

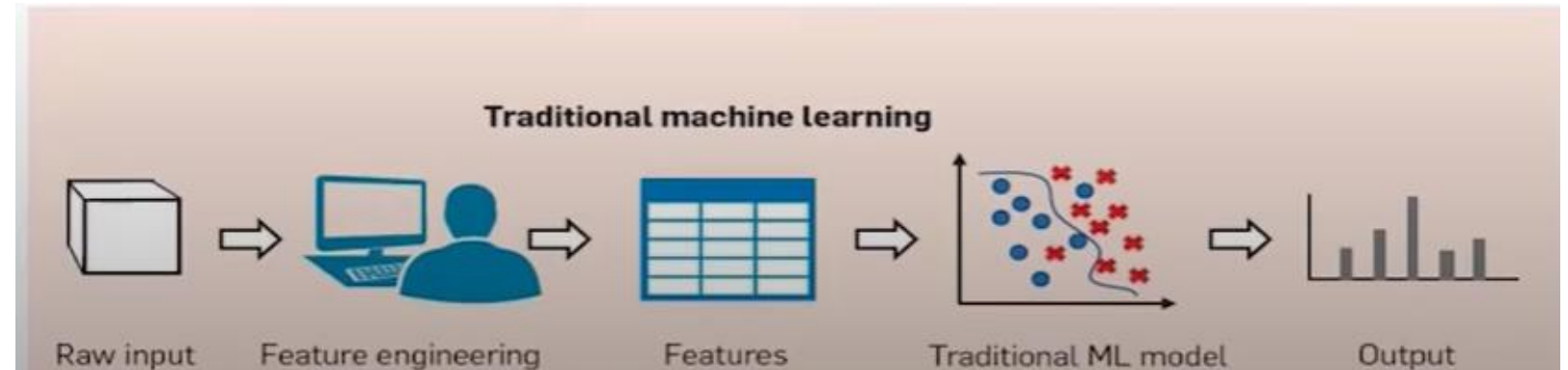
# Deep Learning : Convolutional Neural Network (LeNet)



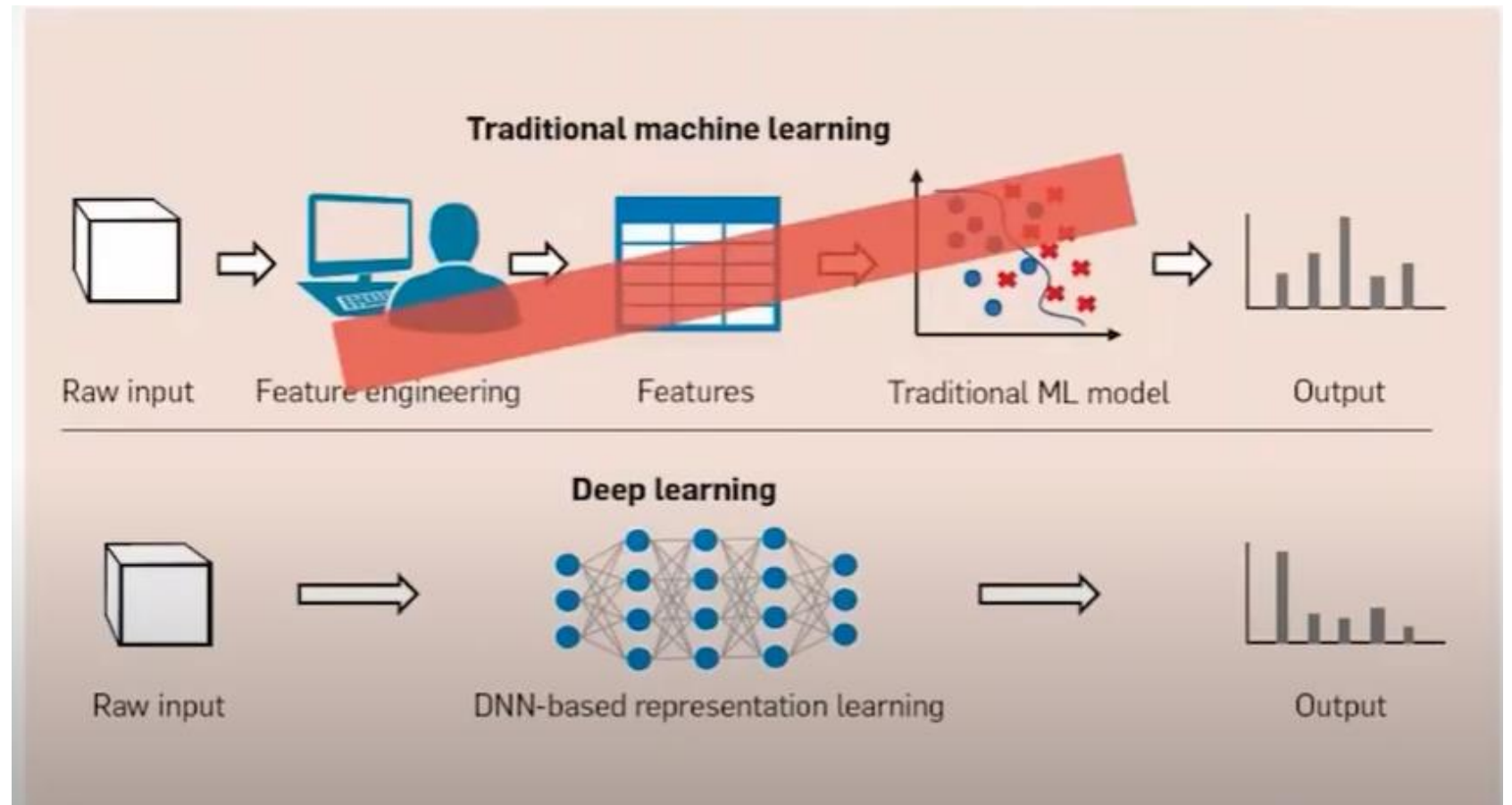
राष्ट्रीय प्रौद्योगिकी संस्थान सिक्किम  
NATIONAL INSTITUTE OF TECHNOLOGY SIKKIM

**Course Instructor:**  
Dr. Bam Bahadur Sinha  
*Assistant Professor*  
*Computer Science & Engineering*  
*National Institute of Technology*  
*Sikkim*

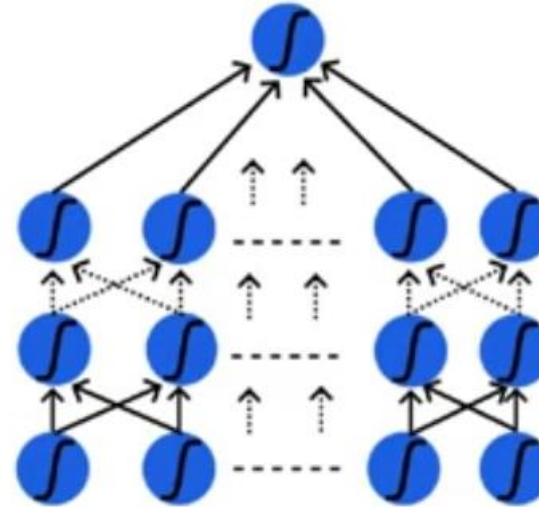
# Traditional Machine Learning



# Deep Learning



# Deep Neural Networks



- UAT says that DNN are powerful function approximators
- Can be trained using backpropagation
- Prone to overfitting
- Gradient can vanish due to long chains

# What Does The Convolution operation do?



$x_0$

$x_1$

$x_2$

$w_{-2}$

$w_{-1}$

$w_0$

$$s_t = \sum_{a=0}^{\infty} x_{t-a} w_{-a} = (x * w)_t$$

	$w_{-6}$	$w_{-5}$	$w_{-4}$	$w_{-3}$	$w_{-2}$	$w_{-1}$	$w_0$
W	0.01	0.01	0.02	0.02	0.04	0.4	0.5

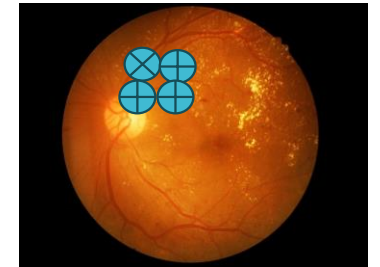
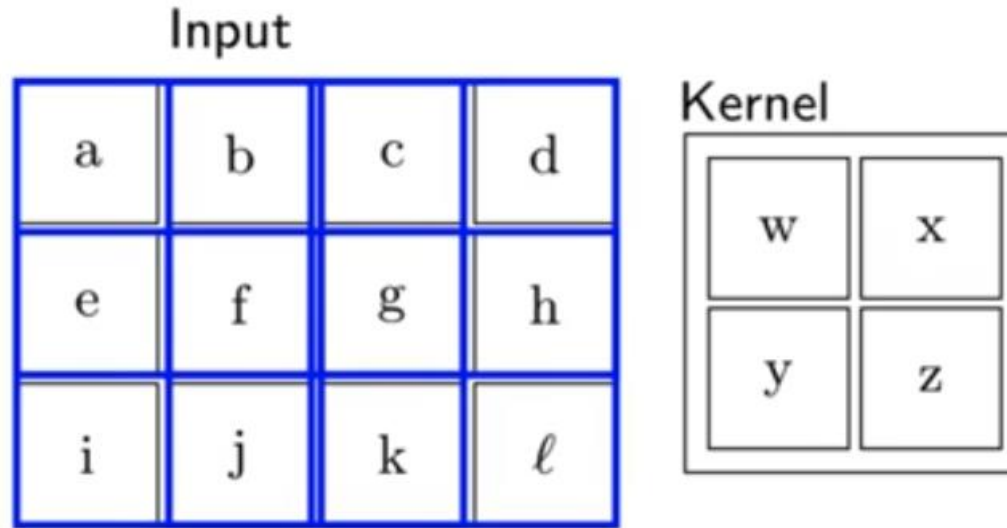
X	1.00	1.10	1.20	1.40	1.70	1.80	1.90	2.10	2.20	2.40	2.50	2.70
---	------	------	------	------	------	------	------	------	------	------	------	------

S							1.80					
---	--	--	--	--	--	--	------	--	--	--	--	--

$$s_6 = x_6 w_0 + x_5 w_{-1} + x_4 w_{-2} + x_3 w_{-3} + x_2 w_{-4} + x_1$$

In 1-D case

# Convolution Operation – 2D Inputs

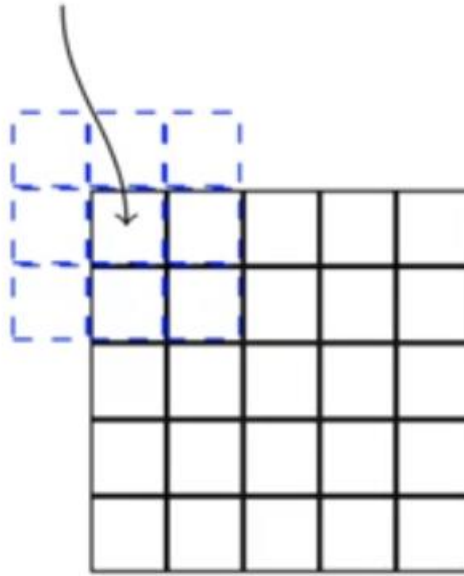


$$S_{ij} = (I * K)_{ij} = \sum_{a=0}^{m-1} \sum_{b=0}^{n-1} I_{i+a,j+b} K_{a,b}$$

Output		
aw+bx+ey+fz	bw+cx+fy+gz	cw+dx+
ew+fx+iy+jz	fw+gx+jy+kz	gw+hx+

# Convolution Operation (Considering previous neighbours)

pixel of interest



$$S_{ij} = (I * K)_{ij} = \sum_{a=\lfloor -\frac{m}{2} \rfloor}^{\lfloor \frac{m}{2} \rfloor} \sum_{b=\lfloor -\frac{n}{2} \rfloor}^{\lfloor \frac{n}{2} \rfloor} I_{i-a, j-b} K_{\frac{m}{2}+a, \frac{n}{2}+b}$$

# Convolution – In Practice



$$\begin{matrix} * & \begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix} & = \end{matrix}$$



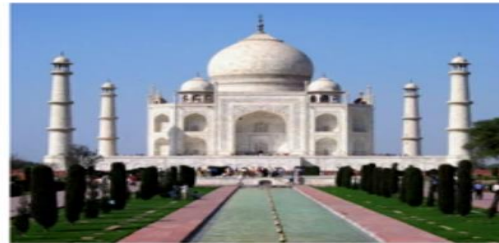
blurs the image



$$\begin{matrix} * & \begin{matrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{matrix} & = \end{matrix}$$



sharpens the image

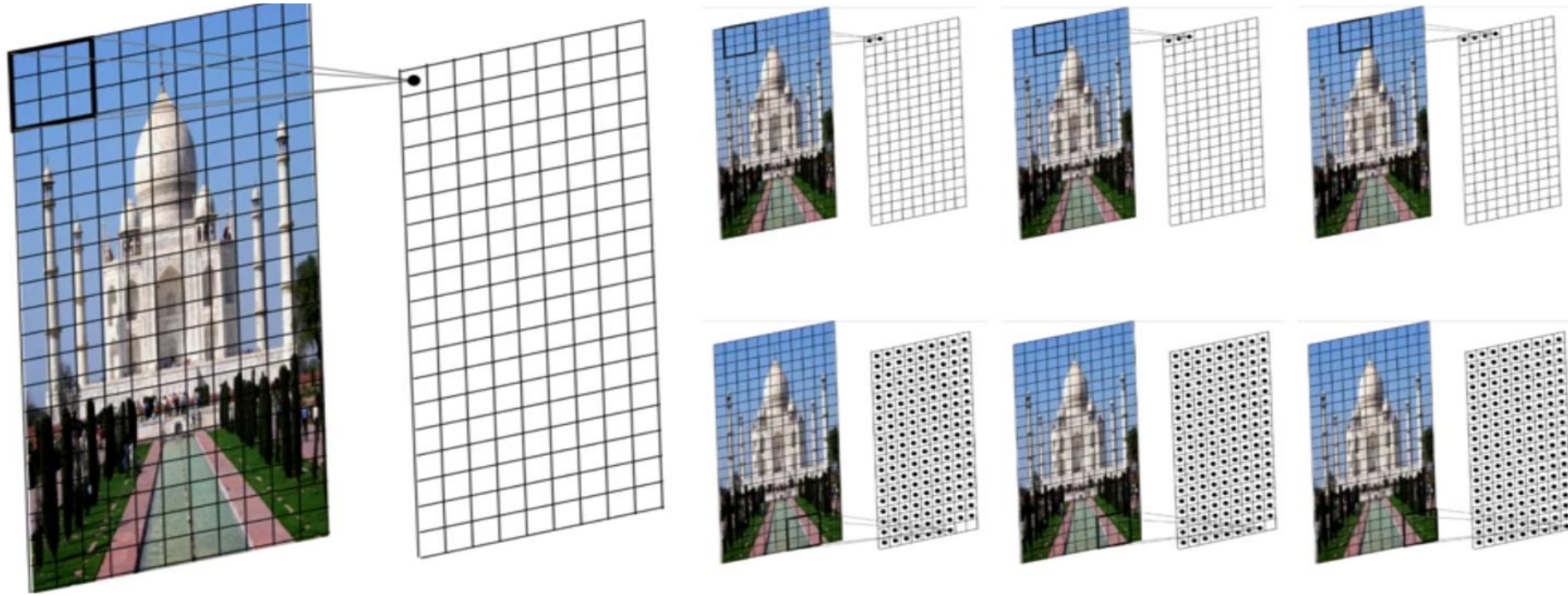


$$\begin{matrix} * & \begin{matrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{matrix} & = \end{matrix}$$



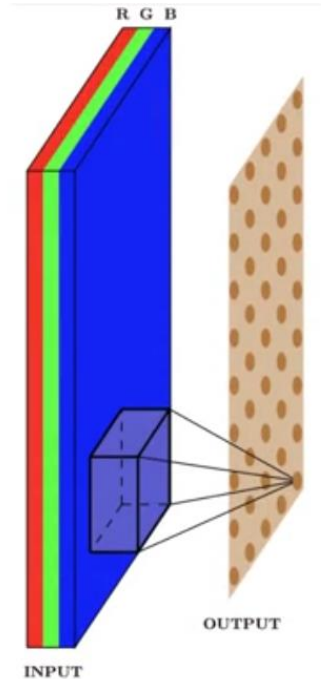
detects the edges





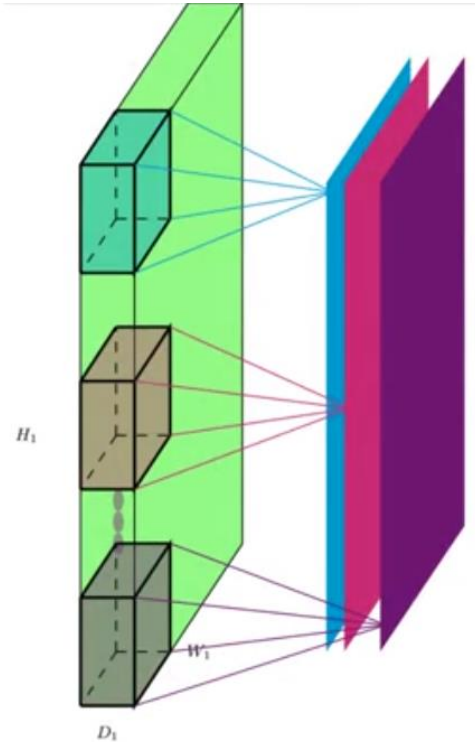
# Convolution – In Practice

# Convolution – In Practice



- Input is 3D
- Filter is also 3D
- But the convolution operation that we are performing is 2D
- We are only sliding vertically & horizontally and not along the path.
- This is because the depth of the filter is the same as the depth of the input.

# Convolution – In Practice



- Can we apply multiple filters to the same image?
- Each filter applied to a 3D input will give a 2D output
- Combining the output of multiple such filters will result in a 3D input

# Terminologies

$W_i,$  • Input Width,  
 $H_i,$  • Input Height and  
 $D_i$  • Input Depth

$F$  • Spatial extent of  
the filter

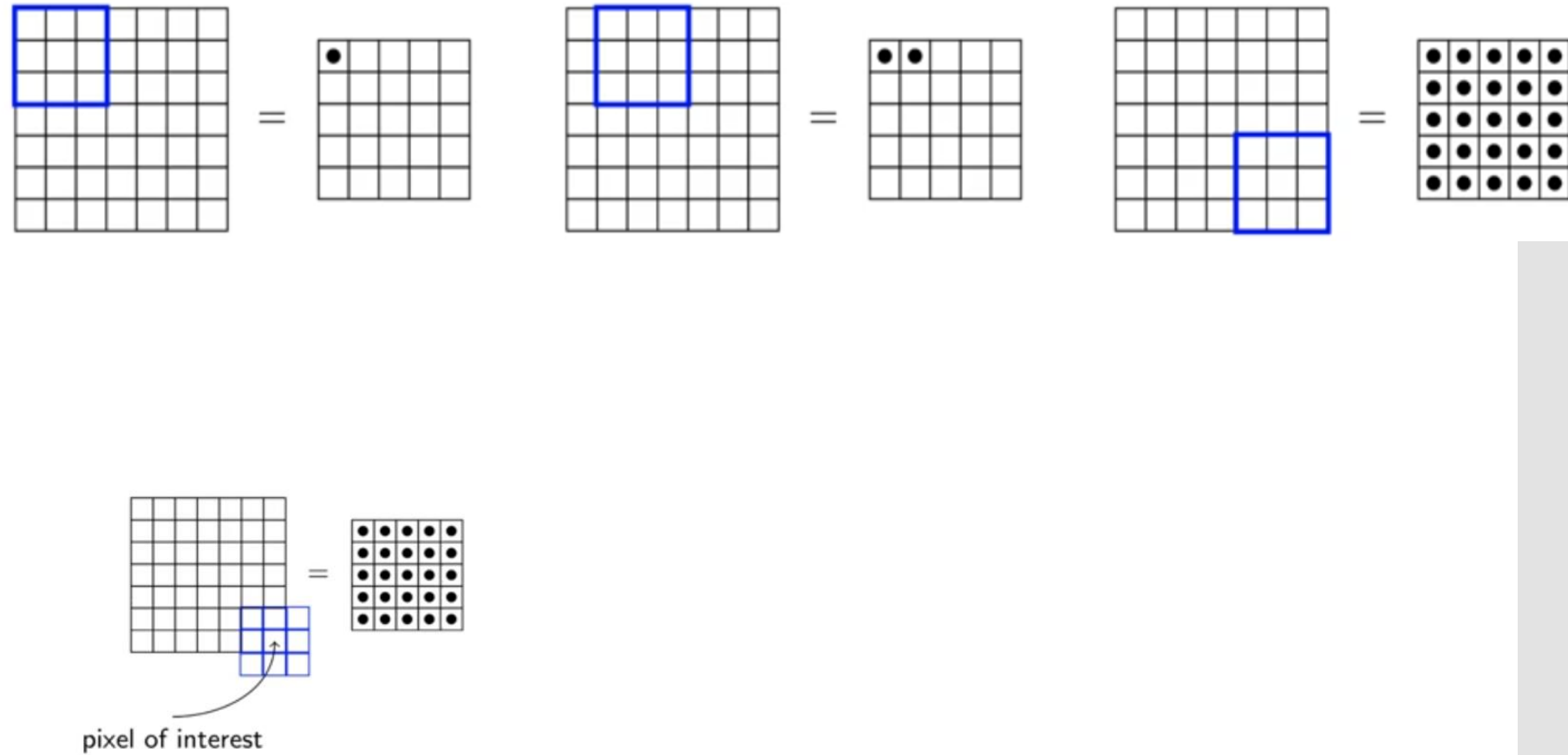
$K$  • Number of Filters

• Output Width,  $W,$   
• Output Height and  $H_o,$   
• Output Depth  $D_o$

• Padding  $P$

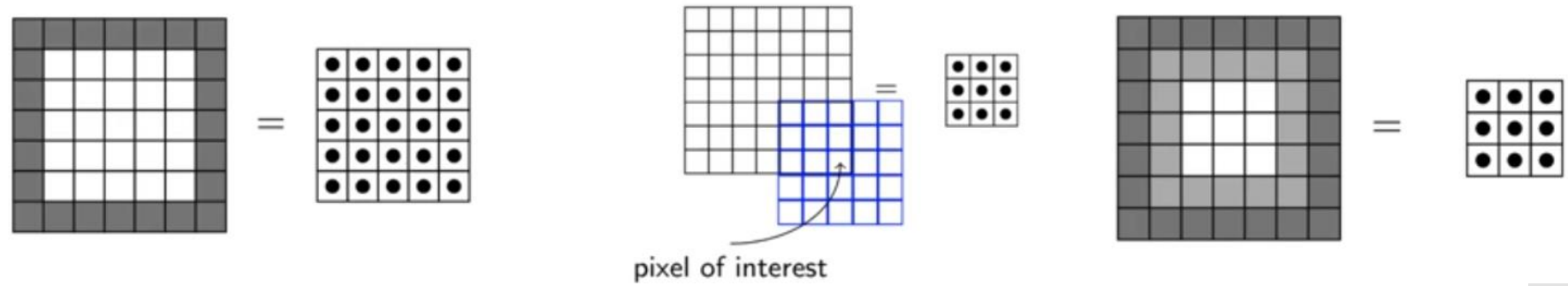
• Stride  $S$

# How do we Compute $W_o$ , $H_o$ , and $D_o$



Size of output will be less than that of the input

How do we  
Compute  $W_O$ ,  
 $H_O$ , and  $D_O$

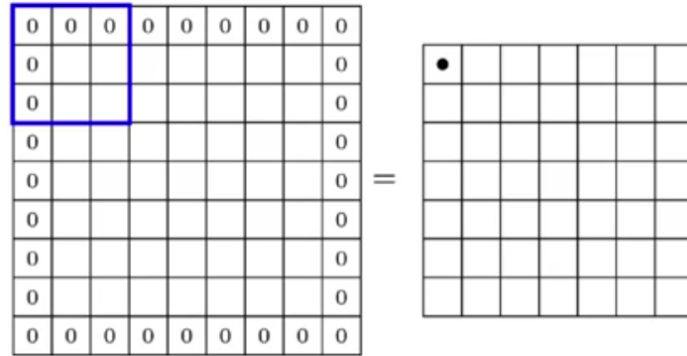


$$W_O = W_I - F + 1$$

$$H_O = H_I - F + 1$$

Size of output will be less than that of the input

What if We  
Want the  
Output to be  
of same size as  
INPUT?



The bigger the kernel size,  
the larger is the padding  
required

$$W_O = W_I - F + 2P + 1$$

$$H_O = H_I - F + 2P + 1$$

# What Does The Stride 'S' Do?

0	0	0	0	0	0	0	0	0	0
0									0
0									0
0									0
0									0
0									0
0									0
0									0
0									0
0	0	0	0	0	0	0	0	0	0

=

•			

0	0	0	0	0	0	0	0	0	0
0									0
0									0
0									0
0									0
0									0
0									0
0									0
0									0
0	0	0	0	0	0	0	0	0	0

=

•	•		
			•

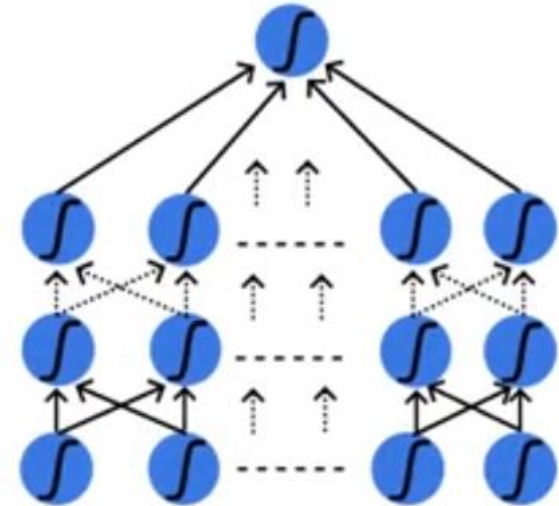
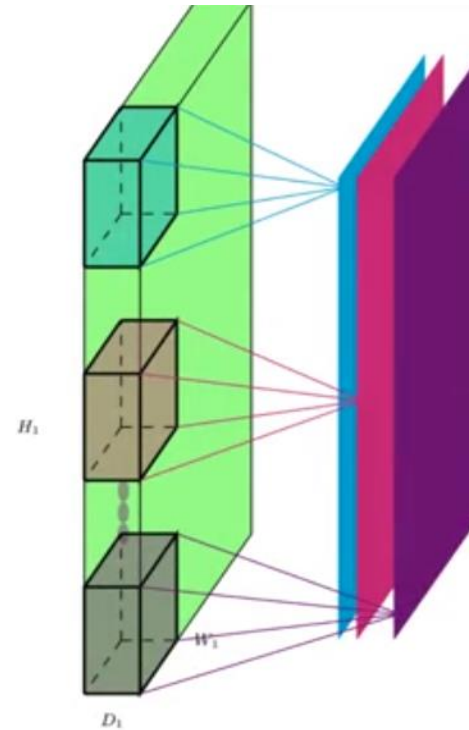
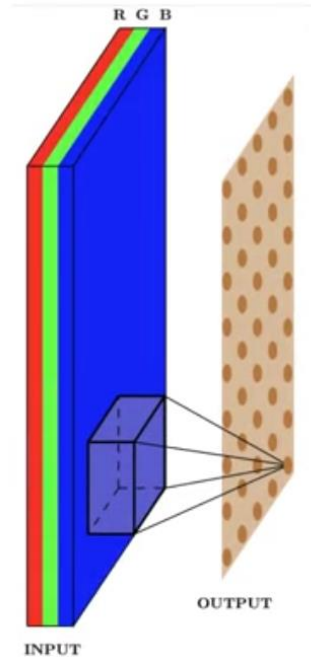
$$W_O = \frac{W_I - F + 2P}{S} + 1$$

$$H_O = \frac{H_I - F + 2P}{S} + 1$$

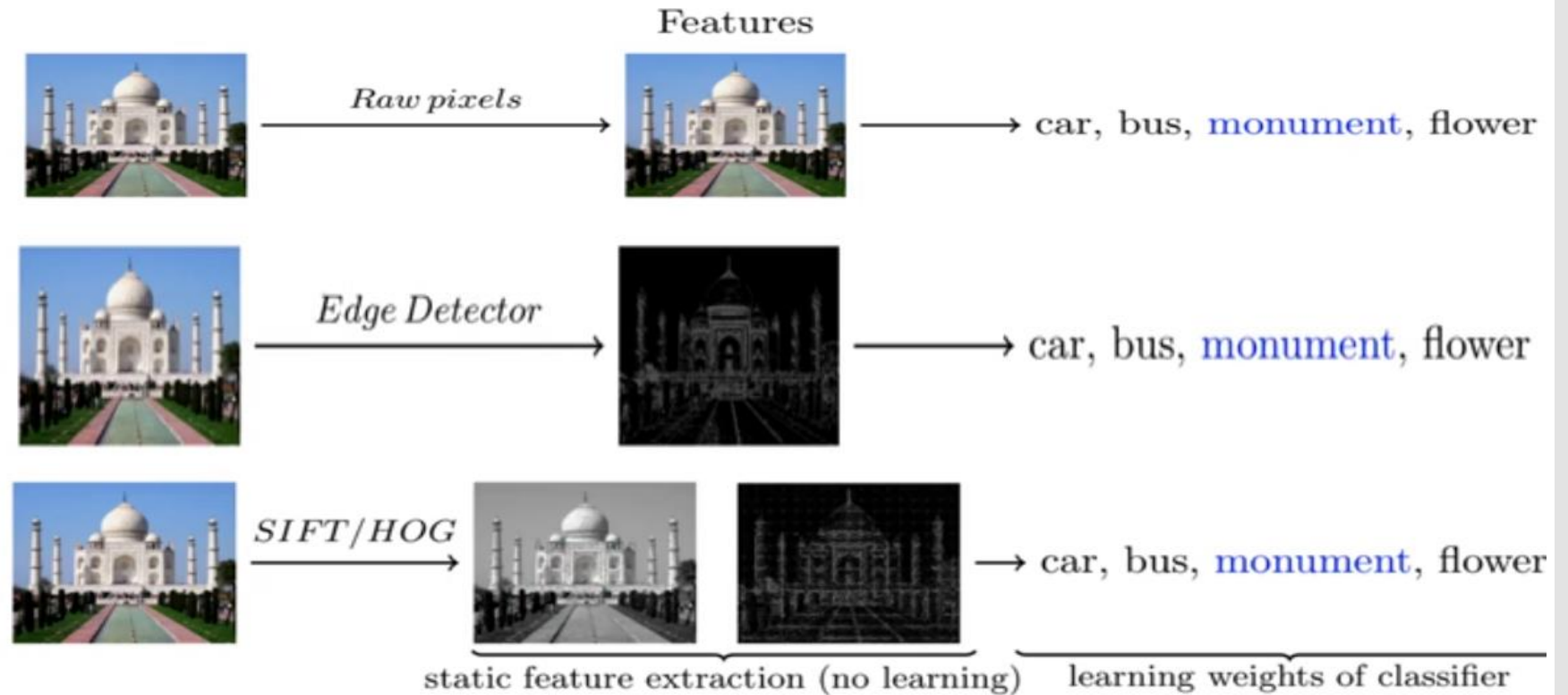
Higher the stride, smaller will be the size of the output



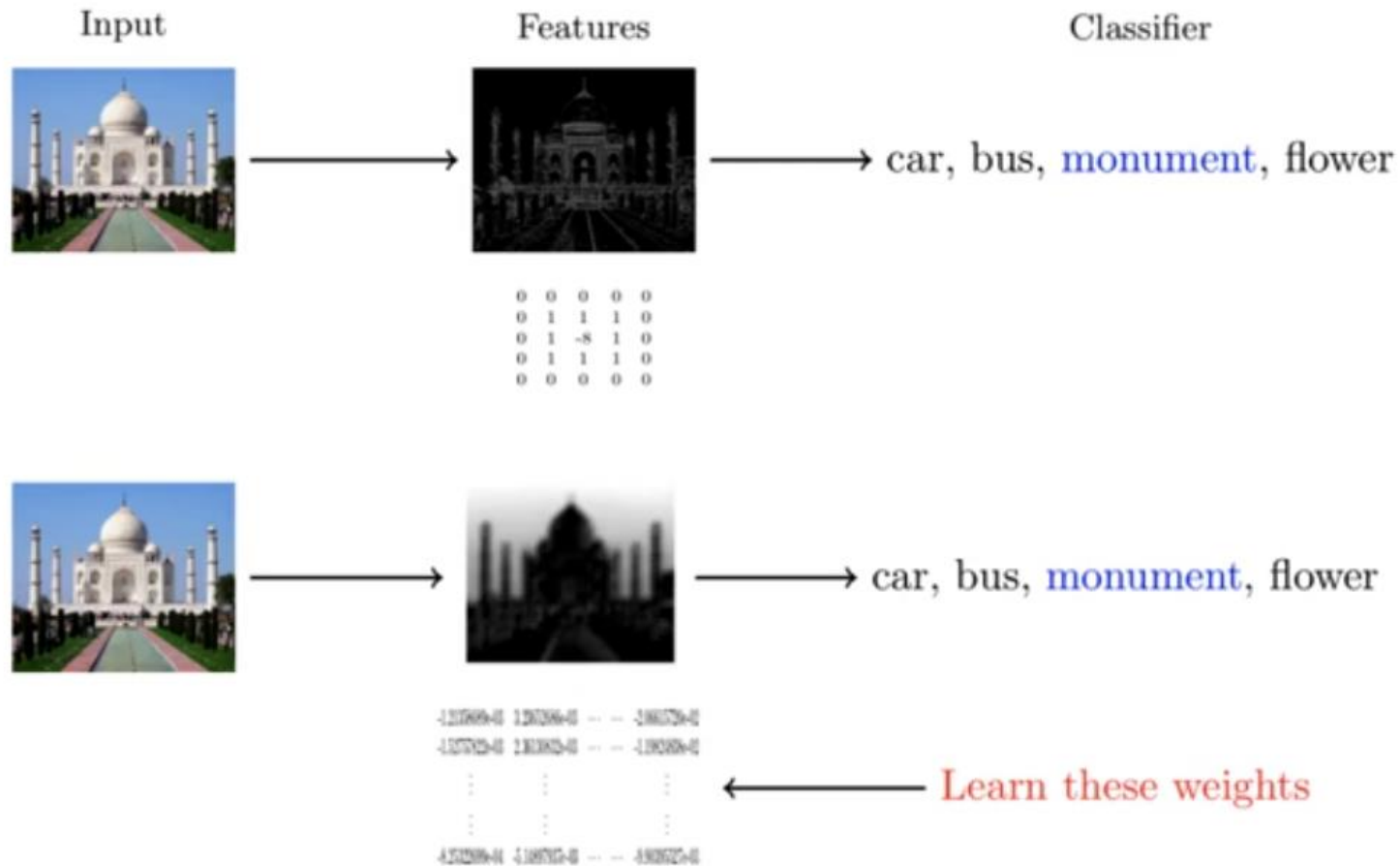
# Relation Between Convolution Operation & Neural Network



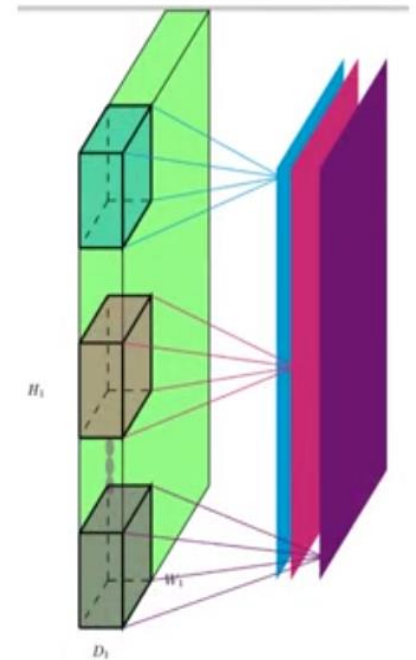
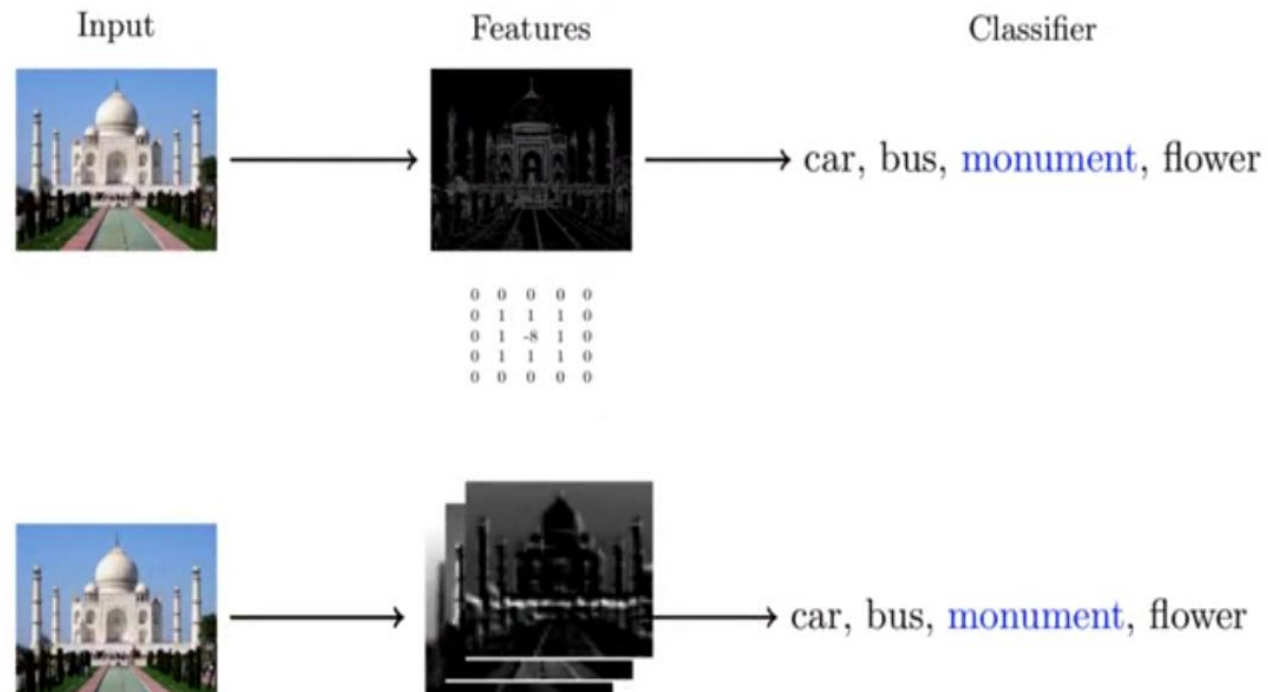
# Convolutional Neural Network Vs Simple Neural Network



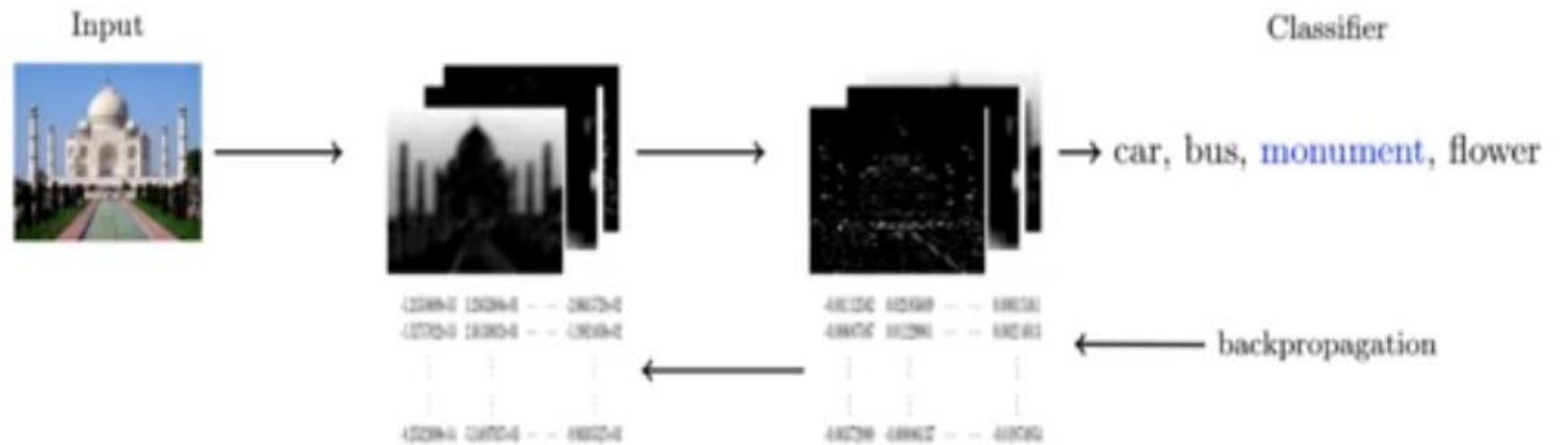
# Let The Network Learn Feature Representations



# Let The Network Learn MULTIPLE Feature Representations

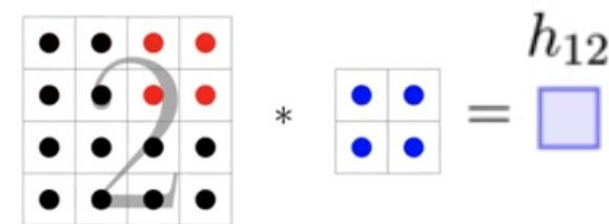
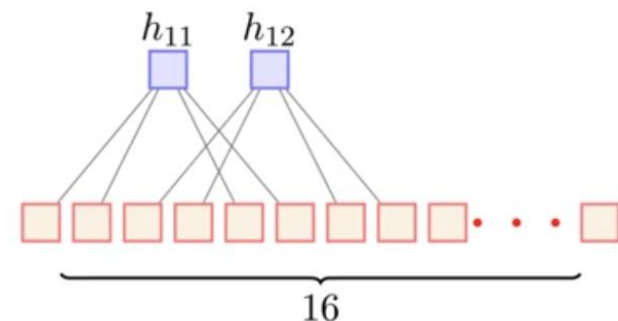
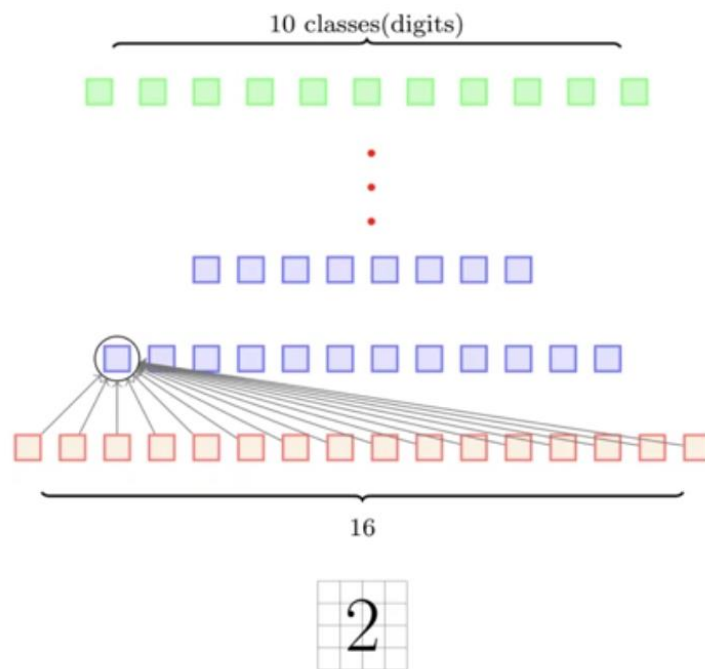


Let The Network  
Learn MULTIPLE  
layers of Feature  
Representations

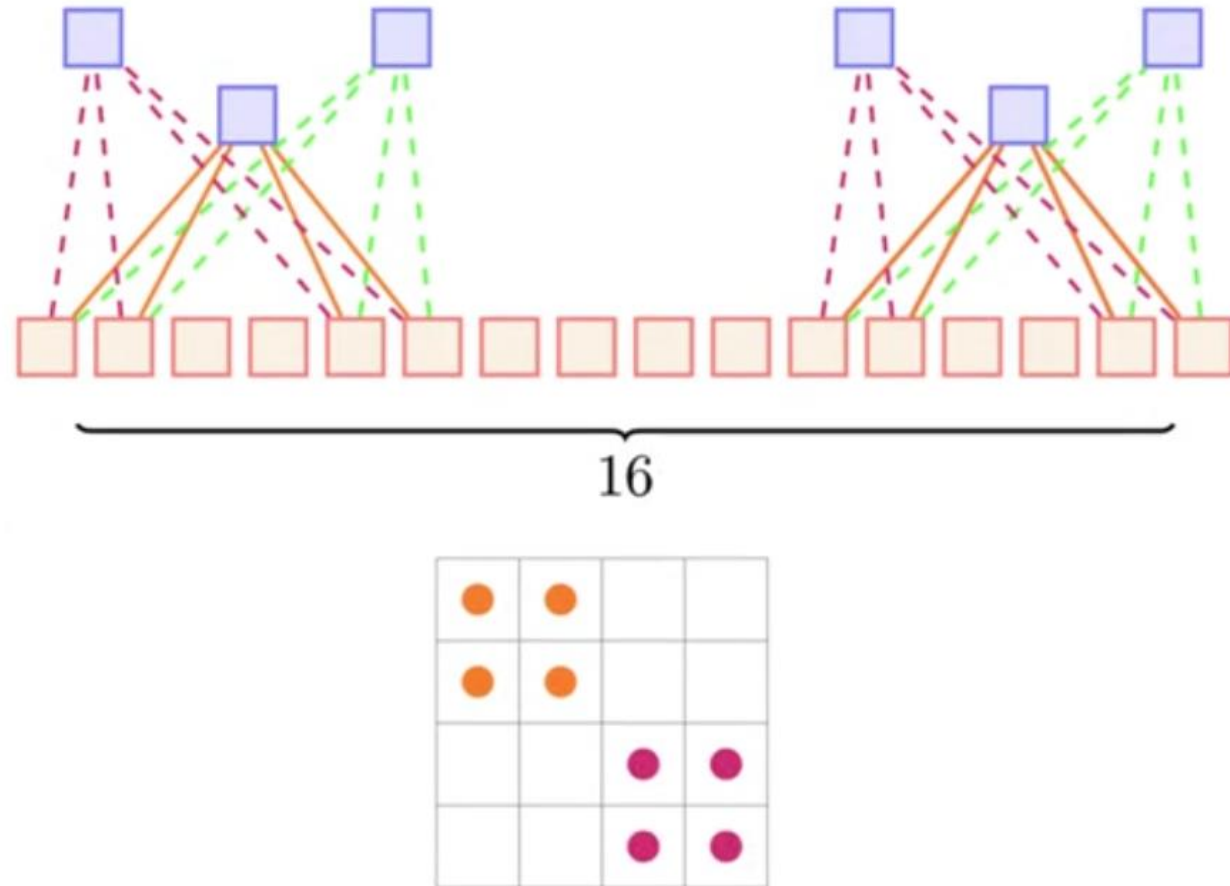


How is CNN  
different from a  
fully Connected  
Neural Network  
?

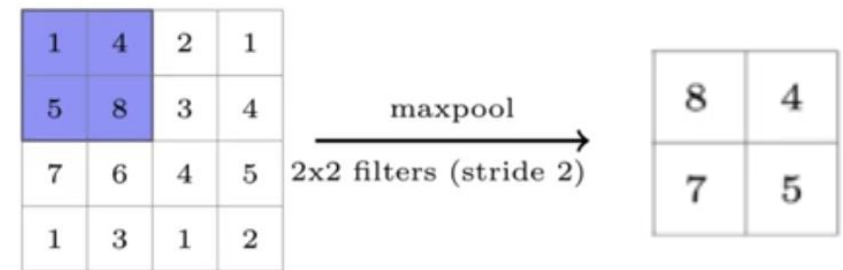
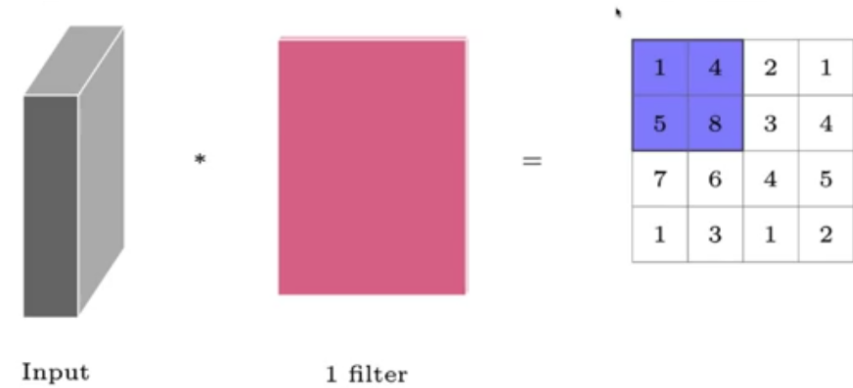
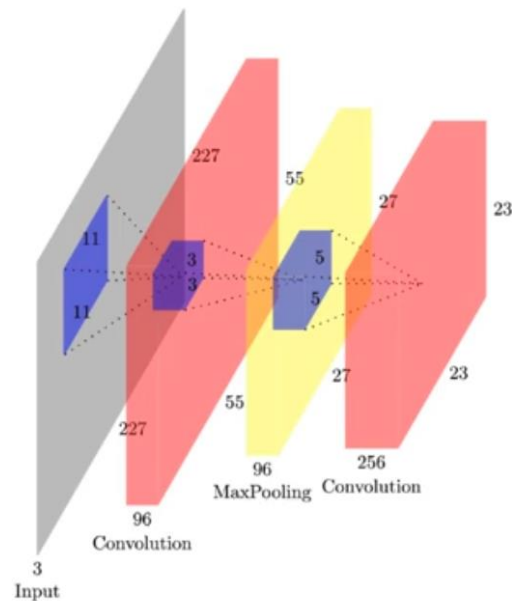
Sparse  
Connectivity &  
Weight Sharing



How is CNN  
different from  
a fully  
Connected  
Neural  
Network?



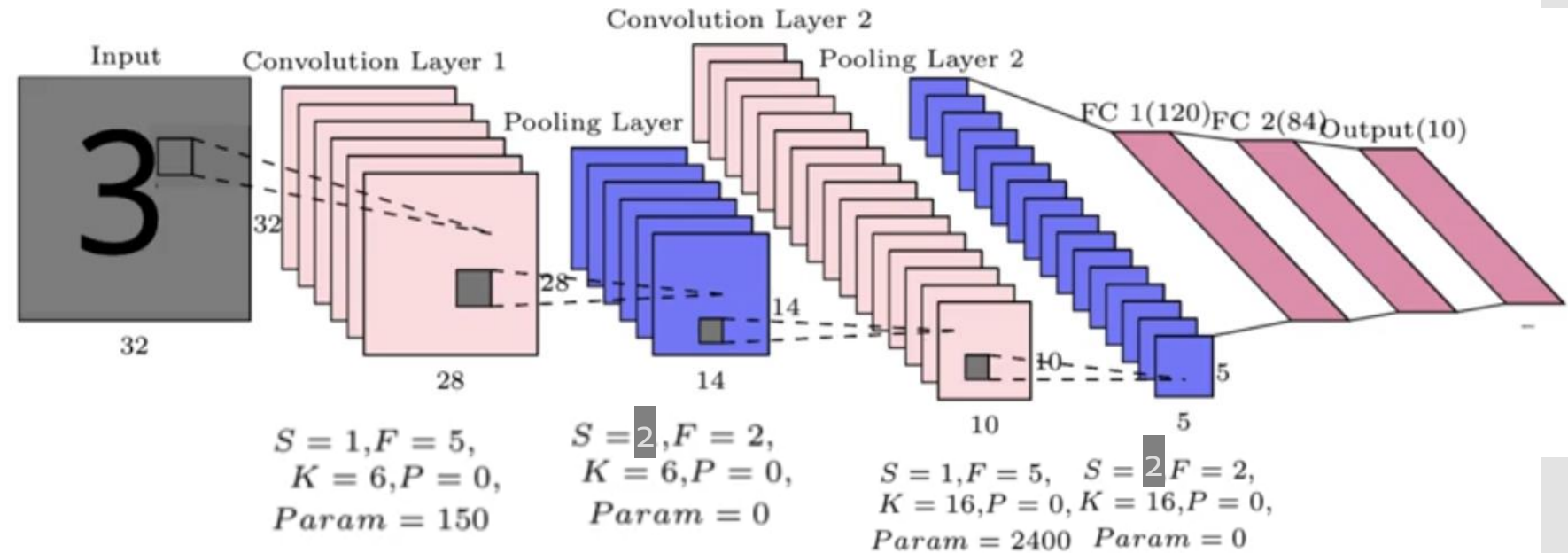
# What Is The Max Pooling Operation



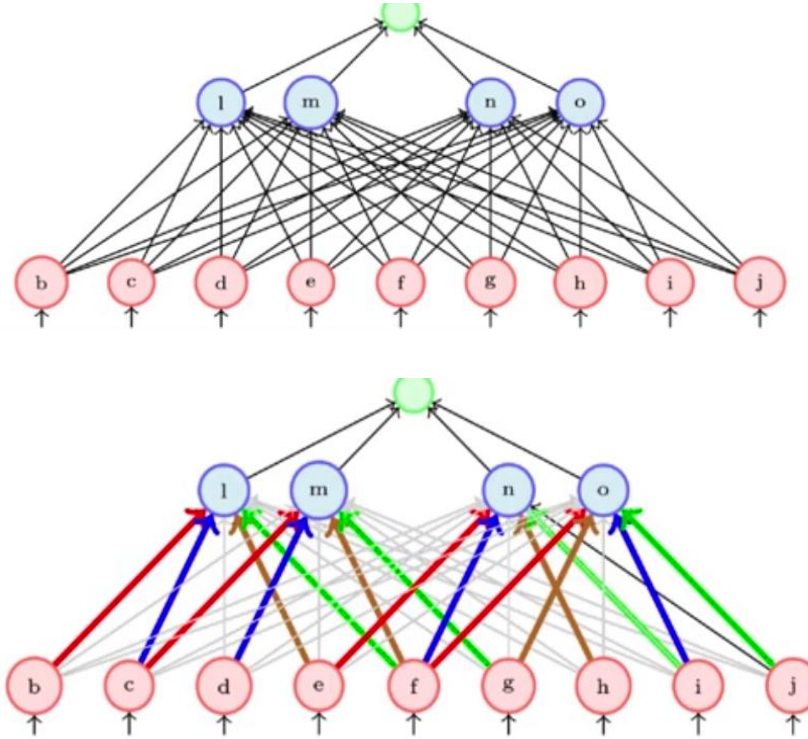


# How To Use CNN for Image Classification

(LeNet  
Architecture)



# How Do We Train A CNN Model?



- A CNN can be implemented as a Feedforward Network
- Only a few weights (in color) are active
- The rest of weights (in grey) are zero/inactive