



清华大学
Tsinghua University



THU×SENSETIME - 80231202

Advanced Computer Vision

Friday, February 25, 2022

Overview This course involves **computer vision**, **deep learning** and other fields of knowledge. It elaborates with the latest academic achievements and practical cases of industrial scenes and explain the classic and state-of-the-art methods in computer vision.

What we have

- Focus on Both Classics and Frontiers
- Combination of Academia and Industry
- Teaching from the shallower to the deeper
- GPU clusters for experiments

What you will learn

- Basic theories and advanced methods in Computer Vision
- Understand and explore practical problems in the industry
- Improve your research ability and innovative ability

What you need

- **Mathematics**
 - Calculus
 - Linear Algebra
 - Basic Probability and Statistics
- **Coding ability**
 - **Python** is recommended
 - Machine Learning

Chapter 1 - Computer Vision Overview and Deep Learning Basics

- Basics of computer vision & image processing
- Introduction of the neural network and deep learning framework

- 1.Computer Vision Basics
- 2.Feature Detection
- 3.CNN & High-level Feature Extraction
- 4.Training Framework and Model Optimization

Chapter 2 - Advanced Computer Vision Tasks

- Cutting-edge research directions in computer vision
- The algorithm model optimization and performance improvement methods in visual scenes.

- 5.Image Classification
- 6.Object Detection
- 7.Image Segmentation
- 8.Video Understanding and Sequence Analysis
- 9.3D Vision
- 10.Low-Level Computer Vision Task
- 11.Neural network Model Acceleration and Compilation
- 12.Representation Learning in Vision Tasks

Chapter 3 - Lectures on industry applications

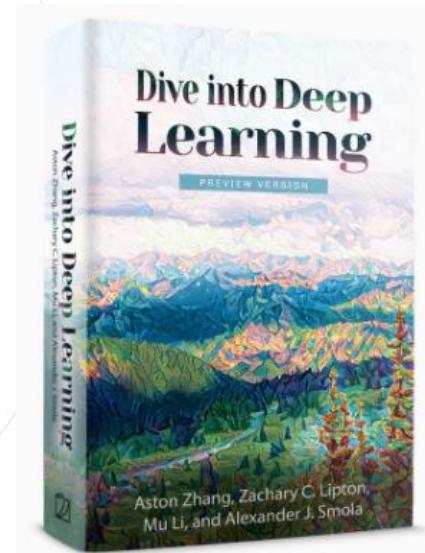
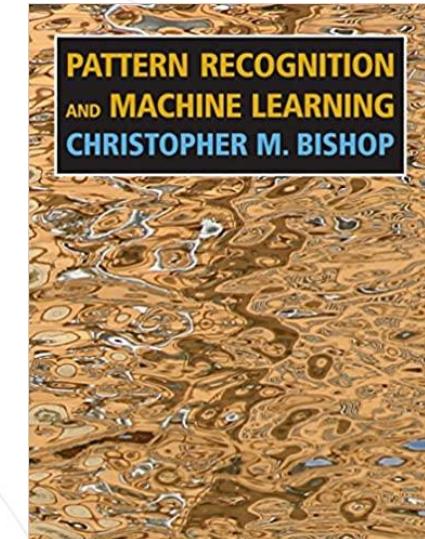
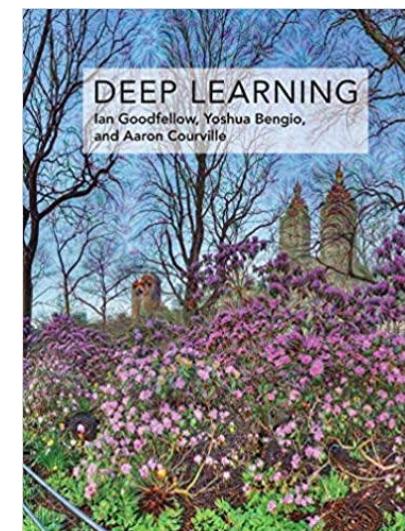
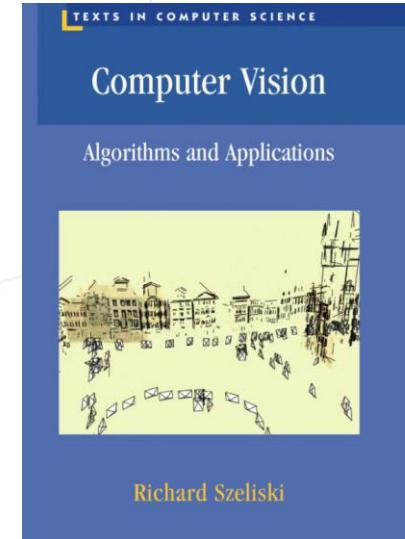
- The practical problems faced by computer vision and the solution ideas in combination with the specific scenes of industry.

- 13.AutoPilot
- 14.3D Vision and Augmented Reality



- **Textbook**

- ***Computer Vision Algorithms and Applications***
 - by Richard Szeliski
 - Preview version: [\[Link\]](#)
- ***Pattern Recognition and Machine Learning***
 - by Christopher Bishop
 - Free online version: [\[Link\]](#)
- ***Deep Learning***
 - by Goodfellow, Bengio, and Courville
 - Index: [\[Link\]](#)
- ***Dive into deep learning***
 - An interactive deep learning book with code, math, and discussions, based on the NumPy interface
 - Free online version: [\[Link\]](#)





• Assignment & Final Project

Assignments (30%)

- 1 Assignments finish after class by one person
- You can finish assignment on your local machines or on clusters provided by SenseTime
- **Topic**
 - Advanced Computer Vision Task
- **Released Date - Due Date**
 - March. 25 - Apr. 8

Final Project (70%)

- Collaboration in groups of up to 3 people
- Choose one topic and finish the project
- **You should submit**
 1. One page proposal and discuss it with TAs (topic, idea, method, experiments)
 2. A term paper of 4 pages (excluding figures) in maximum
 3. Code and sample data
 4. Project presentation

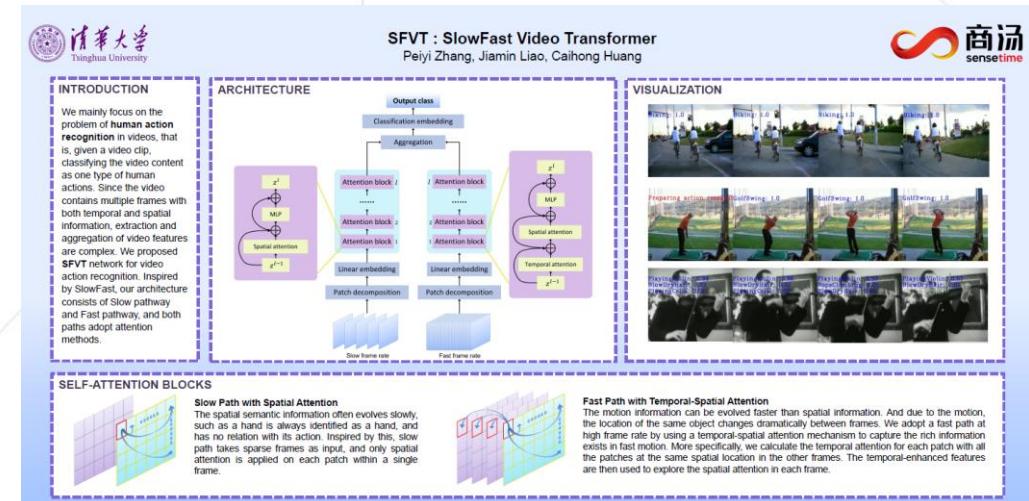
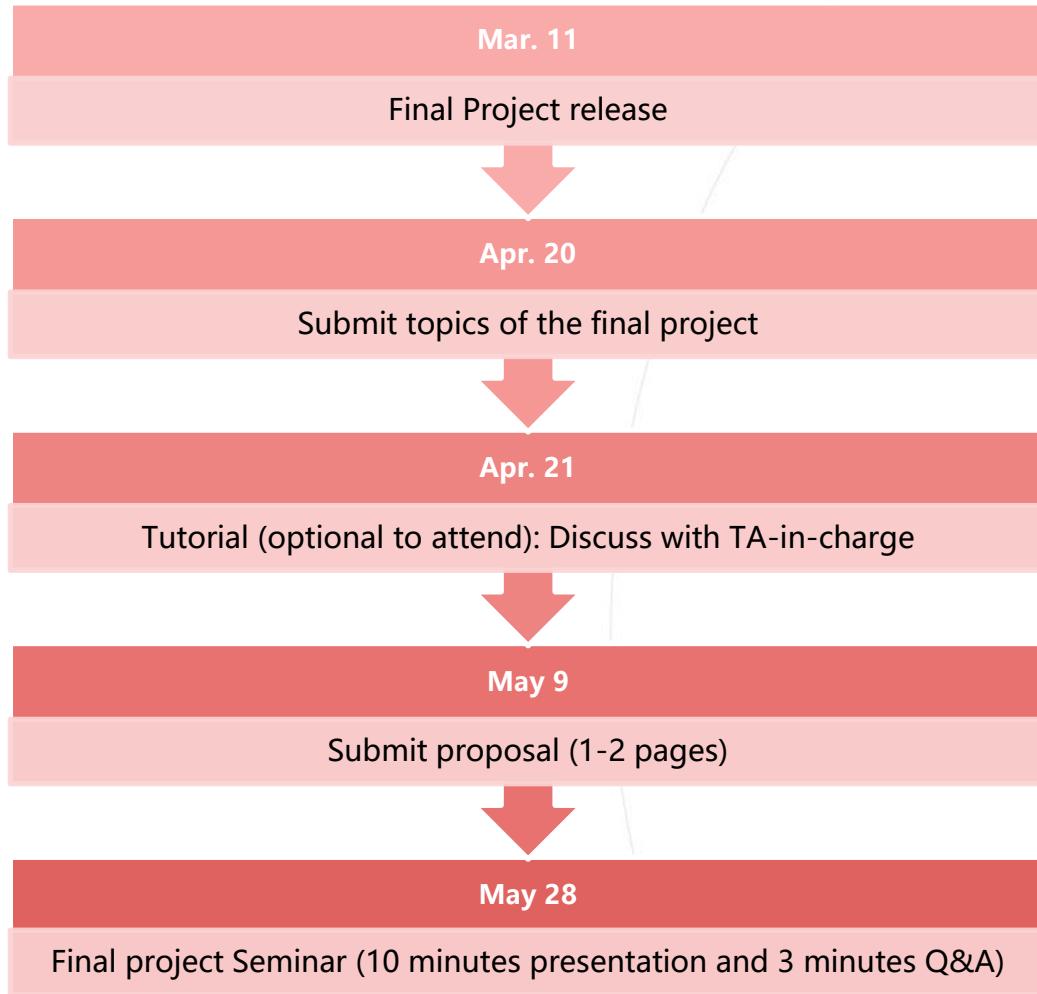
Course Introduction



清华大学
Tsinghua University

商汤
sensetime

• Final Project



- **Instructors**



Dr. Li Yali

- Tsinghua EE Assistant Researcher
- liyali13@mail.tsinghua.edu.cn



Dr. Dai Jifeng

- SenseTime Executive Research Director
- daijifeng@sensetime.com



Dr. Li Hongyang

- SenseTime Senior Research Manager
- lihongyang@sensetime.com

- **TAs**



Dr. Wang Han

- i@hann.wang

- **Coordinators**



Chen Qingchen

chenqingchen@sensetime.com



Zhang Qifan

zhangqifan@sensetime.com

- **Lecture Time & Venue**

- **Friday**, 9:50am-11:25am
- **1102**, No.3 Teaching Building

- **Optional Tutorials & QA Time**

- **Thursday**, 19:00-20:00
- Tencent Meeting Room: 785 271 5223

- **Course Homepage**

- <https://thu-acv.github.io>

- **Discussions**

- WeChat Group
- Tencent Meeting Room: 785 271 5223



2022春-THU高等计算机视觉



该二维码7天内(3月2日前)有效, 重新进入将更新



商汤学术小助手
中国大陆





清华大学
Tsinghua University

Advanced Computer Vision
THU×SENSETIME – 80231202

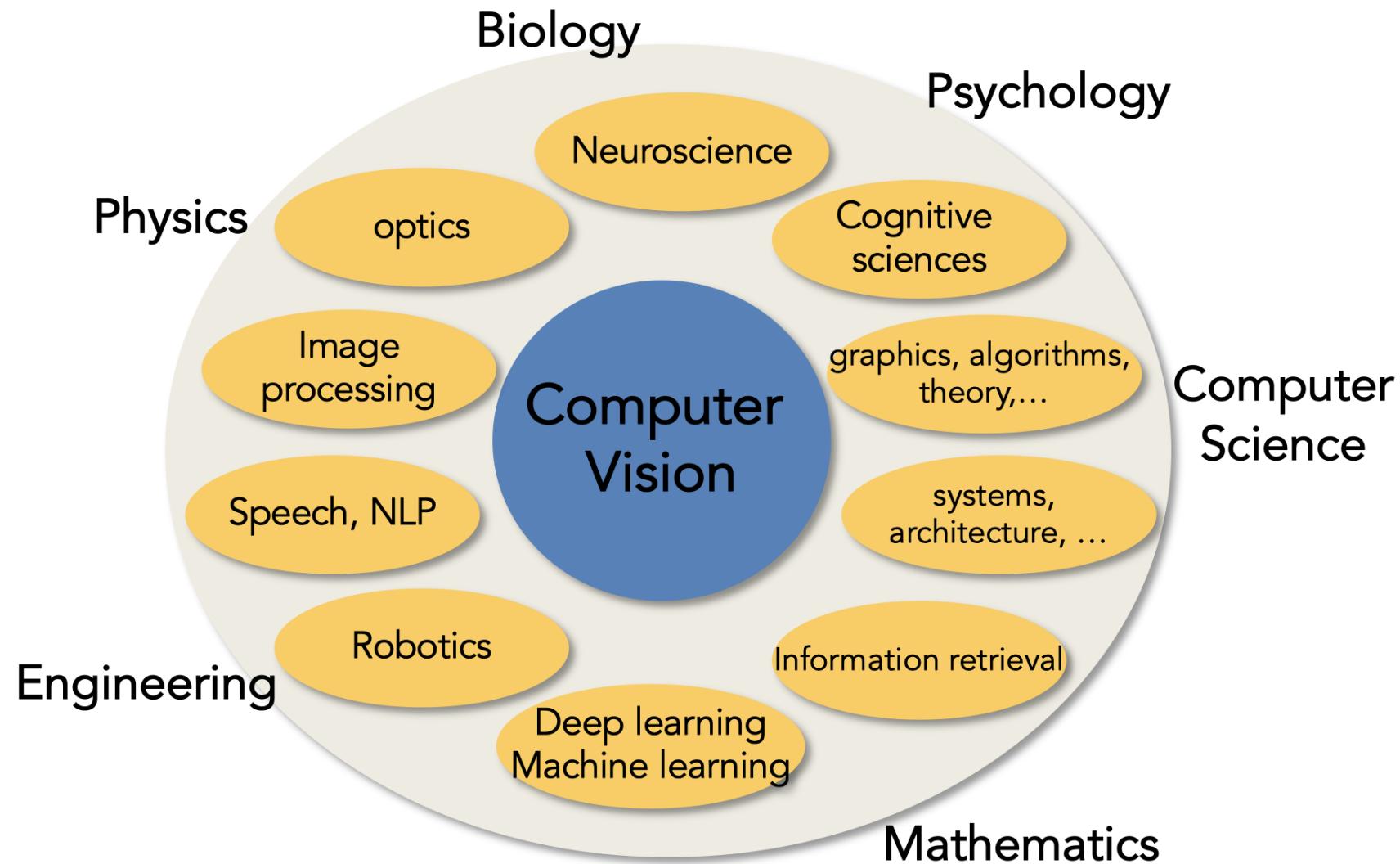


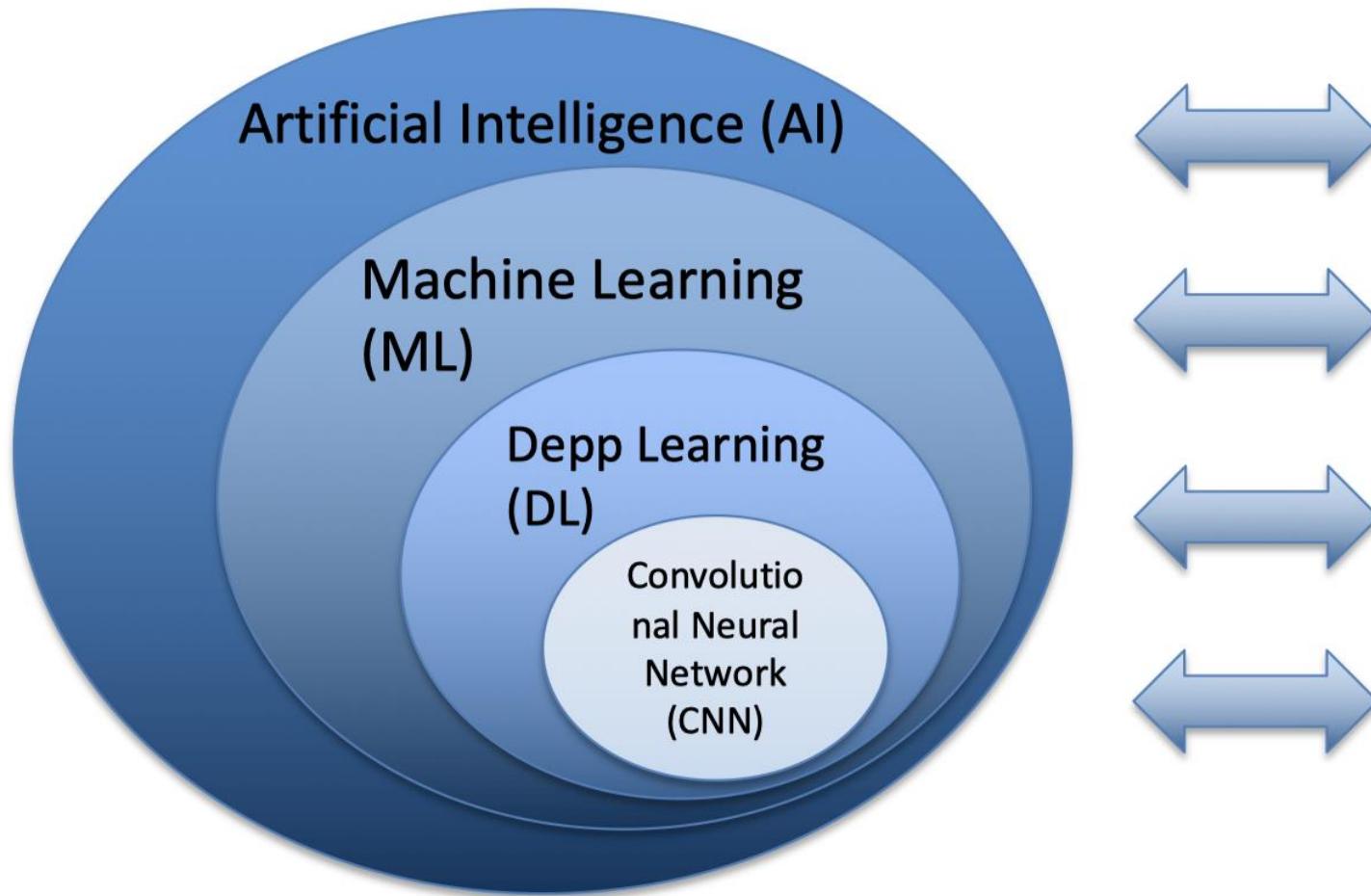
Chapter1 - Section 1 Part 1

Computer Vision Basic

Dr. Dai Jifeng

Friday, February 25, 2022



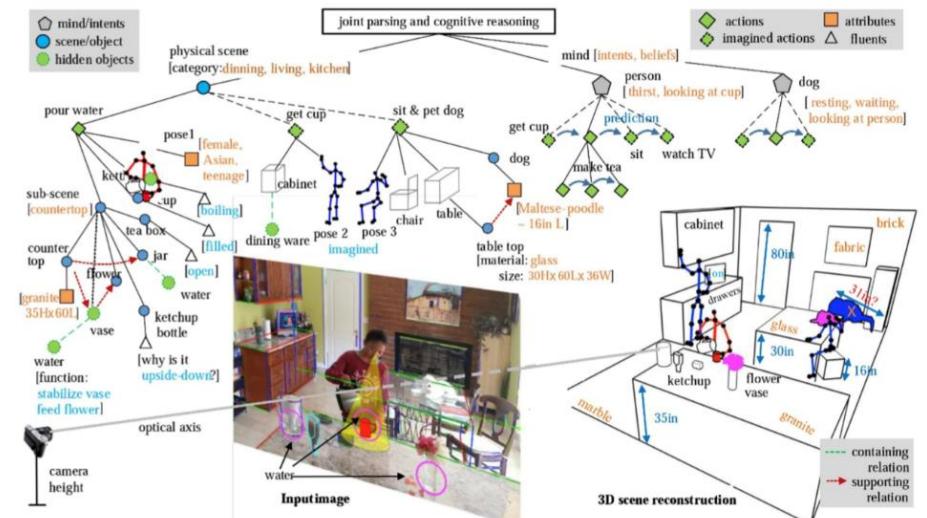
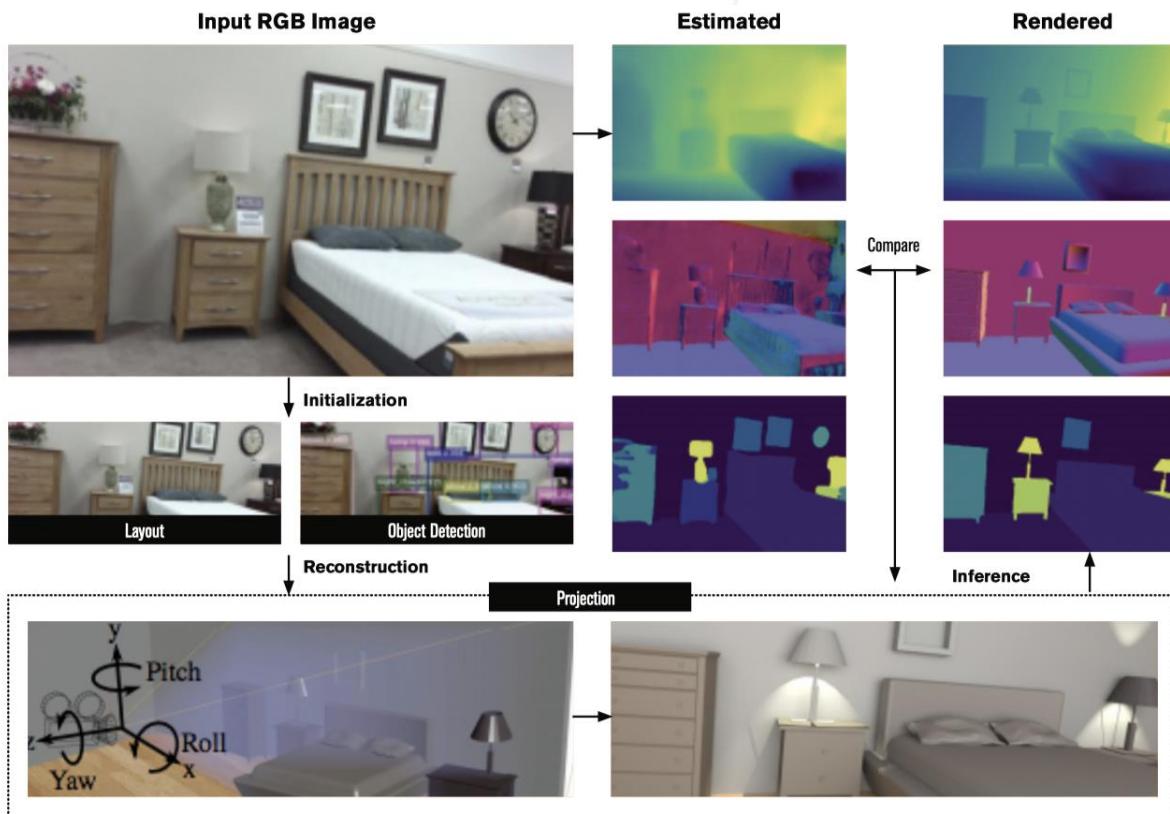


Computer Vision

- Object detection
- Object classification
- Scene understanding
- Semantic scene segmentation
- 3D reconstruction
- Object tracking
- Human pose estimation
- Activity recognition
- VQA
-

What's Computer Vision

Vision is the most important source of information for the human brain and is the “**entrance hall**” of AI.

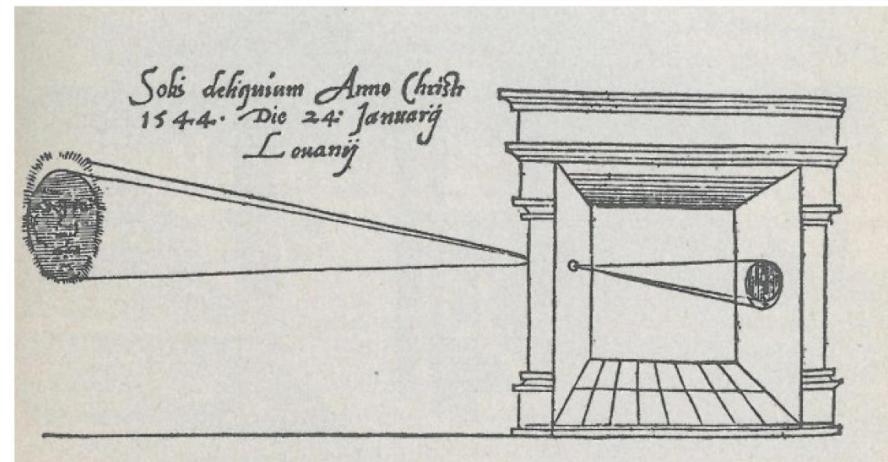


- **Biological Vision**

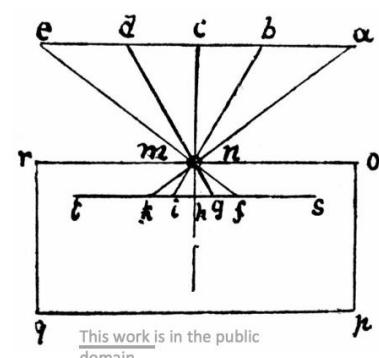


• Ancient Human Vision

Gemma Frisius, 1545

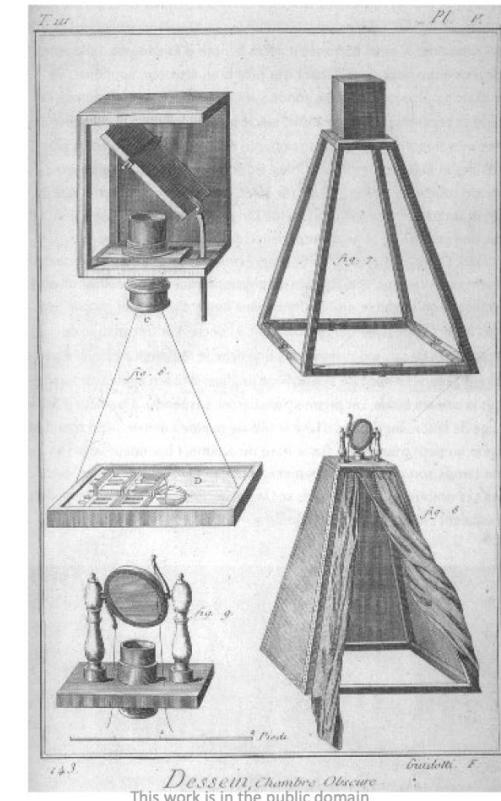


Leonardo da Vinci,
16th Century AD



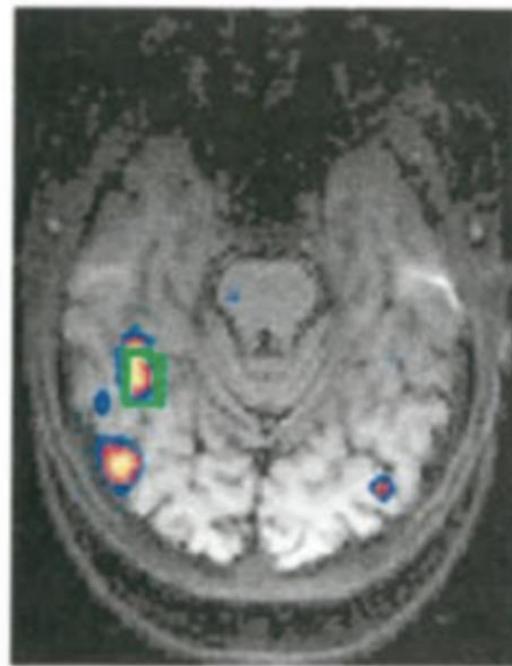
Camera Obscura

Encyclopedia, 18th Century



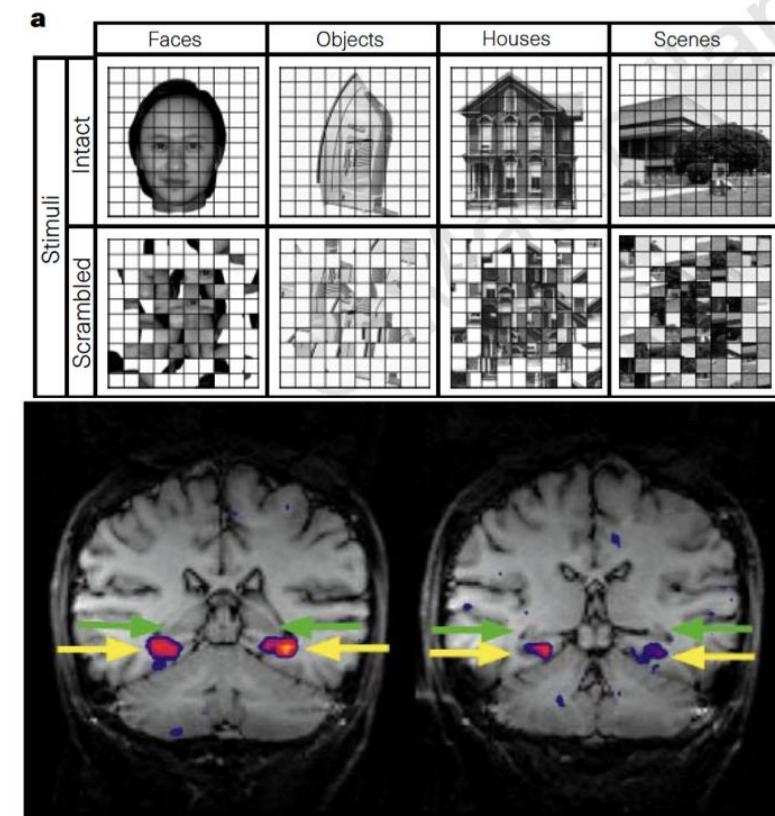
- Neuroscience and Vision

Faces > Houses



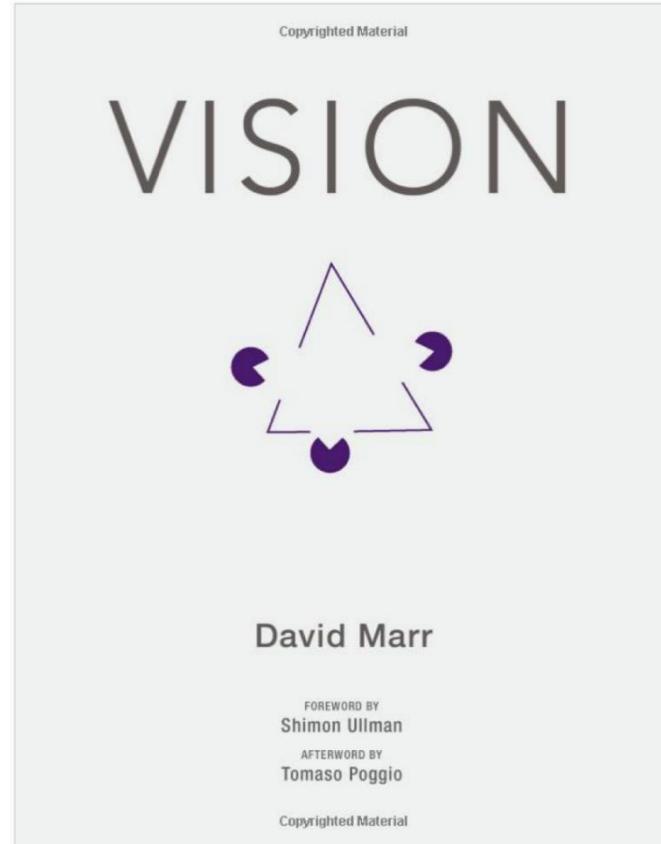
% signal change

Kanwisher et al. J. Neuro. 1997



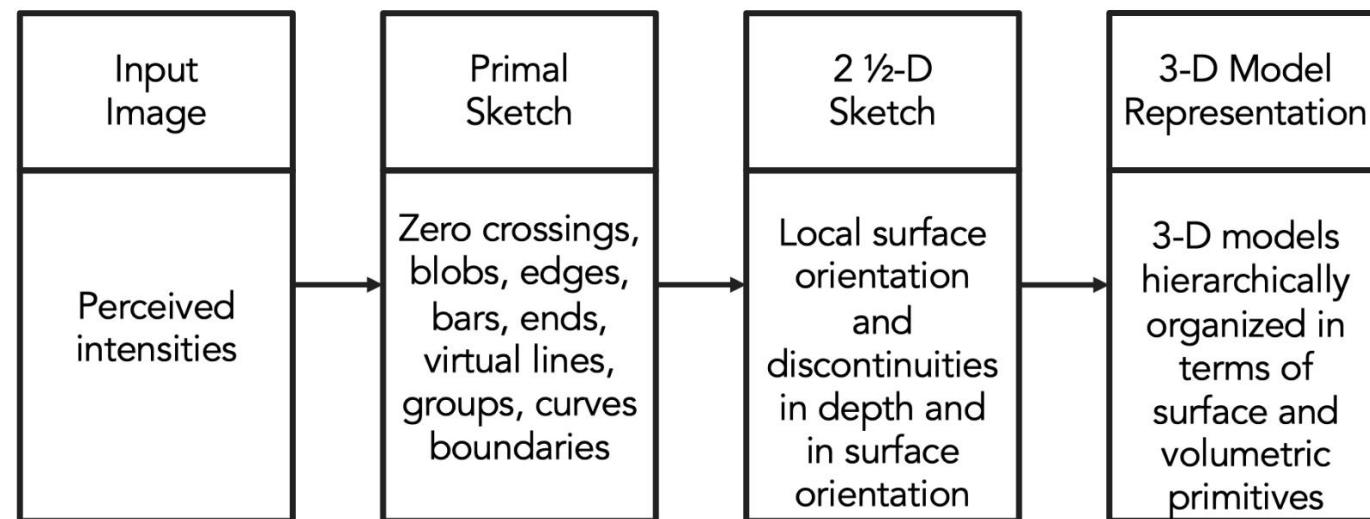
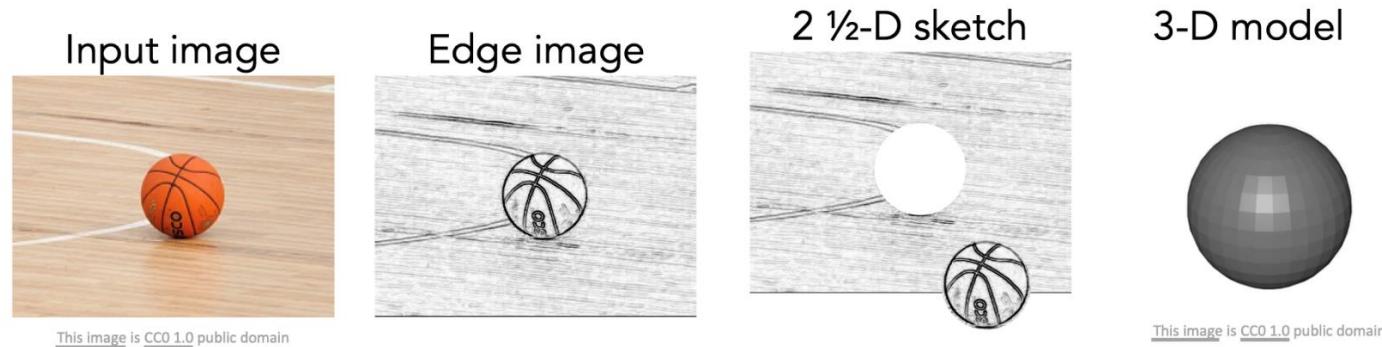
Epstein & Kanwisher, Nature, 1998

- **Marr Computational Vision**



3D Reconstruction
Not talent, but
computation

• Marr Computational Vision

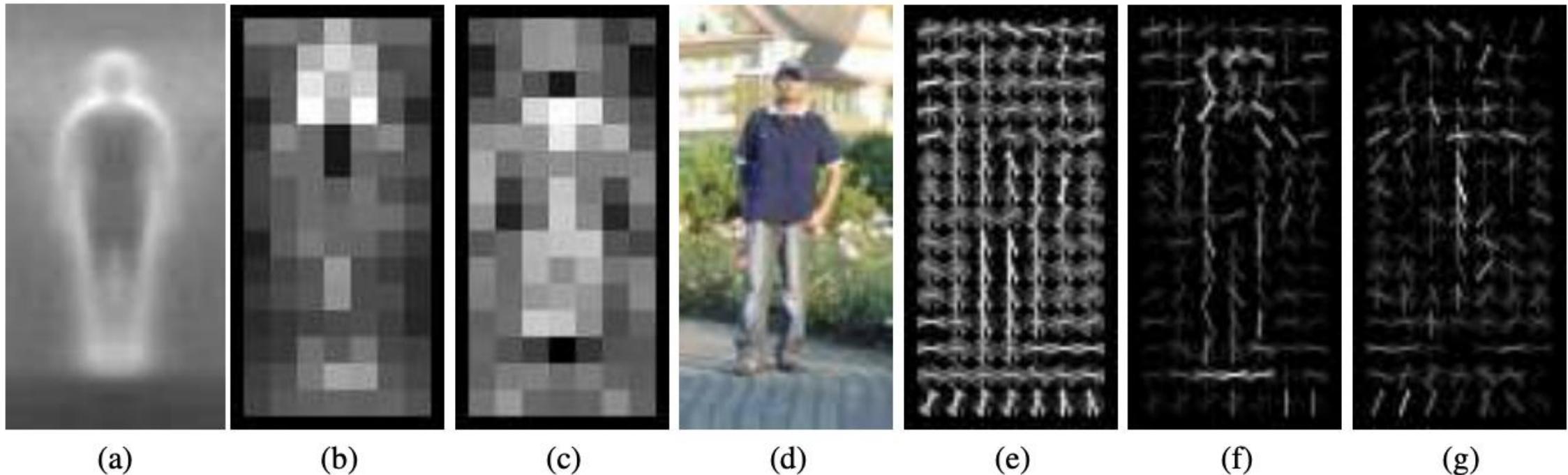


Stages of Visual Representation, David Marr, 1970s

- Feature Detection——SIFT

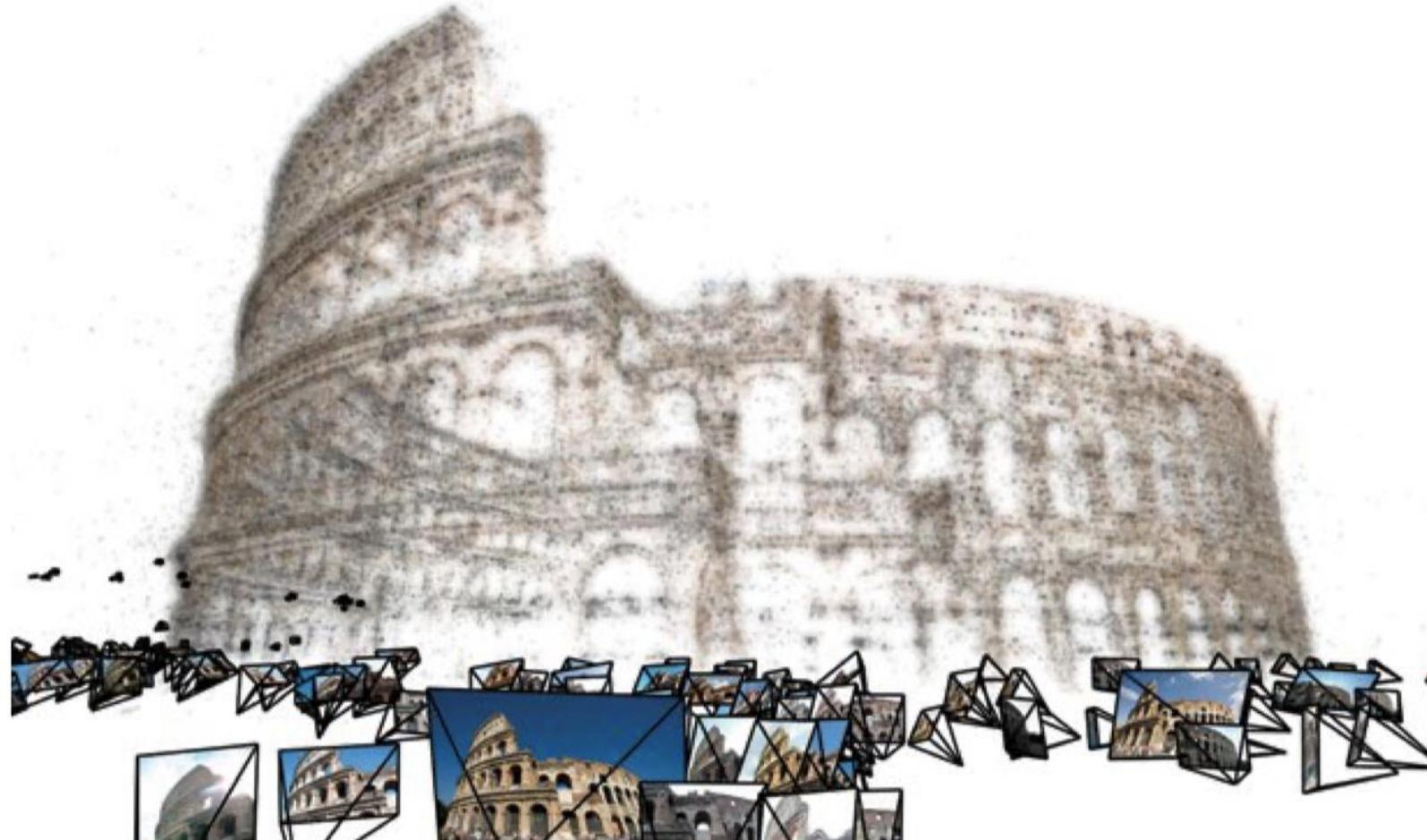


- Feature Detection——HOG



<https://web.archive.org/web/20110408220331/>
<http://www.acemedia.org/aceMedia/files/document/wp7/2005/cvpr05-inria.pdf>

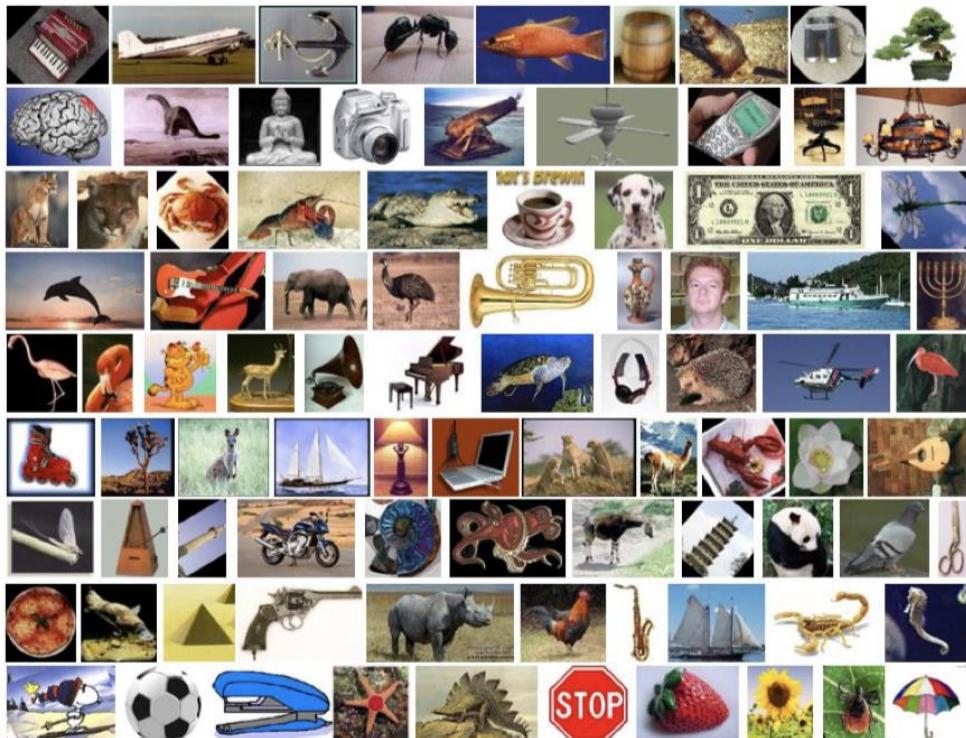
- 3D reconstruction



Agarwal et al.
ICCV, 2009

- **Image Classification**

Caltech 101 images



Fei-Fei et al. 2004



Visual Object Classes Challenge 2009 (VOC2009)



[click on an image to see the annotation]

Everingham et al. 2006-2012

- IMAGENET Challenge



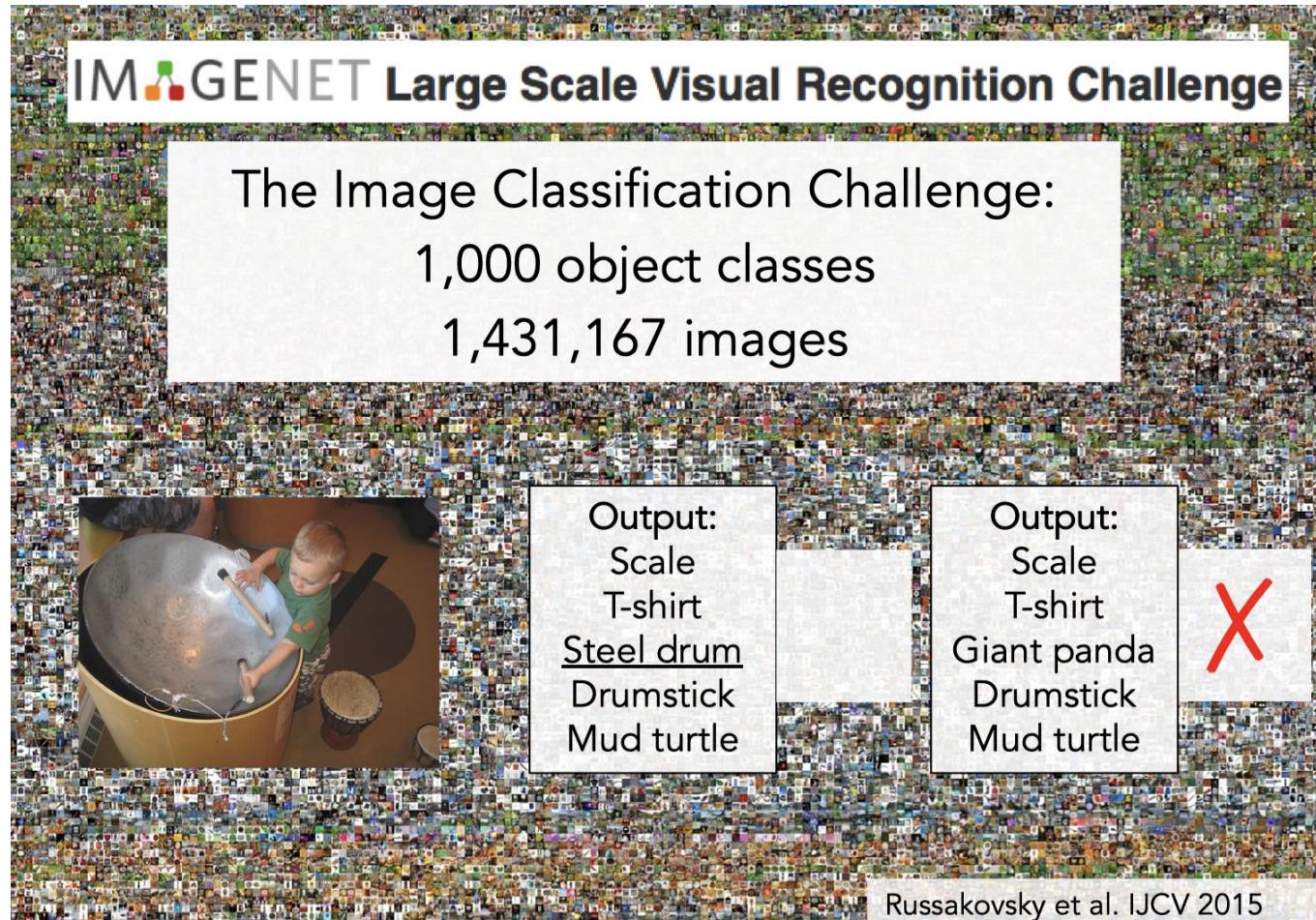
IMAGENET

22,000 categories

15,000,000 images



• IMAGENET Challenge



• IMAGENET Challenge

IMAGENET Large Scale Visual Recognition Challenge

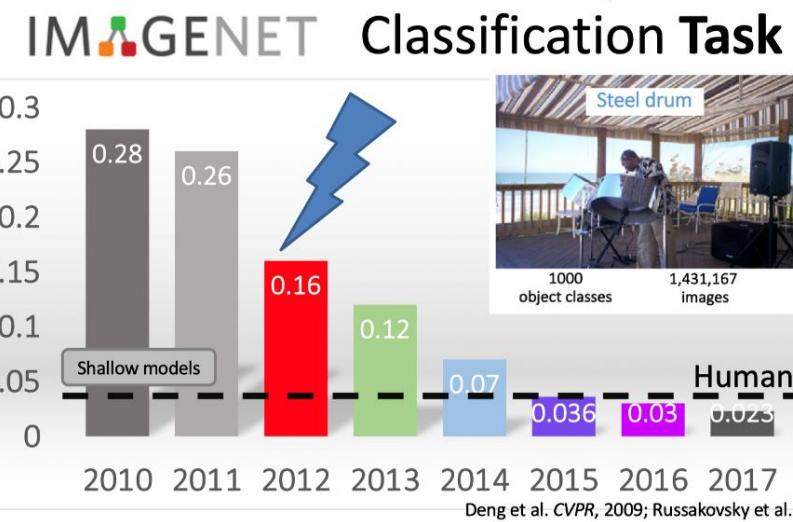
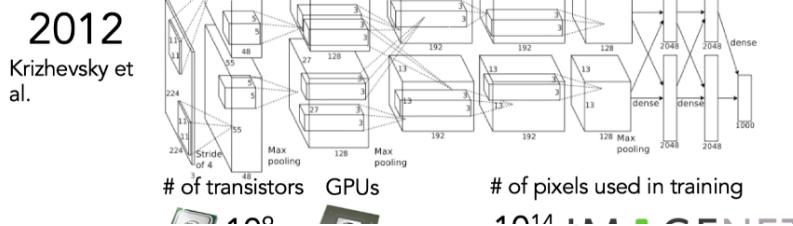
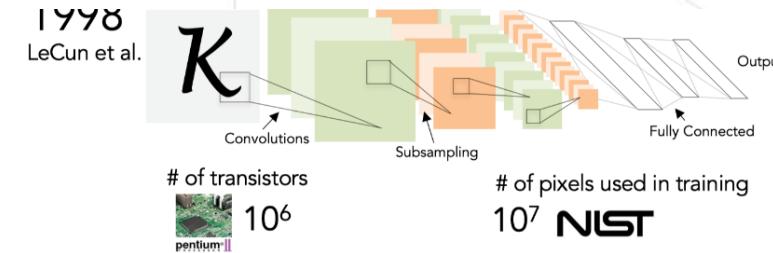
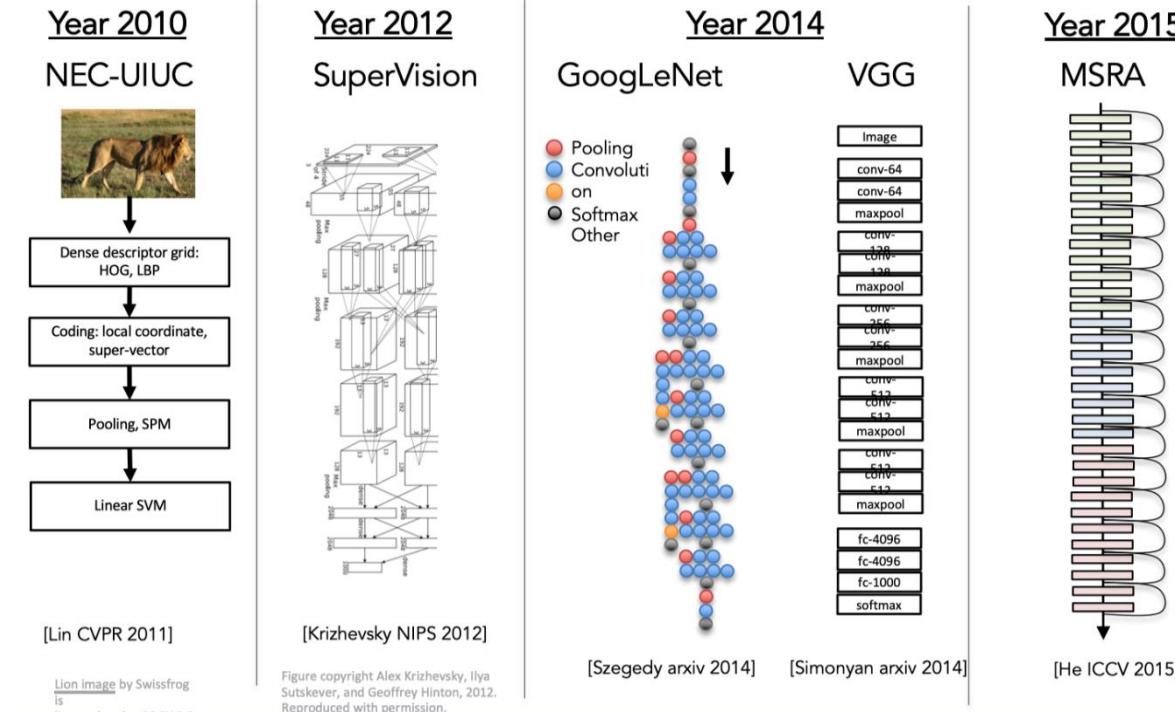
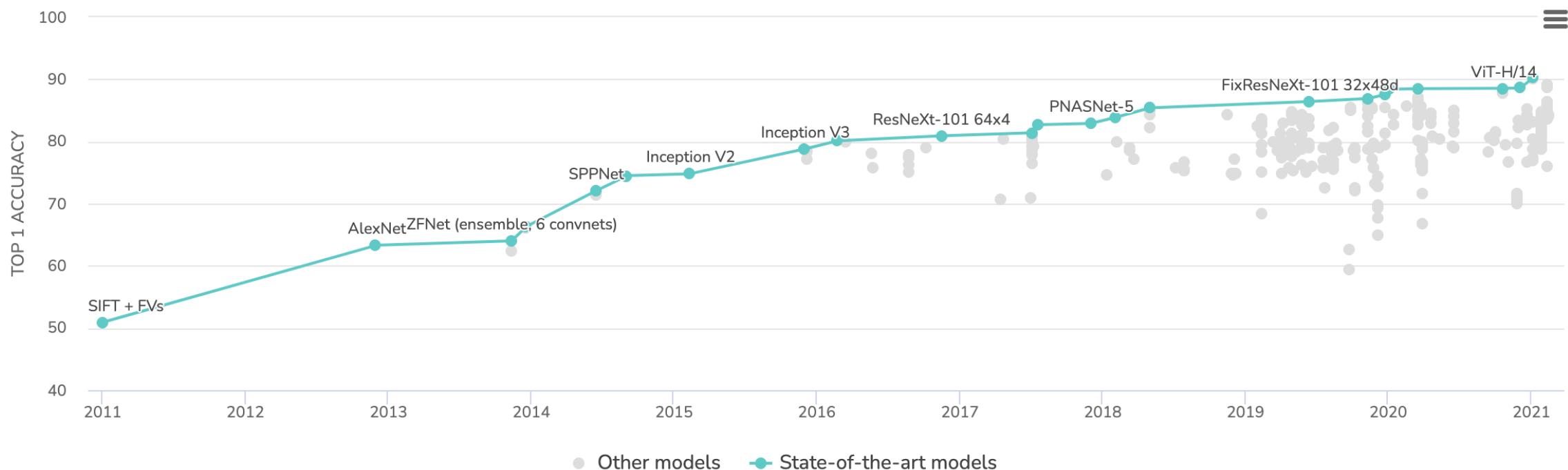


Image Classification on ImageNet

Leaderboard

Dataset



- Object Detection

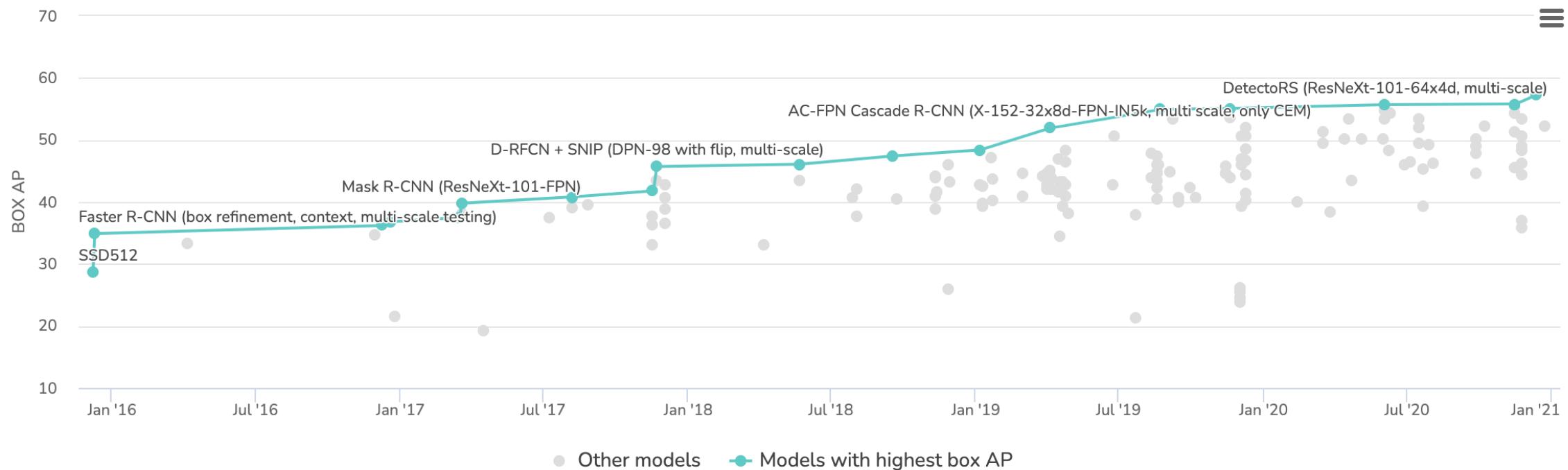


<https://cocodataset.org/>

Object Detection on COCO test-dev

Leaderboard

Dataset



• Instance Segmentation



<https://www.lvisdataset.org/explore>



- Semantic Segmentation and Instance Segmentation**



Input Image

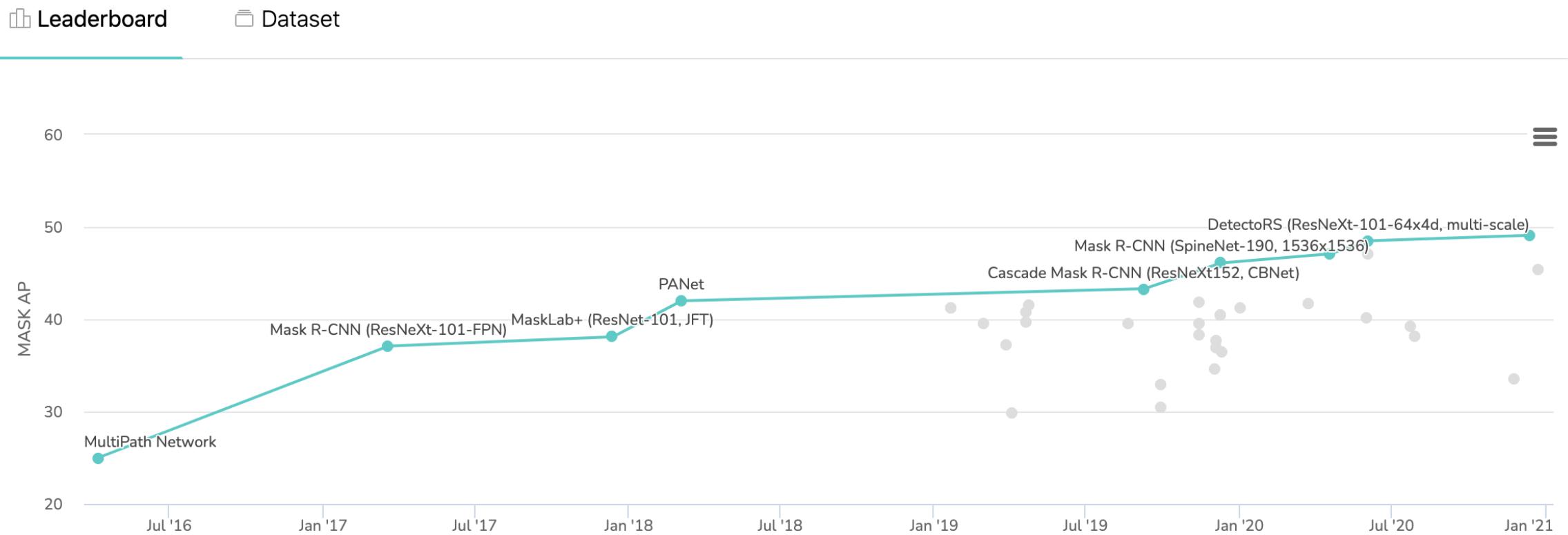


Semantic Segmentation



Instance Segmentation

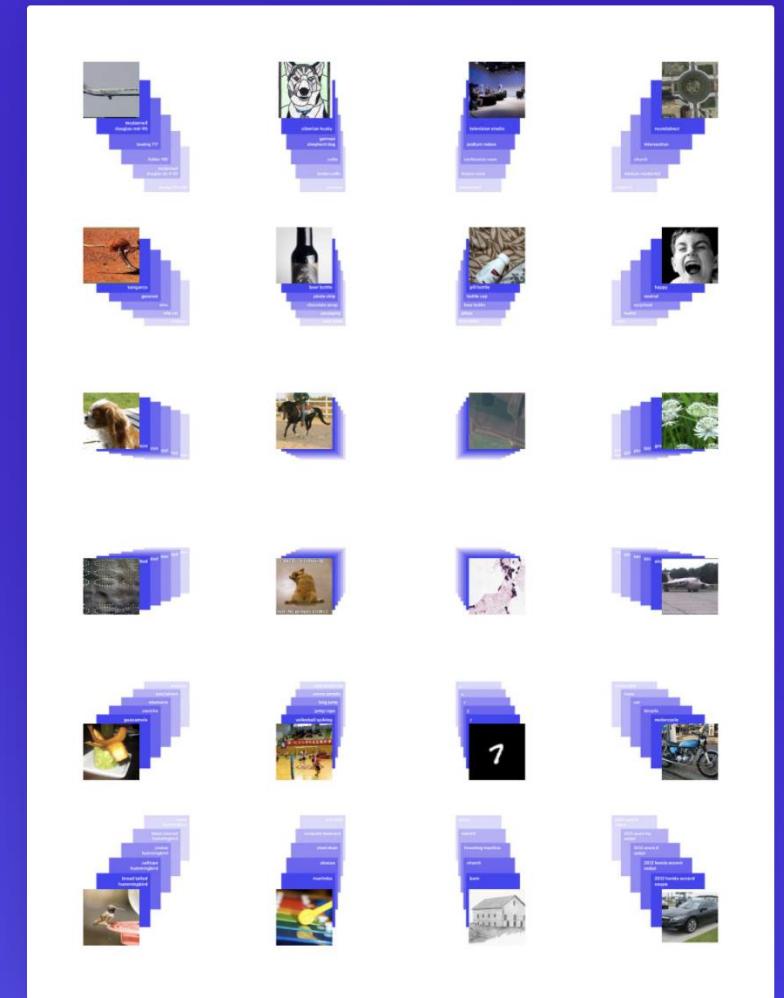
Instance Segmentation on COCO test-dev



CLIP: Connecting Text and Images

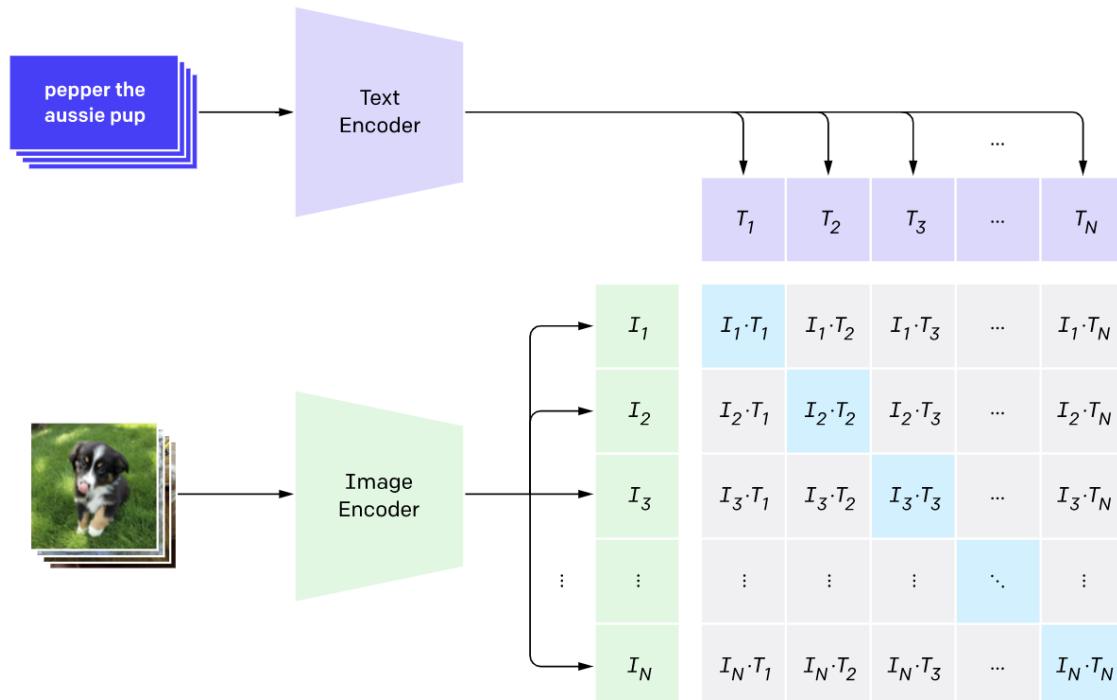
We're introducing a neural network called CLIP which efficiently learns visual concepts from natural language supervision. CLIP can be applied to any visual classification benchmark by simply providing the names of the visual categories to be recognized, similar to the "zero-shot" capabilities of GPT-2 and GPT-3.

January 5, 2021
15 minute read

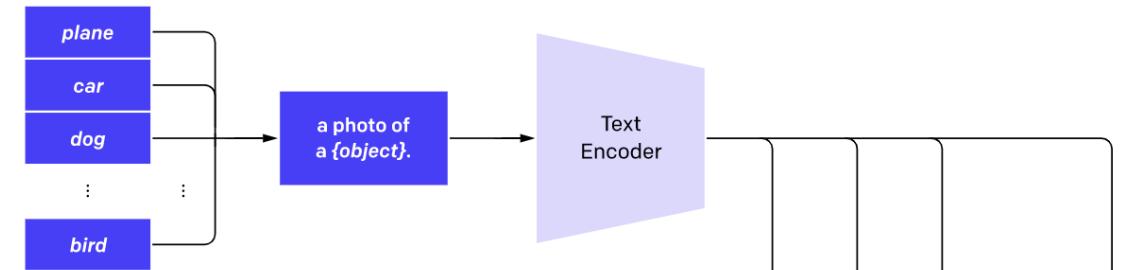


- CLIP: Connecting Text and Images**

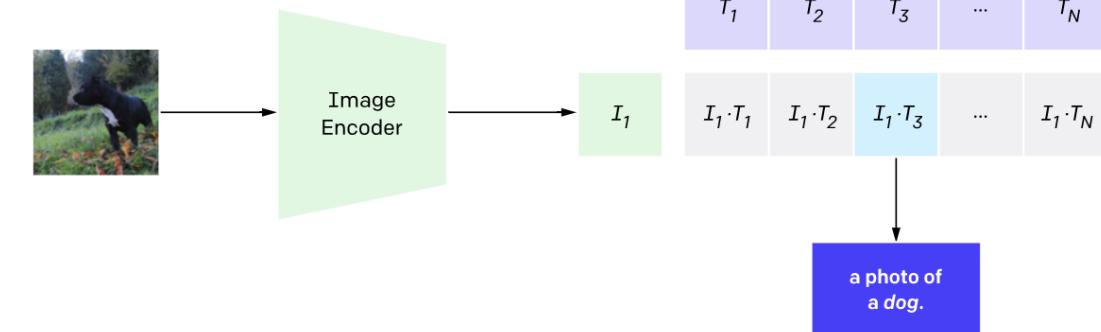
1. Contrastive pre-training



2. Create dataset classifier from label text

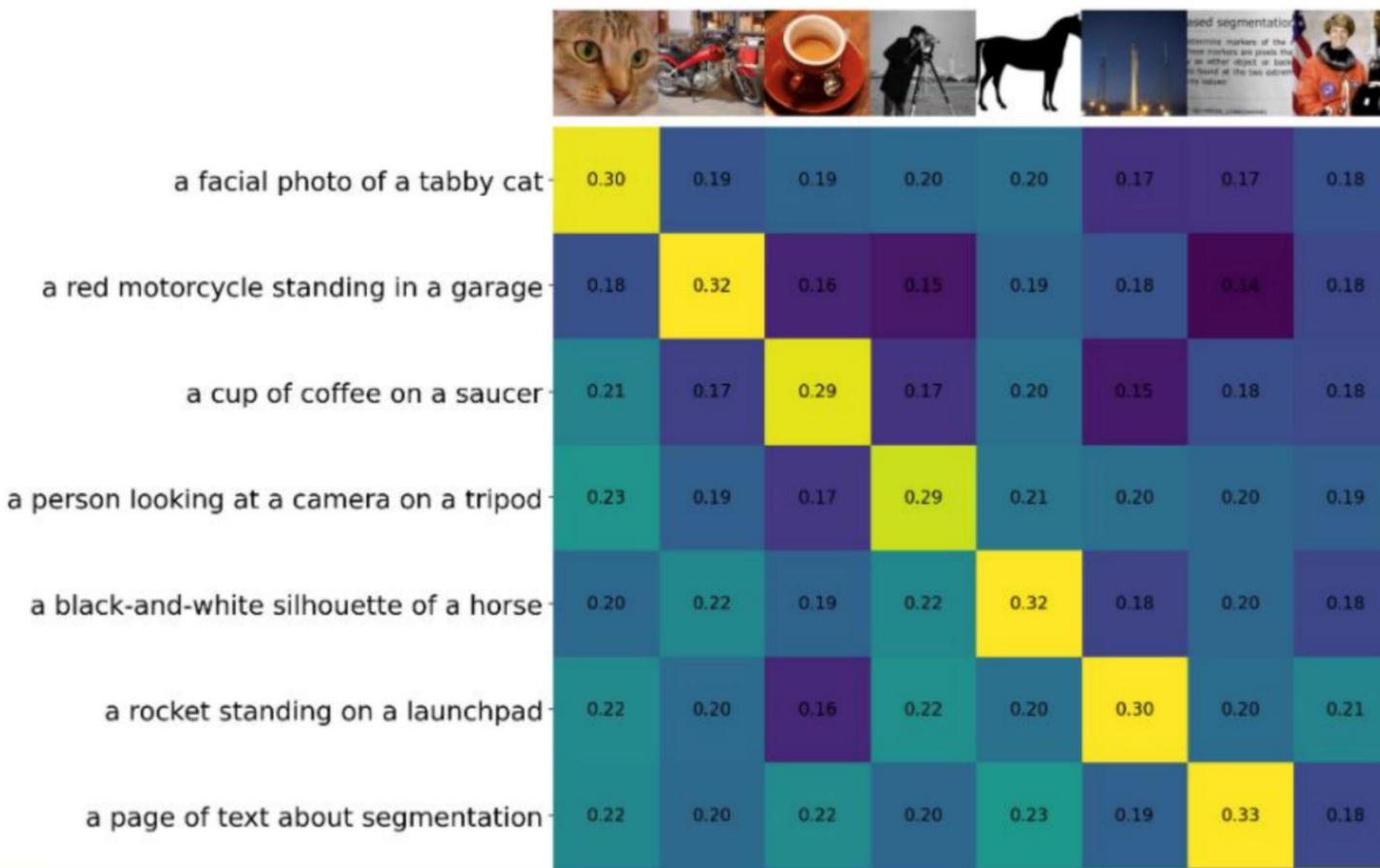


3. Use for zero-shot prediction



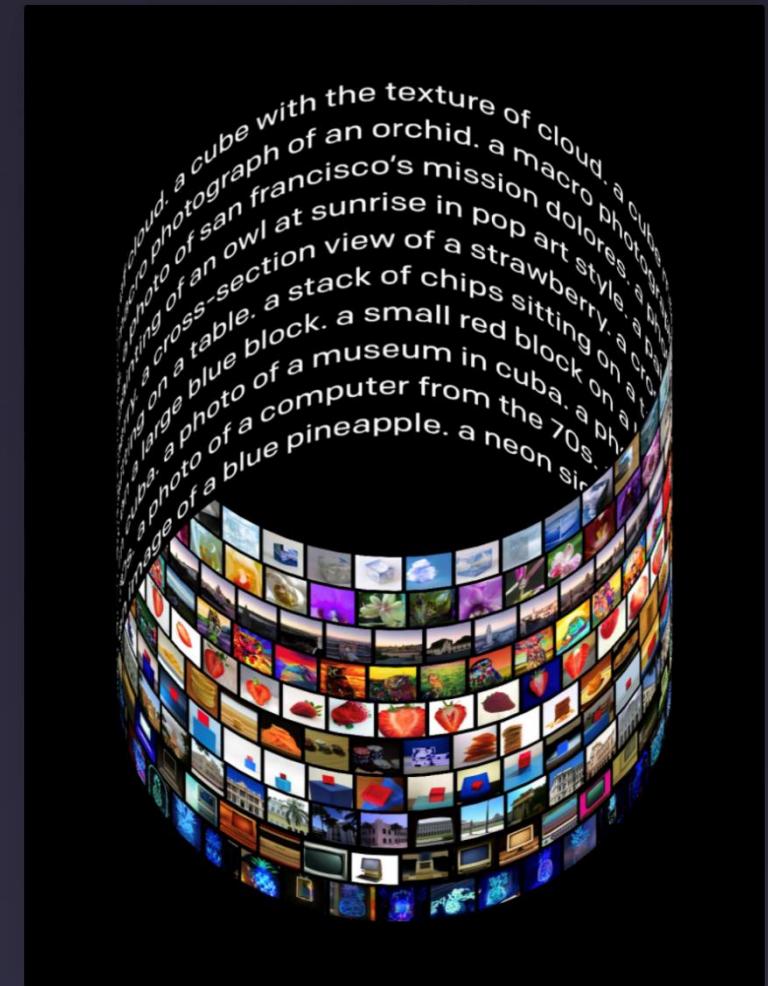
• CLIP: Image-Text Match

Cosine similarity between text and image features



DALL·E: Creating Images from Text

We've trained a neural network called DALL·E that creates images from text captions for a wide range of concepts expressible in natural language.



January 5, 2021
27 minute read

TEXT PROMPT

an illustration of a baby daikon radish in a tutu walking a dog

AI-GENERATED IMAGES



Edit prompt or view more images ↓

TEXT PROMPT

an armchair in the shape of an avocado [...]

AI-GENERATED IMAGES



Edit prompt or view more images ↓

TEXT PROMPT

a store front that has the word 'openai' written on it [...]

AI-GENERATED IMAGES



Edit prompt or view more images ↓

DALL-E

Creating Images from Text

TEXT PROMPT

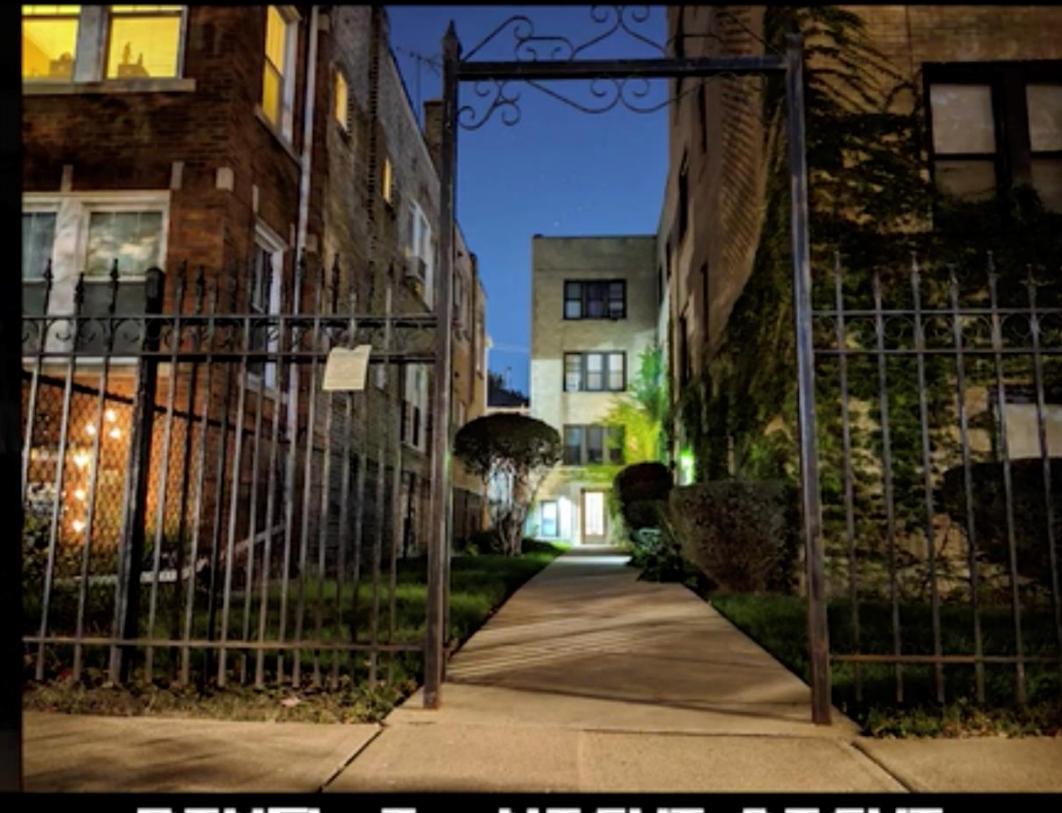
a stained glass window with an image of a blue strawberry

AI-GENERATED IMAGES

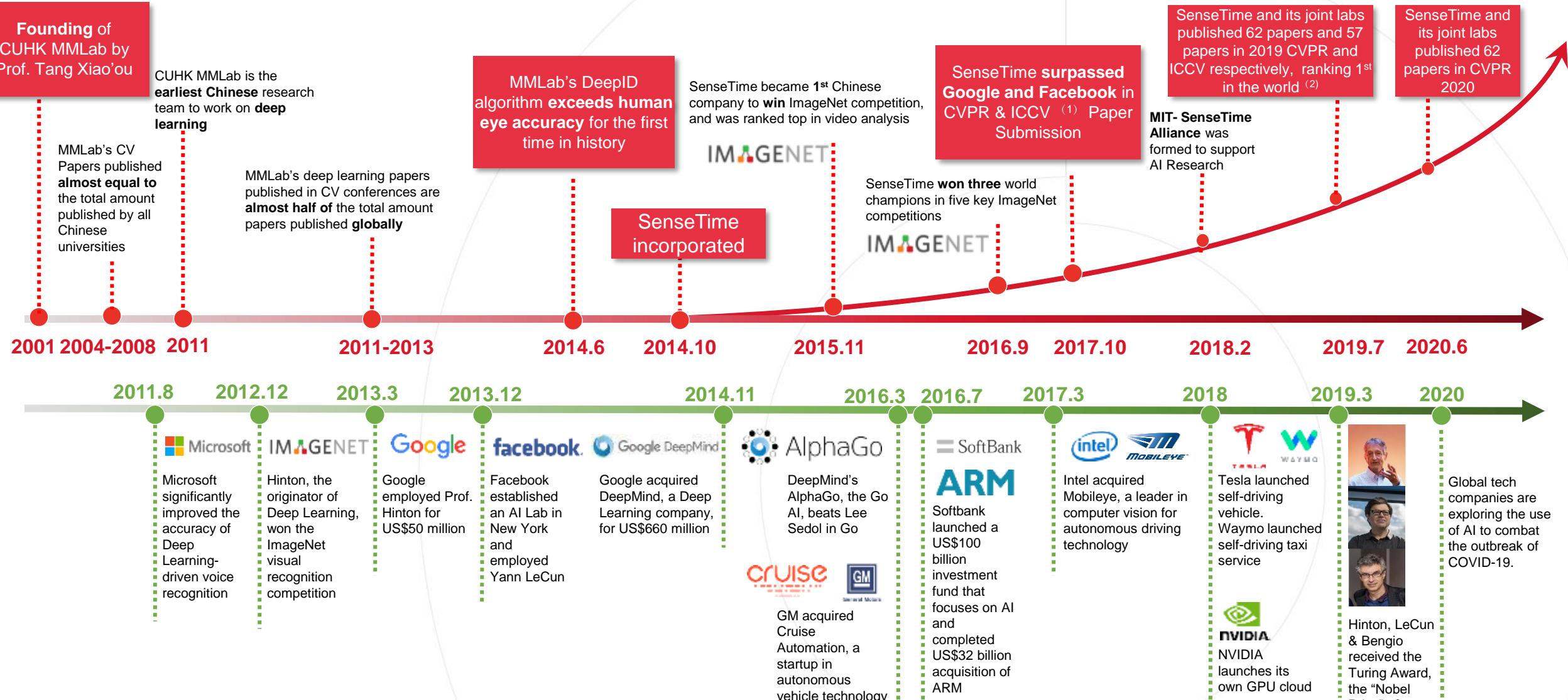




- Low-level Vision



SenseTime – Pioneer in Deep Learning and Computer Vision



(1) CVPR, ICCV, ECCV are the top 3 computer vision conferences worldwide with highest impact factor

They accept the best work on computer vision and deep learning

(2) Based on statistics released by different companies and organizations to date

How to Generate the Best AI

Fundamental research & technological capabilities determine rate of innovation

Expertise



Large amount of high quality data fuels the algorithm iteration

Data



Super fast computing power ensures speed of training

Computing Power



Vertical partnerships ensure technology and data feedback for adaptive improvement

Positive Feedback Loop



SenseTime Excels at All of These Core Capabilities

SenseTime – World Leading AI Innovation Platform

Smart City	Business Intelligence	Mobile Solution	Autonomous Driving	AI Education Package
 Smart Surveillance	 Smart City Management System	 Face Unlock	 Guide Line Prediction	 AI Textbook
 Smart Traffic Management	 Fire Detection	 Photo Processing	 Human Face Prediction	 AI Experiment Platform
 Smart Crowd Management	 Abnormal Behavior Detection	 Image Super Resolution	 Lane Detection	 AI RobotCar
 Garbage Detection	 Illegal Parking Detection	 3D Face Beautification	 Front Vehicle Detection	 AI Lab
 Illegal Occupation Detection	 Abnormal Objects Detection on Road	 AR Platform	 Intelligence Cabin Sensing	 Remote Sensing
 Smart Amusement Park Solution	 Real Estate Sales Management	 AR Live Streaming	 Face Unlock	 Road Network Extraction
		 AR Game	 Gaze Tracking	 Cloud and Snow Detection
		 AR Classroom	 Gesture Tracking	 AI-Enabled Diagnosis, Treatment and Rehabilitation
		 AR Effect	 Drowsiness detection	 Lung AI Application
				 Pathology Application

WONG KAR-WAI'S

IN THE MOOD FOR LOVE





Chapter1 - Section 1 Part 2

Image and Video Processing

Dr. Dai Jifeng

Friday, February 25, 2022

Outline

-
- Part 1 Image and video representation**
 - Part 2 Image processing**
 - Part 3 Video processing**
-

Highlights

Image & video representation in computer

Basic applications of image processing

Traditional video processing and feature extraction methods

Common algorithms for image and video compression

History of digital image processing

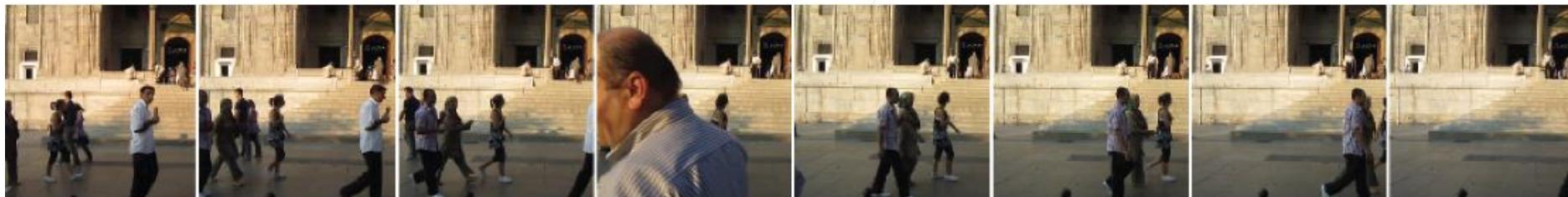
Outline

-
- Part 1 Image and video representation**
 - Part 2 Image processing**
 - Part 3 Video processing**
-

- Image -- A 2D discrete signal

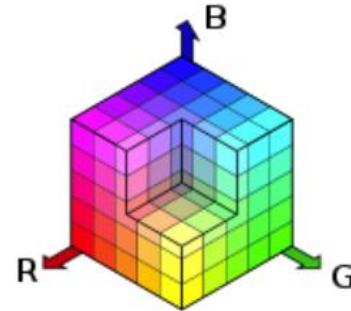
111	115	113	111	112	111	112	111
135	138	137	139	145	146	149	147
163	168	188	196	206	202	206	207
180	184	206	219	202	200	195	193
189	193	214	216	104	79	83	77
191	201	217	220	103	59	60	68
195	205	216	222	113	68	69	83
199	203	223	228	108	68	71	77

- Video -- Sequences of images

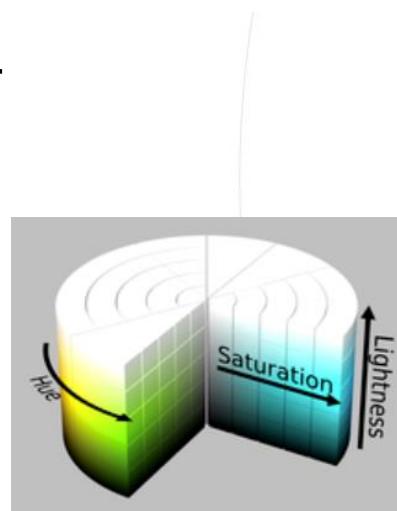


- Color Model

- RGB



- HSL

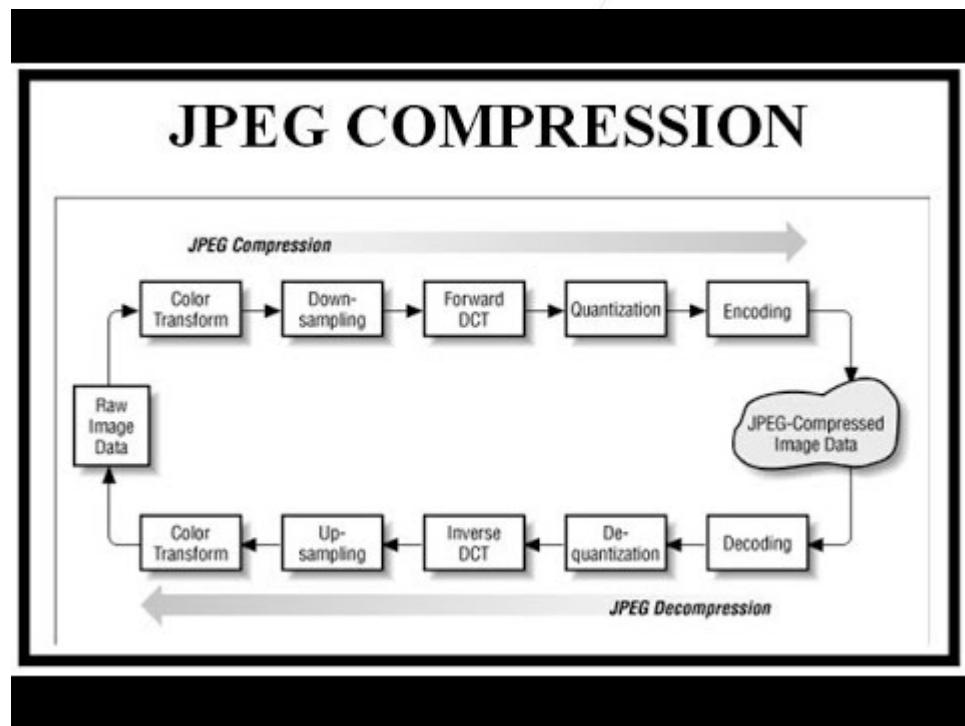


- CMYK

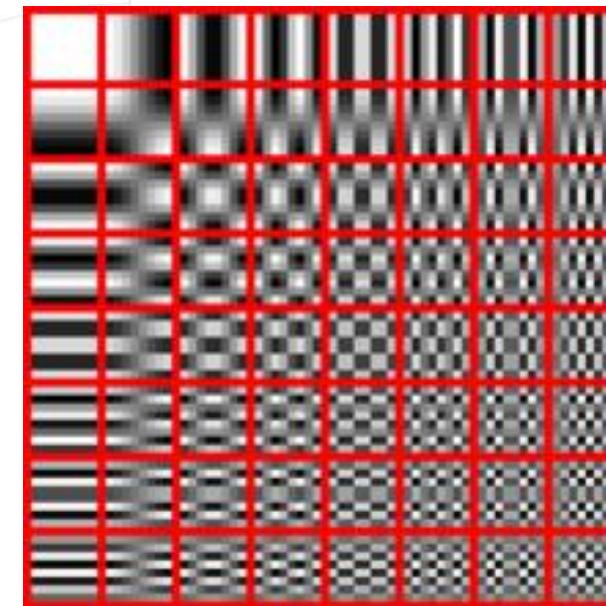


- **Compression methods for image**

- JPG, PNG, GIF, Webm



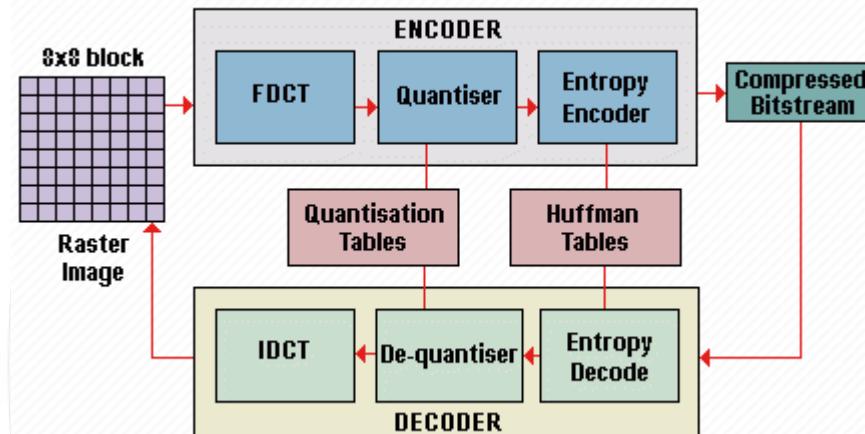
For JPG: discrete cosine transform



The DCT transforms an 8x8 block of input values to a linear combination of these 64 patterns. The patterns are referred to as the two-dimensional DCT basis functions, and the output values are referred to as transform coefficients.

- **Compression method for video**

- H.261, H.262, H.263, H.264, H.265, AV1, WMV



Example: Encoder decoder structure

- **Frame types of video**

Input:



- **I Frame (intra, keyframe)**



An I-frame (reference, keyframe, intra) is a self-contained frame. It doesn't rely on anything to be rendered, an I-frame looks similar to a static photo.

- **P Frame (predicted)**

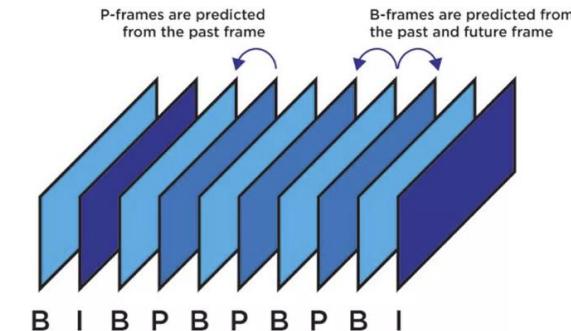


A P-frame takes advantage of the fact that almost always the current picture can be rendered using the previous frame.

- **B Frame (bi-predictive)**



B-frame refers the past and future frames to provide even a better compression



Outline

Part 1 Image and video representation

Part 2 Image processing

Part 3 Video processing



- **History of Digital Image Processing**

1960s: Improvements in computing technology and the onset of the **space race** led to a surge of work in digital image processing

- **1964:** Improve the quality of images of moon
- Such techniques were used in Apollo landings

Image Enhancement



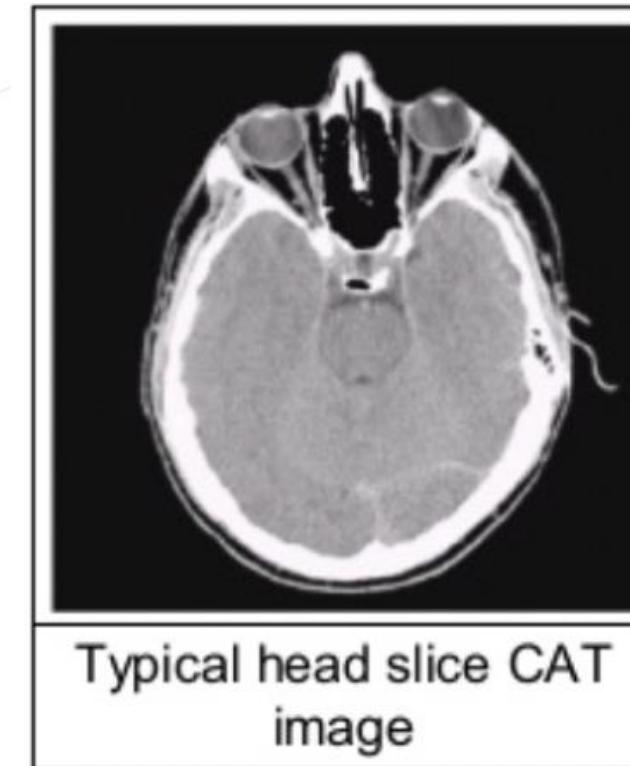
A picture of the moon taken by the Ranger 7 probe minutes before landing

- **History of Digital Image Processing**

1970s: Digital Image processing begins to be used in medical applications

- **1979:** Sir Godfrey & Prof. Allan share the Nobel Prize in medicine for the tomography.

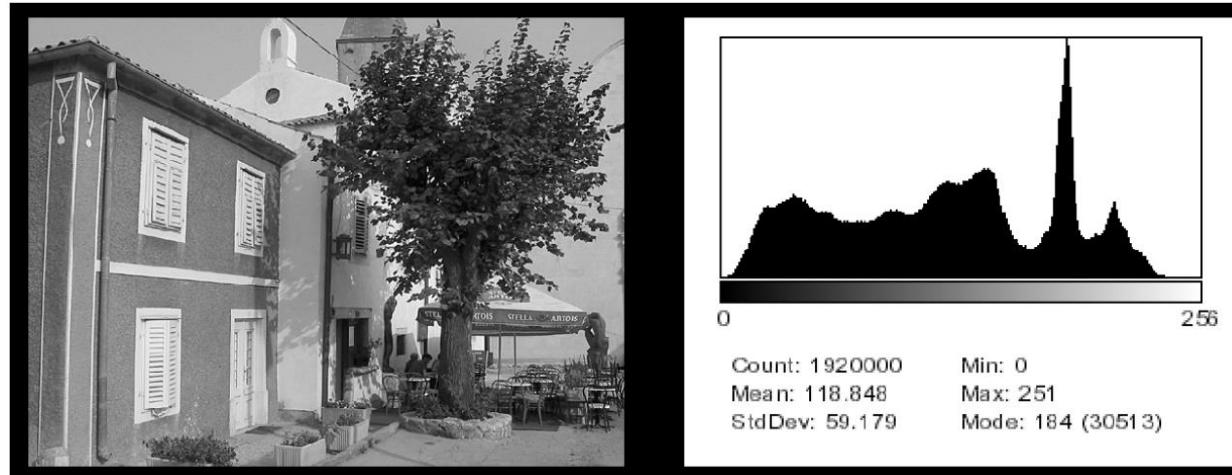
Image Restoration



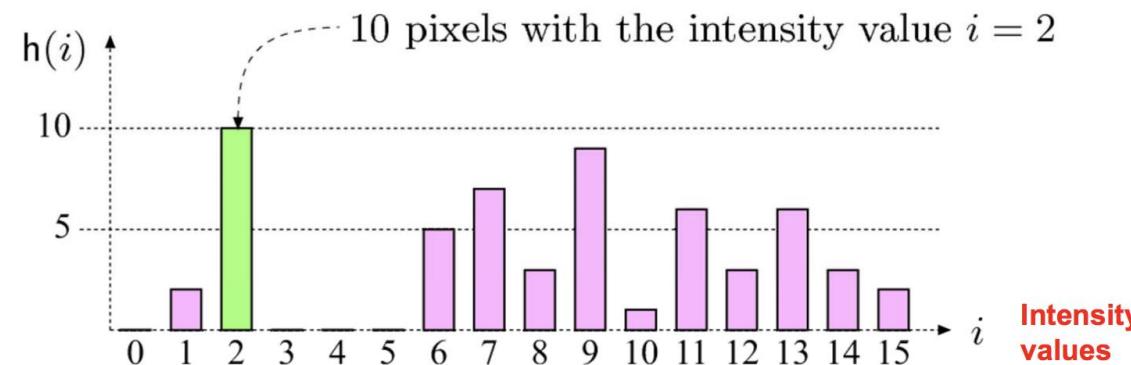


- **Histograms**

- Histograms plots how many times(frequency) each intensity value in image occurs
- **Example:**
 - Image (left) has 256 distinct gray levels (8 bits)
 - Histogram (right) shows frequency (how many times) each gray level occurs



- **Histograms**

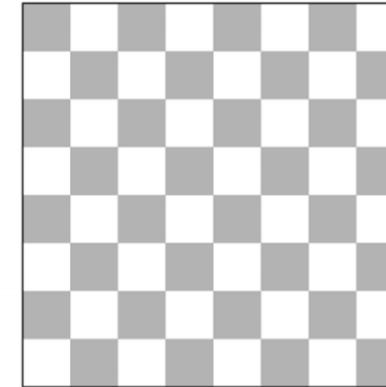
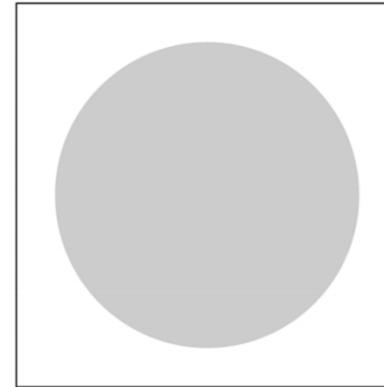
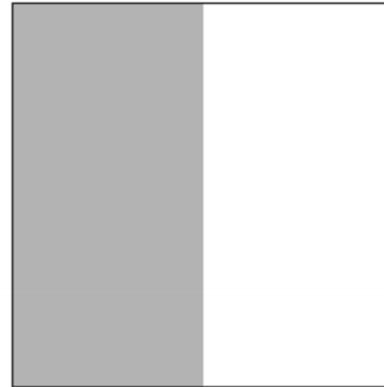


$h(i)$	0	2	10	0	0	0	5	7	3	9	1	6	3	6	3	2
i	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

- Histograms: only statistical information
- No indication of location of pixels

- **Histograms**

- Different images can have same histogram
- 3 images below have same histogram



- Half of pixels are gray, half are white
 - Same histogram = same statistics
 - Distribution of intensities could be different

- **Brightness**

- Brightness of a grayscale image is the average intensity of all pixels in image

$$B(I) = \frac{1}{wh} \sum_{v=1}^h \sum_{u=1}^w I(u, v)$$

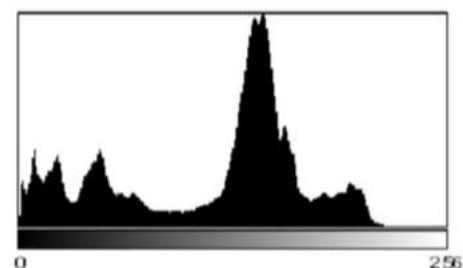
1. Sum up all pixel intensities
2. Divide by total number of pixels



- Brightness and Histogram

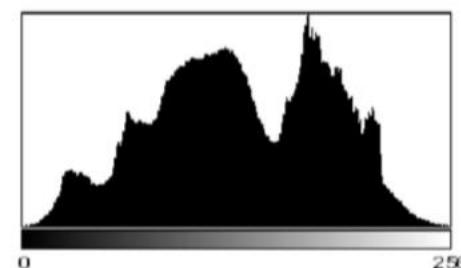


Image



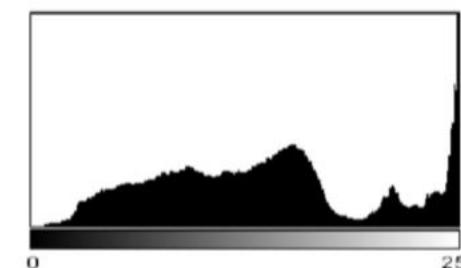
(a)

Underexposed



(b)

Properly Exposed



(c)

Overexposed

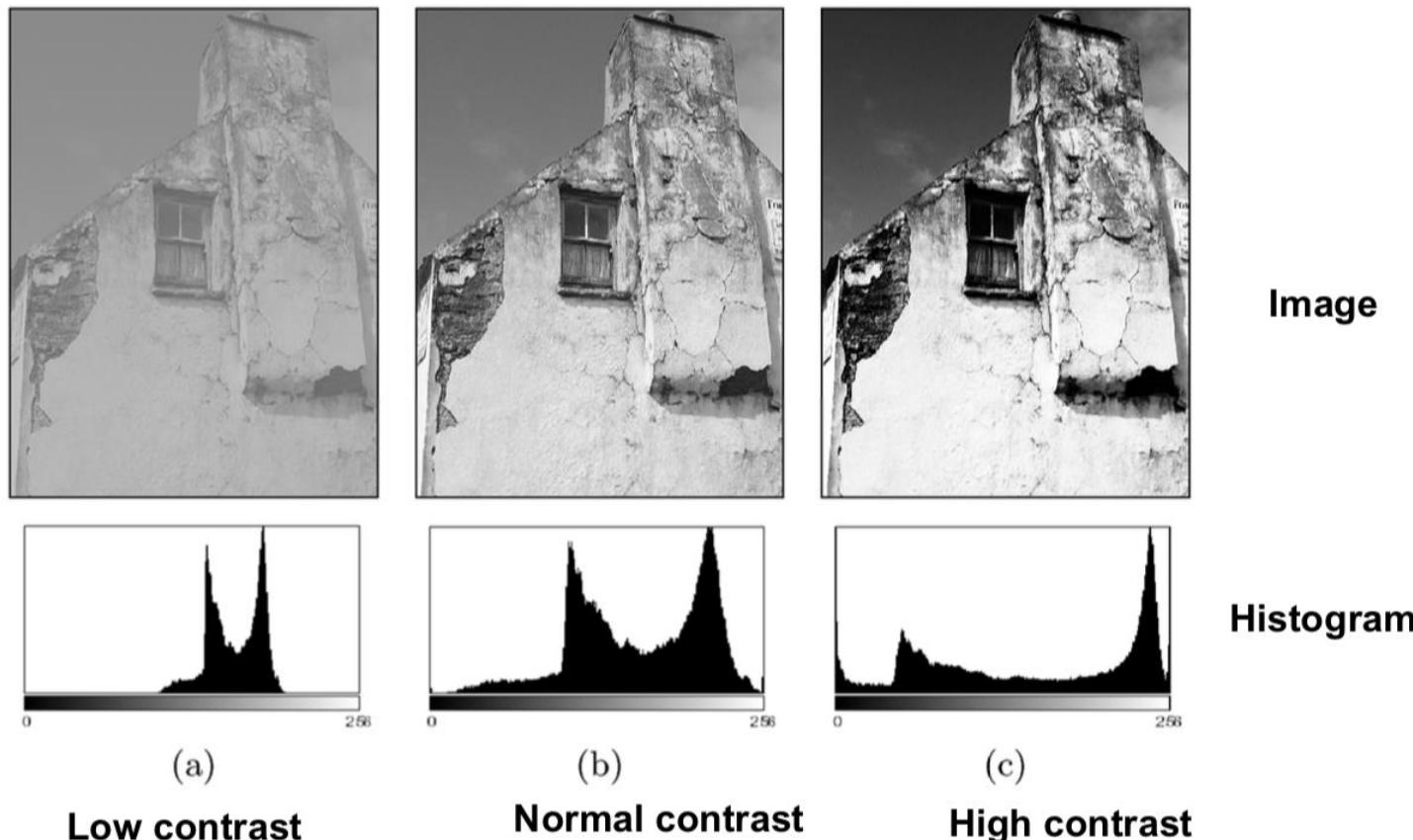
• Image Contrast

- The contrast of a grayscale image indicates how easily objects in the image can be distinguished
 - **High contrast:** many distinct intensity values
 - **Low contrast:** image uses few intensity values
- Many different equations for contrast exist

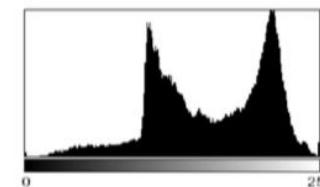
$$\text{Contrast} = \frac{\text{Change in Luminance}}{\text{Average Luminance}}$$



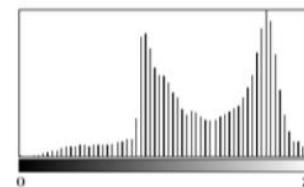
- Contrast and Histogram



- **Dynamic Range and Histogram**
- **Dynamic Range:** Number of distinct pixels in image



(a)
High Dynamic Range



(b)
**Low Dynamic Range
(64 intensities)**



(c)
**Extremely low
Dynamic Range
(6 intensity values)**

- **Image Enhancement - intensity transformation**

- **Image negatives**
- Transform function $T : g(x, y) = L - f(x, y)$,
where L is the max intensity.

```
1 import cv2
2 import numpy as np
3 # Load the image
4 img = cv2.imread('D:/downloads/forest.jpg')
5 # Check the datatype of the image
6 print(img.dtype)
7 # Subtract the img from max value(calculated from dtype)
8 img_neg = 255 - img
9 # Show the image
10 cv2.imshow('negative',img_neg)
11 cv2.waitKey(0)
```



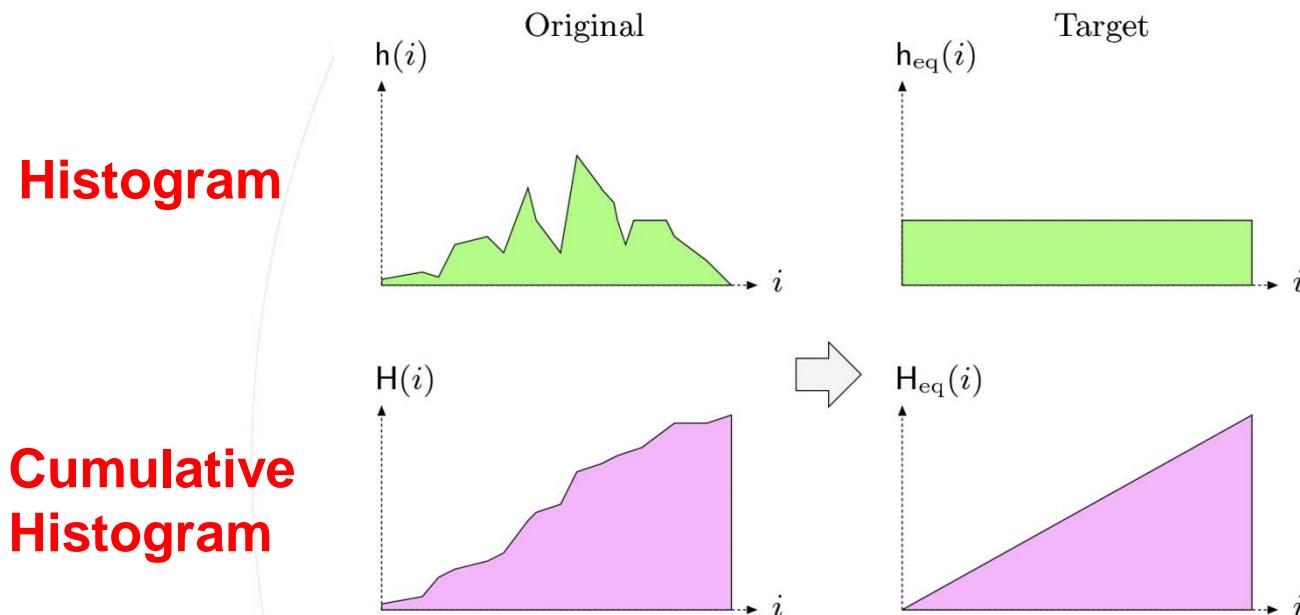
Original



Negative

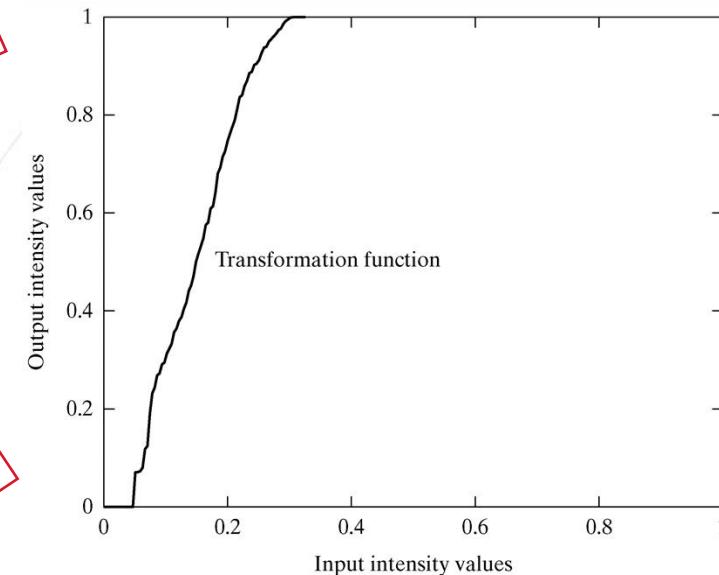
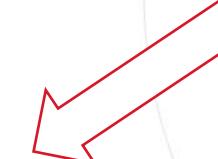
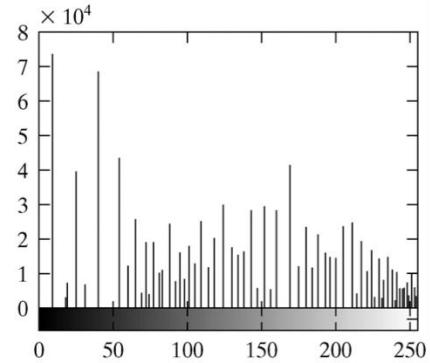
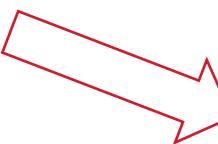
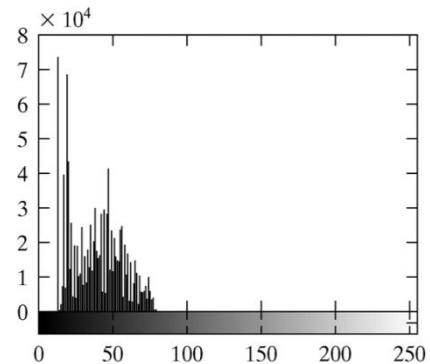
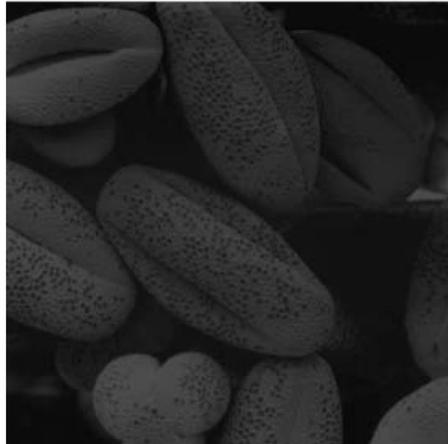
- **Image Enhancement - Histogram equalization**

- Apply a point operation that changes histogram of modified image into **uniform distribution**



```
1 img = cv2.imread('test.jpg',0)
2 equ = cv2.equalizeHist(img)
3 res = np.hstack((img,equ)) #stacking images side-by-side
4 cv2.imwrite('output.png',res)
```

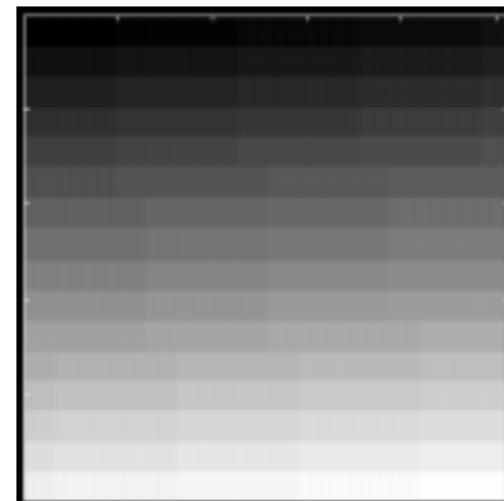
- **Image Enhancement - Histogram equalization**



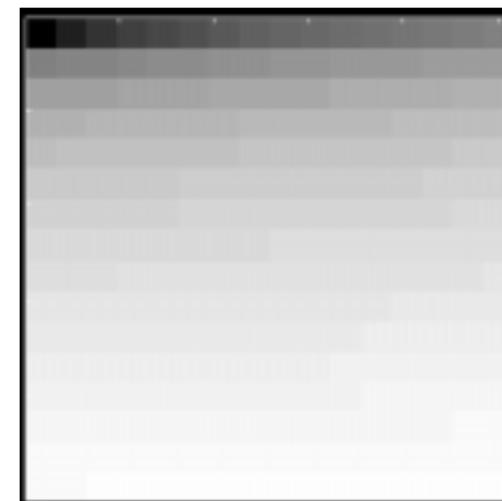
- **Image Enhancement - Compression of dynamic range**

$$s = c \log(1+|r|)$$

- where c is a scaling constant, and the logarithm function performs the desired compression.



Original



Processed output

Image Enhancement - Gray-level slicing

- A function that highlights a range $[A, B]$ of transformation intensities while diminishing all others to a constant.

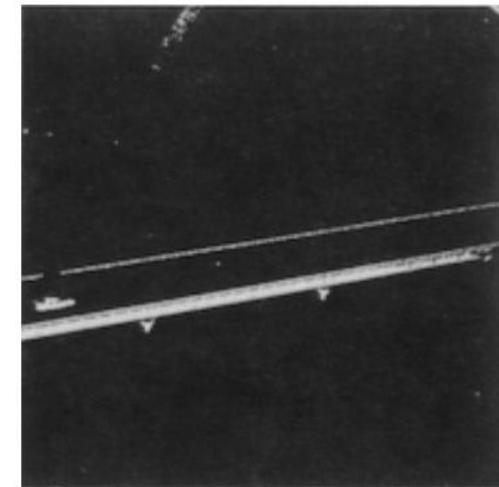
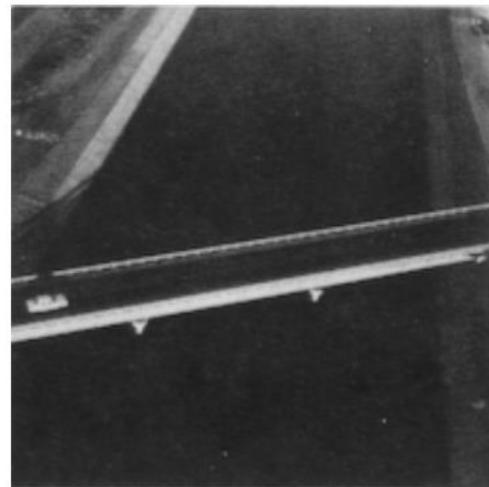
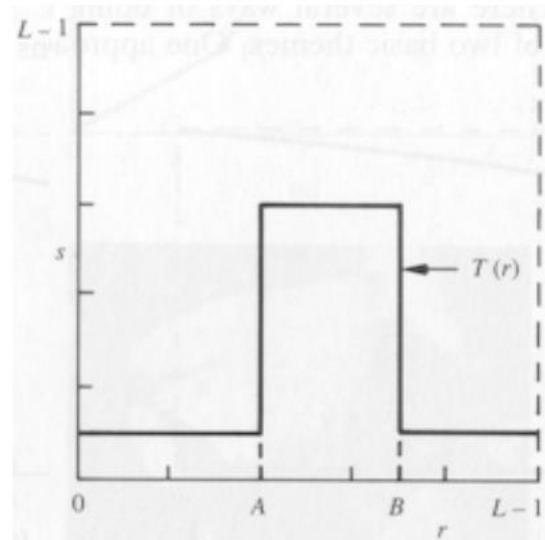


Fig 1. (a) Transfer function, (b) Original image, (c) Processing output.

- **Image Enhancement - Spatial Filtering**

1. Low pass filtering

$$\frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$



Original with (a) spike noise (b) white noise

2. Median filtering

replacing each point with the median of neighboring points.



Median filtering output

3. Sharpening Filter

$$\frac{1}{9} \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$



Low-pass filtering output

- **Image Enhancement in the frequency domain**

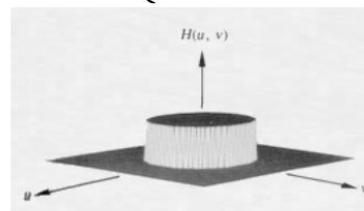
Spatial domain: $g(x,y) = f(x,y) * h(x,y)$

\Updownarrow

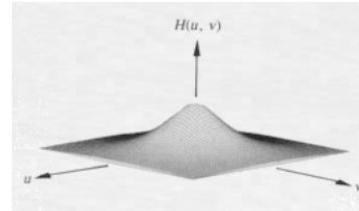
Frequency domain: $G(w_1, w_2) = F(w_1, w_2)H(w_1, w_2)$

- Lowpass filtering

$$H(u,v) = \begin{cases} 1 & \text{if } D(u,v) \leq D_o \\ 0 & \text{else} \end{cases}$$



(a)

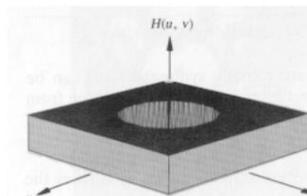


(b)

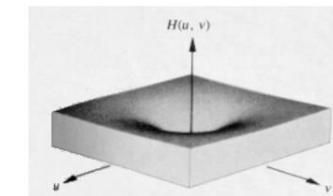
Fig 6. (a) Ideal LPF; (b) Butterworth LPF.

- Highpass filtering

$$H(u,v) = \begin{cases} 0 & \text{if } D(u,v) \leq D_o \\ 1 & \text{else} \end{cases}$$



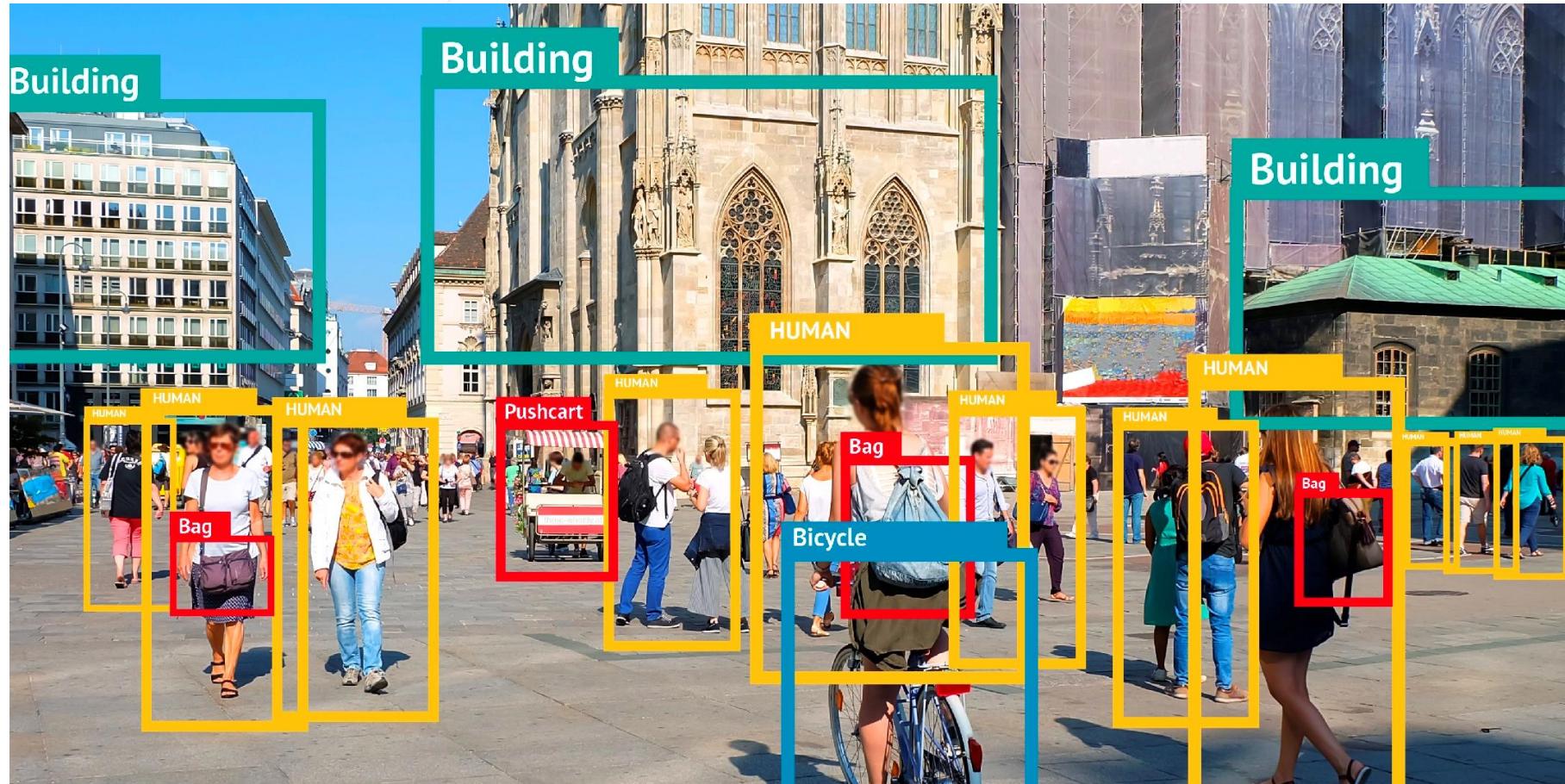
(a)



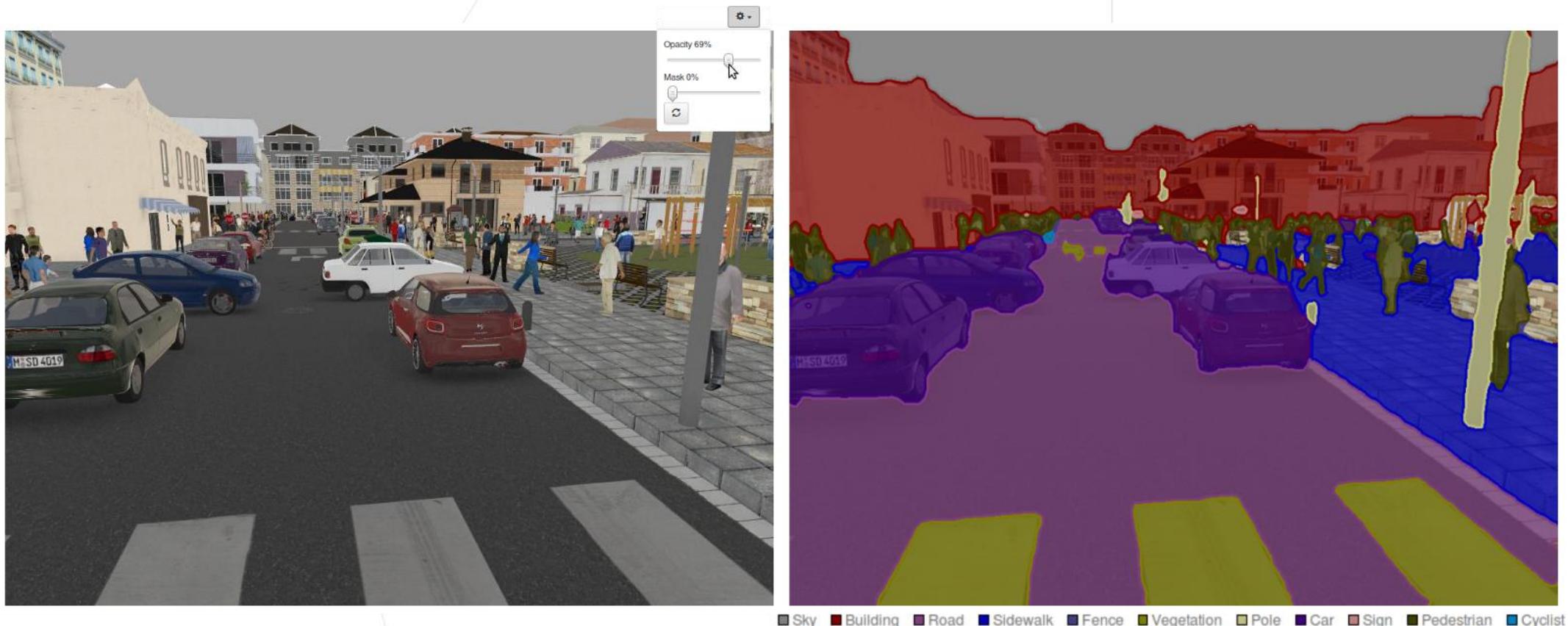
(b)

Fig 7. (a) Ideal HPF; (b) Butterworth HPF.

- **Image Detection**



- **Image Segmentation**



Outline

-
- Part 1 Image and video representation**
 - Part 2 Image processing**
 - Part 3 Video processing**
-

- **Optical Flow**

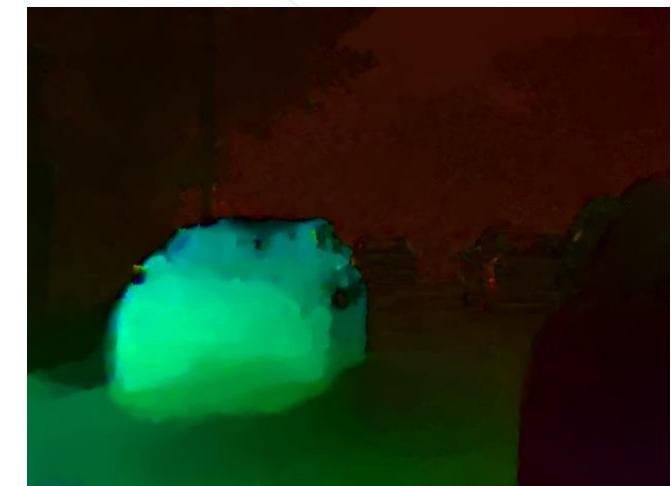
Optical flow is the pattern of apparent motion of objects, surfaces, and edges in a visual scene caused by the relative motion between an observer and a scene.



$T = t$



$T = t + 1$



Optical flow

- Two types of Optical Flow



Sparse



Dense

Gif by: <https://nanonets.com/blog/optical-flow/>

- Optical Flow demo



Gif by: <https://gfycat.com/fr/wetcreepygecko>

• Optical Flow Estimation

$$I(x, y, t) = I(x + \Delta x, y + \Delta y, t + \Delta t)$$

- Assuming the movement is small

$$I(x + \Delta x, y + \Delta y, t + \Delta t) = I(x, y, t) + \frac{\partial I}{\partial x} \Delta x + \frac{\partial I}{\partial y} \Delta y + \frac{\partial I}{\partial t} \Delta t + \text{higher-order terms}$$

- By truncating the higher order terms, a linearization, it follows that

$$\frac{\partial I}{\partial x} \Delta x + \frac{\partial I}{\partial y} \Delta y + \frac{\partial I}{\partial t} \Delta t = 0 \quad \frac{\partial I}{\partial x} V_x + \frac{\partial I}{\partial y} V_y + \frac{\partial I}{\partial t} = 0$$

- Thus

$$I_x V_x + I_y V_y = -I_t$$

- This is an equation in two unknowns and cannot be solved as such. This is known as the aperture problem of the optical flow algorithms
- To find the optical flow another set of equations is needed, given by some additional constraint. All optical flow methods introduce additional conditions for estimating

- **Lucas–Kanade method (Sparse, Local)**

- It assumes that the flow is essentially constant in a local neighborhood of the pixel under consideration, and solves the basic optical flow equations for all the pixels in that neighborhood, by the least squares criterion

$$I_x(q_1)V_x + I_y(q_1)V_y = -I_t(q_1)$$

$$I_x(q_2)V_x + I_y(q_2)V_y = -I_t(q_2)$$

$$\vdots$$

$$I_x(q_n)V_x + I_y(q_n)V_y = -I_t(q_n)$$

$$A = \begin{bmatrix} I_x(q_1) & I_y(q_1) \\ I_x(q_2) & I_y(q_2) \\ \vdots & \vdots \\ I_x(q_n) & I_y(q_n) \end{bmatrix} \quad v = \begin{bmatrix} V_x \\ V_y \end{bmatrix} \quad b = \begin{bmatrix} -I_t(q_1) \\ -I_t(q_2) \\ \vdots \\ -I_t(q_n) \end{bmatrix}$$

$$\begin{bmatrix} V_x \\ V_y \end{bmatrix} = \begin{bmatrix} \sum_i I_x(q_i)^2 & \sum_i I_x(q_i)I_y(q_i) \\ \sum_i I_y(q_i)I_x(q_i) & \sum_i I_y(q_i)^2 \end{bmatrix}^{-1} \begin{bmatrix} -\sum_i I_x(q_i)I_t(q_i) \\ -\sum_i I_y(q_i)I_t(q_i) \end{bmatrix}$$

- Since it is a purely local method, it cannot provide flow information in the interior of uniform regions of the image.

- **Horn–Schunck method (Dense, Global)**

The Horn-Schunck algorithm assumes smoothness in the flow over the whole image. Thus, it tries to minimize distortions in flow and prefers solutions which show more smoothness.

Let the image be $p = (x, y)$ and the underlying flow field be $w(p) = (u(p), v(p), 1)$, where $u(p)$ and $v(p)$ are the horizontal and vertical components of the flow field, respectively.

$$E(u, v) = \int |I_2(p + w) - I_1(p)|^2 + \lambda(|\nabla u|^2 + |\nabla v|^2) dp$$

To solve Eq. (1), we use an iterative flow framework. It assumes that an estimate of the flow field is w , and one needs to estimate the best increment dw ($dw = (du, dv)$), to update w . The objective function in Eq. (1) is then changed to

$$E(du, dv) = \int |I_2(p + w + dw) - I_1(p)|^2 + \lambda(|\nabla(u + du)|^2 + |\nabla(v + dv)|^2) dp$$

The main idea to solve the above equation is to find dU, dV so that the gradient

$$\left[\frac{\partial E}{\partial du}; \frac{\partial E}{\partial dv} \right] = 0$$

- **Horn–Schunck method**

We can derive

$$\frac{\partial E}{\partial dV} = 2((I_y^2 + \lambda L)dV + I_x I_y dU + I_y I_z + \lambda L V)$$

where L is a Laplacian filter defined as

$$I_z(\mathbf{p}) = I_2(\mathbf{p} + \mathbf{w}) - I_1(\mathbf{p})$$

$$\mathbf{L} = \mathbf{D}_x^T \mathbf{D}_x + \mathbf{D}_y^T \mathbf{D}_y$$

$$I_x(\mathbf{p}) = \frac{\partial}{\partial x} I_2(\mathbf{p} + \mathbf{w})$$

$$I_y(\mathbf{p}) = \frac{\partial}{\partial y} I_2(\mathbf{p} + \mathbf{w})$$

The term of dU in gradient is derived similarly. Therefore, solving the gradient equation can be performed in the following linear system

$$\begin{bmatrix} I_x^2 + \lambda L & I_x I_y \\ I_x I_y & I_y^2 + \lambda L \end{bmatrix} \begin{bmatrix} dU \\ dV \end{bmatrix} = - \begin{bmatrix} I_x I_z + \lambda L U \\ I_y I_z + \lambda L V \end{bmatrix}$$

- **Horn–Schunck method**



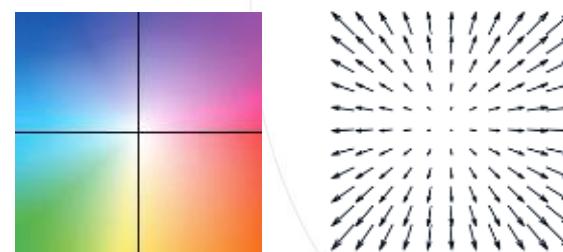
Input two frames



Dense optical flow



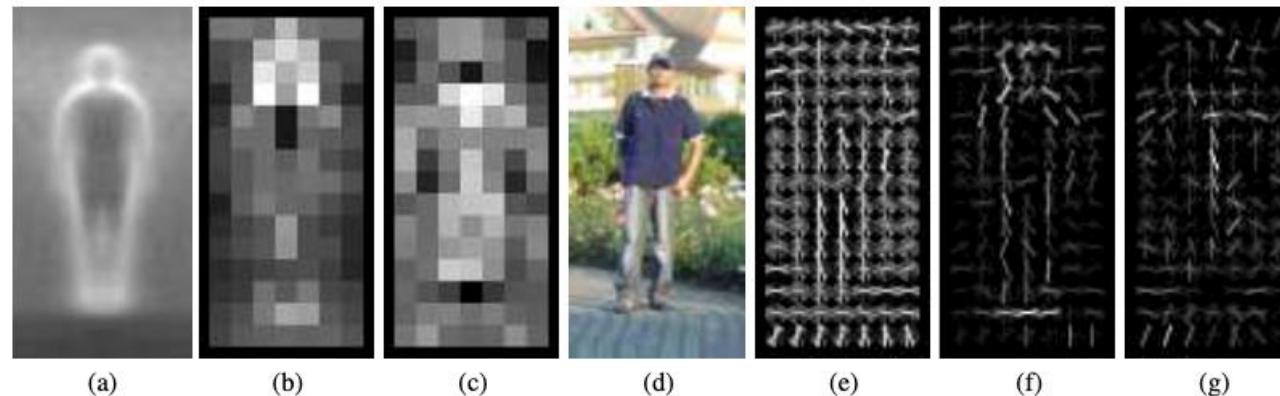
Wrapped frame



Flow Visualization

• Video Descriptors

HOG: Histogram of oriented spatial grad

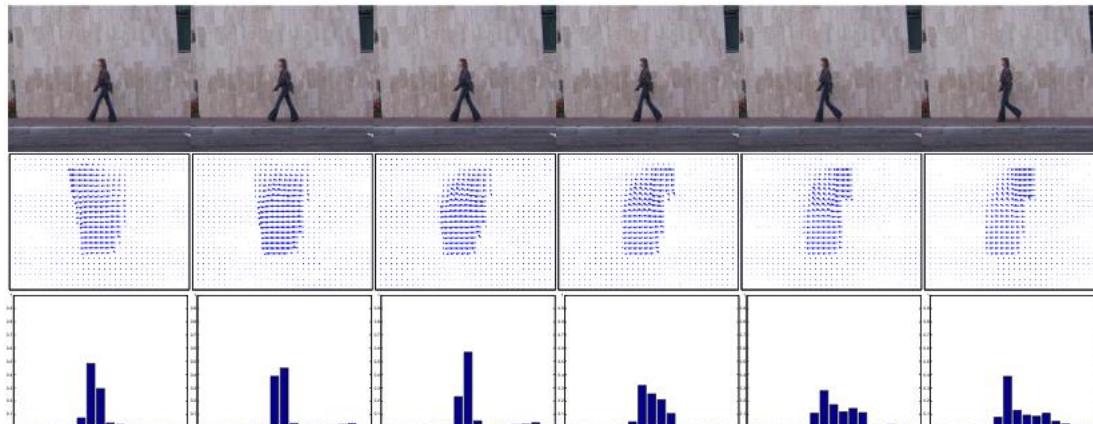


- (a) The average gradient image over the training examples.
- (b) Each ‘pixel’ shows the maximum positive SVM weight in the block centred on the pixel.
- (c) Likewise for the negative SVM weights.
- (d) A test image.
- (e) It’s computed R-HOG descriptor.
- (f,g) The R-HOG descriptor weighted by respectively the positive and the negative SVM weights.

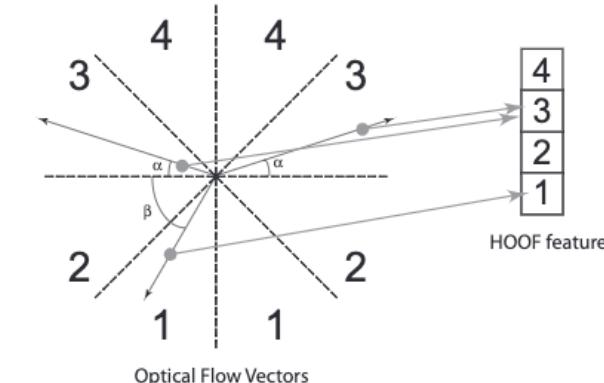
Navneet Dalal, Bill Triggs. Histograms of Oriented Gradients for Human Detection. International Conference on Computer Vision & Pattern Recognition (CVPR '05), Jun 2005, San Diego, United States. pp.886–893, 10.1109/CVPR.2005.177. inria-00548512

- **Video Descriptors**

HOF: Histogram of oriented optical flow



Optical flows and HOF feature trajectories



Histogram formation with four bins, $B=4$

Chaudhry R, Ravichandran A, Hager G, et al. Histograms of oriented optical flow and binet-cauchy kernels on nonlinear dynamical systems for the recognition of human actions[C]/2009 IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2009: 1932-1939.

• Video Descriptors

MBH: Motion Boundary Histograms

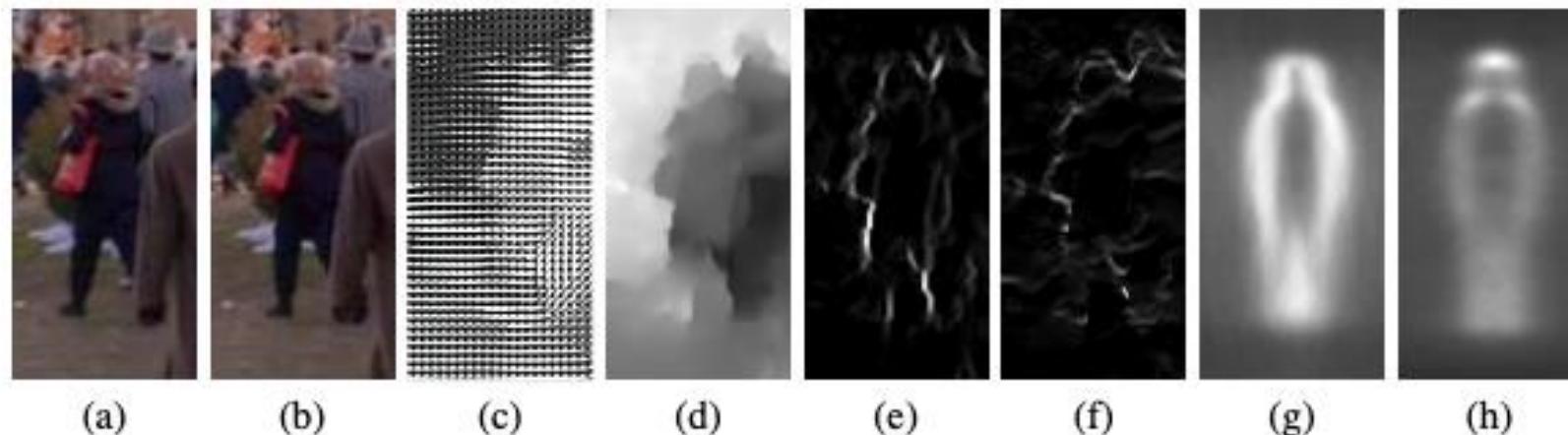


Illustration of the MBH descriptor.

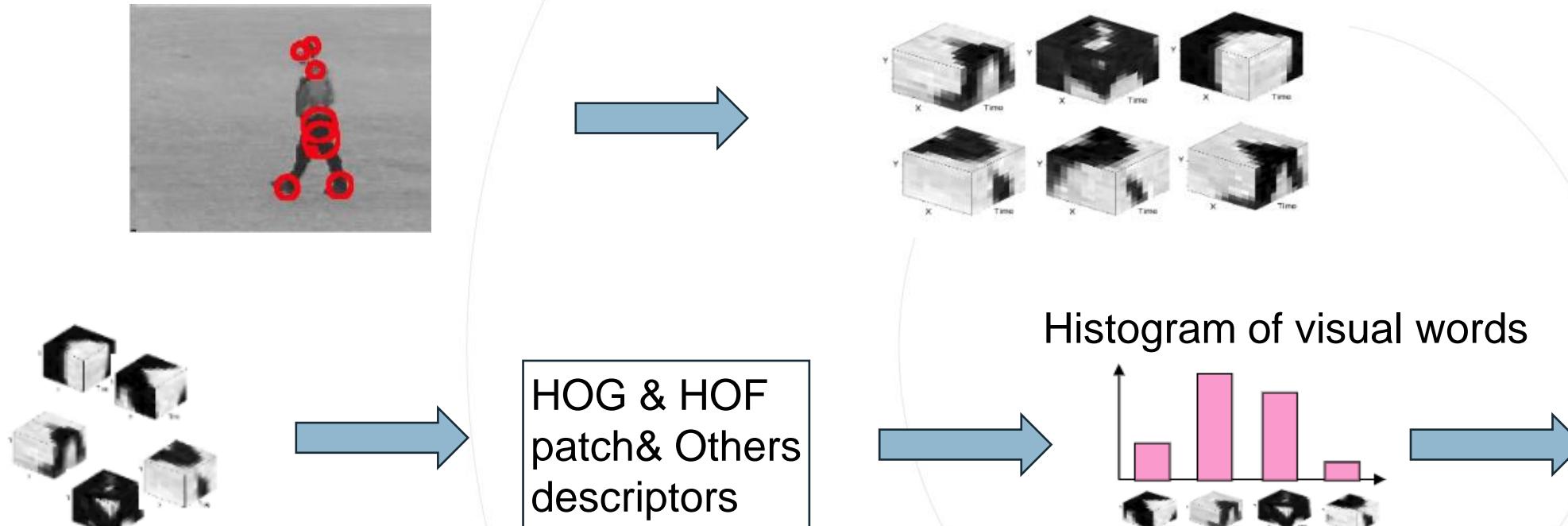
(a,b) Reference images at time t and $t + 1$.

(c,d) Computed optical flow, and flow magnitude showing motion boundaries. (e,f)
Gradient magnitude of flow field J^x, J^y for image pair (a,b). (g,h) Average MBH descriptor
over all training images for flow field J^x, J^y .

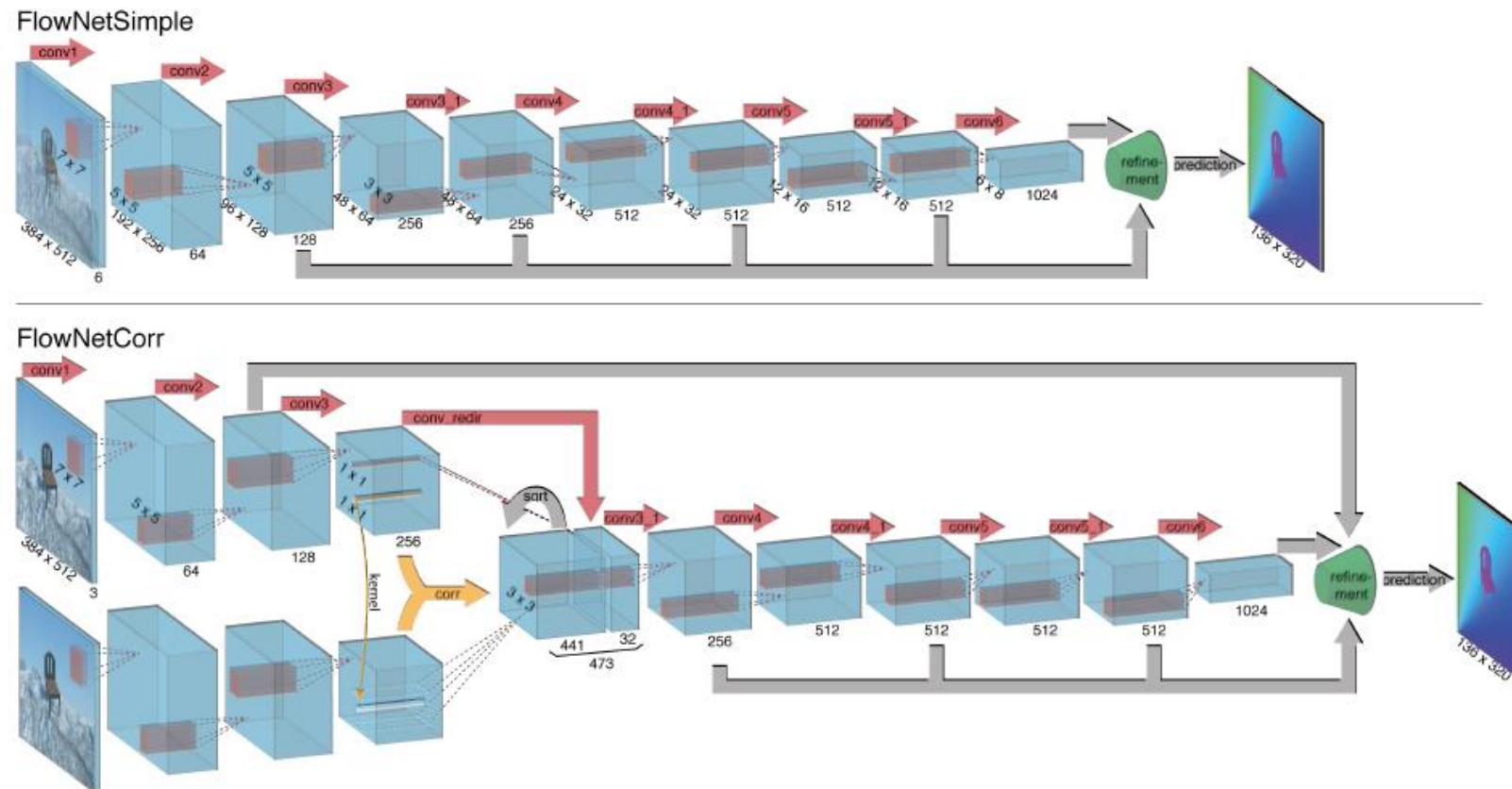
Dalal N, Triggs B, Schmid C. Human detection using oriented histograms of flow and appearance[C]//European conference on computer vision. Springer, Berlin, Heidelberg, 2006: 428-441.

- **Traditional Action classification**

- Bag of space-time features + SVM

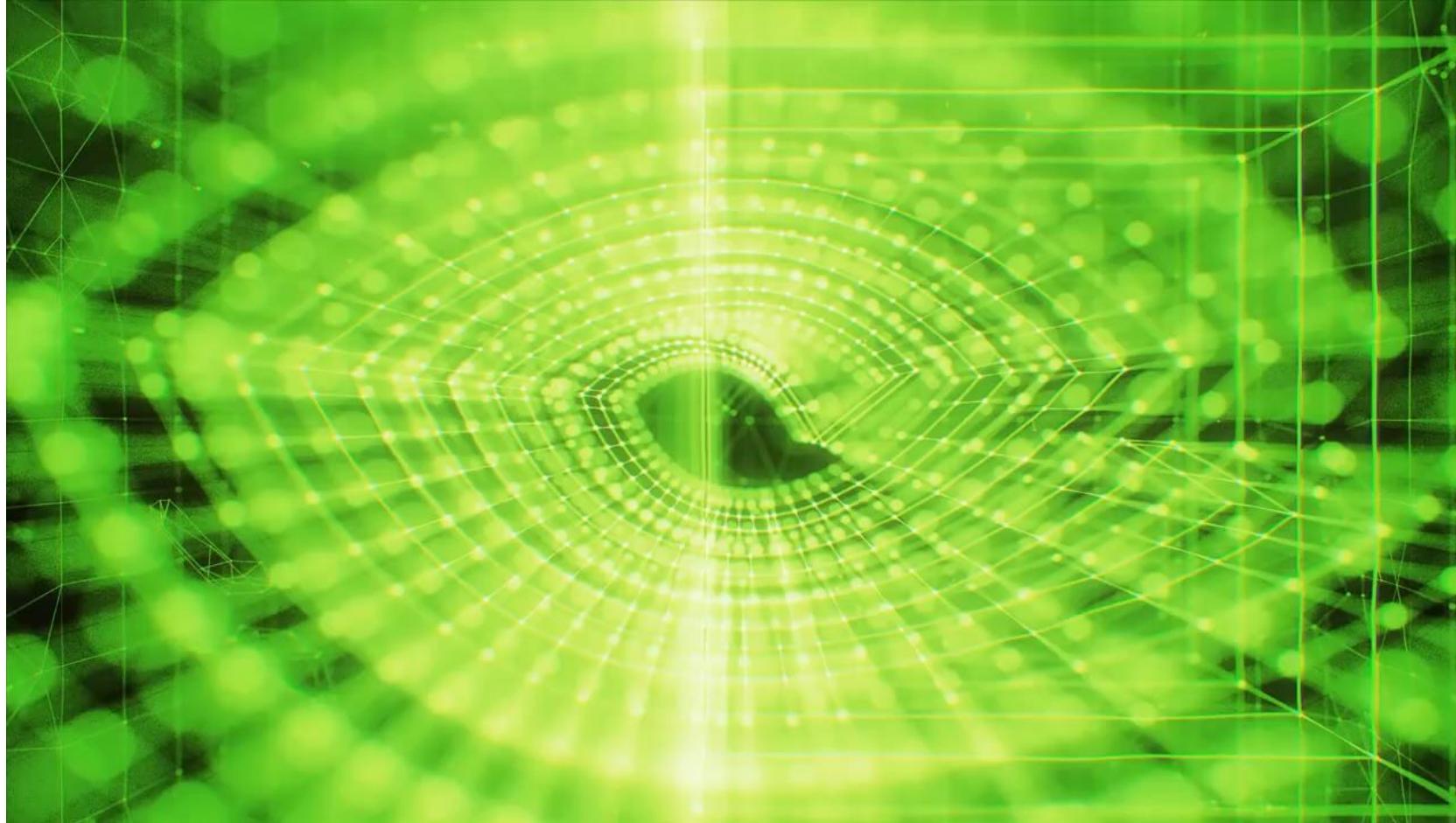


- Optical flow estimation via deep networks**



Fischer et al.: FlowNet: Learning Optical Flow with Convolutional Networks, ICCV 2015.

- Video Interpolation



<http://jianghz.me/projects/superslomo/>

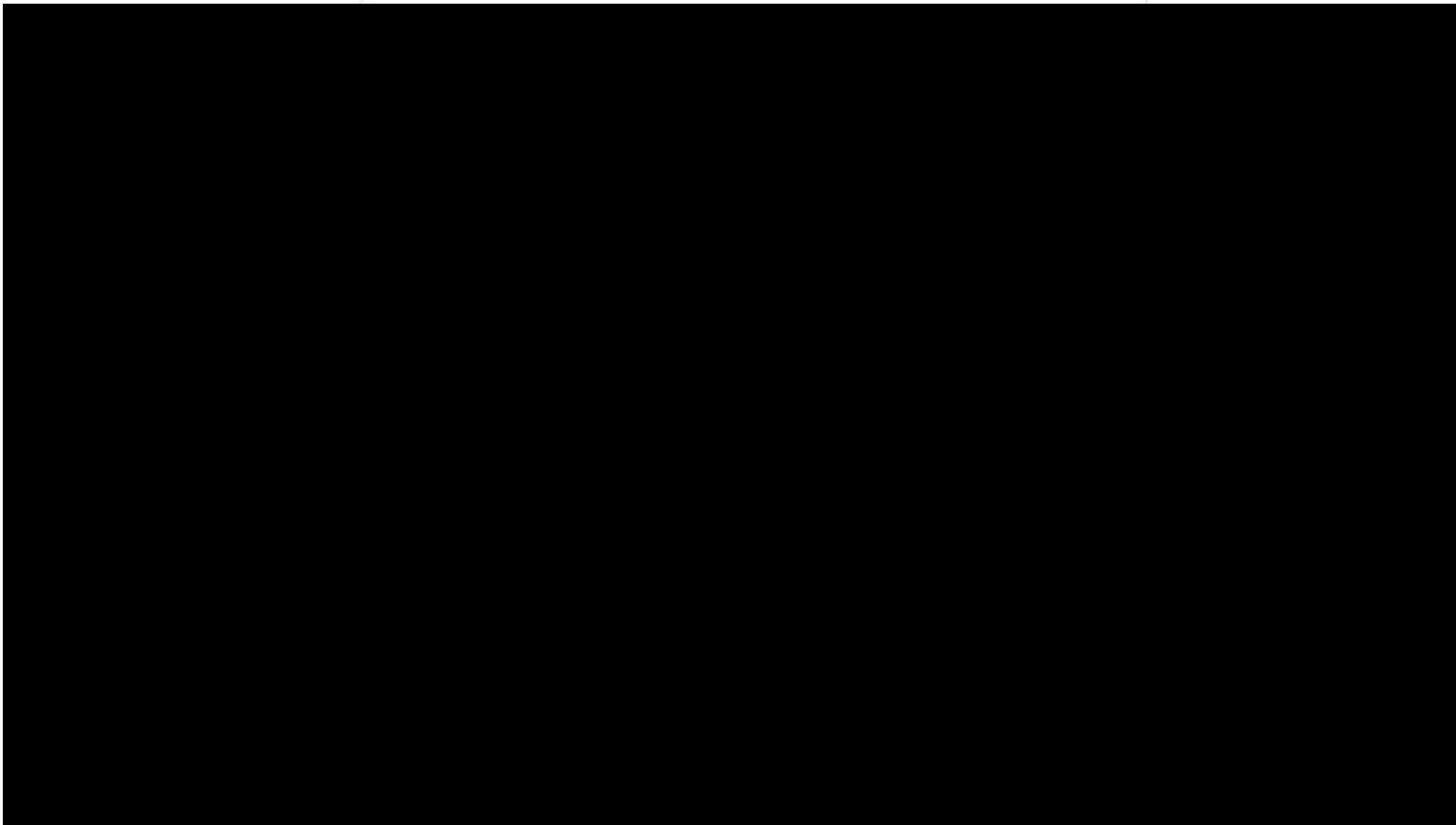
- **Video Stabilization**



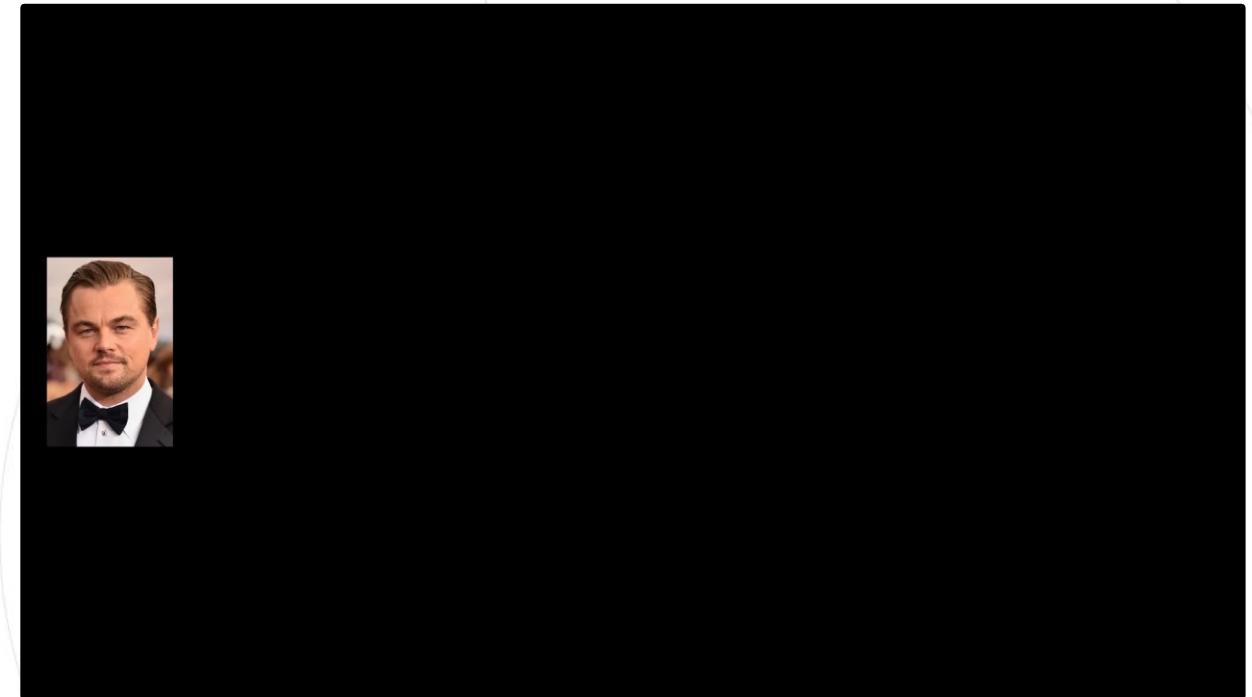
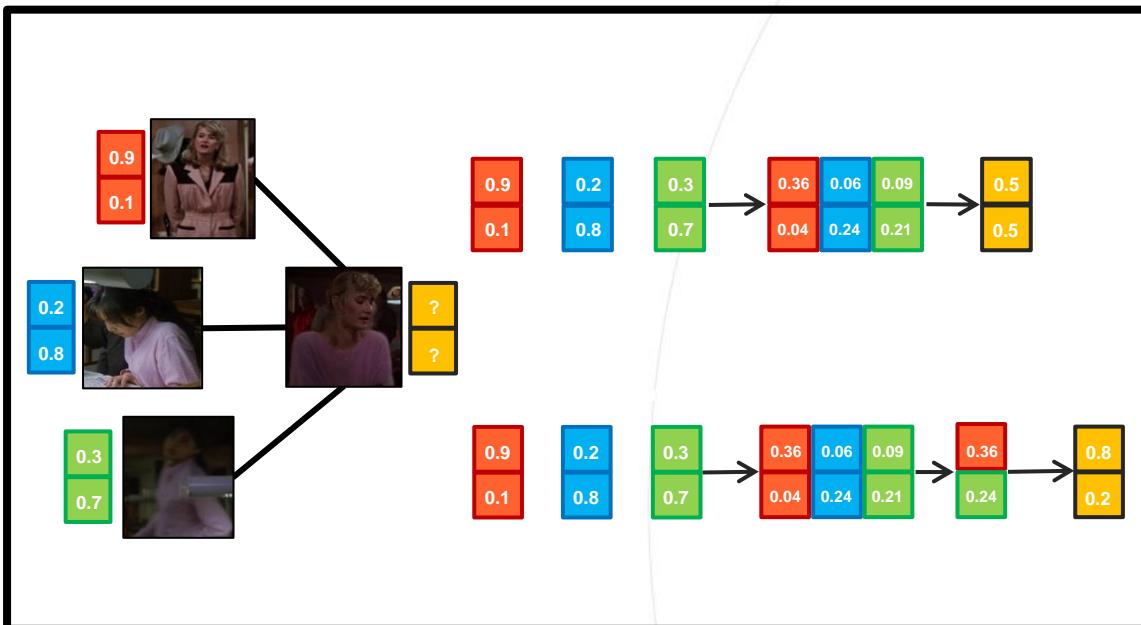
- Video Denosing



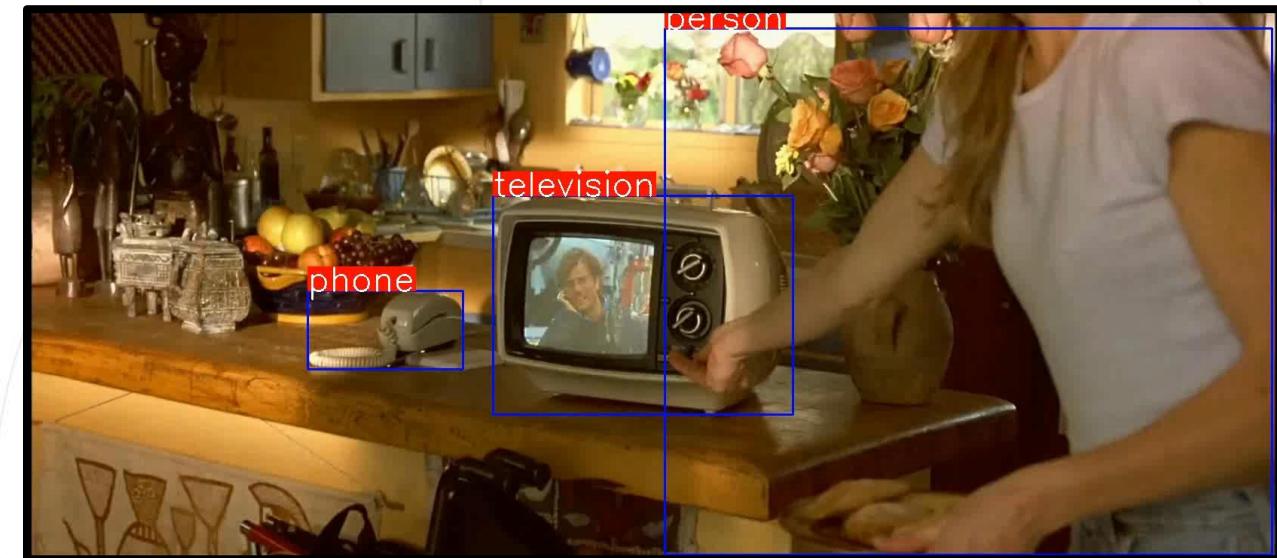
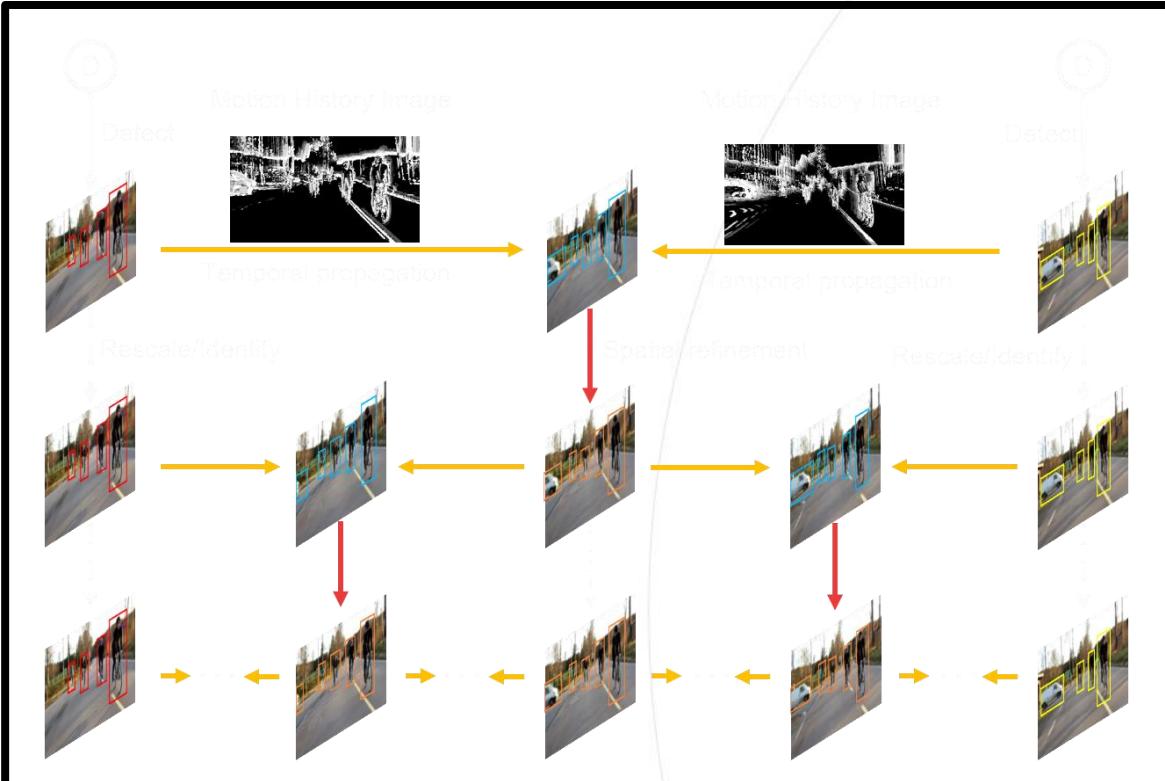
- Video Super-Resolution



- Video Understanding - Human



- Video Understanding - Object



- Video Understanding - Context

