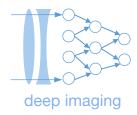


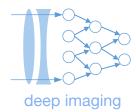
# Lecture 1: Machine Learning and Imaging in a Nutshell

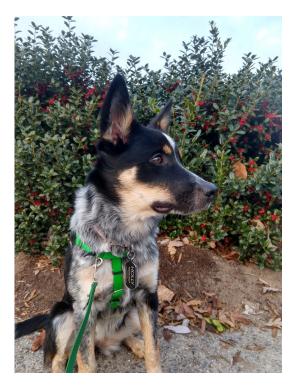
Machine Learning and Imaging BME 548L Roarke Horstmeyer

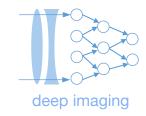


# Announcements

- No labs this week
  - First lab will be M/W 1/22 (1/24) at 4:30pm
- Please complete pre-class survey:
  - <u>https://forms.gle/moFWMQXY3cWRUDWq5</u>
- Please complete Lab #1 pre-exercise before lab:
  - https://canvas.duke.edu/courses/26135/assignments/79632



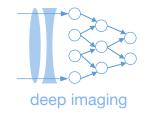




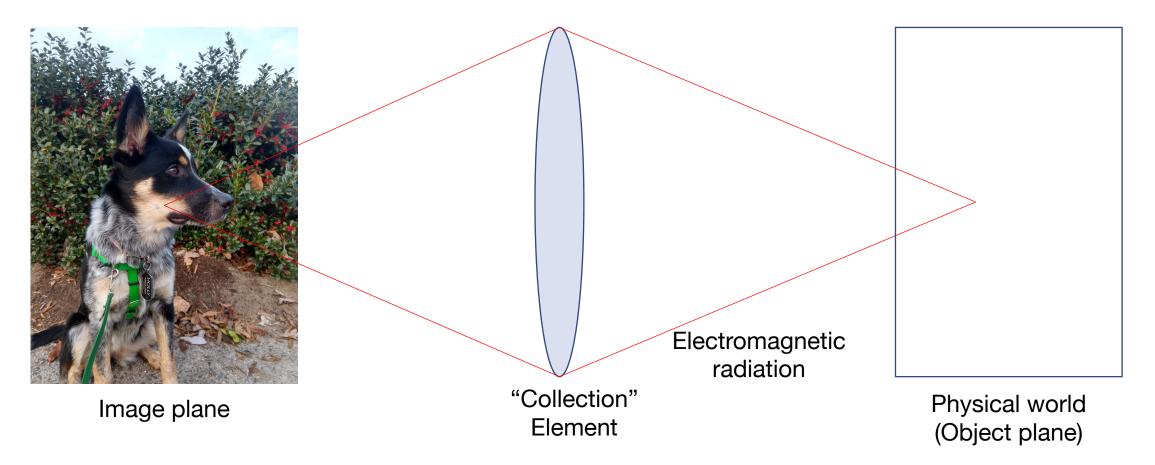


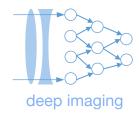
1. "Qualitative" Interpretation

- A re-creation of a visual scene
- A visible impression
- A mental representation or idea

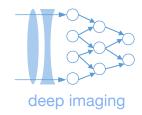


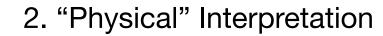
#### 2. "Physical" Interpretation

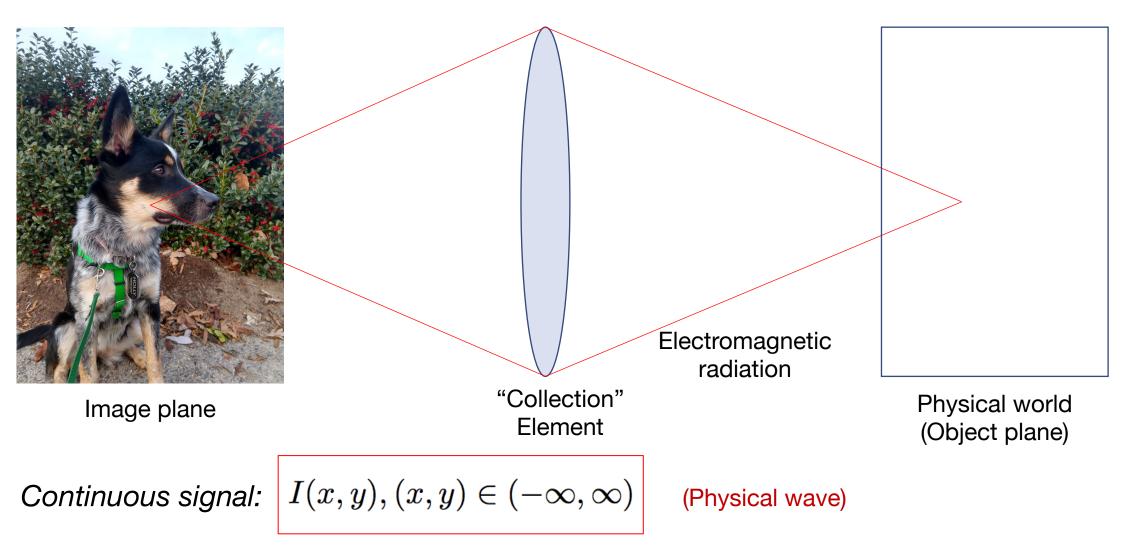


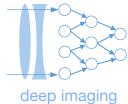


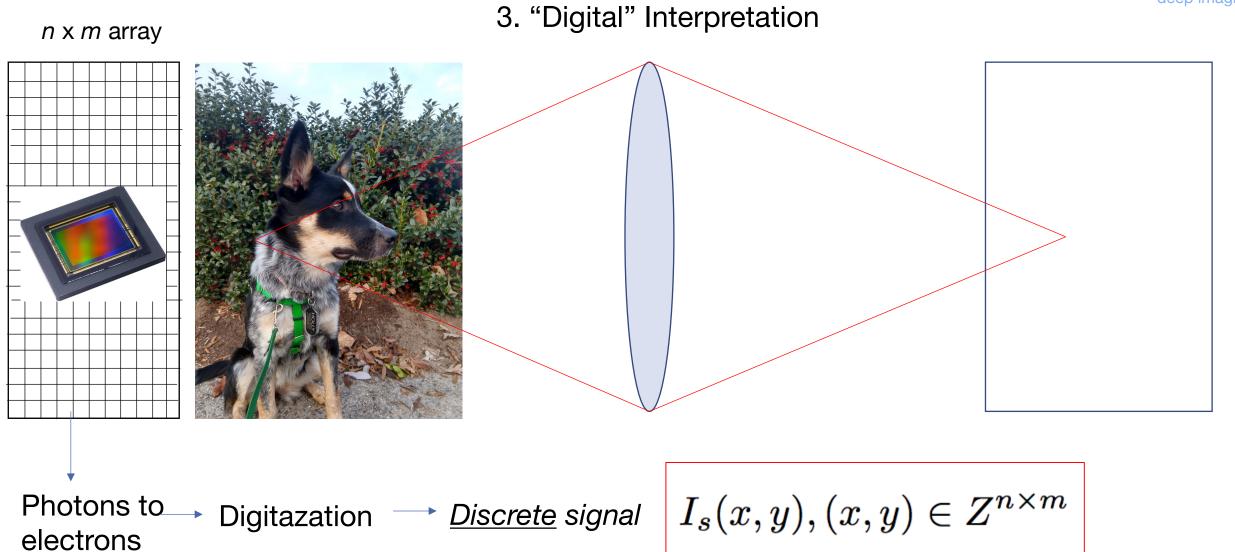




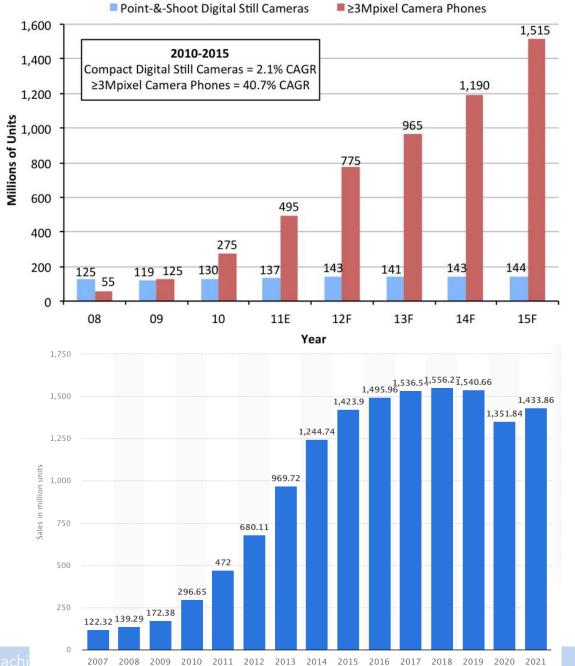


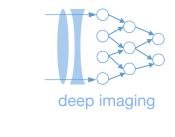


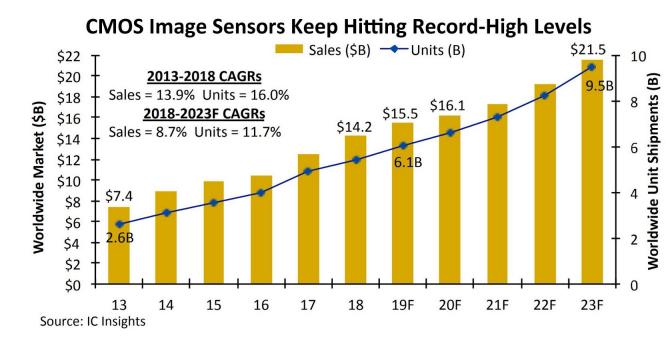




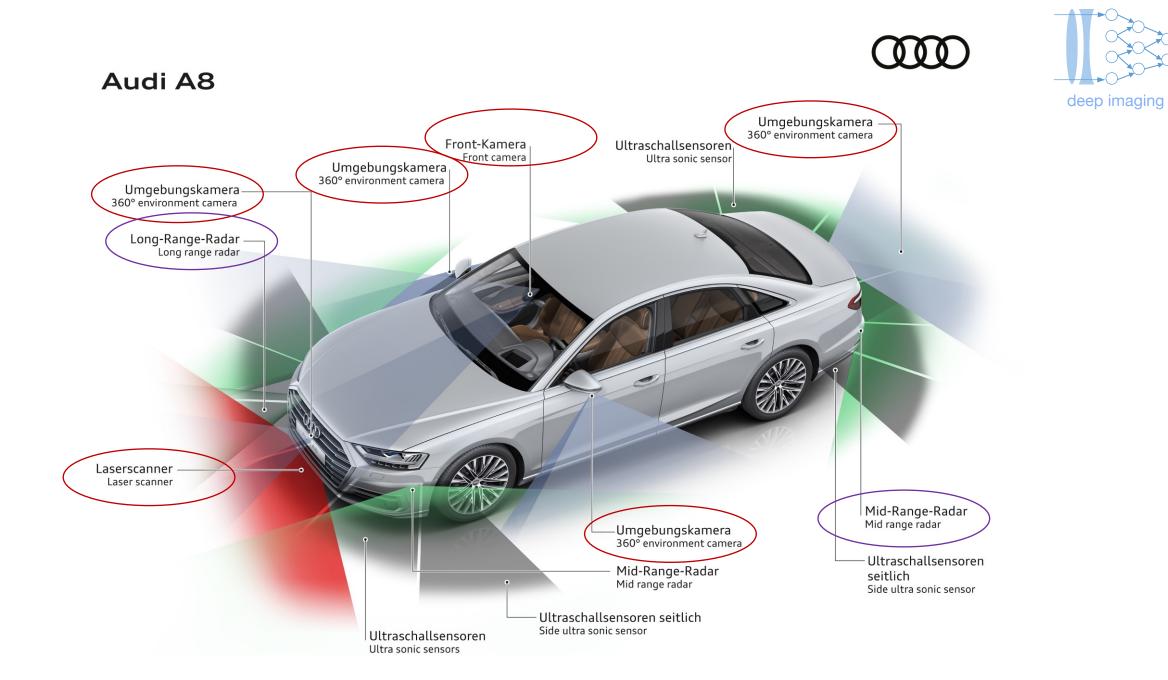
#### **Compact DSCs Vs. "Good Enough" Camera Phones**



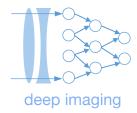




A hypothesis: there are now more discretized images than continuous images in the world!

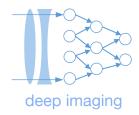


#### Da Vinci Xi Surgical Robot





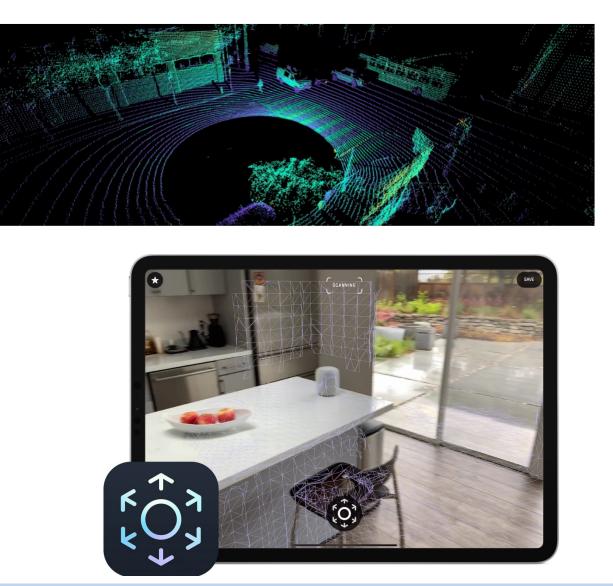




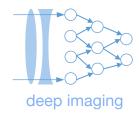
#### New digital image sensor arrays can now also detect depth...

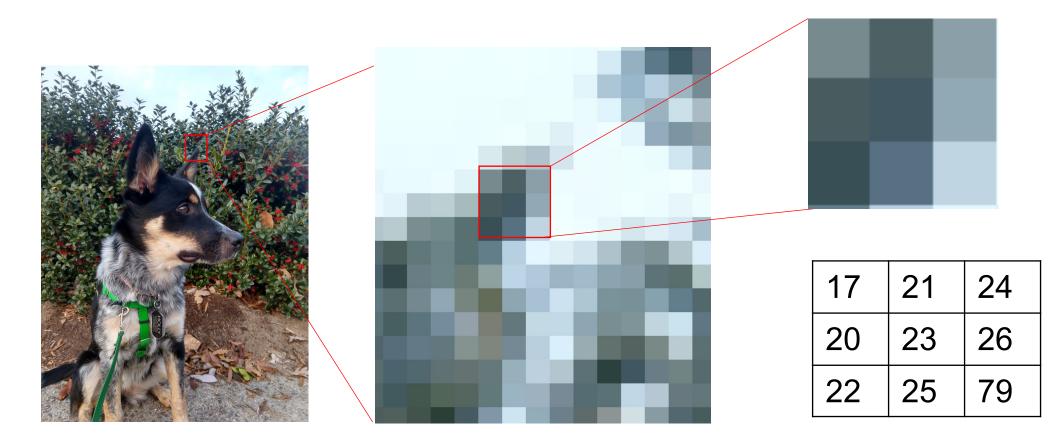


SPAD array sensors – are here now...

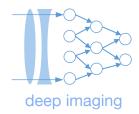


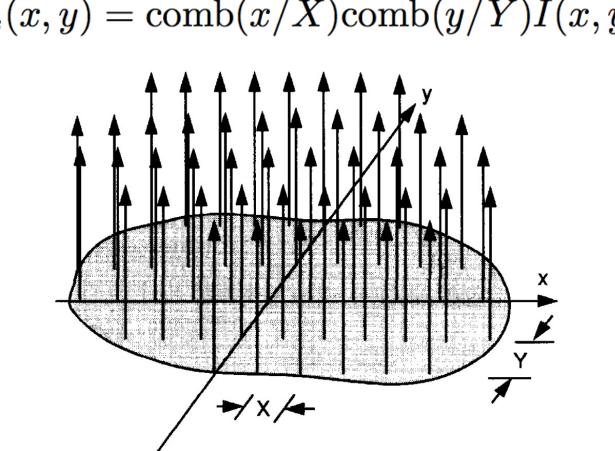
### Images as matrices and vectors





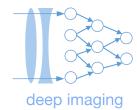
**Continuous versus discrete representation** 



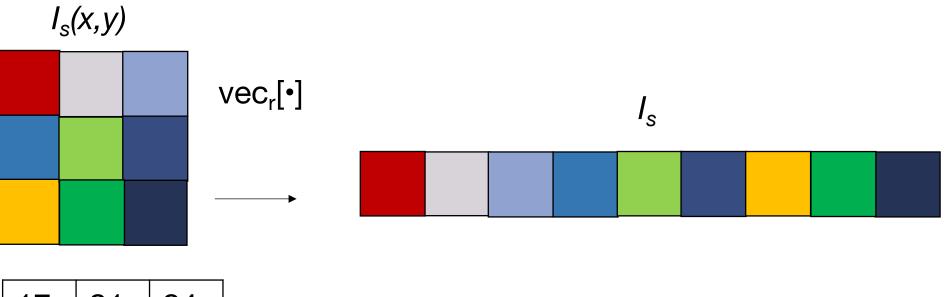


 $I_s(x, y) = \operatorname{comb}(x/X)\operatorname{comb}(y/Y)I(x, y)$ 

From J. Goodman, Introduction to Fourier Optics



# Images unrolled into vectors



17	21	24
20	23	26
22	25	29

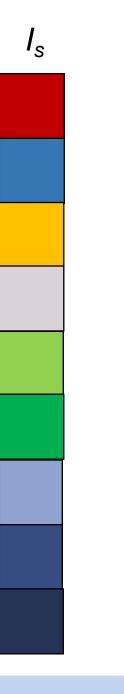
17	21	24	20	23	26	22	25	29
----	----	----	----	----	----	----	----	----

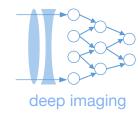
# Images unrolled into vectors

Ι<sub>s</sub>(x,y)

17	21	24
20	23	26
22	25	29

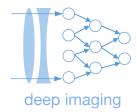






Machine Learning and Imaging – Roarke Horstmeyer (2024

#### **Example manipulations of images**



1. Image addition/subtraction

 $I_o = I_1 + I_2$ 

2. Image multiplication

$$I_o = I_1 \odot I_2$$

3. Image transformation: matrix-vector multiplication

 $I_o = \mathbf{W}I_1$ 

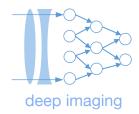
4. Non-linear image operations

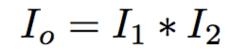
$$I_o = \left| I_1 \right|^2$$

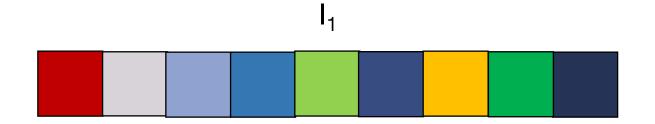
5. Convolution

$$I_o = I_1 * I_2$$

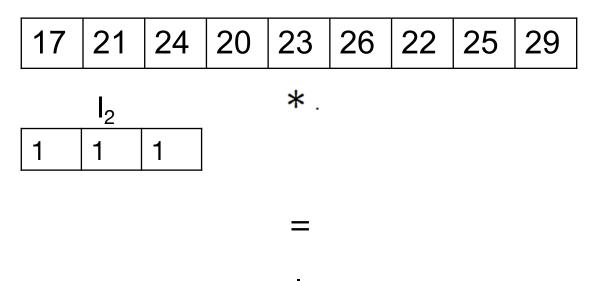
Machine Learning and Imaging – Roarke Horstmeyer (2024)

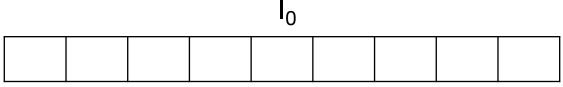


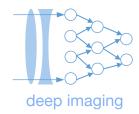




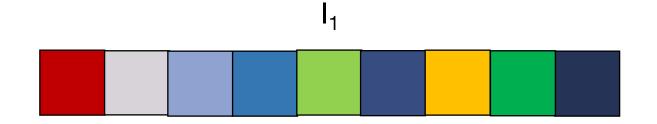
$$I_{o}[n] = \sum_{m=-M}^{M} I_{1}[n-m]I_{2}[m]$$



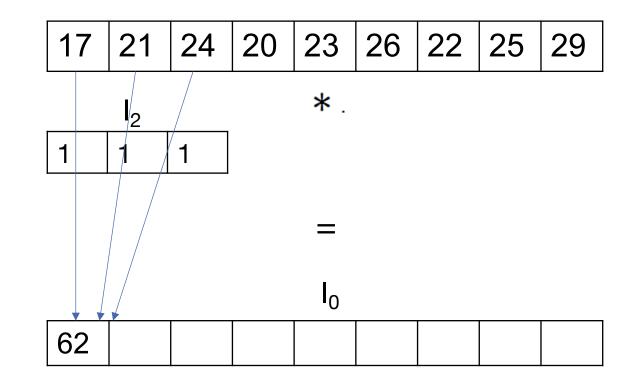


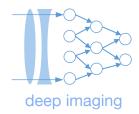


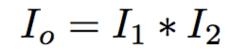
$$I_o = I_1 * I_2$$

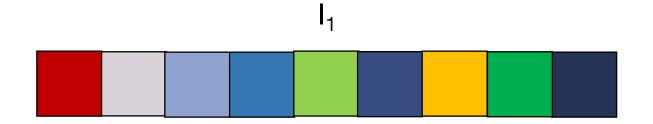


$$I_o[n] = \sum_{m=-M}^{M} I_1[n-m]I_2[m]$$

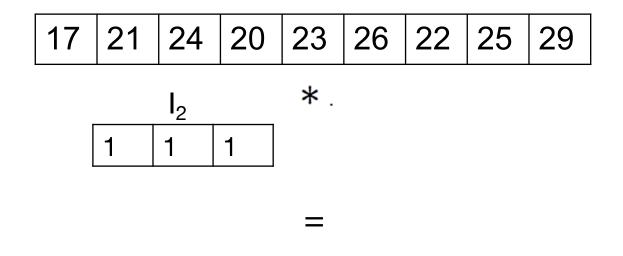


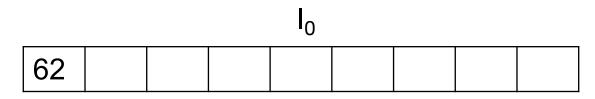


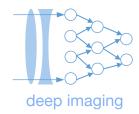




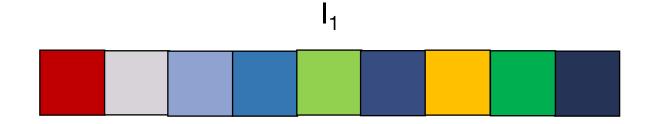
$$I_{o}[n] = \sum_{m=-M}^{M} I_{1}[n-m]I_{2}[m]$$



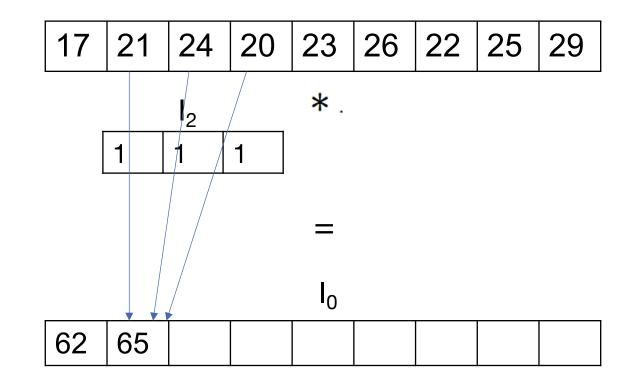


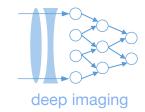


$$I_o = I_1 * I_2$$



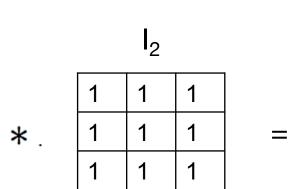
$$I_{o}[n] = \sum_{m=-M}^{M} I_{1}[n-m]I_{2}[m]$$



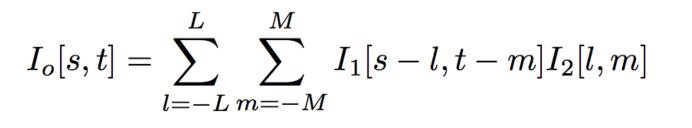


 $I_o[s,t] = \sum_{l=1}^{L} \sum_{m=1}^{M} I_1[s-l,t-m]I_2[l,m]$ l = -L m = -M

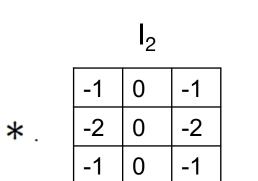




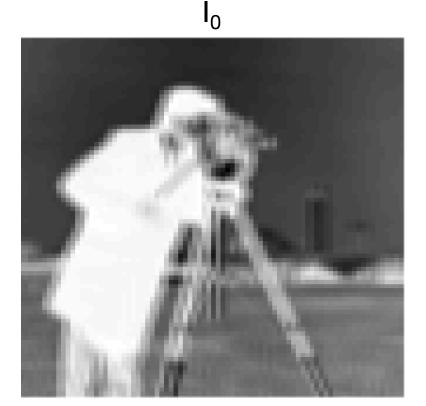


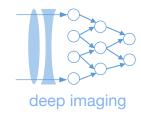




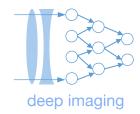


=

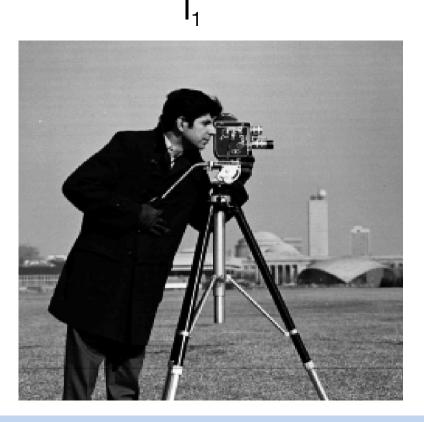




Machine learning: "dynamic" image manipulations



Current goal in machine learning : determine image manipulations to highlight features of interest

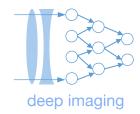


W

	w1	w2	w3	T
*.	w4	w5	w6	=
	w7	w8	w9	

Most useful information possible for computer to use Machine learning: "dynamic" image manipulations

\*



Current goal in machine learning : determine image manipulations to highlight features of interest



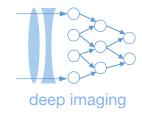
W

w1	w2	w3	
w4	w5	w6	=
w7	w8	w9	

Most useful information possible for computer to use

Determine weights w for particular task: image segmentation, object detection, bw-to-color, etc.

#### **Example tasks for machine learning**

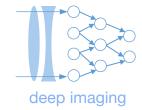




Common ML transformations for detected image:

- A vector of different categories (image is of a man, not a dog)
- A vector of coordinates highlighting features of interest (the man's head is contained in the box of pixels from (x,y,x+a,y+b)
- A segmentation map (the line denoting the boundary of the man is 1, rest is 0)

#### Image formation as a set of discrete equations

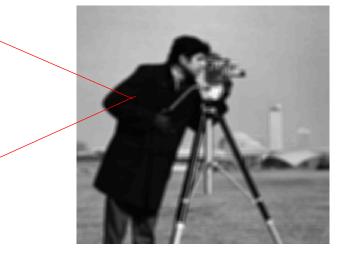


• Can also model the behavior of the imaging system before the radiation hits the image detector

Physical world

 $n \ge m$  image I<sub>1</sub>

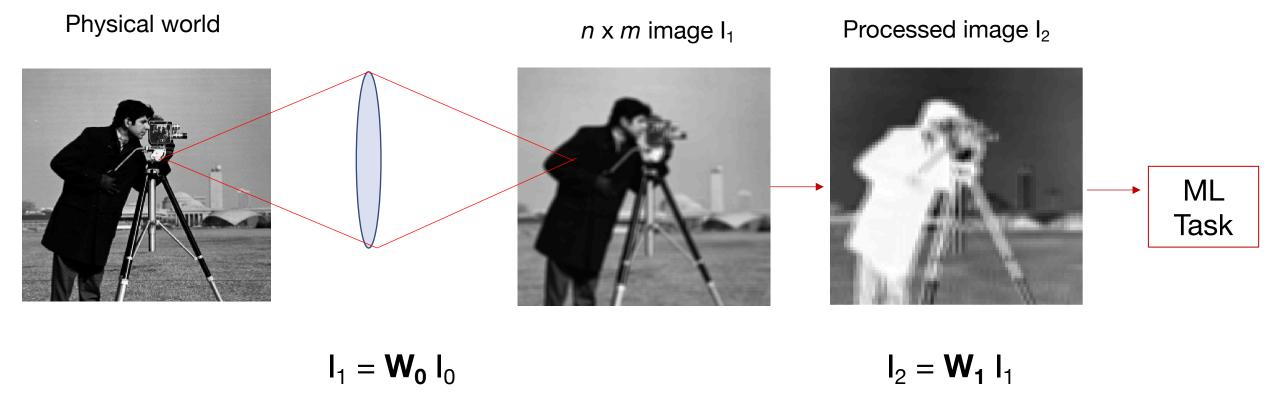


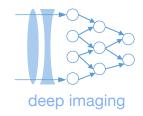


 $\mathbf{I}_1 = \mathbf{W_0} \ \mathbf{I}_0$ 

#### Image formation as a set of discrete equations

• Can also model the behavior of the imaging system before the radiation hits the image detector



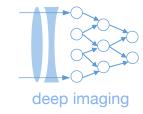


#### Image formation as a set of discrete equations

• Can also model the behavior of the imaging system before the radiation hits the image detector

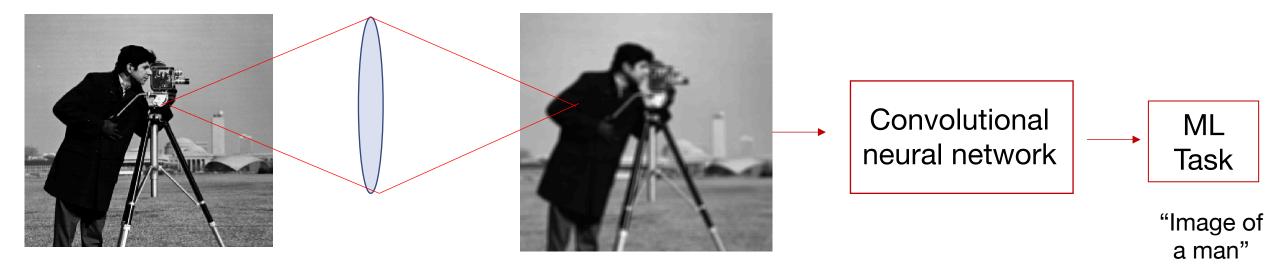
Physical world  $n \ge m$  image  $I_1$  Processed image  $I_2$  The set of the s

 $I_2 = W_1 W_0 I_0$  Linear mapping



# Bringing together physical and digital image representations

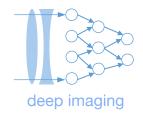
Physical world

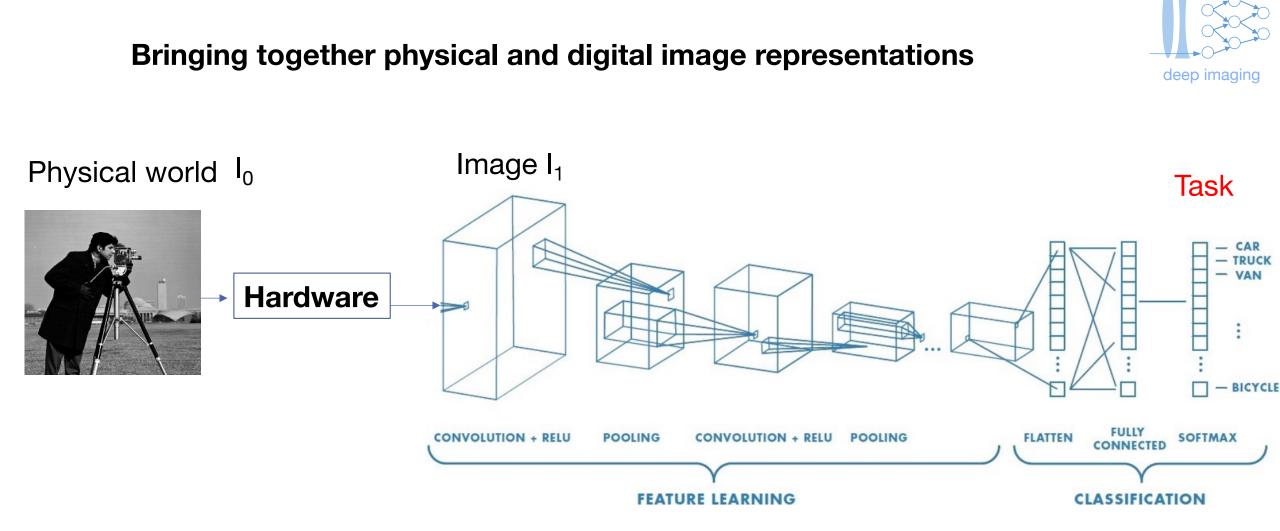


 $n \ge m$  image  $I_1$ 

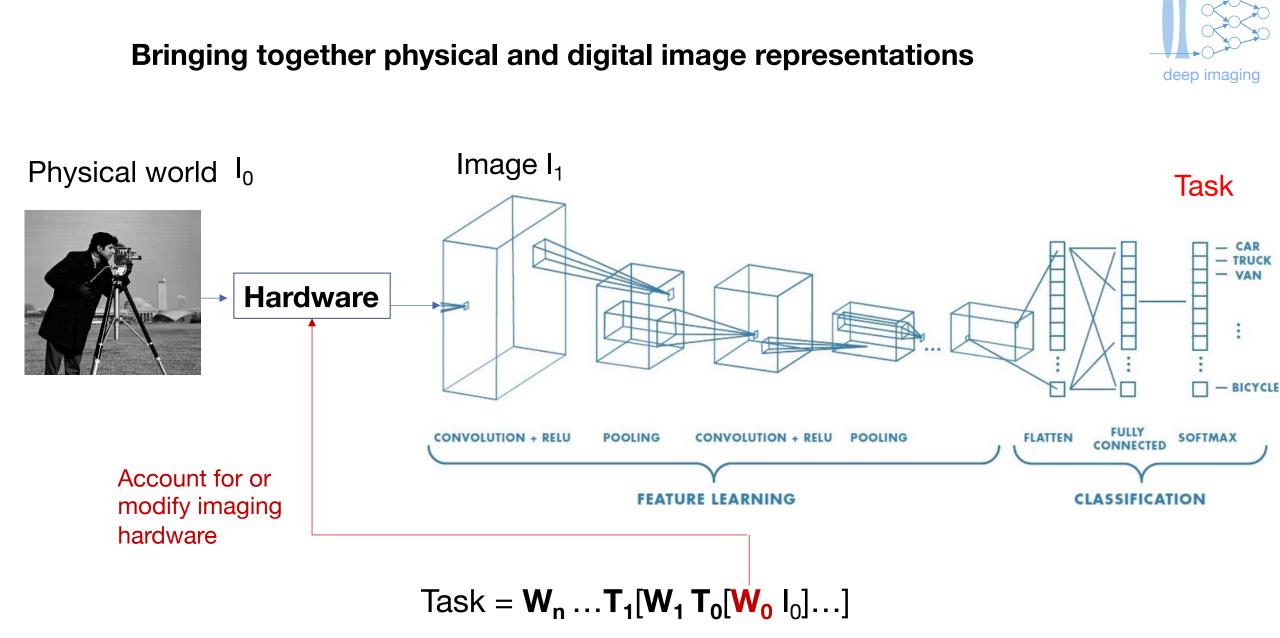
# $Task = \mathbf{W}_{n} \dots \mathbf{T}_{1}[\mathbf{W}_{1} \mathbf{T}_{0}[\mathbf{W}_{0} \mathbf{I}_{0}] \dots] \qquad \text{Nonlinear mapping}$

lachine Learning and Imaging – Roarke Horstmeyer (2024)





 $\mathsf{Task} = \mathbf{W}_{n} \dots \mathbf{T}_{1} [\mathbf{W}_{1} \mathbf{T}_{0} [\mathbf{W}_{0} \mathbf{I}_{0}] \dots]$ 



# Bringing together physical and digital image representations

