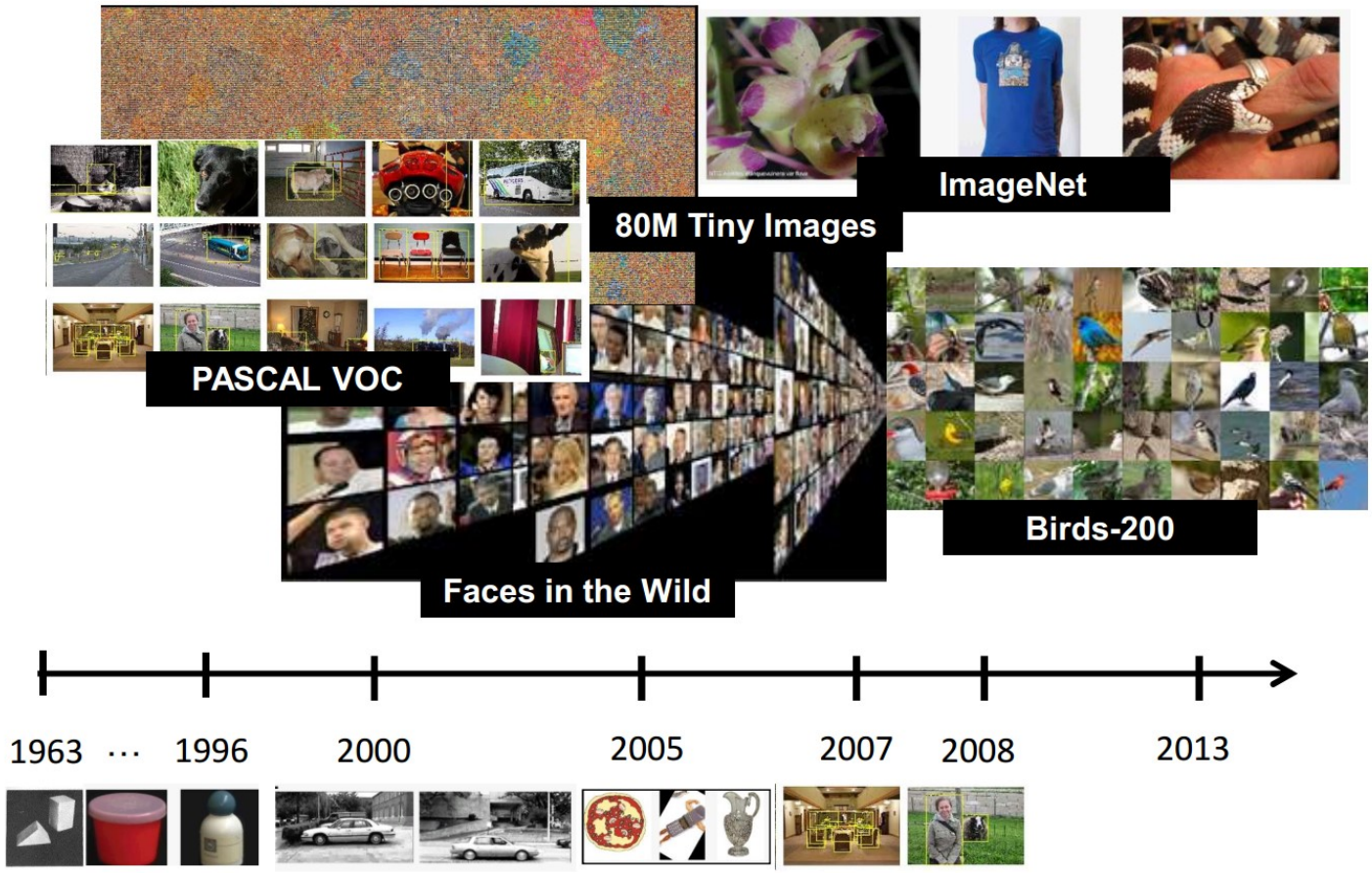
MSRC 21 Objects

Caltech-101

Caltech-256

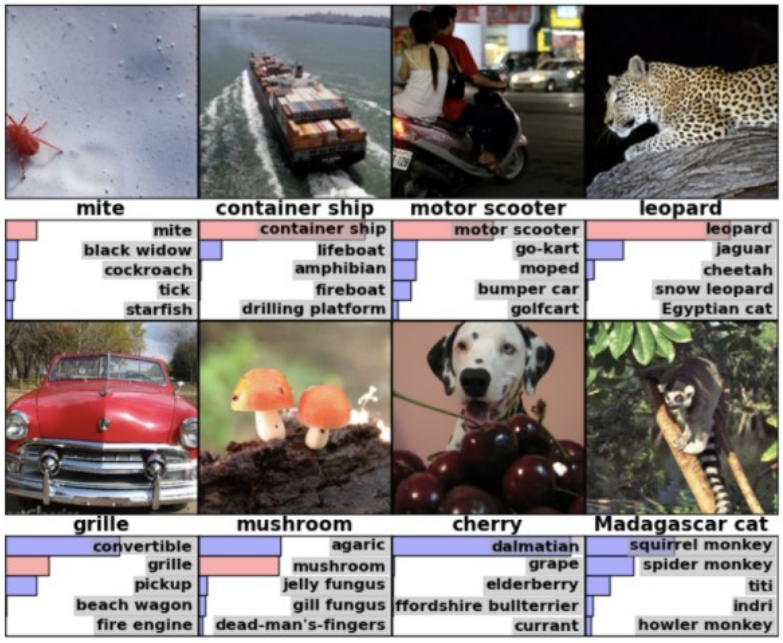


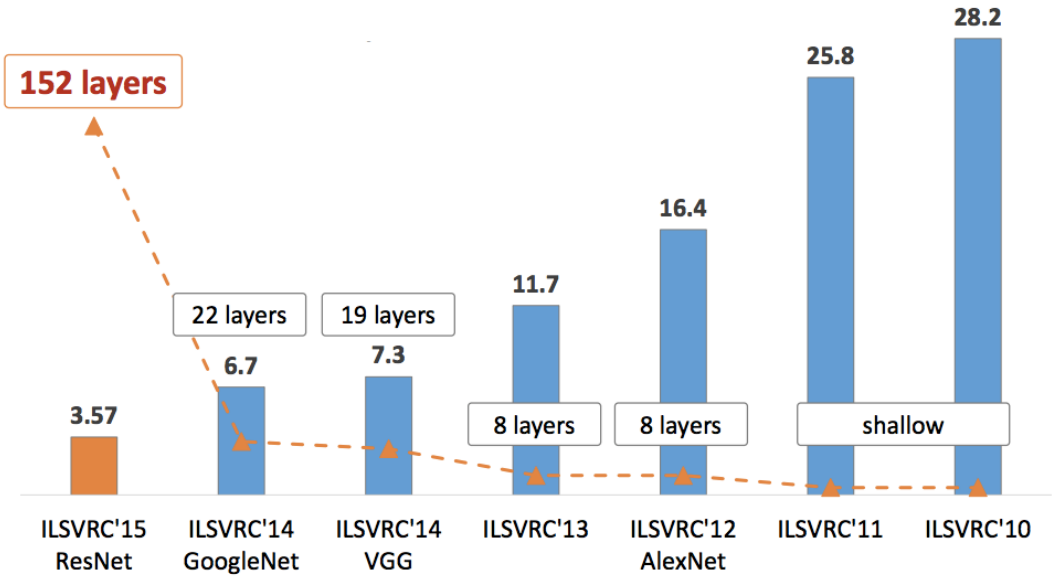
Progress charted by dataset



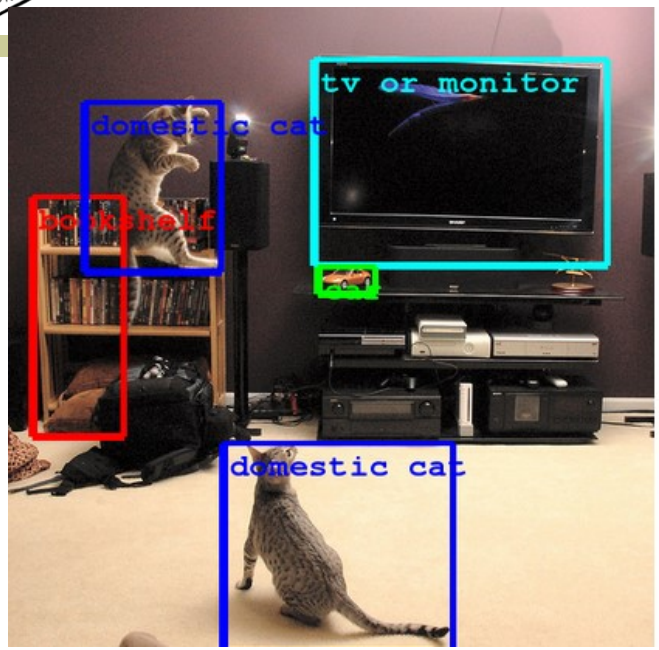
Recognition: General categories

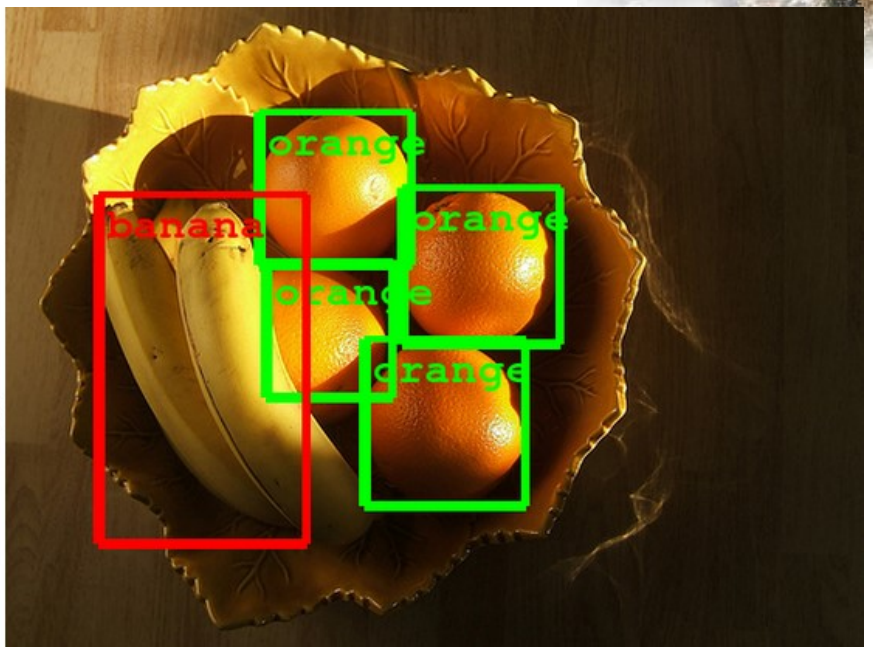
- ImageNet challenge



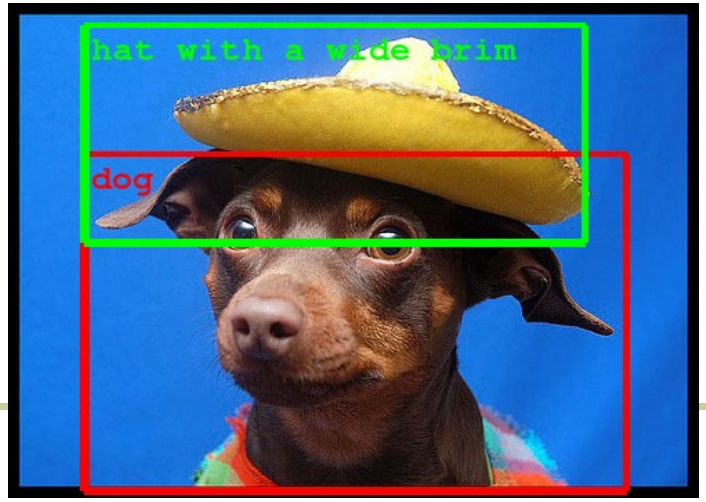


Recognition: General categories





- 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



Large scale recognition

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USE THE URL CHOOSE A FILE INSTEAD

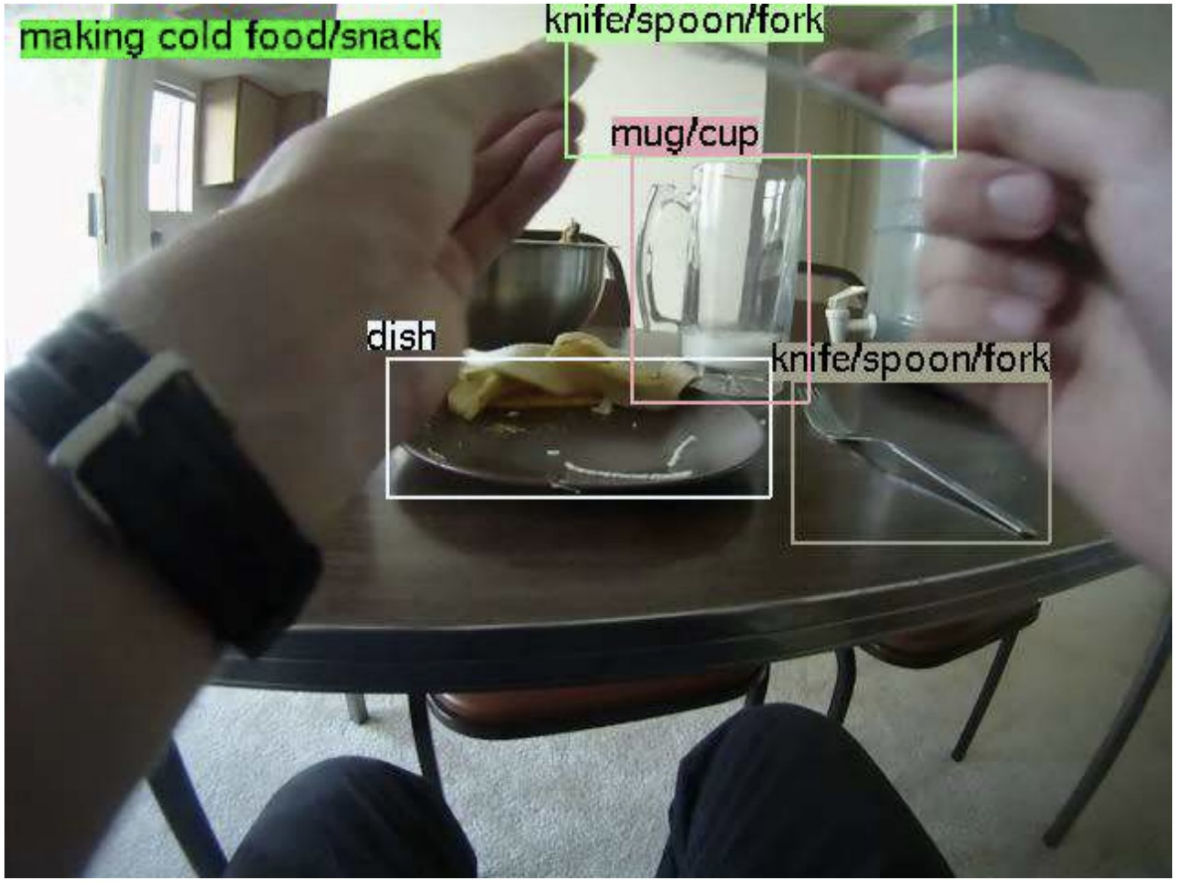
*By using the demo you agree to our terms of service

Predicted Tags

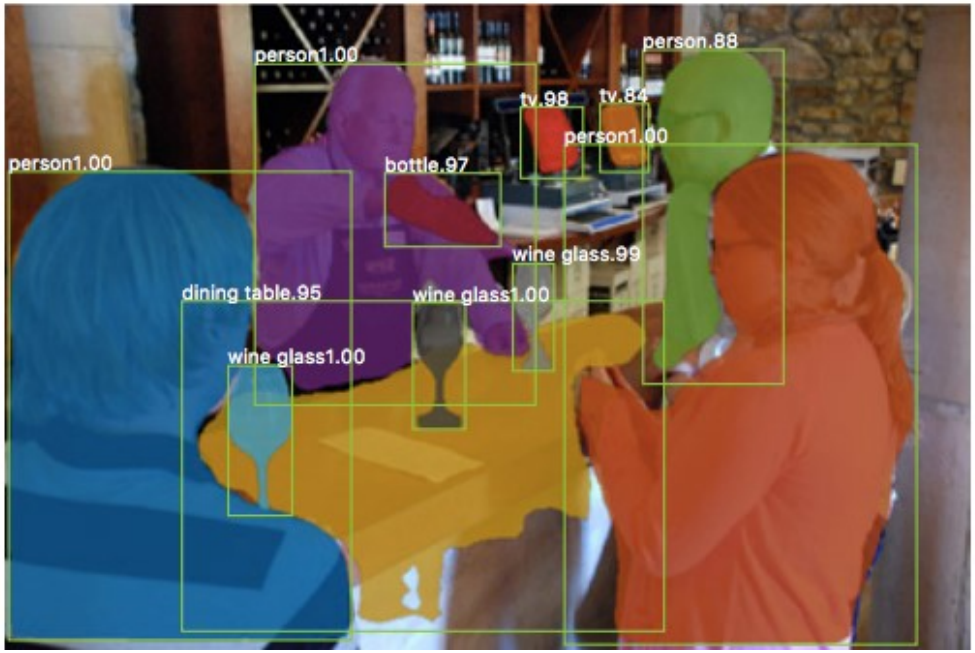
mammal livestock cattle pasture agriculture bovine farm nobody meadow grass

Similar Images

Recognition in first-person view



Object detection, instance segmentation



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

Image captioning

Describes without errors	Describes with minor errors	Somewhat related to the image	Unrelated to the image
 A person riding a motorcycle on a dirt road.	 Two dogs play in the grass.	 A skateboarder does a trick on a ramp.	 A dog is jumping to catch a frisbee.
 A group of young people playing a game of frisbee.	 Two hockey players are fighting over the puck.	 A little girl in a pink hat is blowing bubbles.	 A refrigerator filled with lots of food and drinks.
 A herd of elephants walking across a dry grass field.	 A close up of a cat laying on a couch.	 A red motorcycle parked on the side of the road.	 A yellow school bus parked in a parking lot.

Image generation

- Faces: 1024x1024 resolution, CelebA-HQ

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

Image generation

- BigGAN: 512 x 512 resolution, ImageNet

A. Brock, J. Donahue, K. Simonyan, Large scale GAN training for high fidelity natural image synthesis, arXiv 2018

Image generation

- BigGAN: 512 x 512 resolution, ImageNet

A. Brock, J. Donahue, K. Simonyan, Large scale GAN training for high fidelity natural image synthesis, arXiv 2018

Image generation

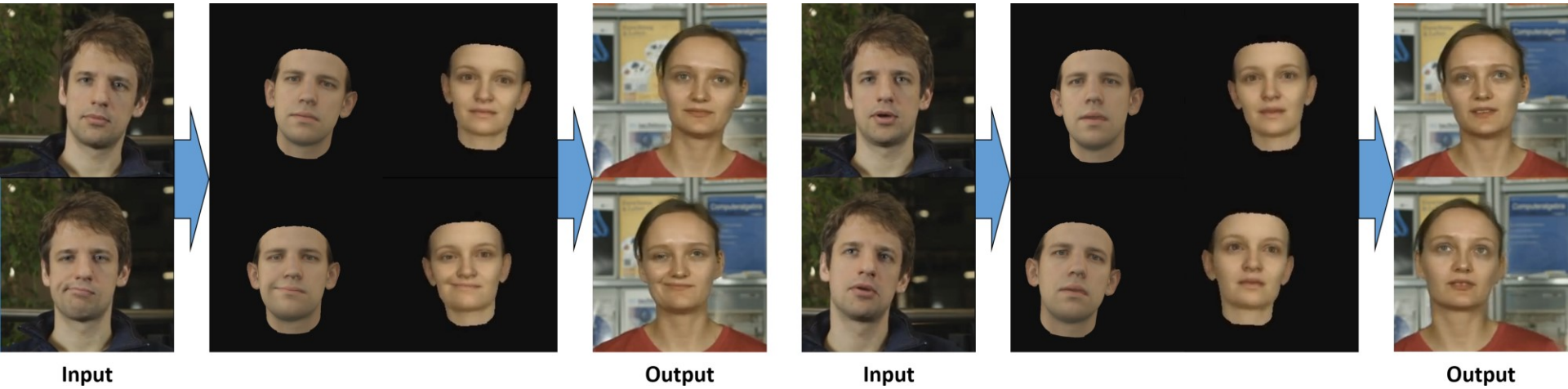
- BigGAN: 512 x 512 resolution, ImageNet

Easy classes

Difficult classes

A. Brock, J. Donahue, K. Simonyan, Large scale GAN training for high fidelity natural image synthesis, arXiv 2018

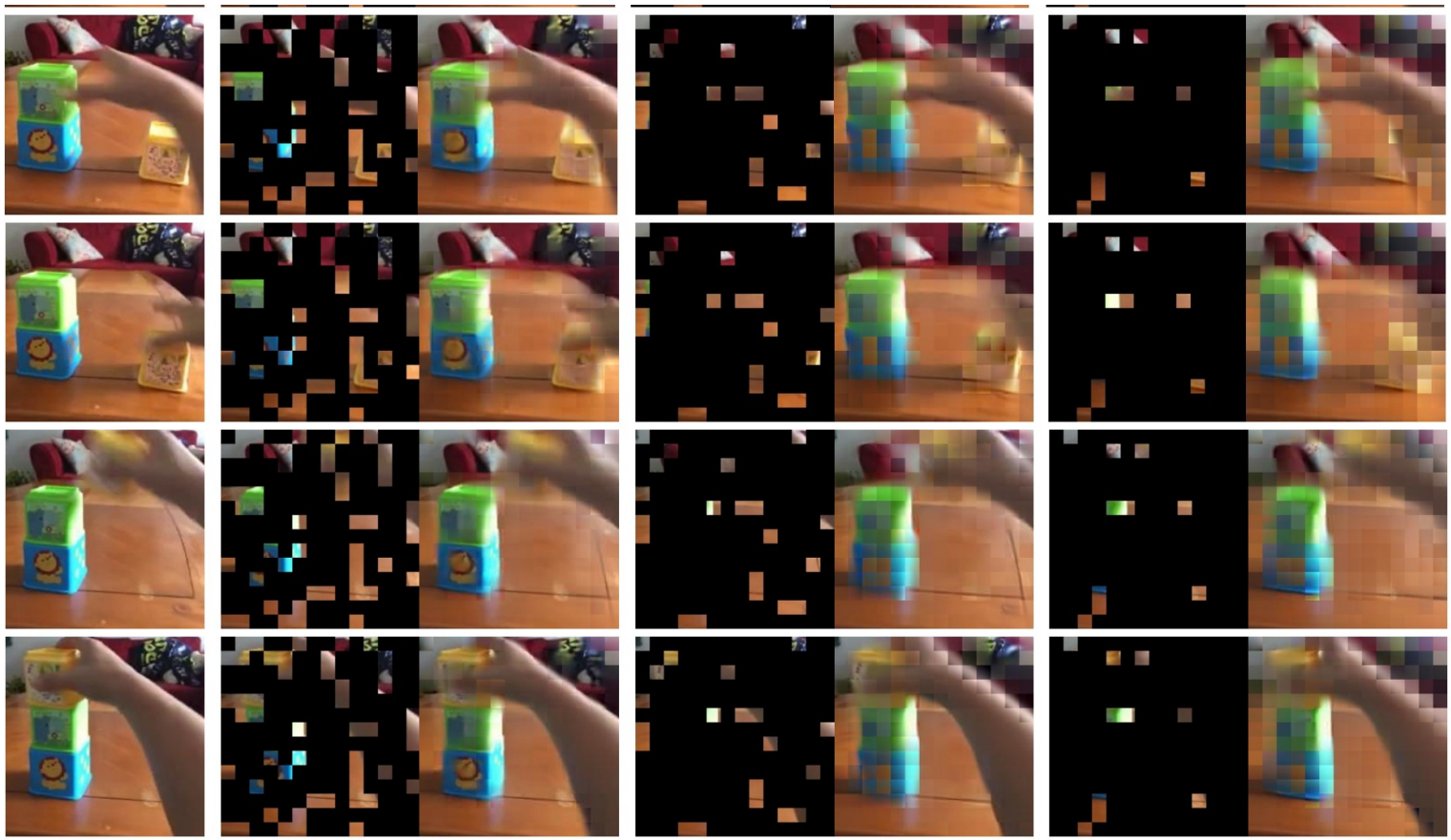
DeepFakes



"A quiet wager has taken hold among researchers who study artificial intelligence techniques and the societal impacts of such technologies. They're betting whether or not someone will create a so-called Deepfake video about a political candidate that receives more than 2 million views before getting debunked by the end of 2018" – IEEE Spectrum, 6/22/2018

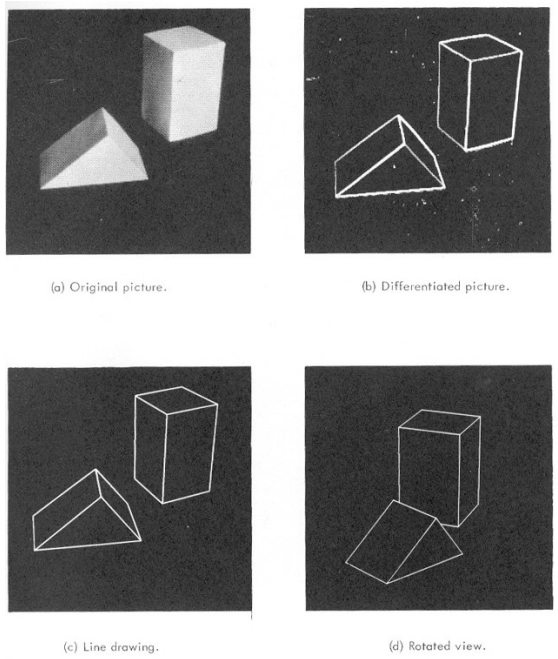
Masked Image Modeling

Masked Video Modeling



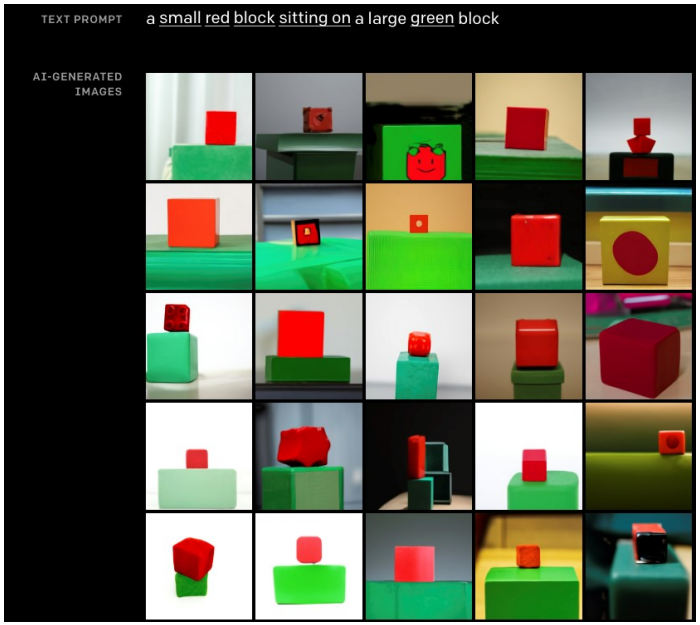
Progress Comparison

How it started



L. G. Roberts, 1963

How it's going



OpenAI DALL-E, 2020

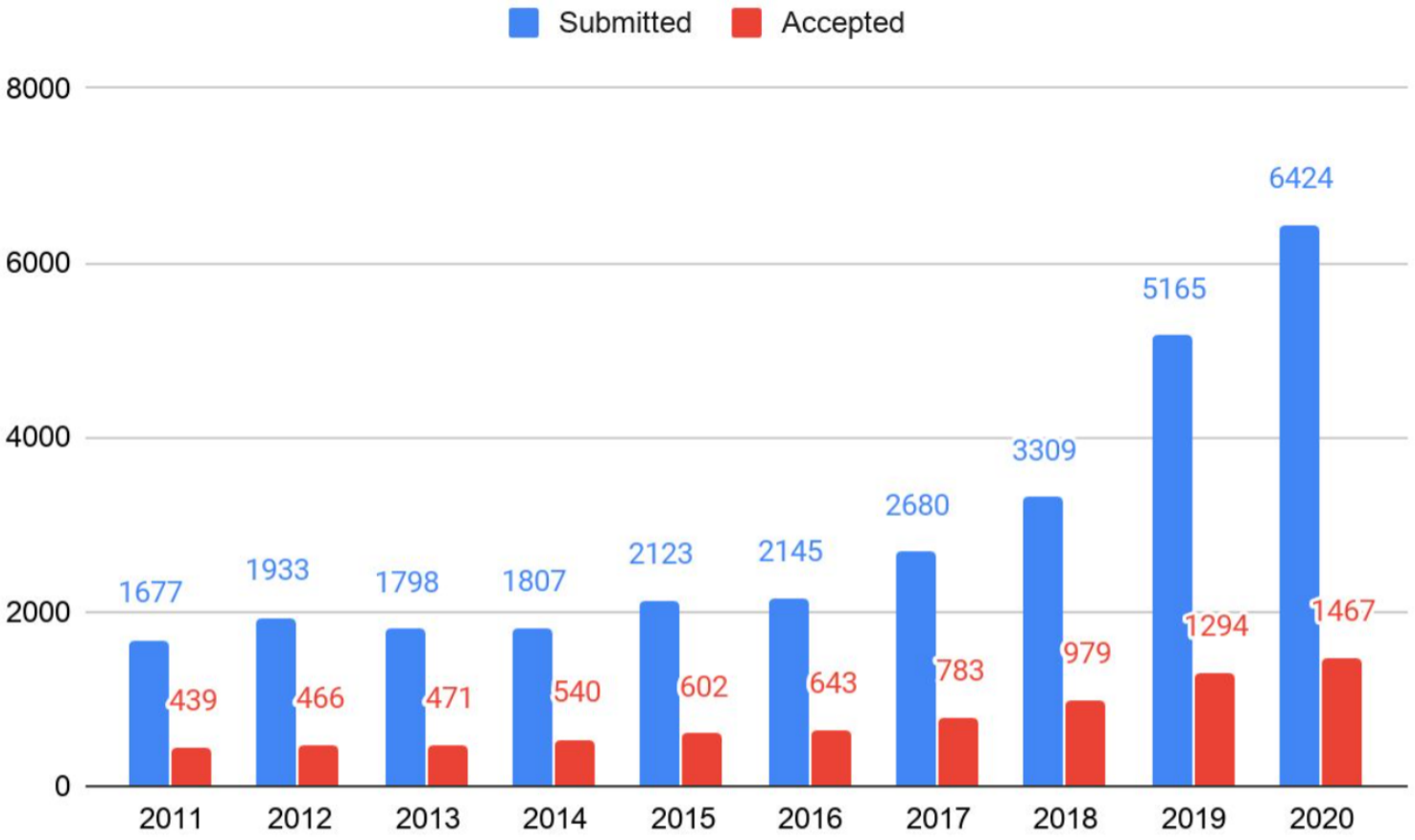
Decade by decade

- **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
- 2020s: ?

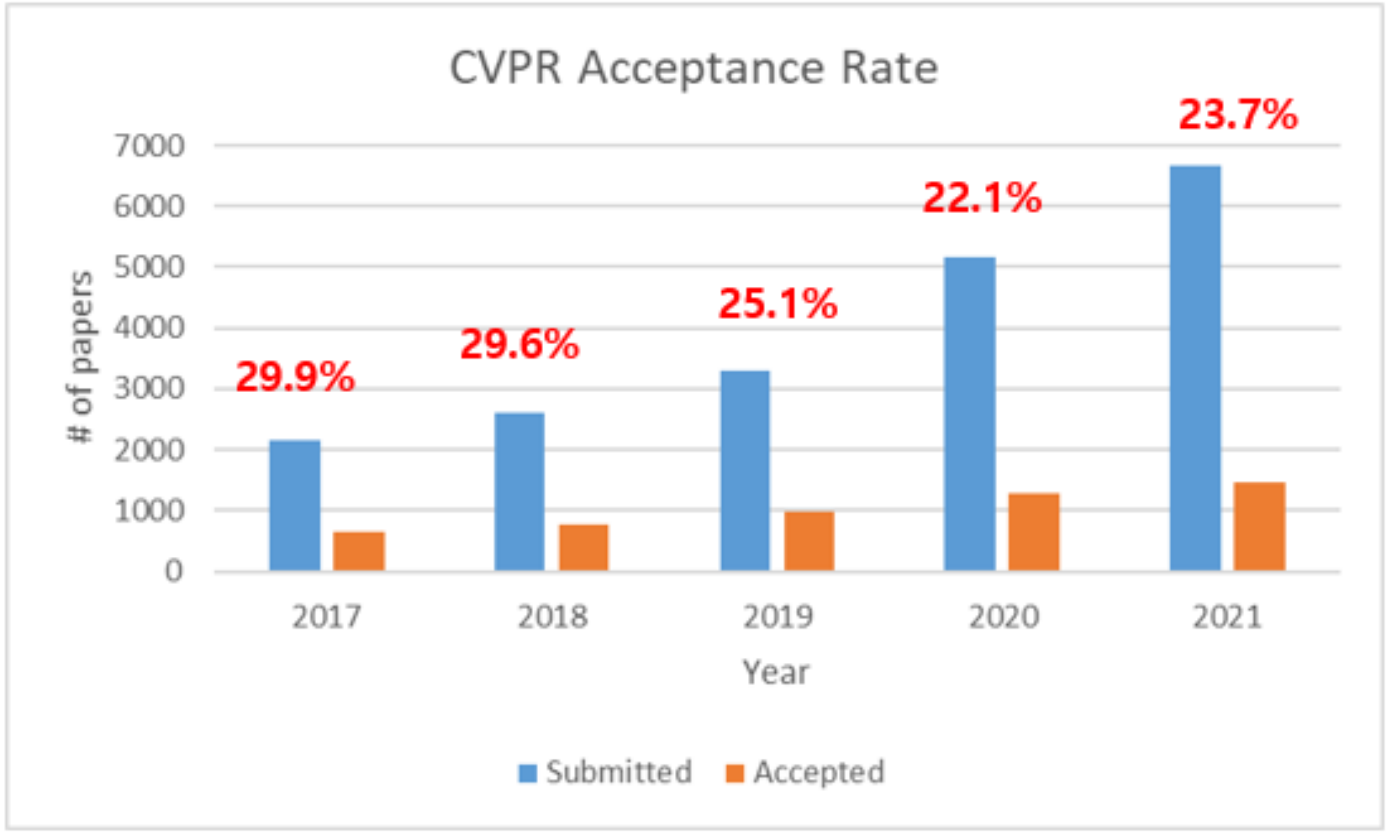
- For much more detail: see my historical overview

Adapted from J. Malik

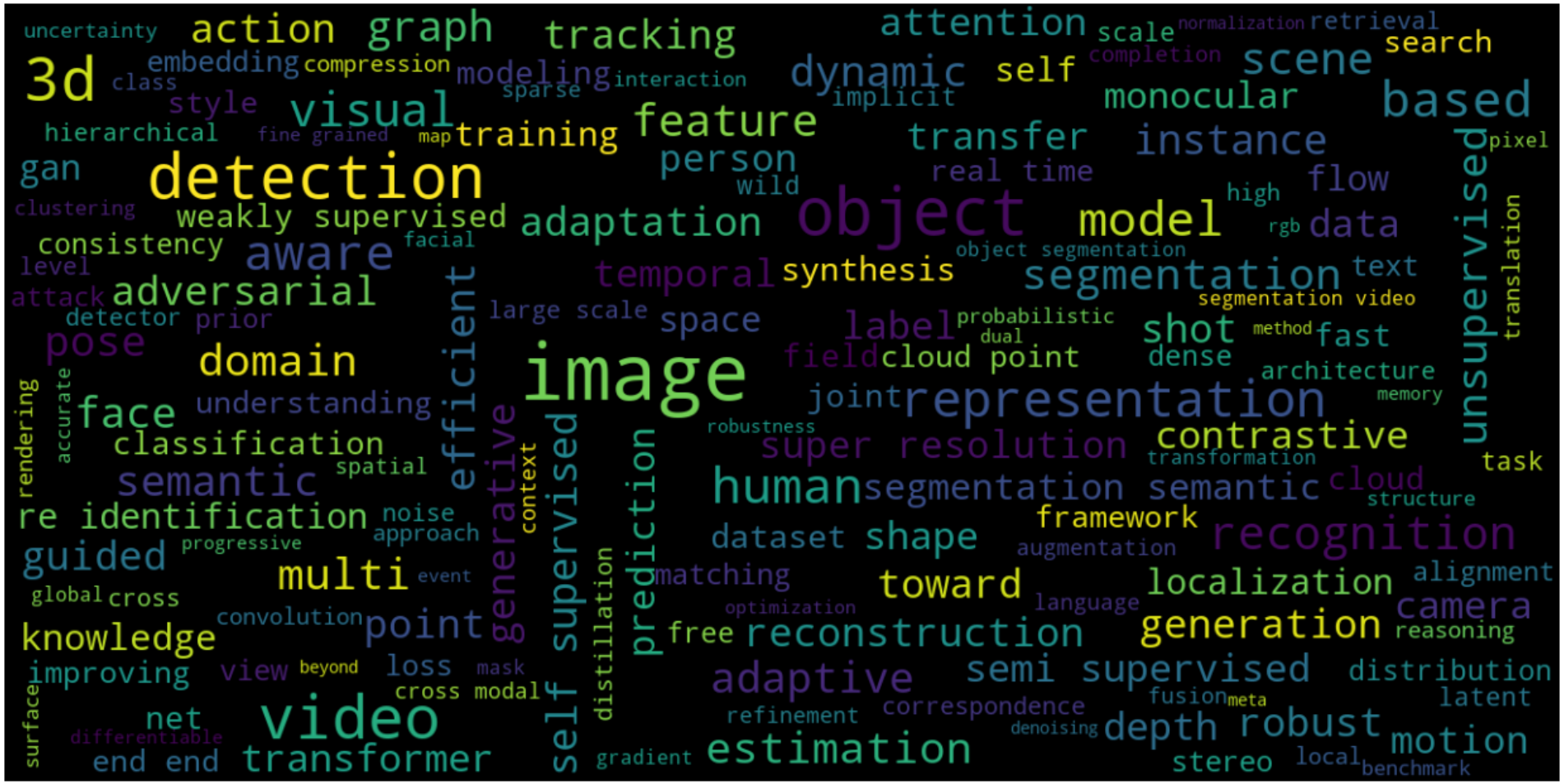
CVPR:10 YEARS



CVPR 2021


CVPR Acceptance Rate
# of papers
7000
6000
5000
4000
3000
2000
1000
0
29.9%
29.6%
25.1%
22.1%
23.7%
2017
2018
2019
2020
2021
Year
Submitted
Accepted

Keyword


uncertainty
action graph
tracking
attention
scale
normalization
retrieval
search
3d
embedding
compression
modeling
interaction
dynamic
self
completion
scene
class
sparse
implicit
monocular
based
style
visual
feature
hierarchical
fine grained
map
training
transfer
instance
pixel
gan
detection
person
real time
flow
clustering
weakly supervised
adaptation
object
model
high
rgb
data
consistency
aware
facial
object segmentation
level
temporal
synthesis
segmentation
text
attack
adversarial
segmentation video
detector
prior
large scale
space
label
probabilistic
dual
shot
method
fast
pose
domain
image
field
cloud point
dense
architecture
rendering
accurate
face
understanding
efficient
joint
representation
memory
classification
robustness
super resolution
contrastive
spatial
transformation
task
semantic
generative
context
human
segmentation
semantic
cloud
re identification
noise
framework
structure
guided
progressive
approach
dataset
shape
recognition
augmentation
multi
event
matching
toward
localization
alignment
global
cross
optimization
language
camera
knowledge
convolution
point
free
reconstruction
generation
reasoning
improving
view
beyond
loss
mask
adaptive
semi supervised
distribution
cross modal
fusion
meta
latent
net
video
refinement
correspondence
depth
robust
motion
differentiable
end end
transformer
gradient
estimation
denoising
stereo
local
benchmark
surface
self supervised
distillation
prediction

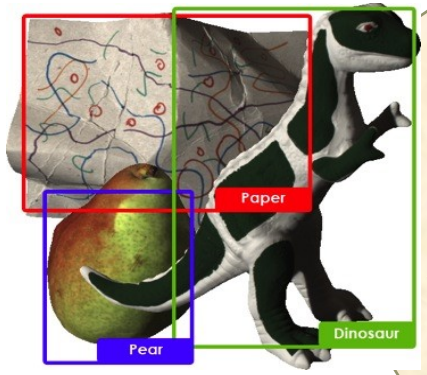
Marr's vision framework

- computational level: what does the system do (e.g.: what problems does it solve or overcome) and similarly, why does it do these things
- algorithmic/representational level: how does the system do what it does, specifically, what representations does it use and what processes does it employ to build and manipulate the representations
- implementational/physical level: how is the system physically realised (in the case of biological vision, what neural structures and neuronal activities implement the visual system)

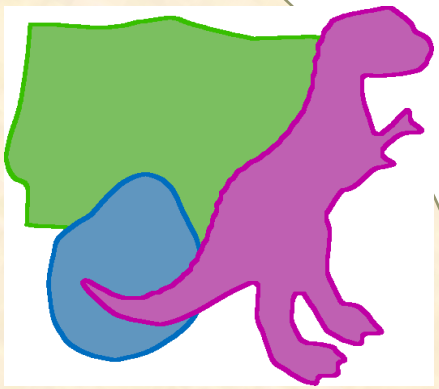
Marr's vision framework

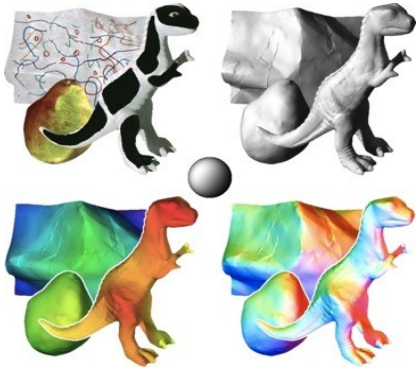
- Marr described vision as proceeding from a two-dimensional visual array (on the retina) to a three-dimensional description of the world as output. His stages of vision include:
  - a ***primal sketch*** of the scene, based on feature extraction of fundamental components of the scene, including edges, regions, etc. Note the similarity in concept to a pencil sketch drawn quickly by an artist as an impression.
  - a ***2.5D sketch*** of the scene, where textures are acknowledged, etc. Note the similarity in concept to the stage in drawing where an artist highlights or shades areas of a scene, to provide depth.
  - a ***3D model***, where the scene is visualised in a continuous, 3-dimensional map.

Malik's Perspective



Recognition





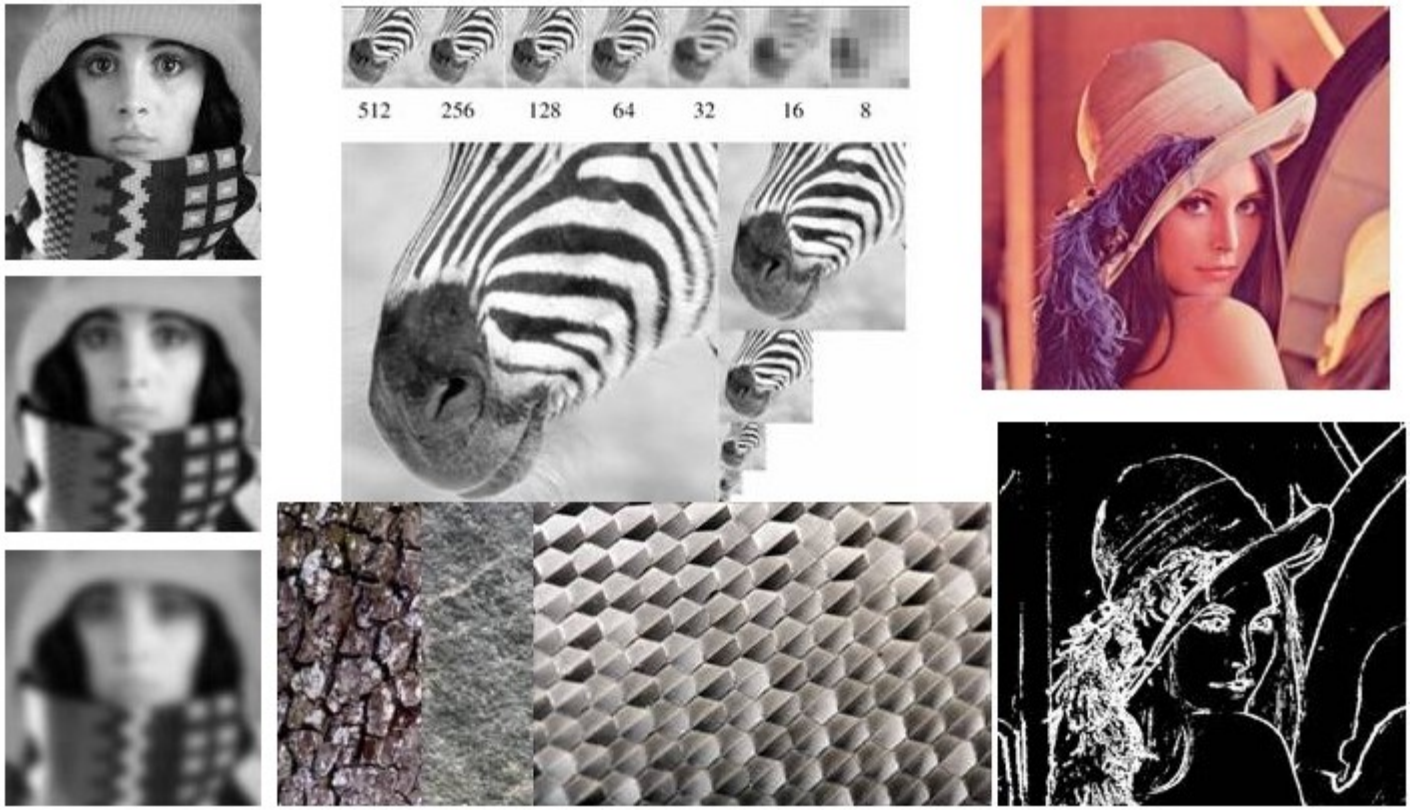
Reconstruction

Reorganization

Overview

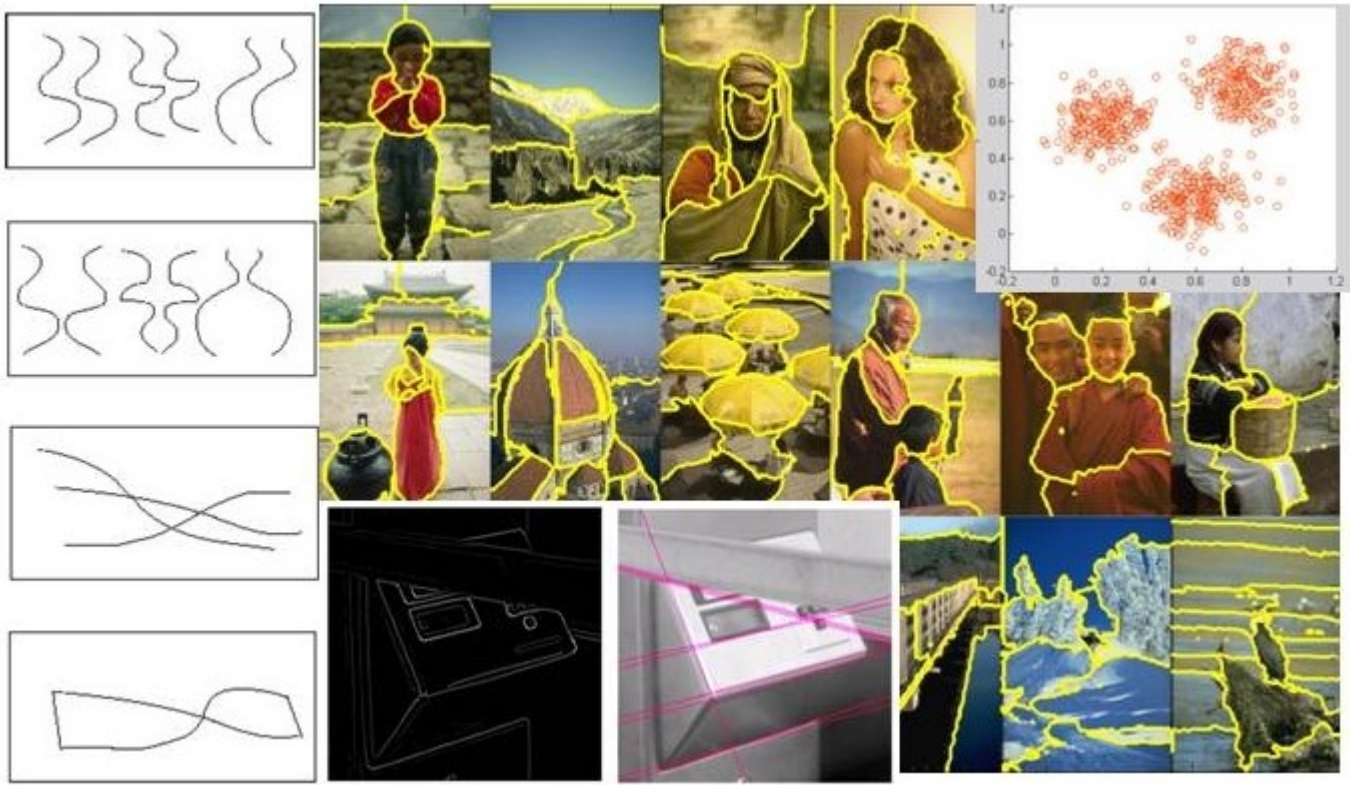
- What is computer vision about?
- Computer vision is useful.
- Computer vision is difficult.
- History and progress of computer vision
- **Course overview**

I. Features and filters



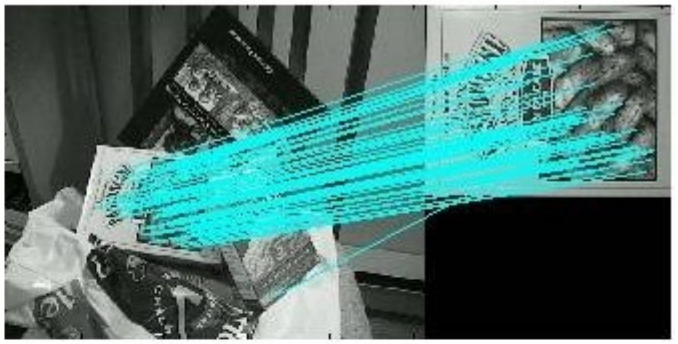
Transforming and describing images: textures, colors, edges

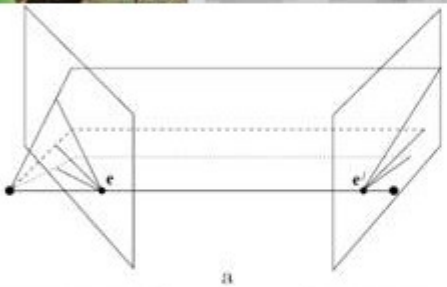
II. Grouping and fitting



Clustering, segmentation, fitting: what parts belong together

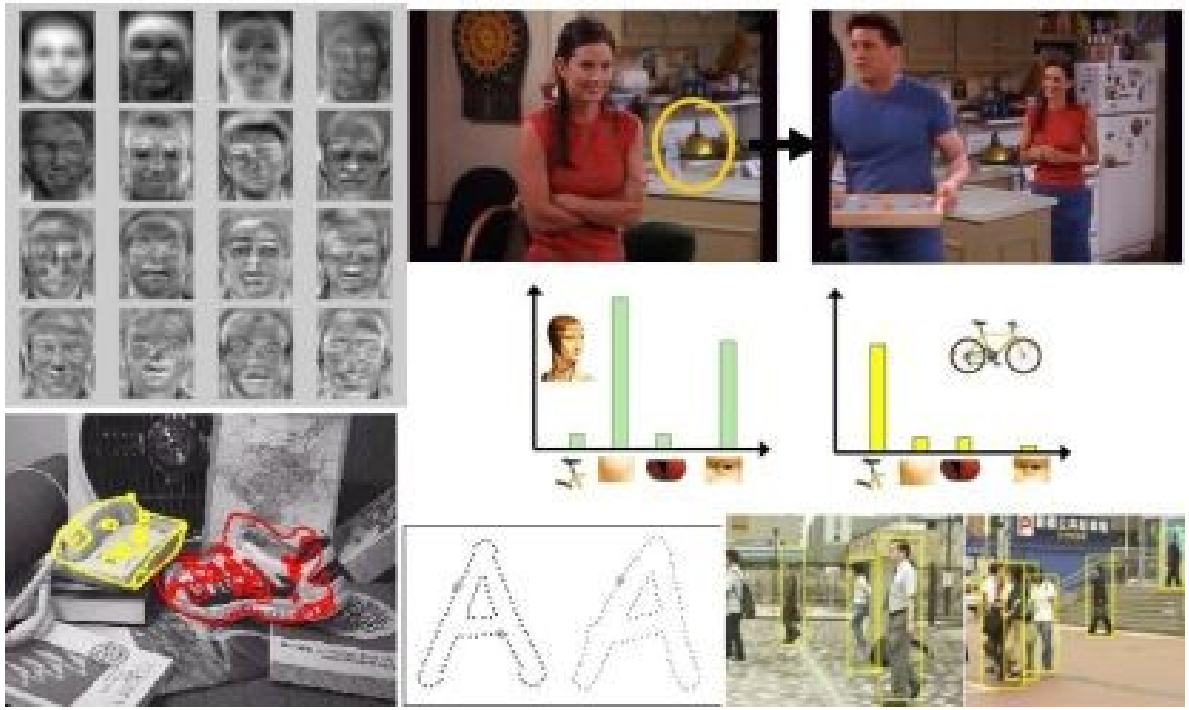
III Matching and Alignment





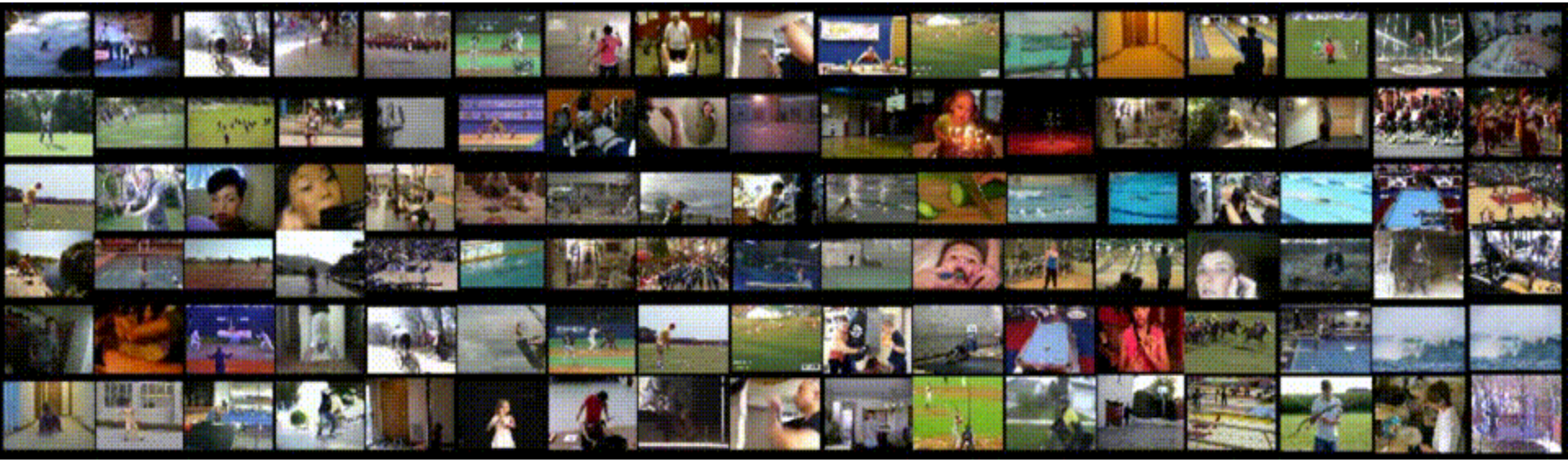
a

IV. Recognition



Recognizing categories and deep learning techniques

V. Video Understanding



Understanding videos: motion, action, event etc.

Course overview

- Chapter 1. Introduction
- Chapter 2. Images and Filter
- Chapter 3. Frequency Domain and Sampling
- Chapter 4. Template, Pyramid, and Filter Banks
- Chapter 5. Edges
- Chapter 6. Segmentation and Grouping
- Chapter 7 & 8. Interest Points
- Chapter 9. Fitting and Alignment
- Chapter 10. Alignment and Instance Recognition
- Chapter 11. Image Classification
- Chapter 12. Object Detection
- Chapter 13. Video Understanding

Summary

- What is computer vision
- Computer vision is useful
- Computer vision is difficult
- Computer vision is fast developing
- Course overview

Important note:

In general, computer vision does not work

(except in certain situations/conditions)

Hope you enjoy the course!