

BLG 453E

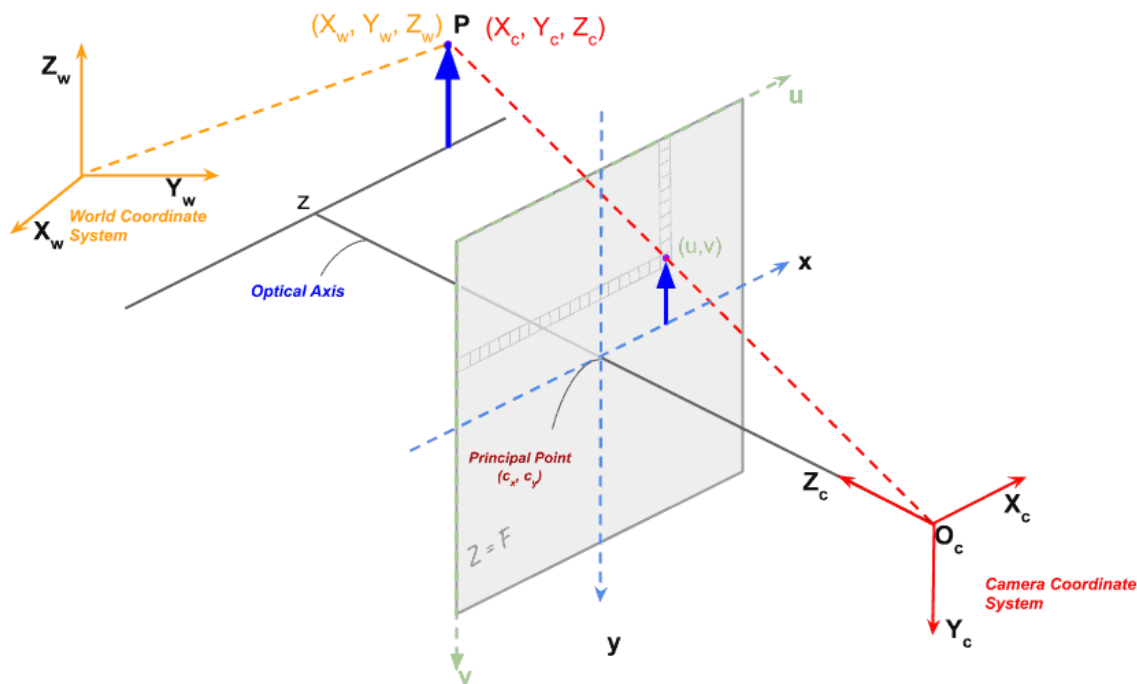
Week 1

Introduction to Computer Vision and Image Data

Dr. Yusuf H. Sahin

Computer Vision & Image Formation

- In a broad sense, vision is the inverse of image formation.
 - **Image formation:** How objects create images
 - Computer Vision:** How to use the image to understand objects in space.



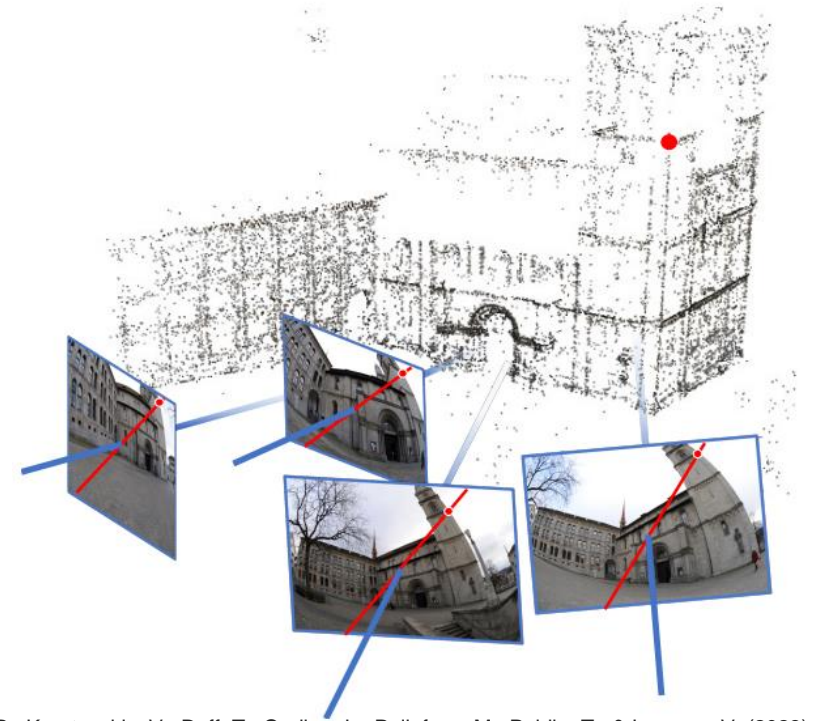
<https://learnopencv.com/geometry-of-image-formation/>

In order to establish a precise correspondence between points in 3-D space (with respect to a fixed global reference frame) and their projected images in a 2-D image plane (with respect to a local coordinate frame), a mathematical model for this process must account for three types of transformations:

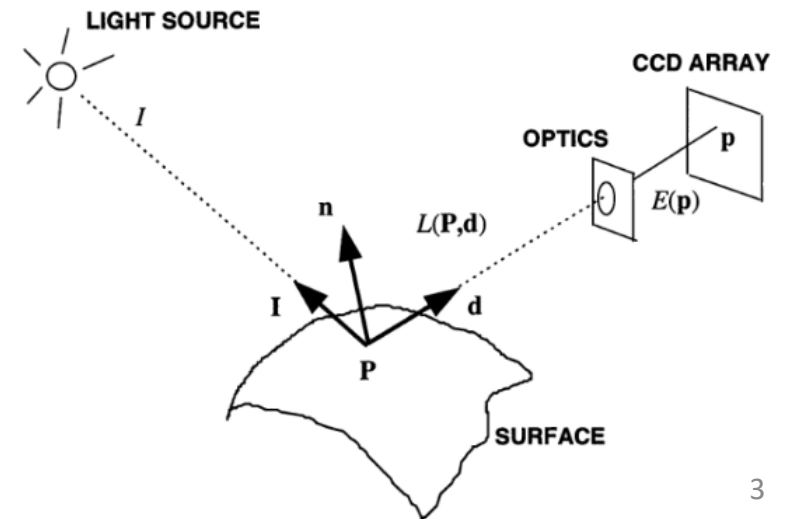
- I. coordinate transformations between the camera frame and the world frame (coordinate transform)
- II. projection of 3-D coordinates onto 2-D image coordinates (perspective transform)
- III. coordinate transformation between possible choices of image coordinate frame (pixel coordinates)

Steps of Image Formation

- **Geometric image formation** deals with points, lines, and planes, and how these are mapped onto images using projective geometry and other models (including radial lens distortion).
- **Photometric image formation** covers radiometry, which describes how light interacts with surfaces in the world.
- **Optics** deals with the light rays which enter the camera through an angular aperture and hit a screen or image plane, the camera's photosensitive device which registers light intensities.

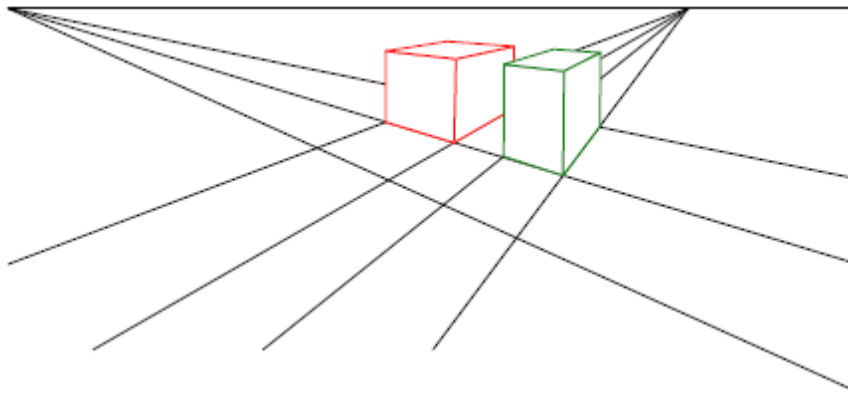


Hruby, P., Korotynskiy, V., Duff, T., Oeding, L., Pollefeys, M., Pajdla, T., & Larsson, V. (2023). Four-view geometry with unknown radial distortion. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 8990-9000).

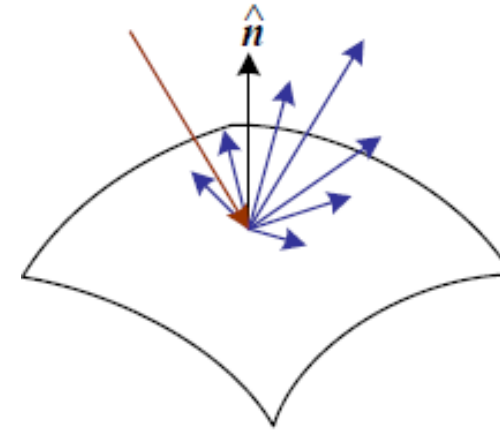


The Full Process

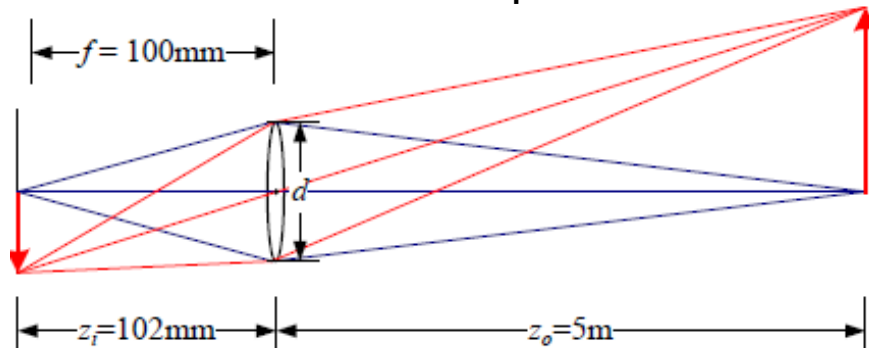
perspective projection



light scattering



lens optics

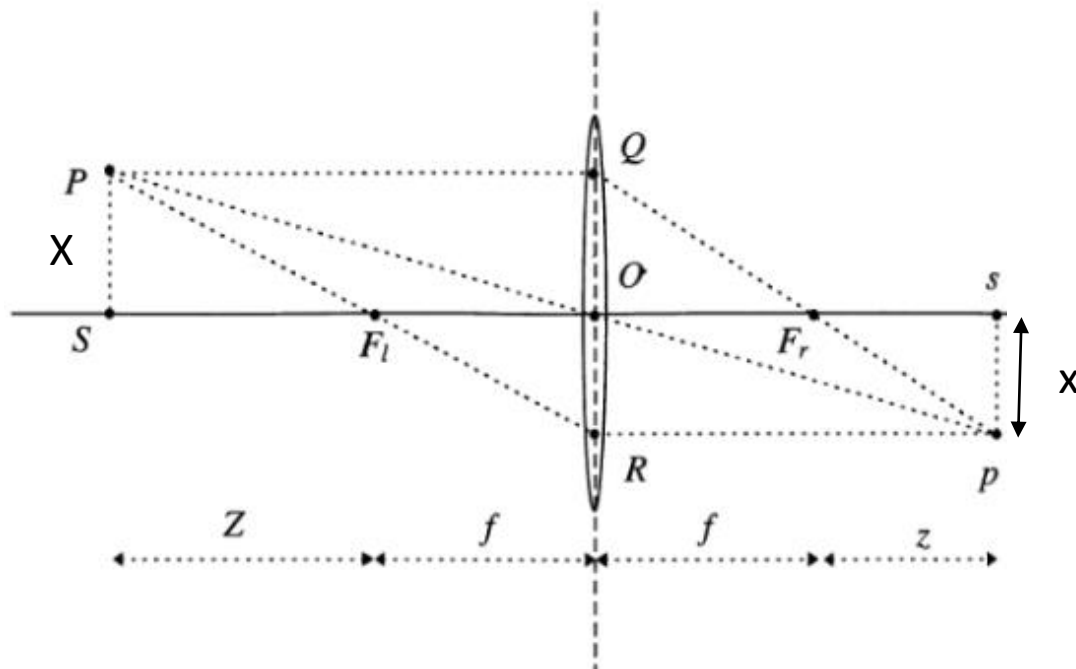


Charge-Coupled Devices with Bayer pattern

G	R	G	R
B	G	B	G
G	R	G	R
B	G	B	G

Basic Optics: Thin Lens Model

- A thin lens deflects all rays parallel to the optical axis and coming from one side onto the focus on the other side, as described by two basic properties:
 - (1) Any ray entering the lens parallel to the axis on one side goes through the focus on the other side.
 - (2) Any ray entering the lens from the focus on one side emerges parallel to the axis on the other side.



For a point P , not too far from the optical axis,

- $Z + f$ be the distance of P from the lens along the optical axis.

- Using the two pairs of similar triangles

$$\triangle P, F_l, S \sim \triangle R, O, F_l$$

$$\triangle p, s, F_r \sim \triangle Q, O, F_r$$

$$\frac{x}{z} = \frac{X}{f} \quad \frac{X}{Z} = \frac{x}{f} \quad \longrightarrow \quad Zz = f^2$$

- Setting $\hat{Z} = Z + f$ and $\hat{z} = z + f$

$$f^2 = (\hat{Z} - f)(\hat{z} - f)$$

$$f(\hat{Z} + \hat{z}) = \hat{Z}\hat{z}$$

$$\frac{1}{f} = \frac{\hat{Z} + \hat{z}}{\hat{Z}\hat{z}}$$

$$\boxed{\frac{1}{f} = \frac{1}{\hat{Z}} + \frac{1}{\hat{z}}}$$

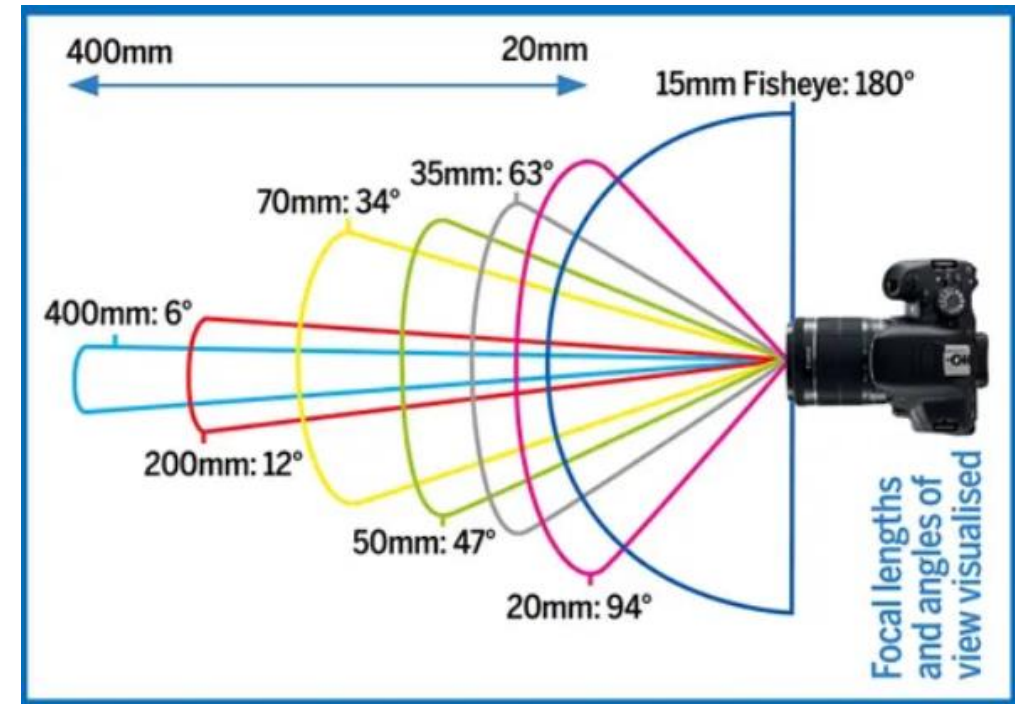
Field of View

- The thin lens has two parameters: its focal length f and its diameter $2r$.
- We define the field of view (FOV) to be the angle subtended by the spatial extent of the sensor as seen from the optical center. If $2r$ is the largest spatial extension of the sensor (e.g., the side of the CCD), then the field of view is

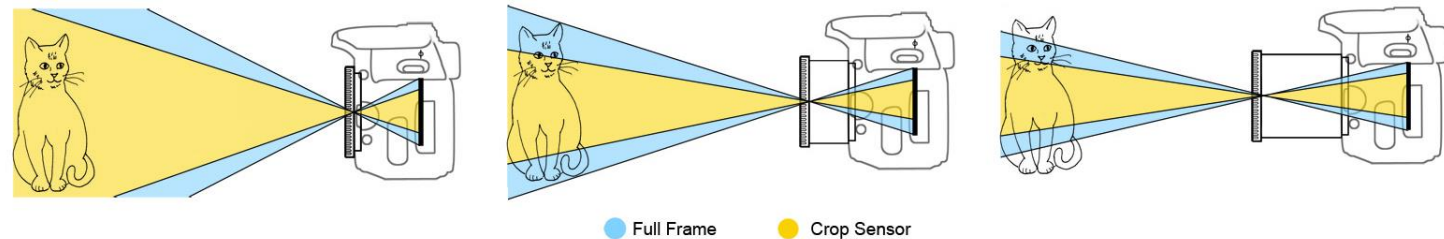
$$\theta = 2 * \arctan\left(\frac{r}{f}\right)$$

- For a full-frame sensor (36 mm in modern cameras), and focal length of 35 mm:

$$2 * \arctan\left(\frac{18}{35}\right) \cong 63^\circ$$

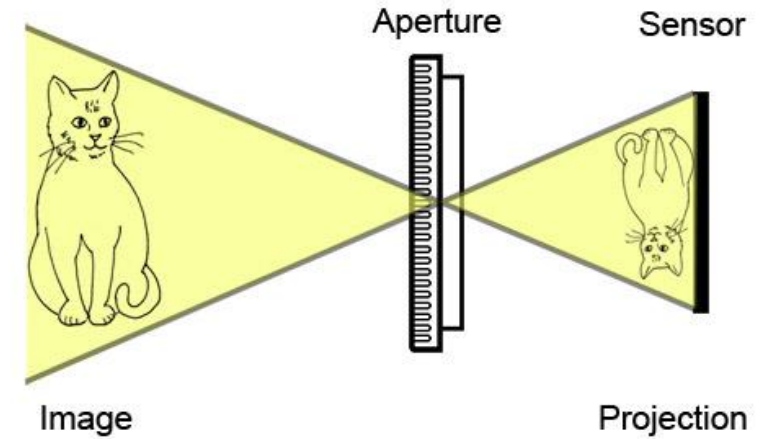


<https://www.digitalcameraworld.com/tutorials/photography-cheat-sheet-what-is-field-of-view-fov>



<https://daystarlaser.com/education/pinhole-photography-primer/>

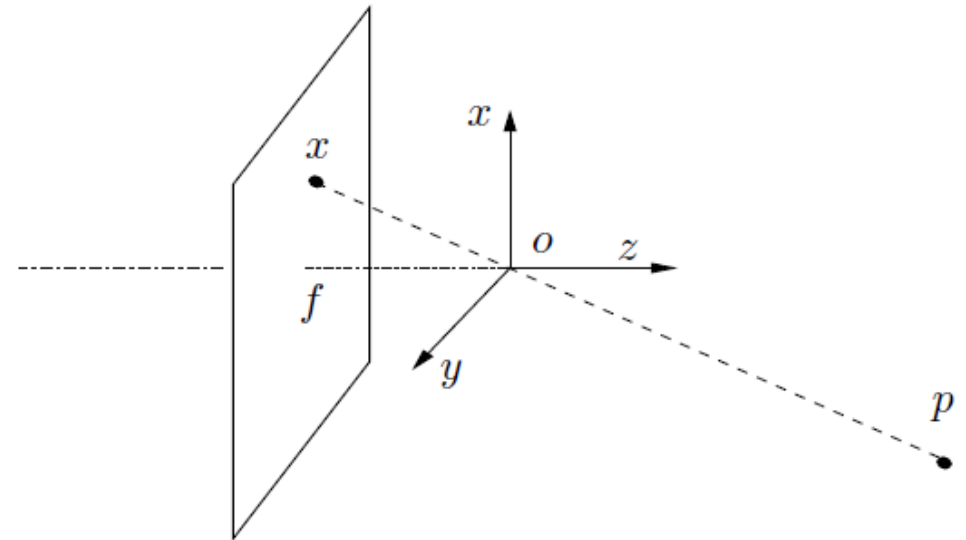
Pinhole Camera Model



- Reducing the camera's aperture to a point, called a pinhole.
- Only one ray from any given point can enter the camera, and creates a one-to-one correspondence between visible points, rays, and image points.
- This results in very sharp, undistorted images of objects at different distances from the camera.
- If a point p has coordinates $X = [X, Y, Z]^T$ relative to a reference frame centered at the optical center o , with its z -axis being the optical axis (of the lens), then it is immediate to see from similar triangles
 - The ideal perspective projection.

$$x = -f \frac{X}{Z} \quad y = -f \frac{Y}{Z}$$

- Negative sign: Upside down

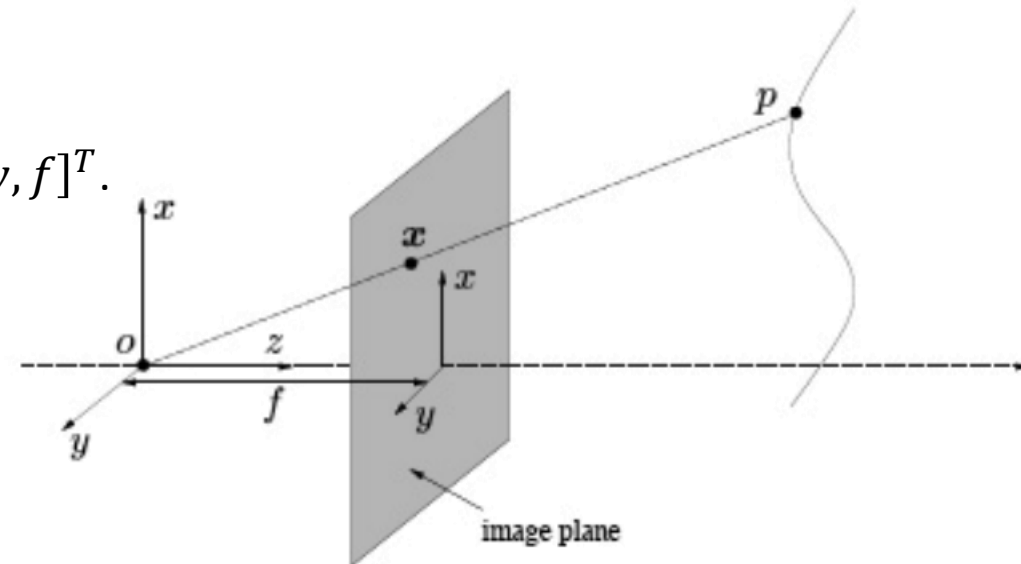


Frontal Pinhole Camera Model

- To eliminate negative sign, we can simply flip the image: $(x, y) \rightarrow (-x, -y)$.
- This corresponds to placing the image plane $\{z = -f\}$ in front of the optical center instead $\{z = +f\}$.

$$x = f \frac{X}{Z} \quad y = f \frac{Y}{Z}$$

- In the camera frame, the third component of an image point is always equal to the focal length (as the equation of the plane is $z = f$).
- For this reason, we will often write $p = [x, y]$ instead of $p = [x, y, f]^T$.



Ideal Perspective Camera Model

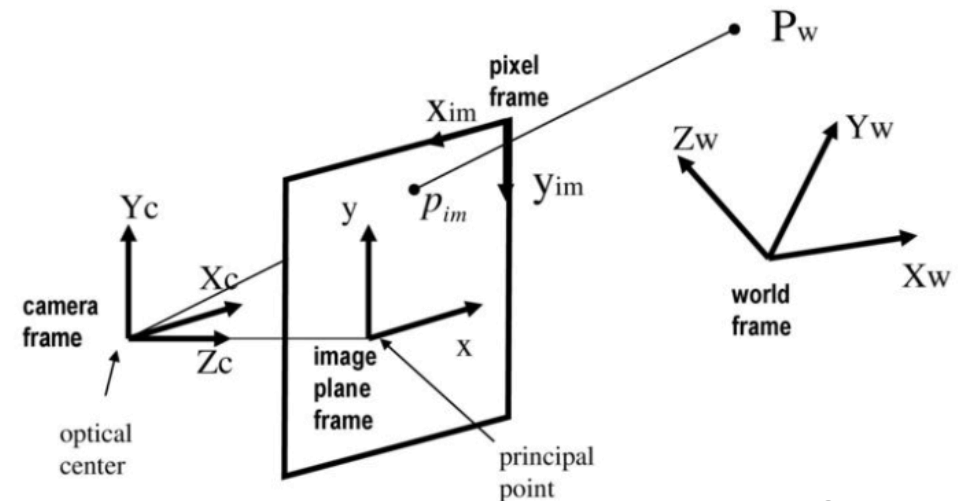
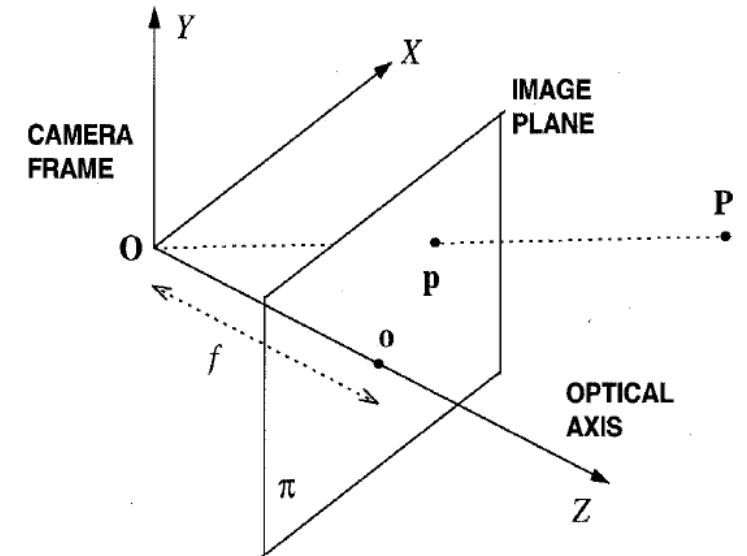
- Sometimes, we simply write the projection as a map π :

- $\pi: \mathbb{R}^3 \rightarrow \mathbb{R}^2; X \mapsto x$

- $x = \pi(X)$

$$x = f \frac{X}{Z} \quad y = f \frac{Y}{Z}$$

- The intersection between image plane and the optical axis, is named principal point or image center.
- p , the image of P , is the point at which the straight line through P and O intersects the image plane.
- Camera Frame:** The 3D reference frame in which O is the origin and the plane π is orthogonal to the Z axis.



Approximate Camera Models

- **Orthographic Projection**

- The light rays in the orthographic model travel along the lines parallel to the optical axis.

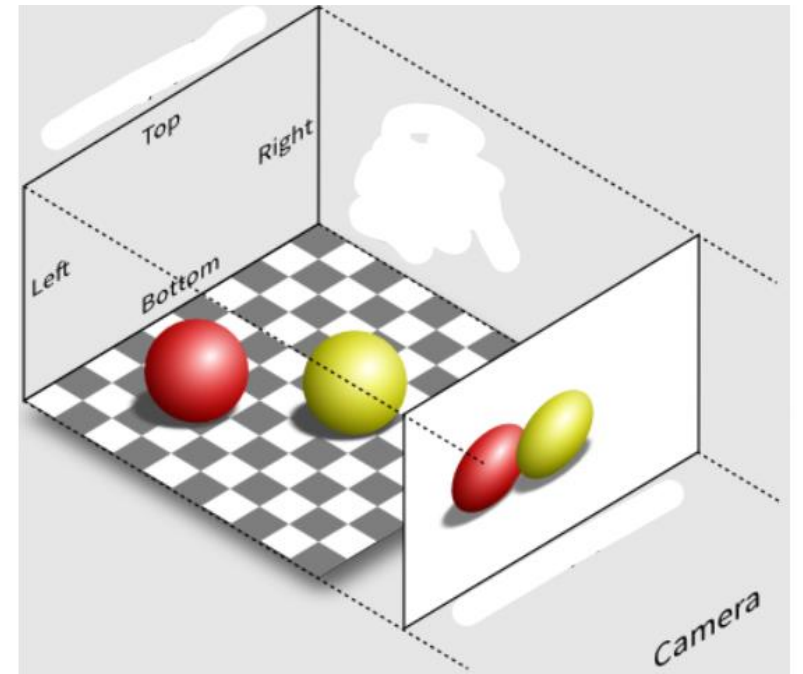
$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

- **Weak Perspective Camera Model (Scaled Orthographic)**

- If the average depth of the scene, \bar{Z} , is much larger than the relative distance

$$x = f \frac{X}{\bar{Z}} \quad y = f \frac{Y}{\bar{Z}}$$

$$\begin{bmatrix} x \\ y \end{bmatrix} = s \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}, s = \frac{f}{\bar{Z}}$$



Computer Vision

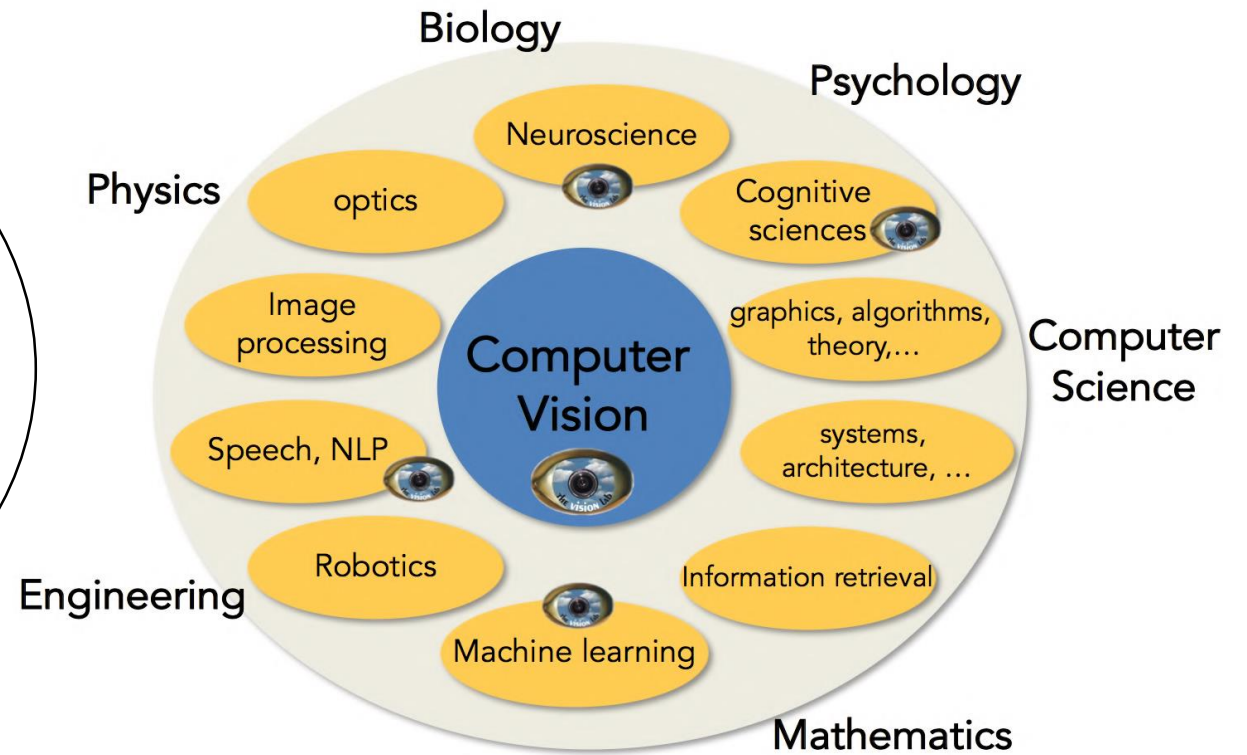
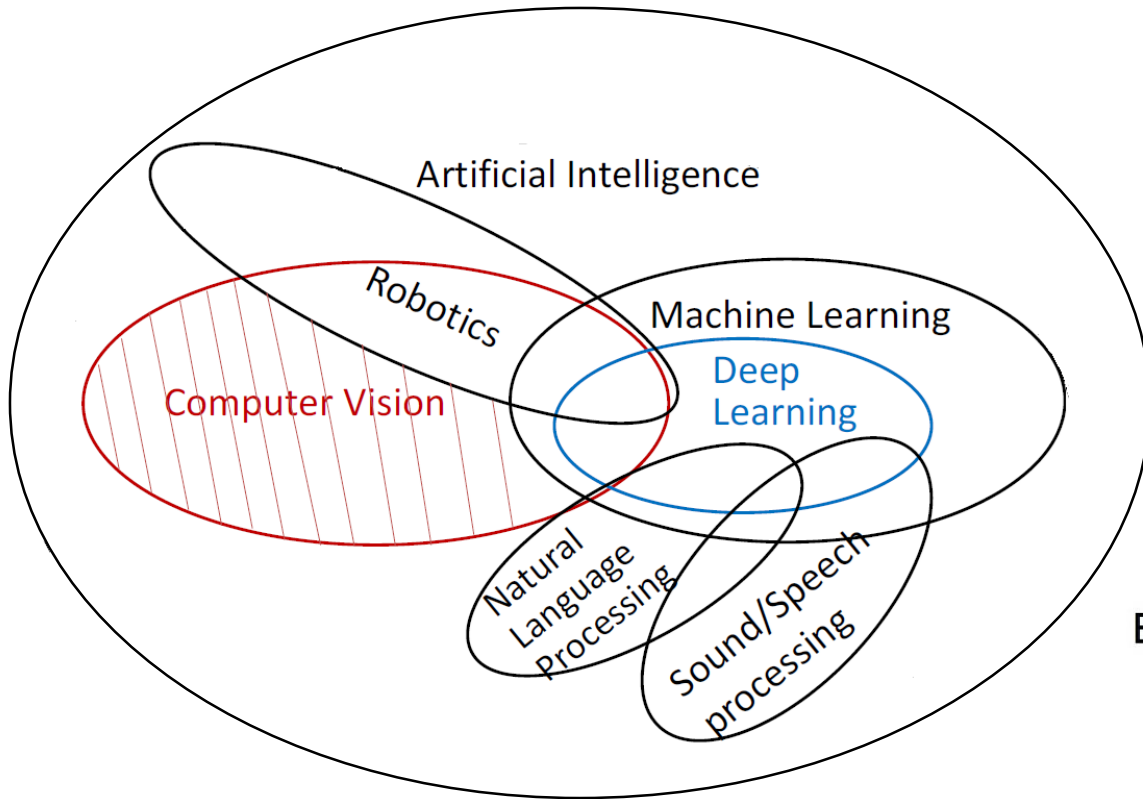
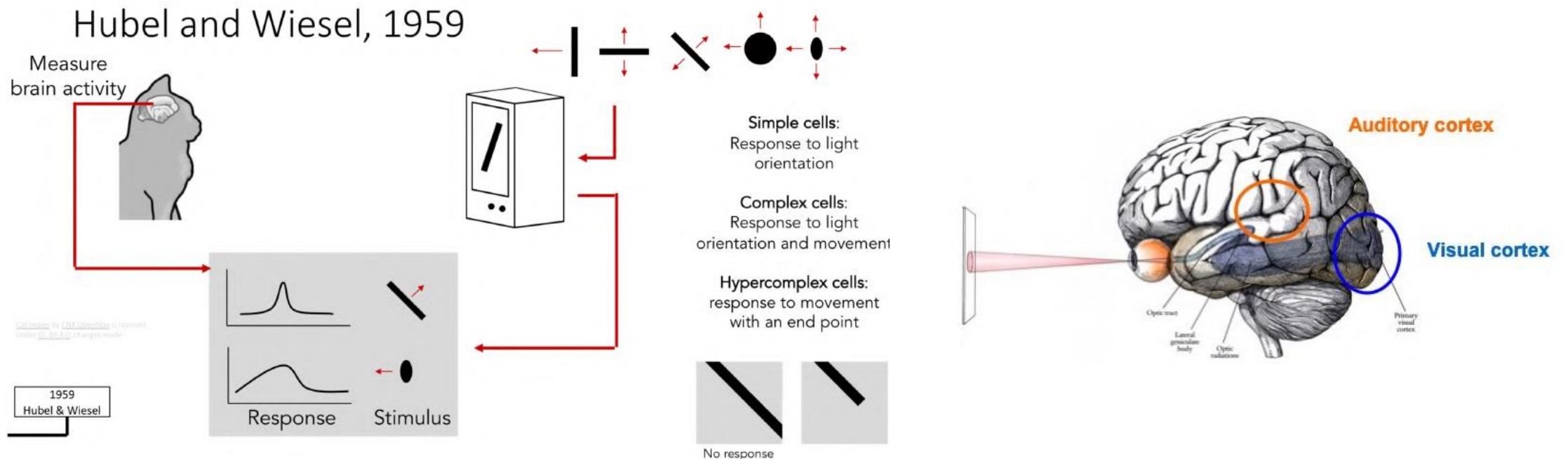


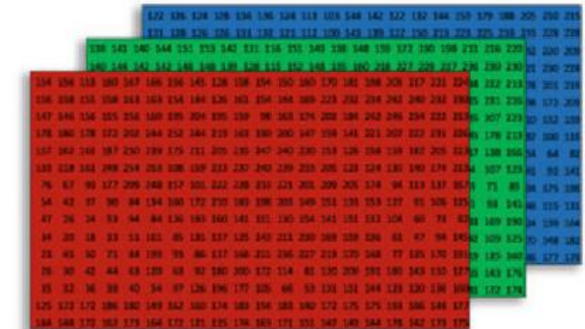
Image Formation In Brain

- Hubel and Wiesel received the Nobel Prize in 1981 for their discoveries concerning the visual system.
- Their findings helped identify how early visual processing occurs through hierarchical cell types that respond to progressively complex visual stimuli.



Preliminaries for the Lecture

- Python programming
 - Numpy, matplotlib, opencv
 - Pytorch (For some homeworks)
- Linear Algebra
 - Matrices, SVD, Eigenvalue decomposition etc.
- Probability Theory
 - Probability for Machine Learning



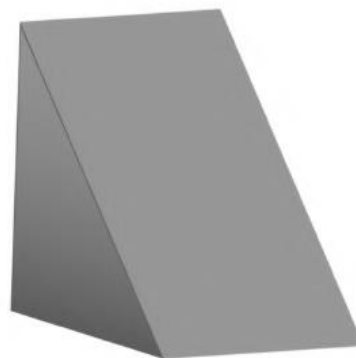
RGB Channels

Ng, D., & Feng, M. (2020). Medical Image Recognition: An Explanation and Hands-On Example of Convolutional Networks. *Leveraging Data Science for Global Health*, 263-284.

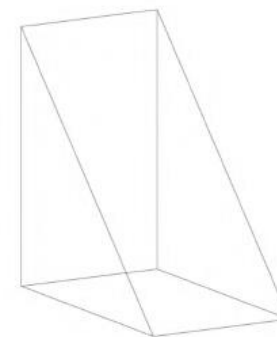
A bit of history...*

- Block World
 - The first PhD thesis on CV

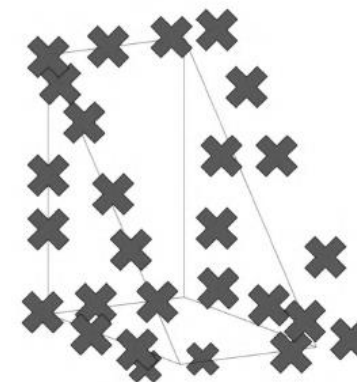
Larry Roberts, 1963



(a) Original picture

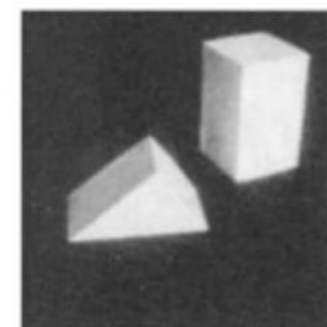
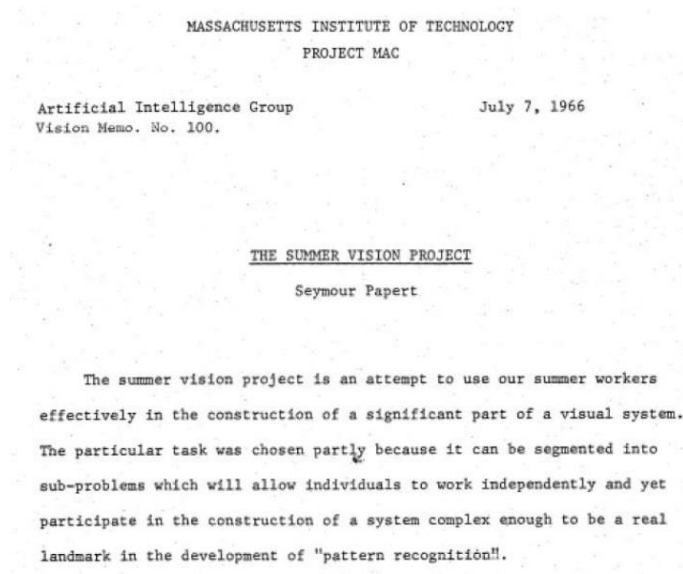


(b) Differentiated picture

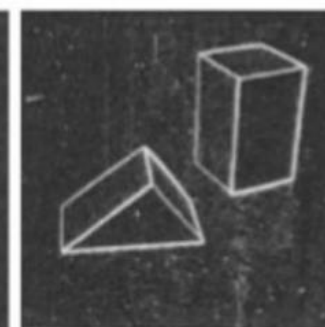


(c) Feature points selected

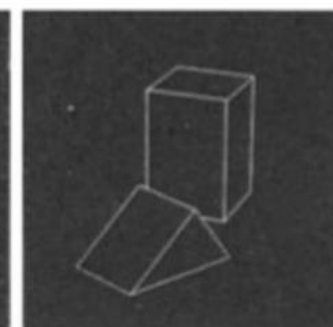
- The Summer Vision Project in MIT (1966)



Input image



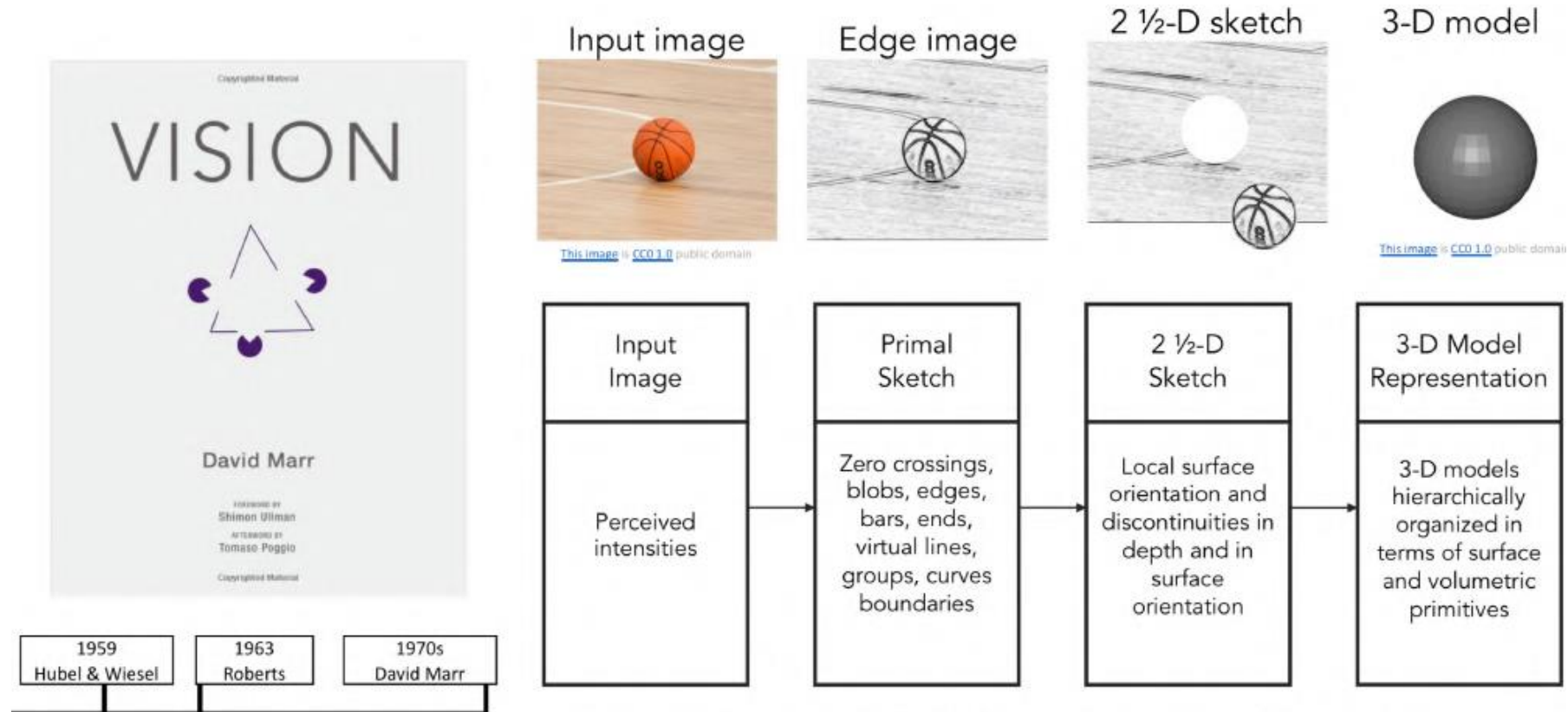
2x2 gradient operator



computed 3D model
rendered from new viewpoint

A bit of history...

- To obtain a complete 3D representation from a 2D image, multiple steps must be followed
 - inspired from evidence in neuroscience

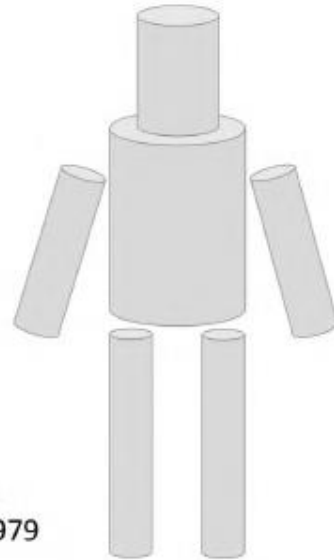


Stages of Visual Representation, David Marr, 1970s

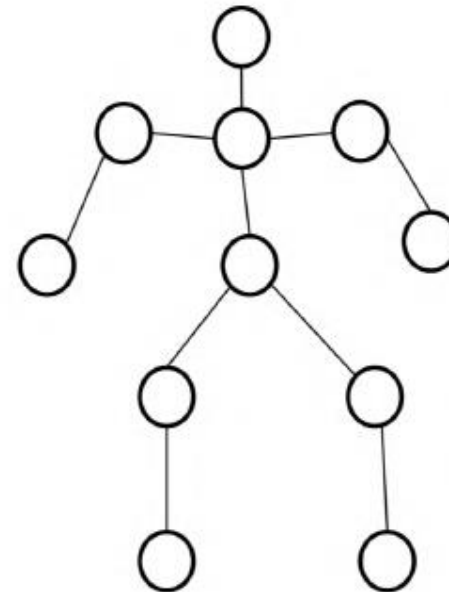
A bit of history...

- Every geometric object consist of simple geometric primitives.

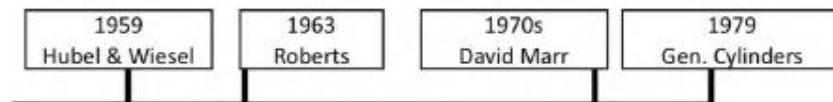
Recognition via Parts (1970s)



Generalized Cylinders,
Brooks and Binford, 1979

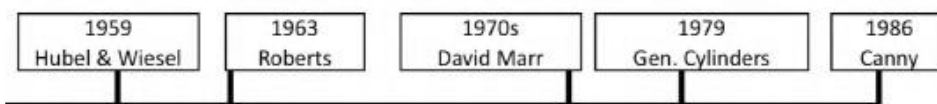


Pictorial Structures,
Fischler and Elshlager, 1973



A bit of history...

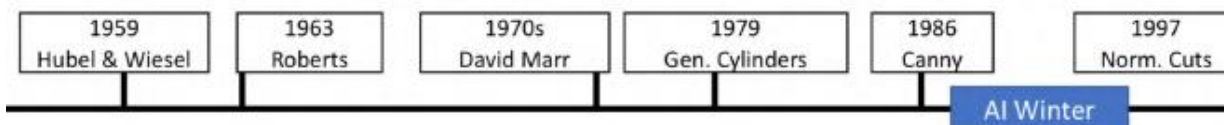
Recognition via Edge Detection (1980s)



John Canny, 1986
David Lowe, 1987

A bit of history...

Recognition via Grouping (1990s)



Normalized Cuts, Shi and Malik, 1997

[Left image is CC-BY 3.0](#) [Middle image is public domain](#) [Right image is CC-BY 3.0; changes made](#)

A bit of history...

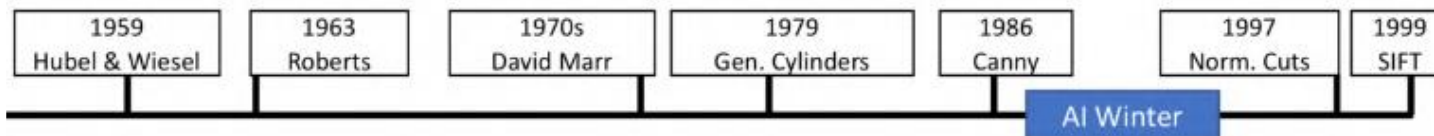
Recognition via Matching (2000s)



[Image](#) is public domain



[Image](#) is public domain



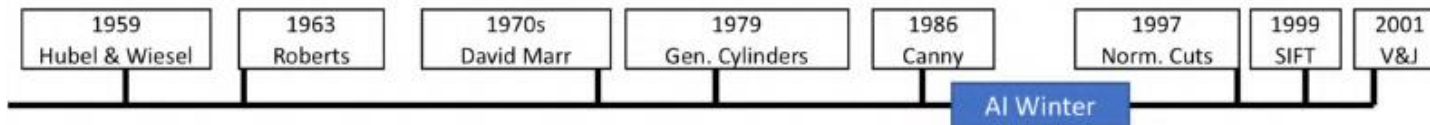
SIFT, David
Lowe, 1999

A bit of history...

Face Detection

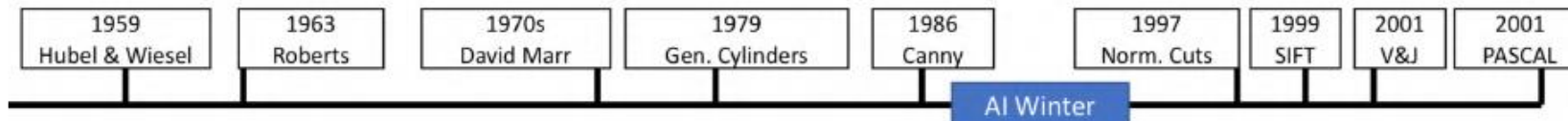
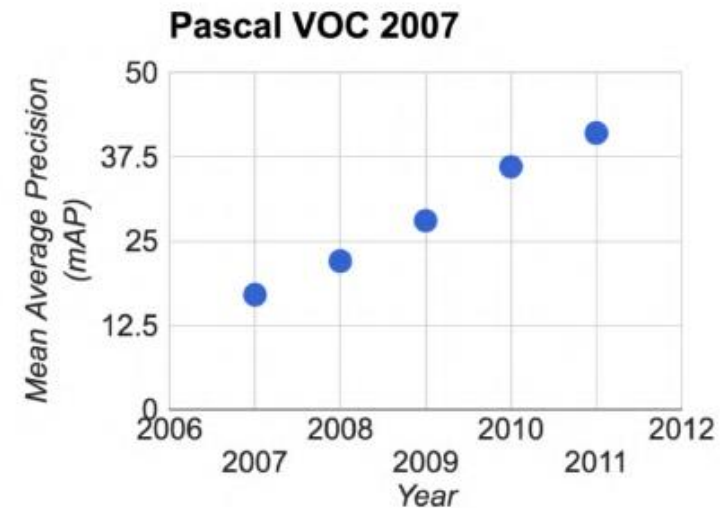
Viola and Jones, 2001

One of the first successful applications of machine learning to vision

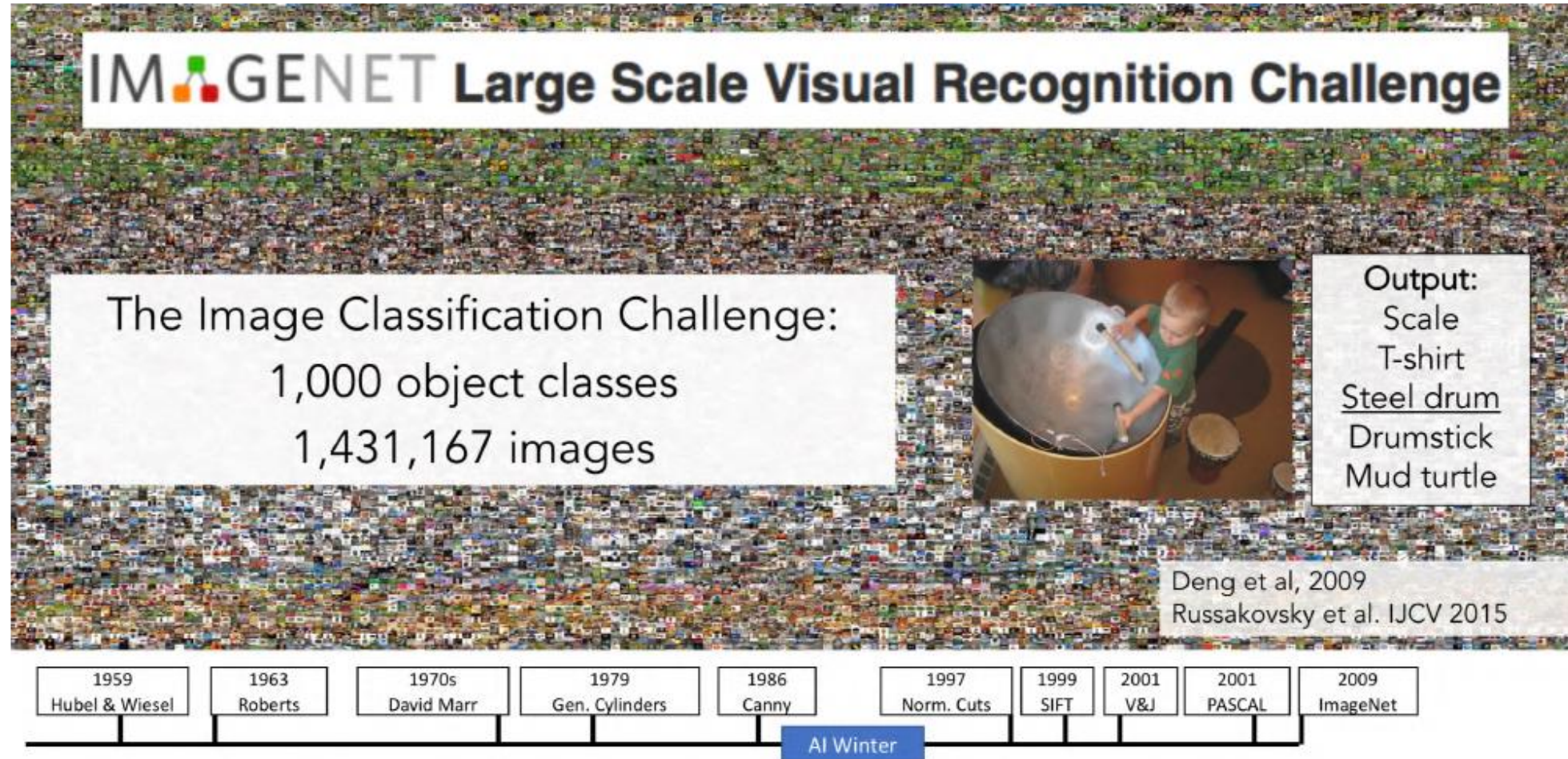


A bit of history...

PASCAL Visual Object Challenge



A bit of history...



Machine Learning Objectives and CV

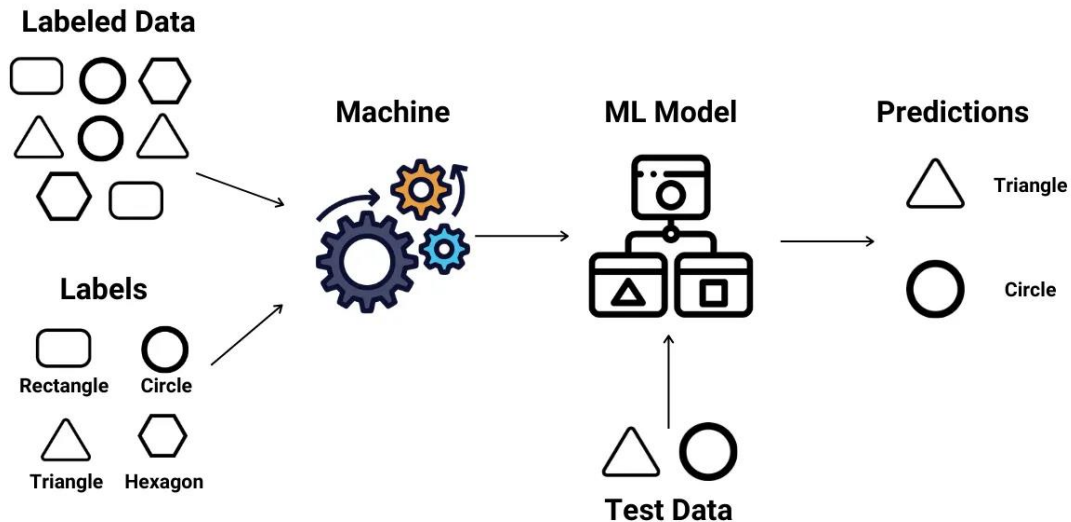
- Supervised Learning
 - Input: Training data + Example training outputs
- Unsupervised Learning
 - Input: Training data (independent of outputs)
- Semi-Supervised Learning
 - Input: Training data + Some example training outputs
- Reinforcement Learning
 - Input: Action processes with reward/punishment outcomes

Supervised Learning

Classification:

Determining the class for given examples

Supervised Learning



Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon



Detecting visual design principles in art and architecture through deep convolutional neural networks

Gözdenur Demir^a, Aslı Çekmiş^{a,*}, Vahit Buğra Yeşilkaynak^b, Gozde Unal^b

^a Istanbul Technical University, Faculty of Architecture, Department of Architecture, Istanbul 34437, Turkey

^b Istanbul Technical University, Faculty of Computer and Informatics Engineering, Department of AI & Data Engineering, Istanbul 34469, Turkey

EMPHASIS
Color



BALANCE
Symmetric



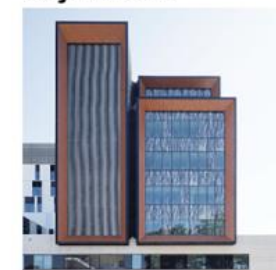
RHYTHM
Regular



Isolation



Asymmetric



Progressive



Shape



Crystallographic



Flowing



Supervised Learning

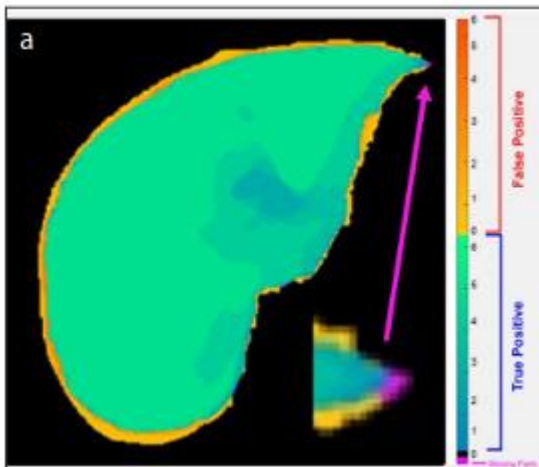
Segmentation:
Pixelwise classification

DIR

Diagn Interv Radiol 2020; 26:11–21
© Turkish Society of Radiology 2020

ABDOMINAL IMAGING
ORIGINAL ARTICLE

Comparison of semi-automatic and deep learning-based automatic methods for liver segmentation in living liver transplant donors

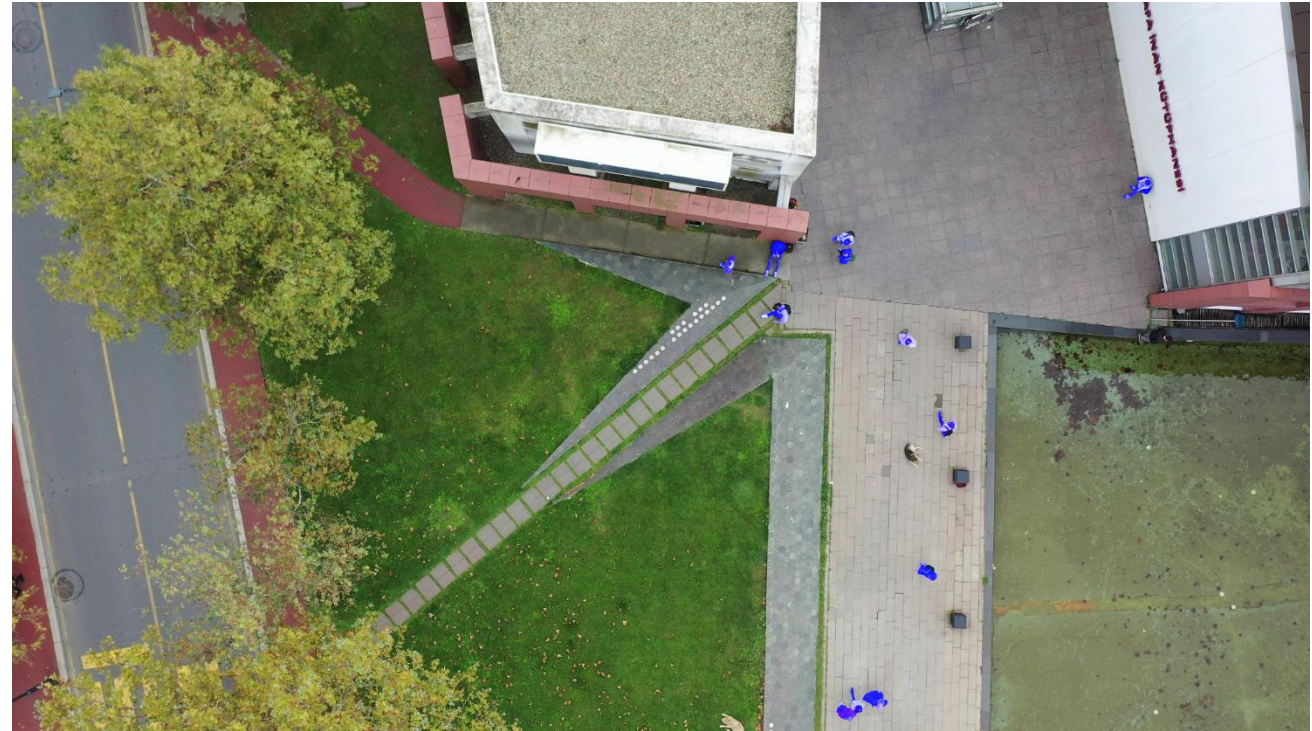


P2-23

18th International Conference on Machine Vision Applications (MVA)
Hamamatsu, Japan, July 23-25, 2023.





TinyPedSeg: A Tiny Pedestrian Segmentation Benchmark for Top-Down Drone Images

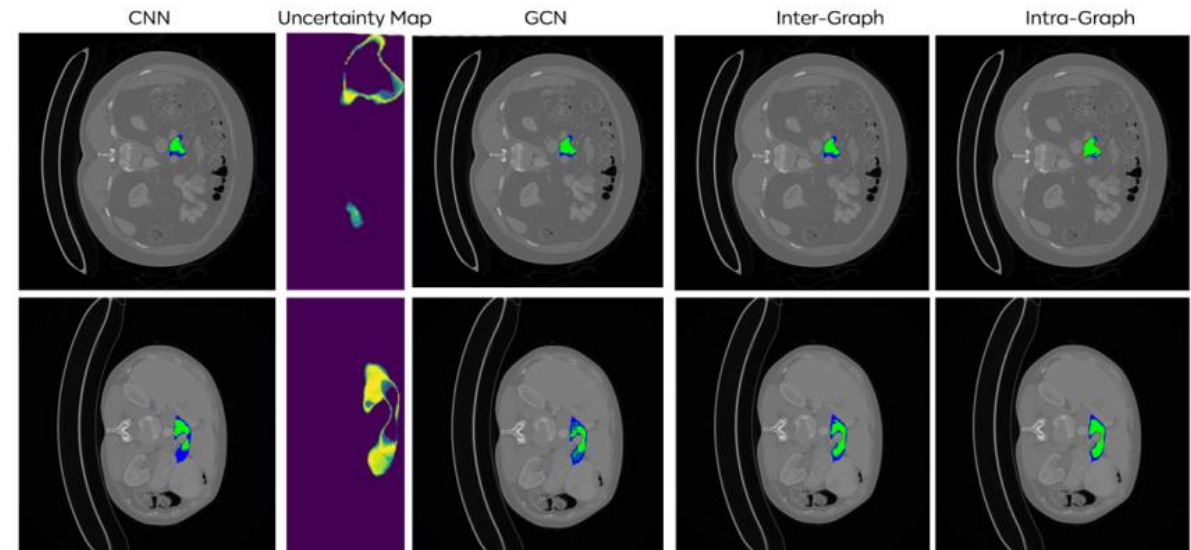
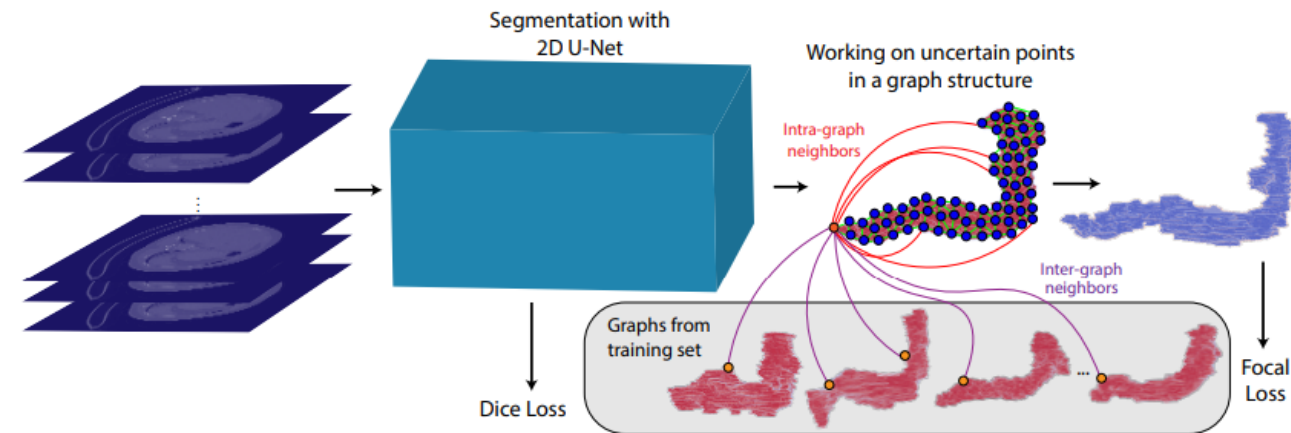
Yusuf H. Sahin, Elvin Abidinli, M. Arda Aydın, Gozde Unal
Istanbul Technical University, Faculty of Computer and Informatics
{sahinyu, abdinli18, aydinmu19, gozde.unal}@itu.edu.tr



Semi-Supervised Learning

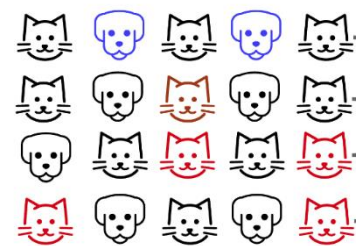
Uncertainty-Based Dynamic Graph Neighborhoods For Medical Segmentation

Ufuk Demir^{*1}, Atahan Ozer^{*1}, Yusuf H. Sahin¹, and Gozde Unal²



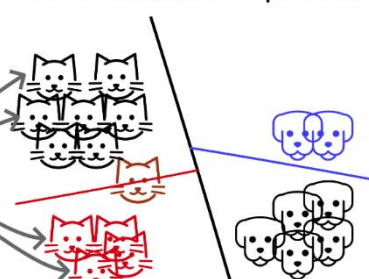
Unsupervised Learning

Default Representation



Deep Neural Network

"Good" Semantic Representation



Cat by Martin LEBRETON, Dog by Serhii Smirnov from the Noun Project

Rethinking CNN-Based Pansharpening: Guided Colorization of Panchromatic Images via GANs

Furkan Ozcelik, Ugur Alganci, Elif Sertel, and Gozde Unal



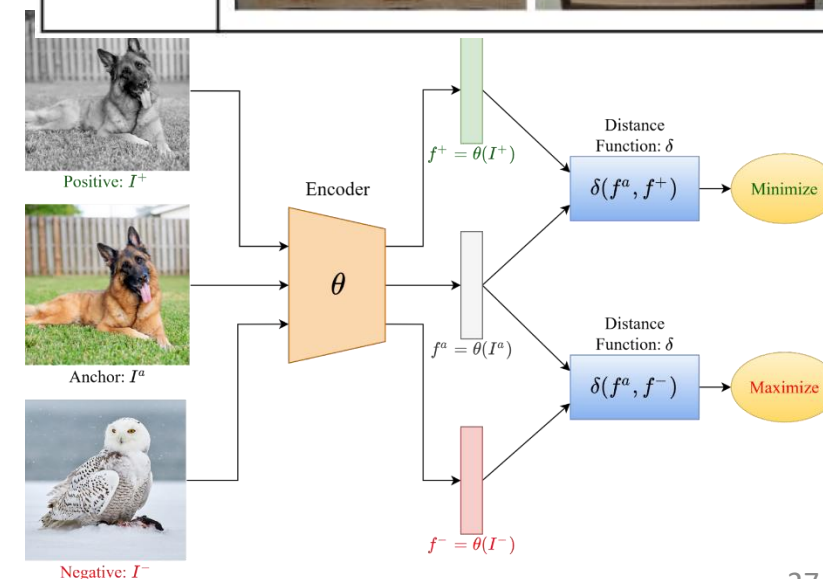
Textile Pattern Generation Using Diffusion Models

Halil Faruk Karagoz^{1,*}, Gulcin Baykal¹, Irem Arikan Eksi², Gozde Unal³

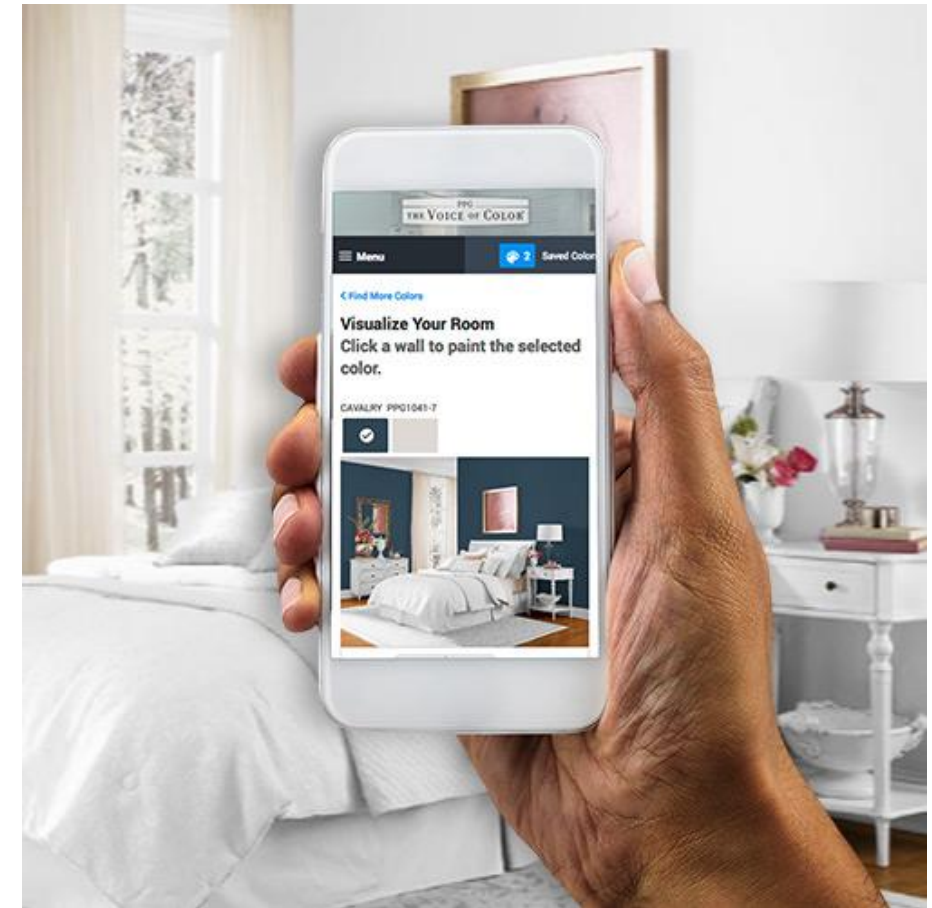
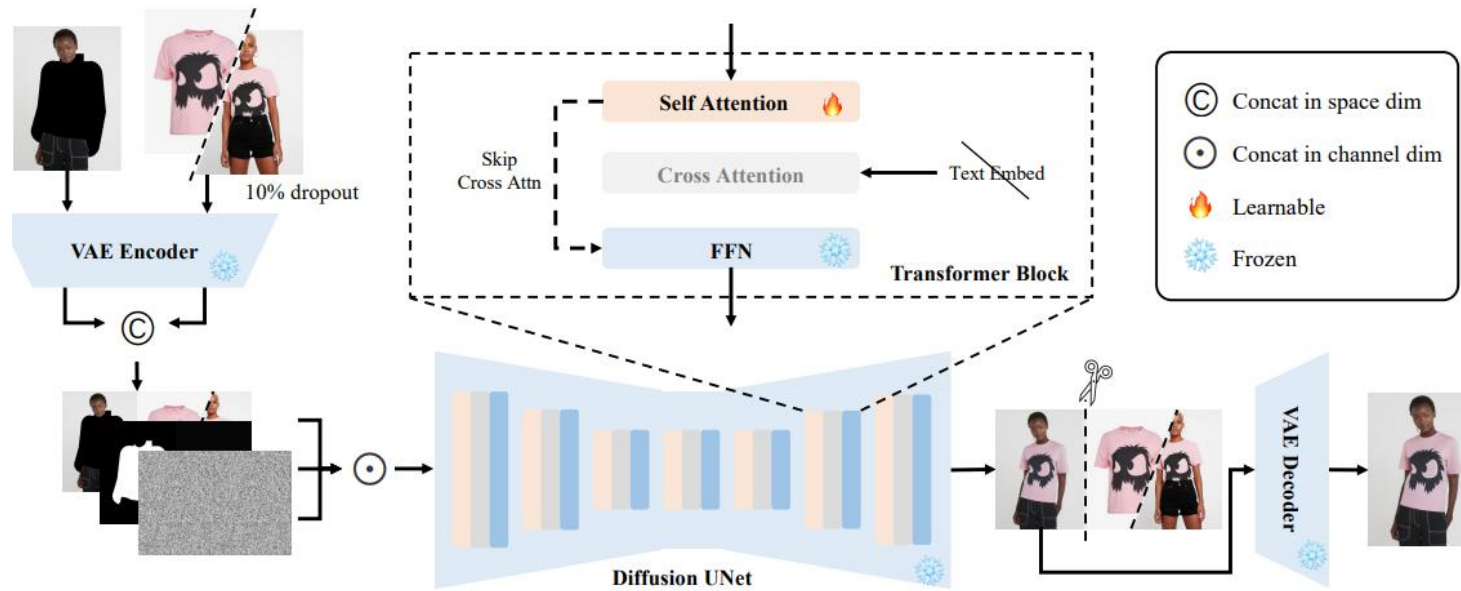
Turkish Patterns



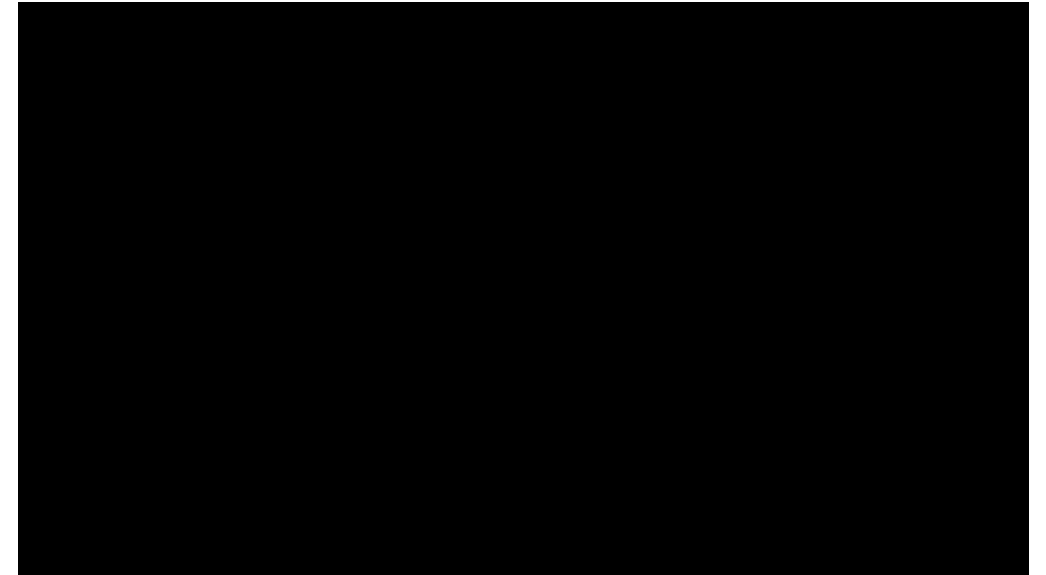
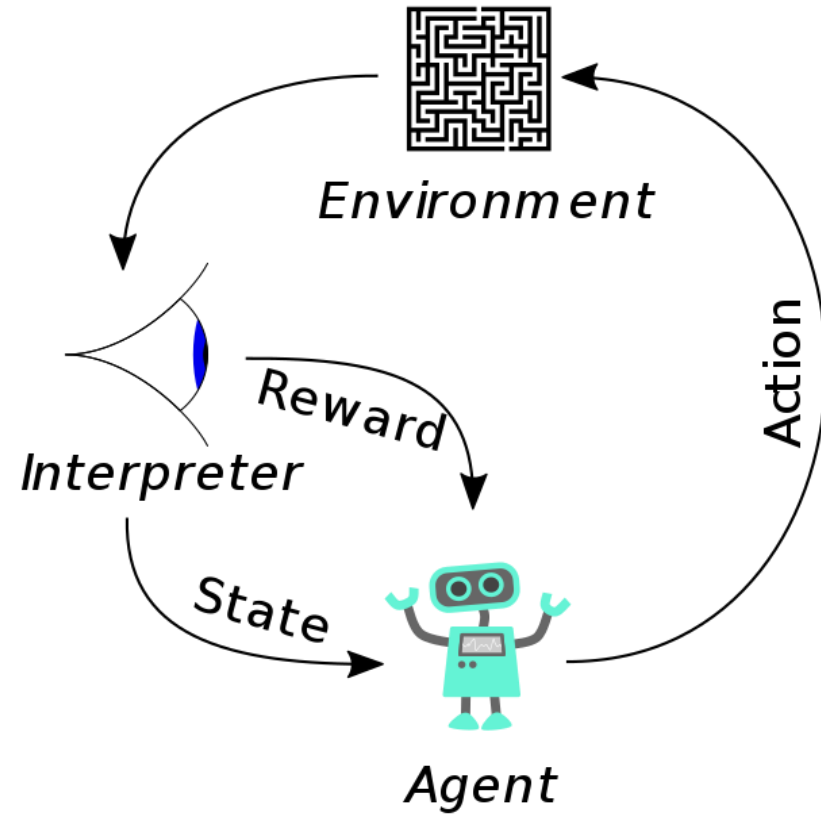
Ottoman Embroidery Patterns



Unsupervised Learning



Reinforcement Learning



<https://www.youtube.com/watch?v=0xo1Ldx3L5Q>