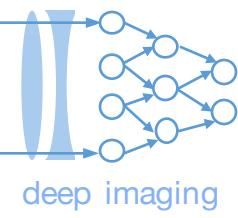


# Lecture 1: Machine Learning and Imaging in a Nutshell

Machine Learning and Imaging

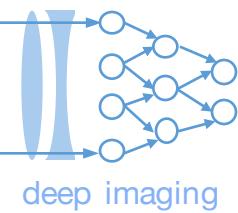
BME 590L

Roarke Horstmeyer



# What is an image?



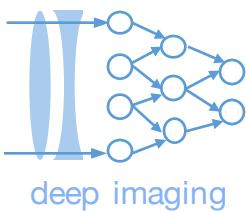


# What is an image?

## 1. “Qualitative” Interpretation



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

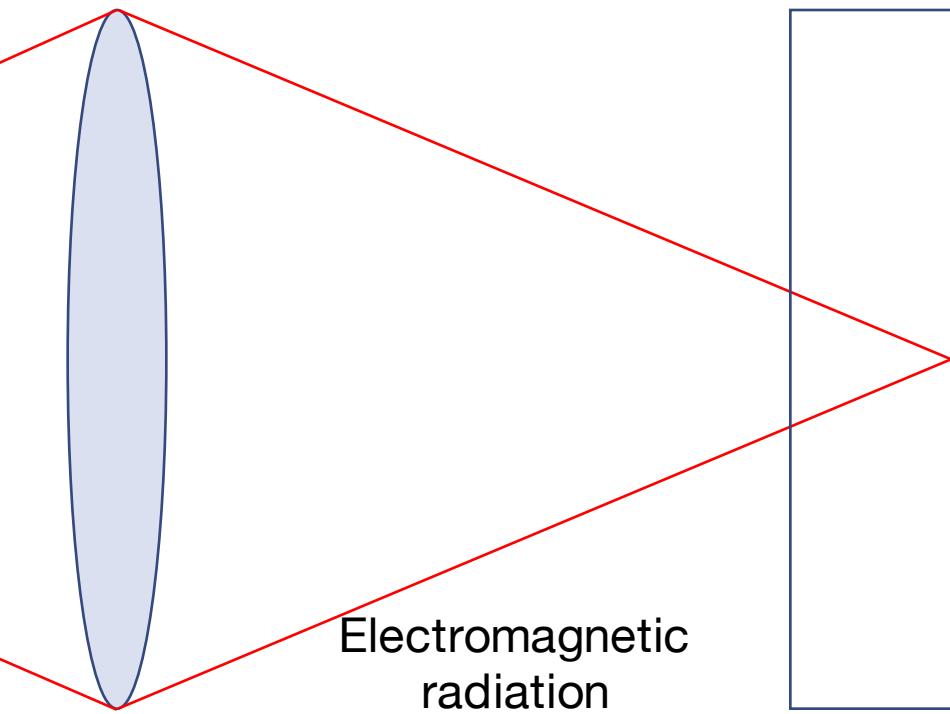


# What is an image?

## 2. “Physical” Interpretation

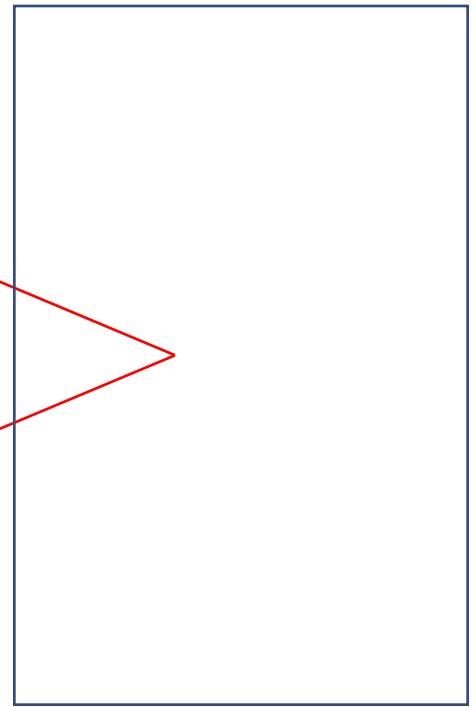


Image plane

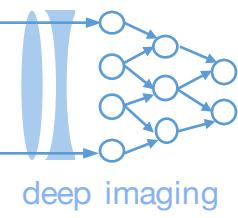


“Collection”  
Element

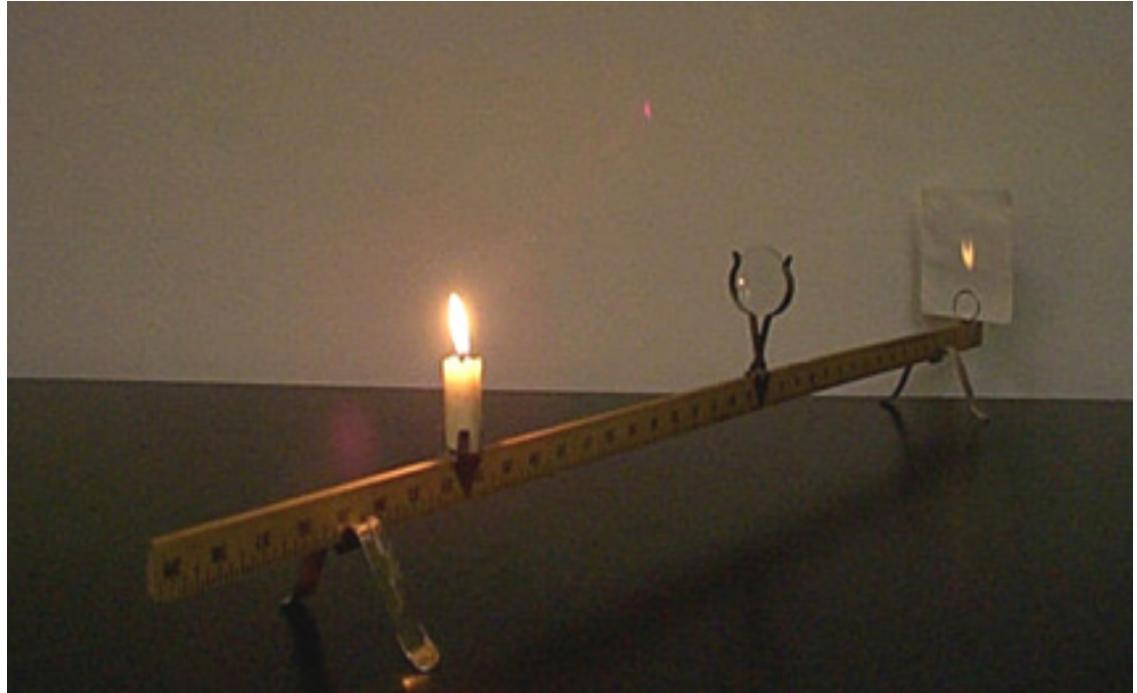
Electromagnetic  
radiation

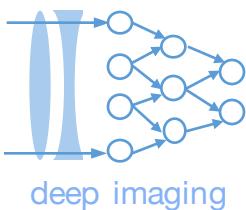


Physical world  
(Object plane)



# What is an image?



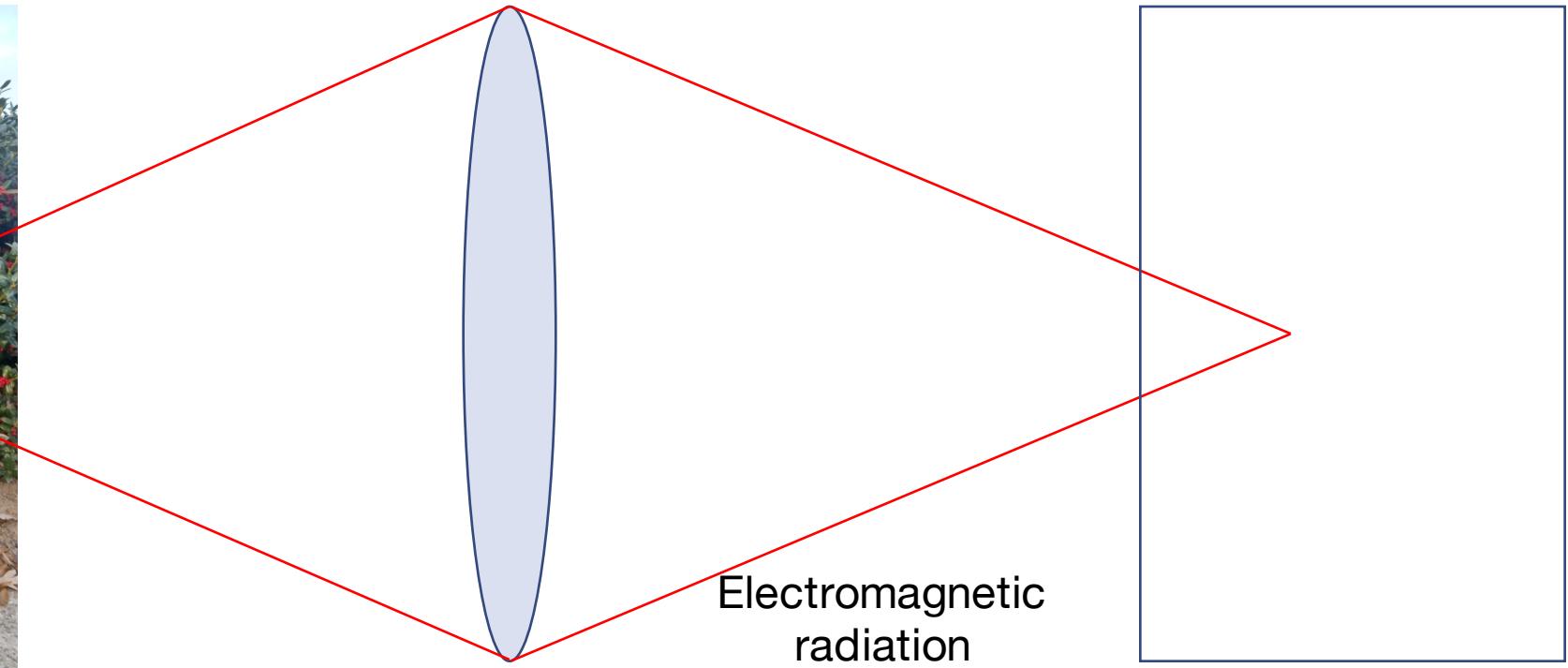


# What is an image?

## 2. “Physical” Interpretation



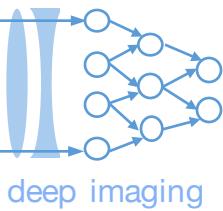
Image plane



*Continuous signal:*

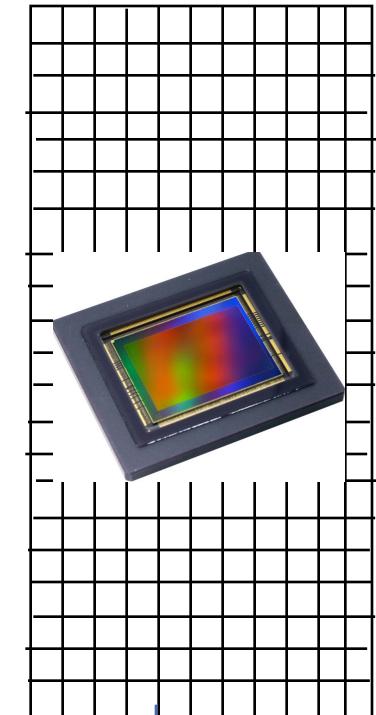
$$I(x, y), (x, y) \in (-\infty, \infty)$$

(Physical wave)

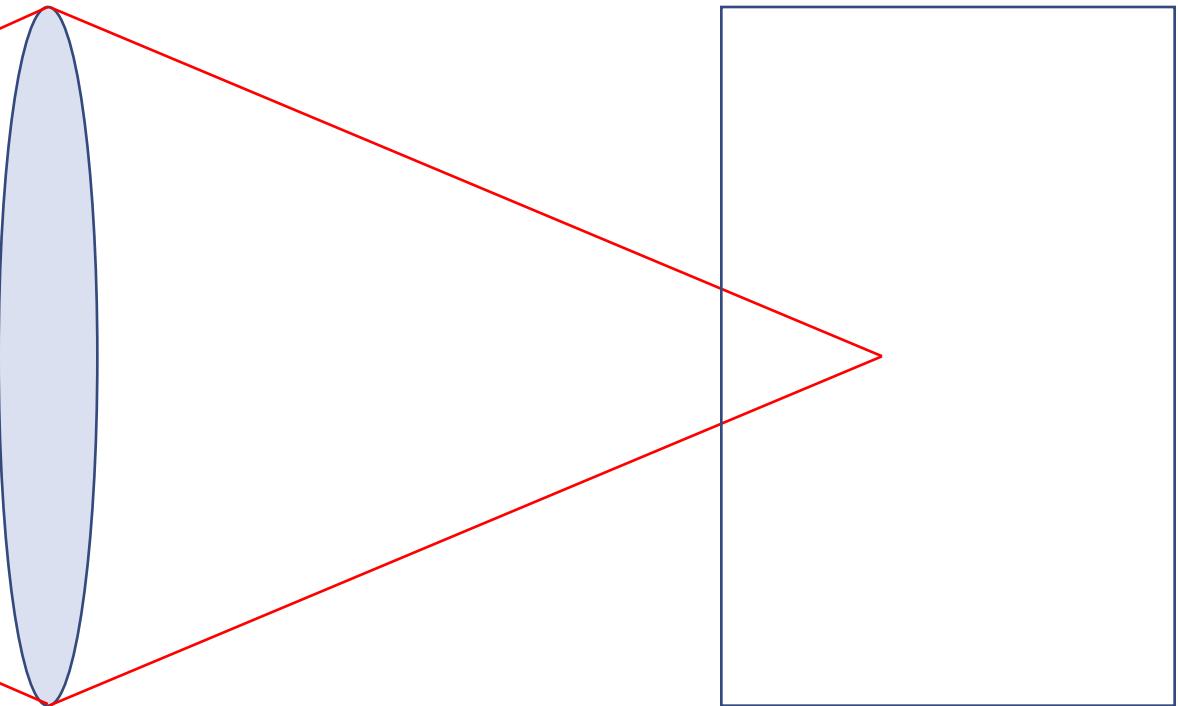


# What is an image?

$n \times m$  array

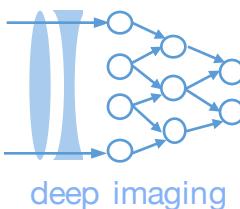


## 3. “Digital” Interpretation

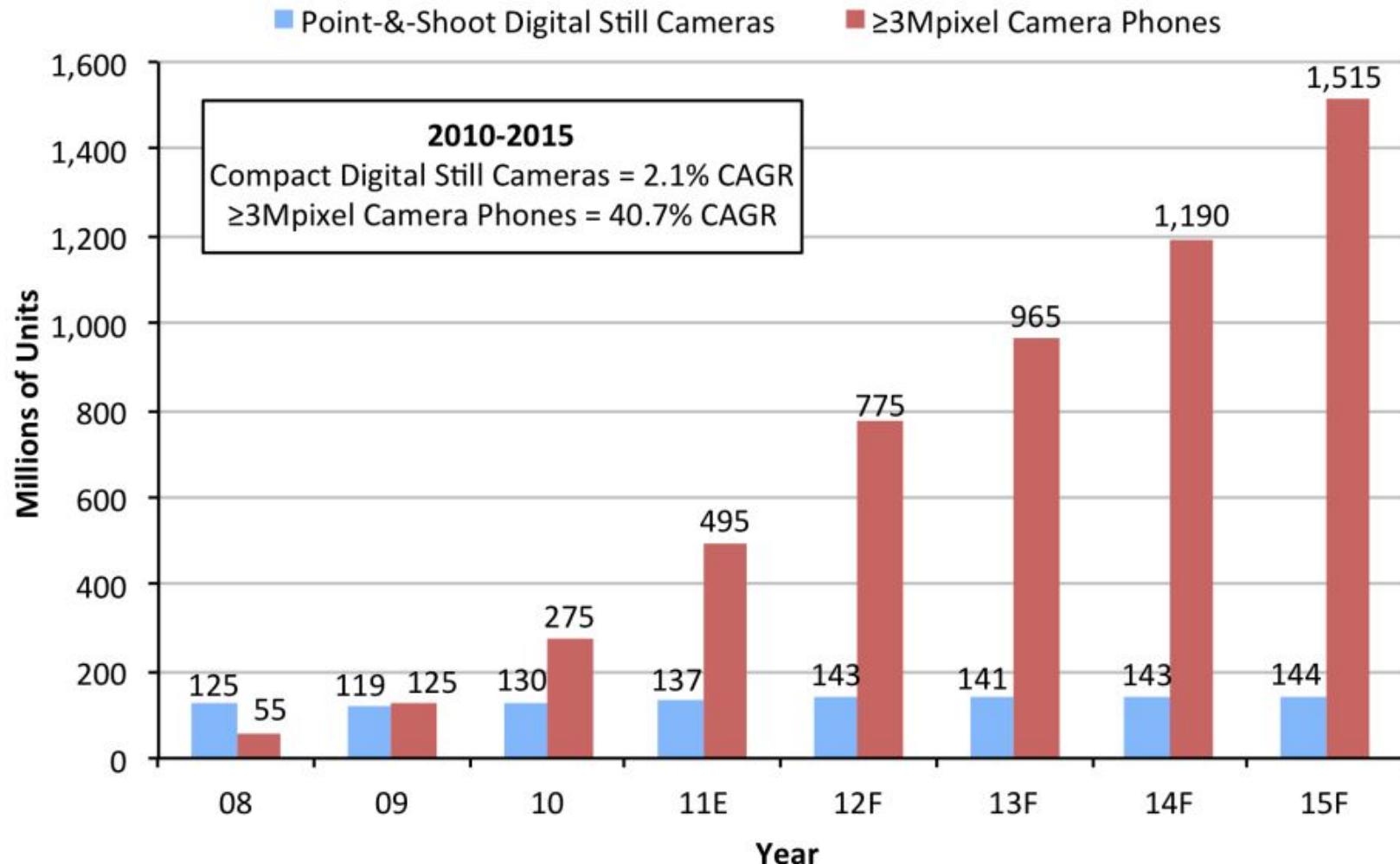


Photons to electrons → Digitazation → Discrete signal

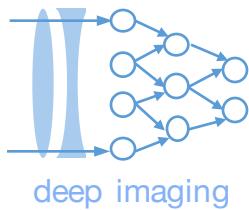
$$I_s(x, y), (x, y) \in Z^{n \times m}$$



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



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



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

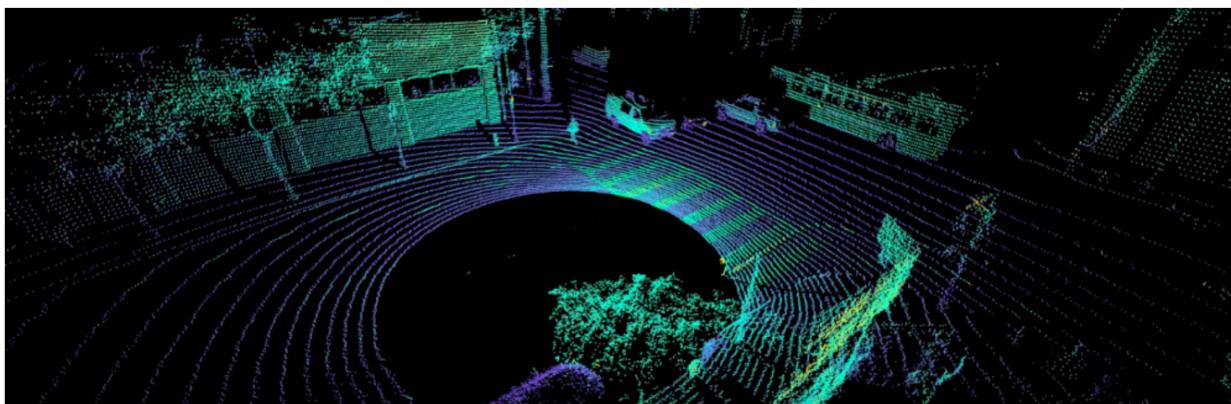
[HOME](#) [PRODUCTS](#) [DOWNLOADS](#) [COMPANY](#) [CAREERS](#) [MEDIA](#) [CONTACT](#) [TALK TO SALES](#)

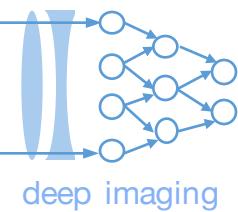
## A Novel CMOS ASIC with SPAD Detectors

The second chip in our flash lidar is our custom designed CMOS detector ASIC that incorporates an advanced single photon avalanche diode (SPAD) array. SPADs are a relatively new type of photo sensor that creates a binary pulse when a photon is detected as opposed to a traditional camera pixel which generates an analog signal that varies continuously with the amount of light on the detector. SPADs have single photon sensitivity, low noise, and extremely good timing resolution (jitter between 10 ps and 100 ps is typical. That's picoseconds - mere trillionths of second!), all of which make them perfect for detecting and timing the ultra short laser pulses in our lidar.

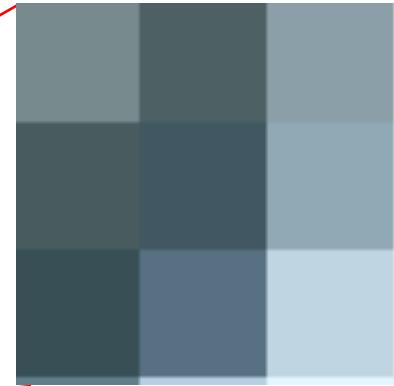
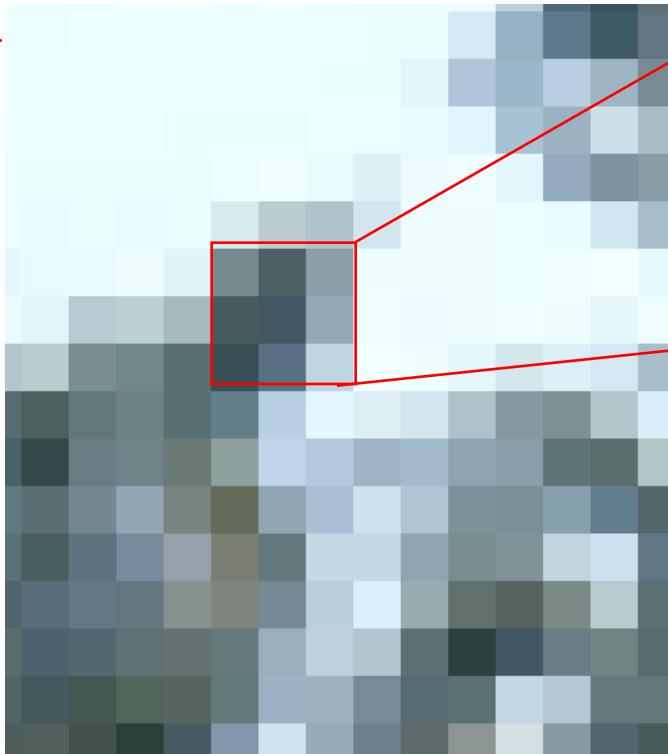
Like VCSELs, CMOS SPADs have many practical advantages over the traditional approaches from other lidar manufacturers. Most important is that they can be directly integrated in a CMOS wafer, which makes it possible to incorporate massive amounts of signal processing on the silicon die right next to the detectors.

As lidar resolutions and data rates continue to increase, on-chip signal processing is essential - the current OS1-64 detector is capable of counting and storing over **one trillion photons per second into on-chip memory**. This is a titanic amount of data, and we've included over **100 GMACs per second** (1 GMAC = 1 billion multiply accumulate operations) of signal processing logic in over 10 million transistors to ultimately produce the millions of 3D points per second that our customers use to drive cars, map environments, and identify obstacles.

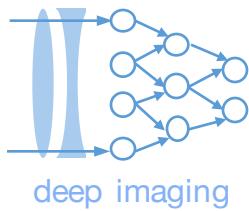




# Images as matrices and vectors

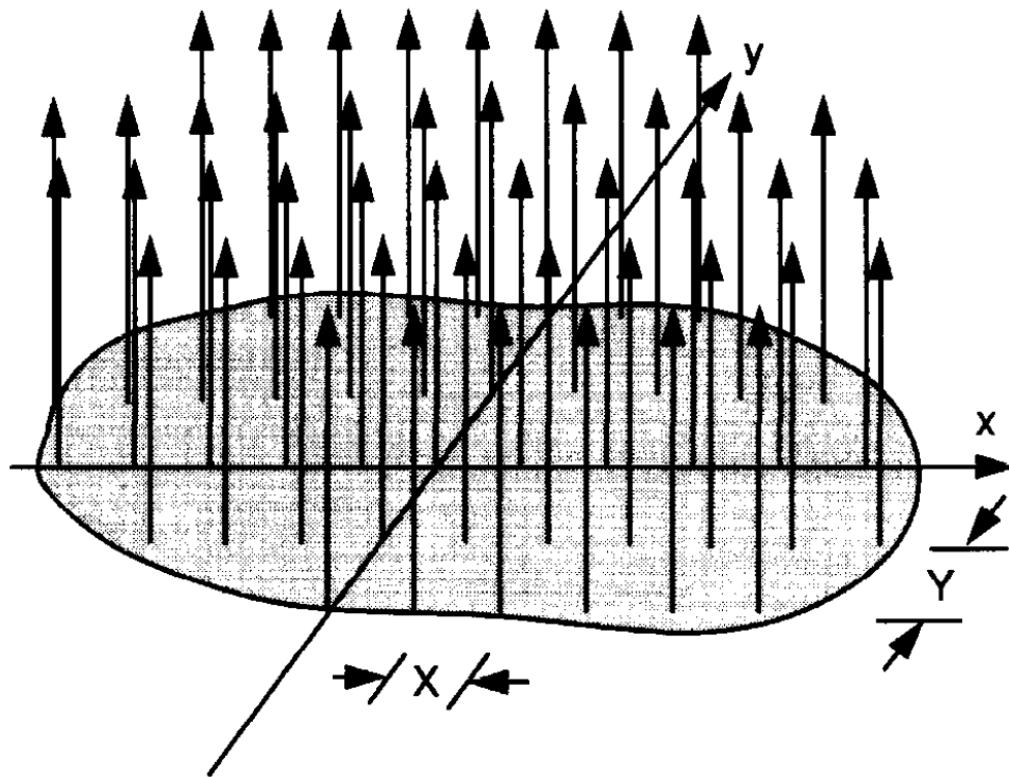


1	2	2
7	1	4
2	2	2
0	3	6
2	2	7
2	5	9

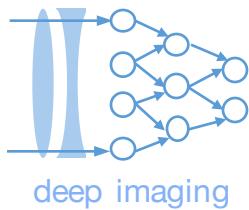


## Continuous versus discrete representation

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

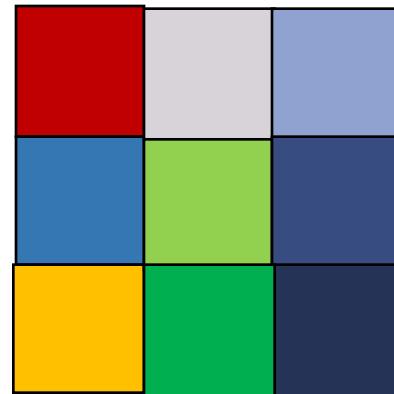


From J. Goodman, *Introduction to Fourier Optics*



## Images unrolled into vectors

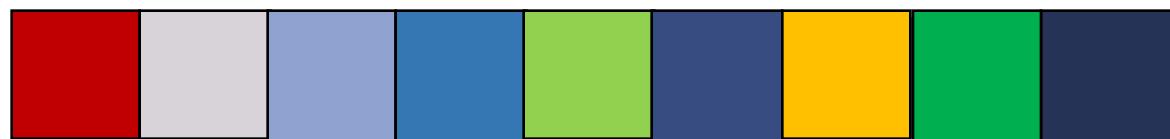
$I_s(x, y)$



$\text{vec}_r[\cdot]$

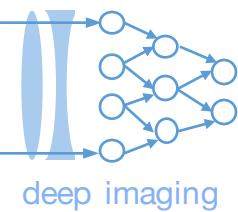


$I_s$



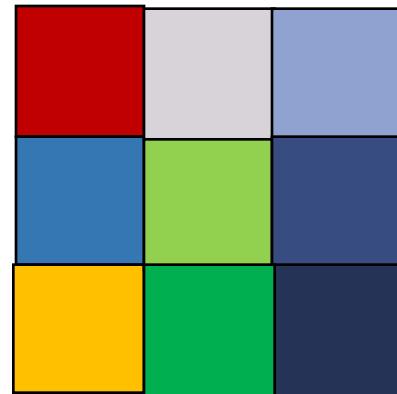
1	2	2
7	1	4
2	2	2
0	3	6
2	2	2
2	5	9

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



## Images unrolled into vectors

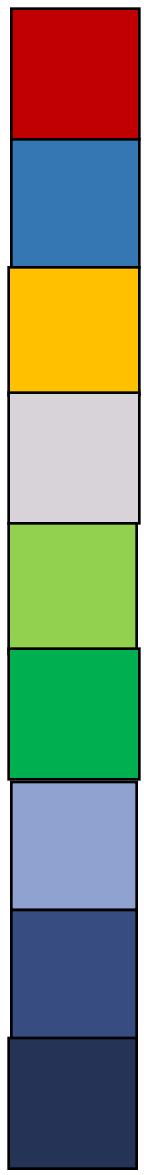
$$I_s(x, y)$$



$$\text{vec}_c[\cdot]$$



$$I_s$$



17

20

22

21

23

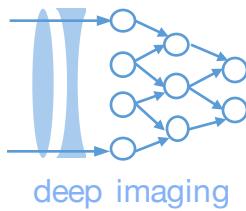
25

24

26

29

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



## 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

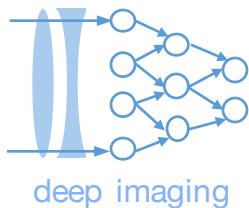
$$I_o = \mathbf{W}I_1$$

4. Non-linear image operations

$$I_o = |I_1|^2$$

5. Convolution

$$I_o = I_1 * I_2$$



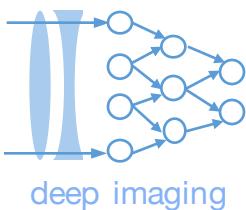
## Important image manipulation: convolution

$$I_o = I_1 * I_2$$

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

$$\begin{array}{c} I_1 \\ \hline \text{---} | \text{---} \\ \text{red} | \text{grey} | \text{blue} | \text{blue} | \text{green} | \text{dark blue} | \text{yellow} | \text{green} | \text{dark blue} \end{array}$$
$$\begin{array}{c} I_2 \\ \hline \text{---} | \text{---} | \text{---} \\ 1 | 1 | 1 \end{array} * \begin{array}{c} I_o \\ \hline \text{---} | \text{---} \end{array} = \begin{array}{c} I_0 \\ \hline \text{---} | \text{---} \end{array}$$

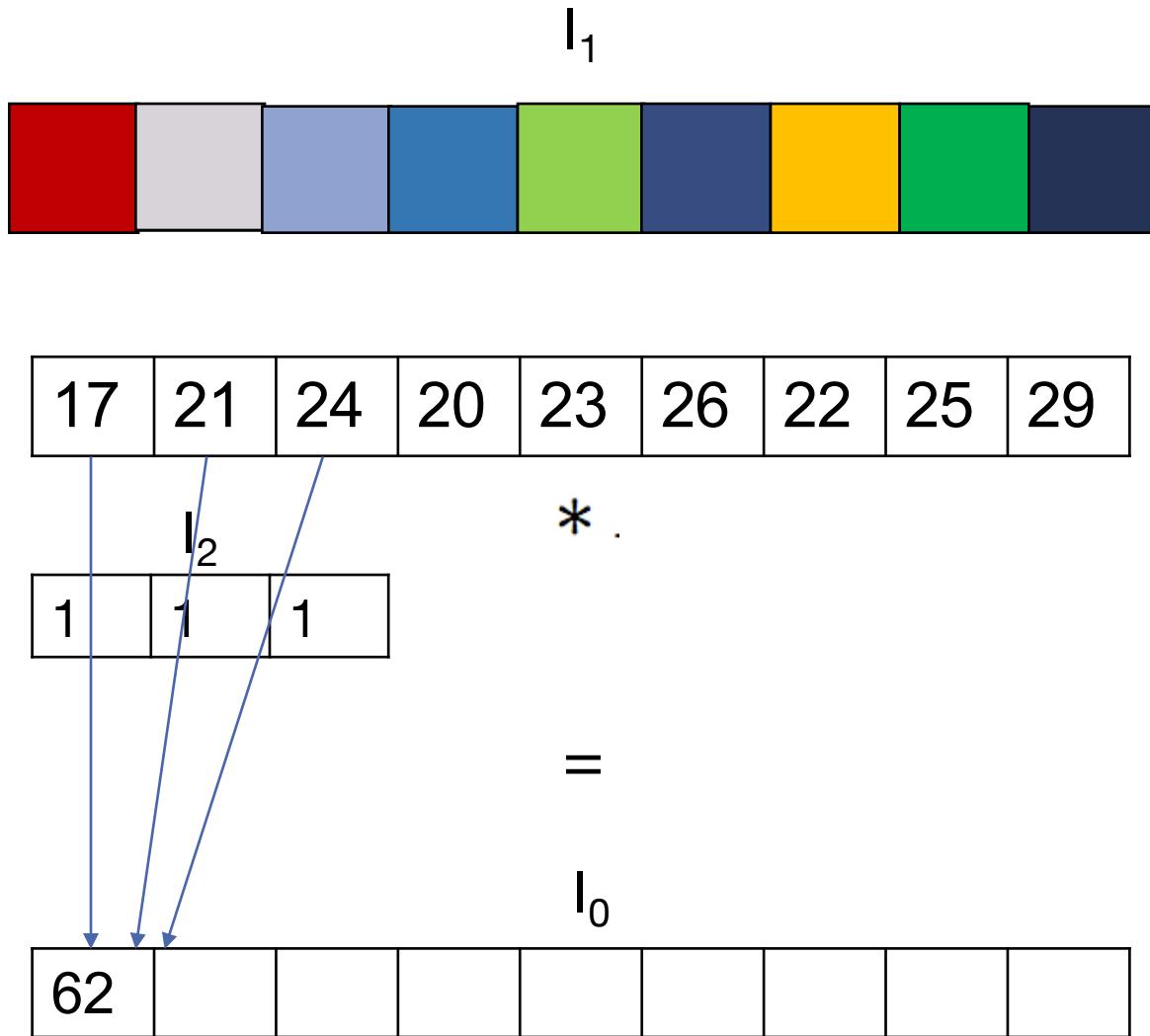
The diagram illustrates the convolution operation.  $I_1$  is a 1D input vector of length 9, containing values red, grey, blue, blue, green, dark blue, yellow, green, and dark blue.  $I_2$  is a 1D kernel vector of length 3, containing values 1, 1, and 1. The convolution operation is performed using a stride of 1, resulting in the output  $I_o$ , which is a 1D vector of length 7, consisting of 7 blank cells.

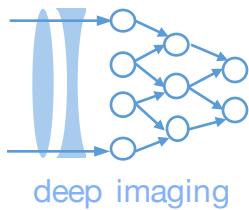


## Important image manipulation: convolution

$$I_o = I_1 * I_2$$

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





## Important image manipulation: convolution

$$I_o = I_1 * I_2$$

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

$I_1$

$I_2$

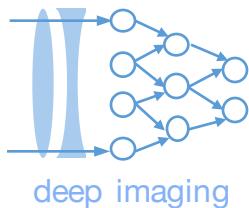
17	21	24	20	23	26	22	25	29
----	----	----	----	----	----	----	----	----

\*

$I_o$

62								
----	--	--	--	--	--	--	--	--

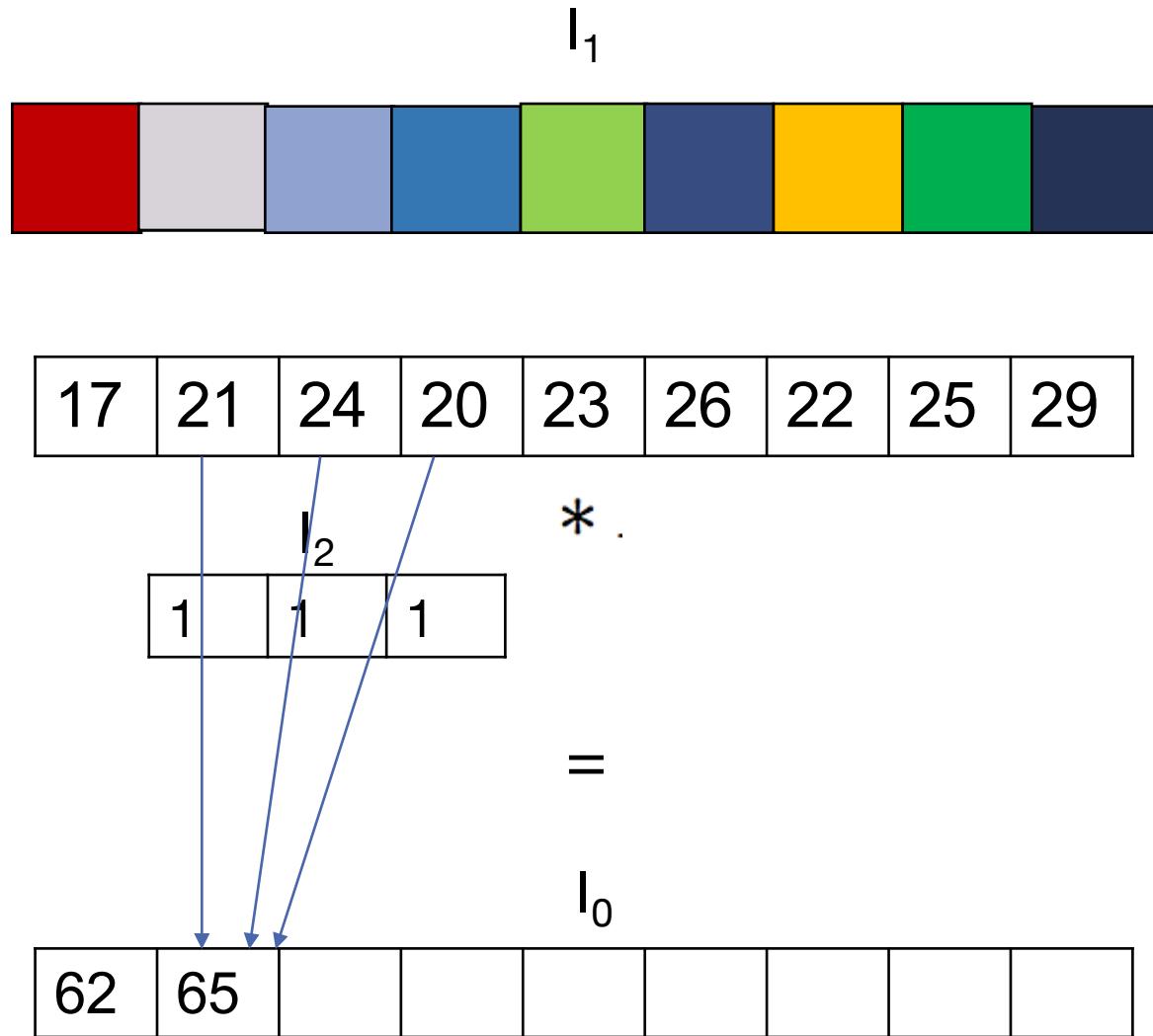
=

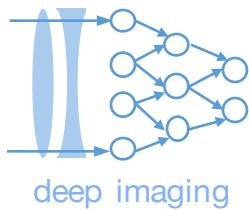


## Important image manipulation: convolution

$$I_o = I_1 * I_2$$

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





## Important image manipulation: convolution

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

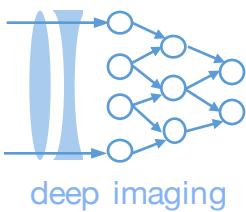


$I_1$

$$\begin{matrix} & I_2 \\ * & \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array} \end{matrix} =$$



$I_0$



## Important image manipulation: convolution

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

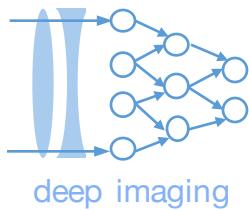


$I_1$

$$\begin{matrix} I_2 \\ * \quad . \quad = \\ \begin{array}{|c|c|c|} \hline -1 & 0 & -1 \\ \hline -2 & 0 & -2 \\ \hline -1 & 0 & -1 \\ \hline \end{array} \end{matrix}$$



$I_0$

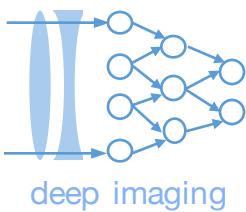


## Machine learning: “dynamic” image manipulations

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



$$I_1 \cdot * \begin{matrix} W \\ \begin{array}{|c|c|c|} \hline w & w & w \\ \hline 1 & 2 & 3 \\ \hline w & w & w \\ \hline 4 & 5 & 6 \\ \hline w & w & w \\ \hline 7 & 8 & 9 \\ \hline \end{array} \end{matrix} = \text{Most useful information possible for computer to use}$$



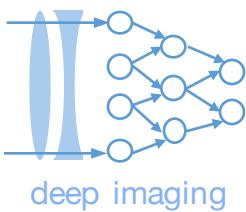
## Machine learning: “dynamic” image manipulations

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



$$I_1 \cdot * \begin{matrix} & W \\ \begin{matrix} w_1 & w_2 & w_3 \\ w_4 & w_5 & w_6 \\ w_7 & w_8 & w_9 \end{matrix} \end{matrix} = \text{Most useful information possible for computer to use}$$

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

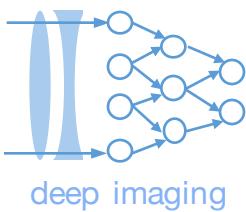


## Example tasks for machine learning



Common ML transformations for detected image:

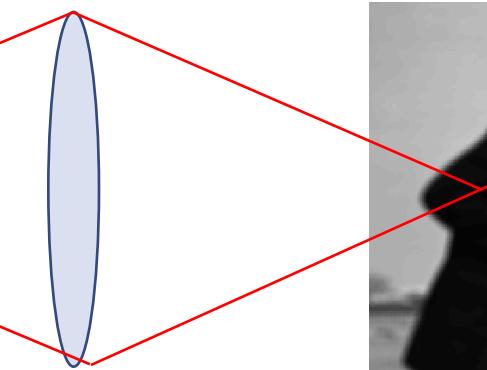
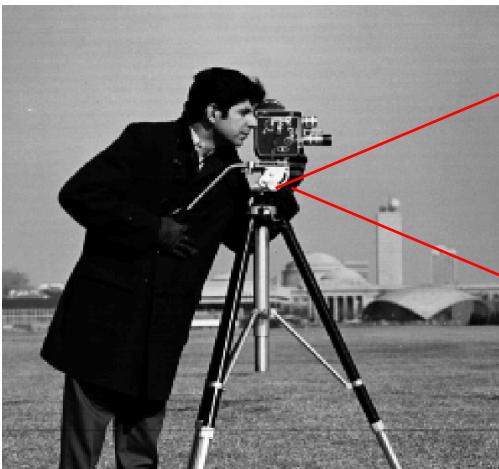
- A vector of different categories (image is of a man, not a dog)
- A vector of coordinates highlighting features of interest (the man's head is contained in the box of pixels from  $(x,y,x+a,y+b)$ )
- A segmentation map (the line denoting the boundary of the man is 1, rest is 0)



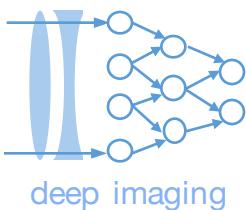
## Image formation as a set of discrete equations

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

Physical world



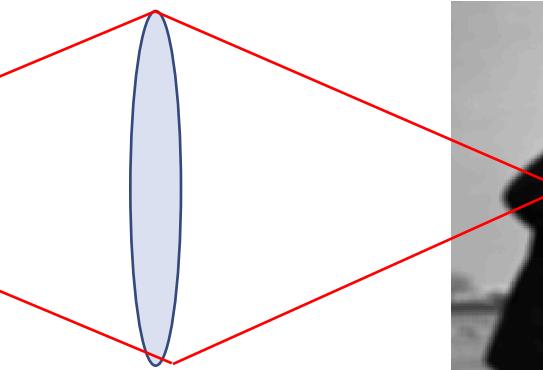
$$I_1 = W_0 I_0$$



## Image formation as a set of discrete equations

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

Physical world



$n \times m$  image  $I_1$



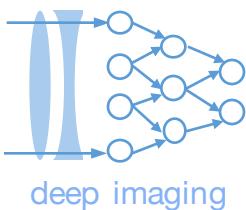
Processed image  $I_2$



ML  
Task

$$I_1 = W_0 I_0$$

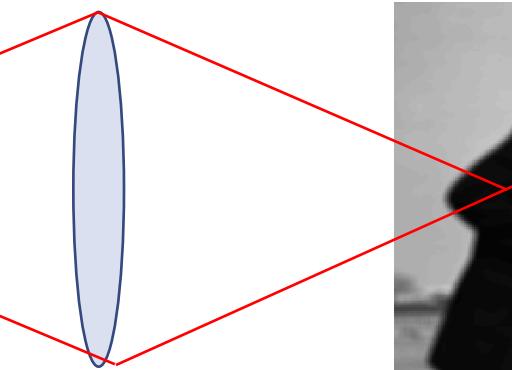
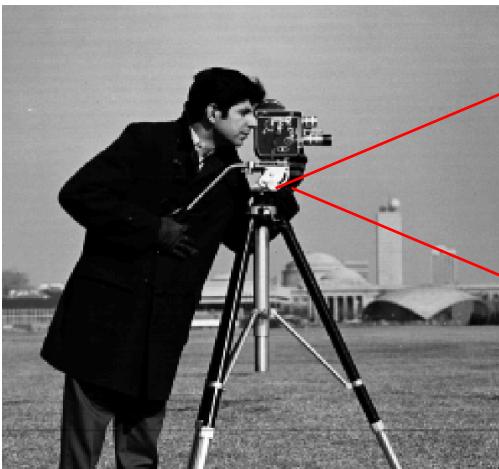
$$I_2 = W_1 I_1$$



## 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



$n \times m$  image  $I_1$



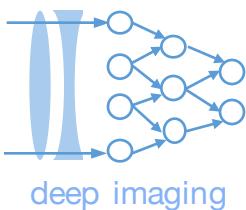
Processed image  $I_2$



ML  
Task

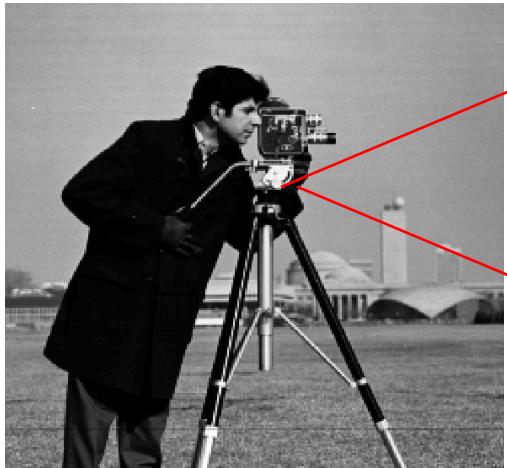
$$I_2 = W_1 W_0 I_0$$

Linear mapping



# Bringing together physical and digital image representations

Physical world



$n \times m$  image  $I_1$



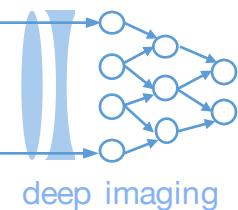
Convolutional  
neural network

ML  
Task

"Image of  
a man"

$$\text{Task} = \mathbf{W}_n \dots \mathbf{T}_1 [\mathbf{W}_1 \mathbf{T}_0 [\mathbf{W}_0 I_0] \dots]$$

Nonlinear mapping



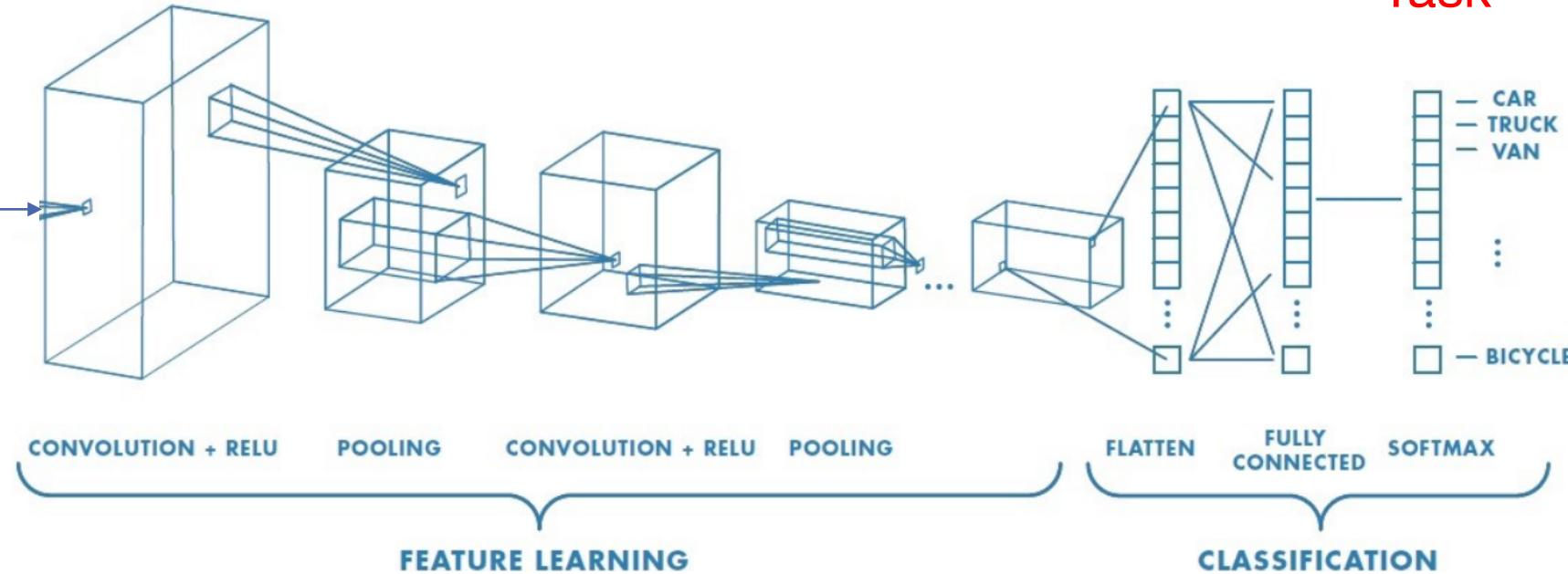
# Bringing together physical and digital image representations

Physical world  $I_0$



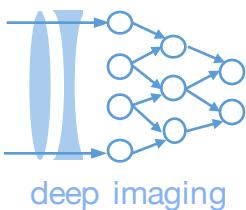
→ **Hardware**

Image  $I_1$



$$\text{Task} = \mathbf{W}_n \dots \mathbf{T}_1 [\mathbf{W}_1 \mathbf{T}_0 [\mathbf{W}_0 I_0] \dots]$$

From <https://towardsdatascience.com/>



# Bringing together physical and digital image representations

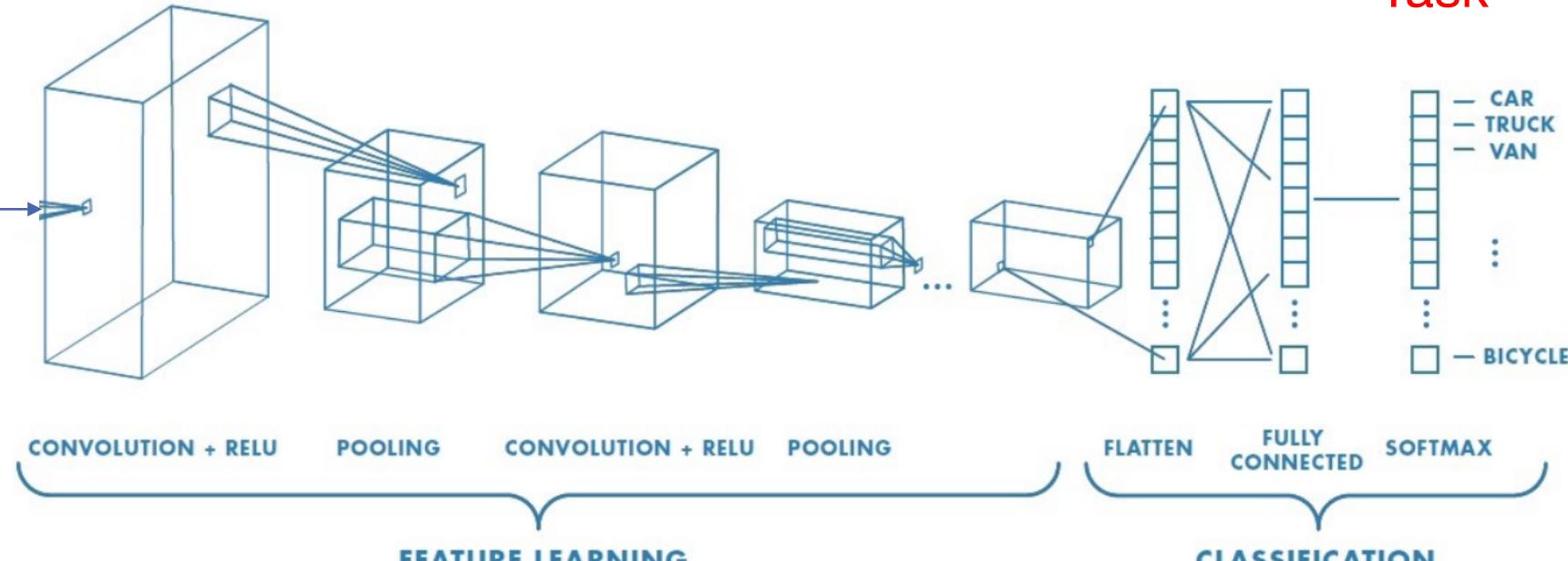
Physical world  $I_0$



→ **Hardware**

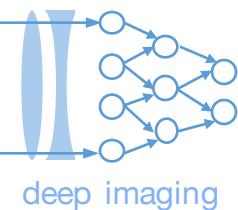
Account for or  
modify imaging  
hardware

Image  $I_1$



$$\text{Task} = W_n \dots T_1 [W_1 T_0 [W_0 I_0] \dots]$$

From <https://towardsdatascience.com/>



# Bringing together physical and digital image representations

Physical world



$n \times m$  image  $I_1$



Convolutional  
neural network

ML  
Task

"Image of  
a man"

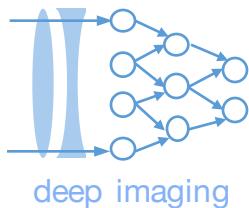
Illumination

Imaging device (lens, coils, transducers)

Detector design

Properties of sample of interest

$$\text{Task} = W_n \dots T_1 [W_1 T_0 [W_0 I_0] \dots]$$

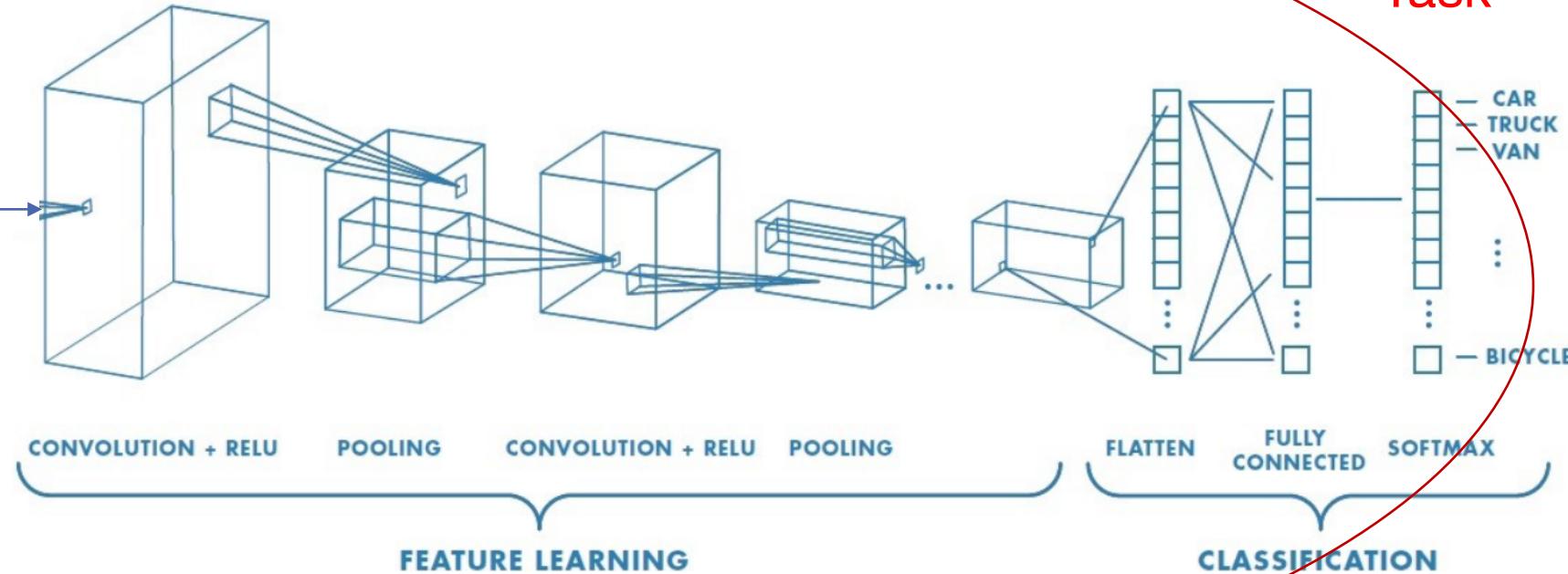


# Bringing together physical and digital image representations

Physical world  $I_0$



Image  $I_1$



Final project: try to optimize all of this together!