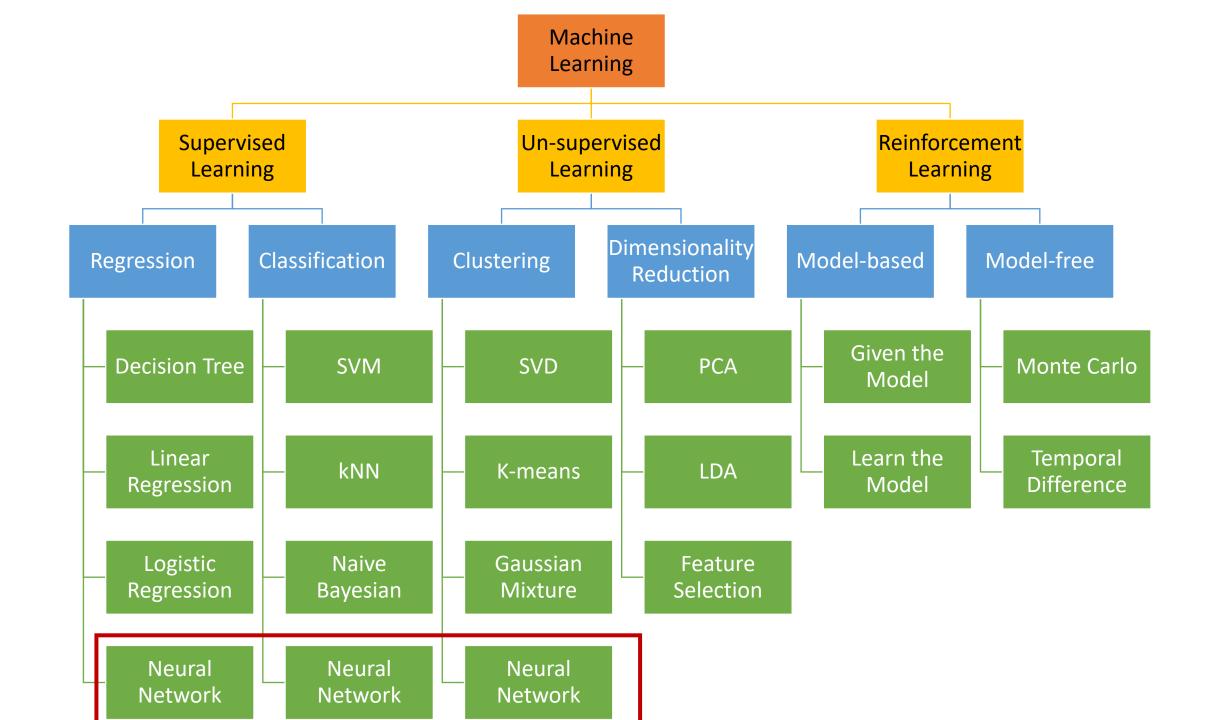
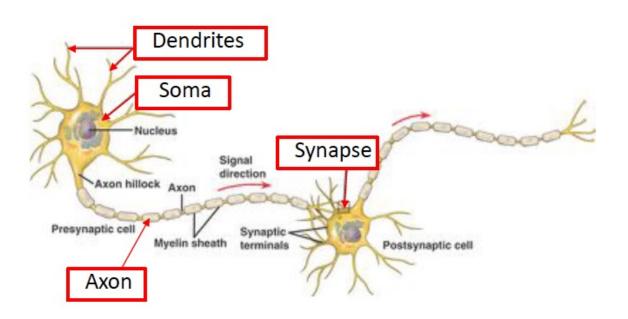
Applied Machine Learning Convolutional Neural Networks

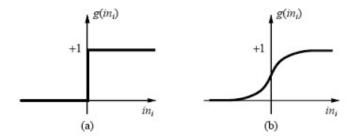
Ngan Le thile@uark.edu

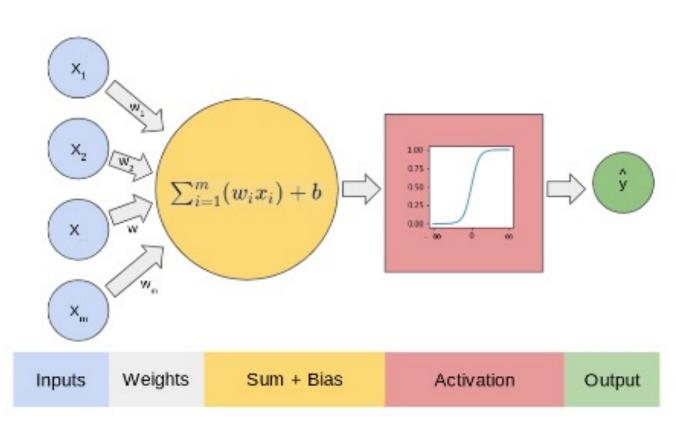


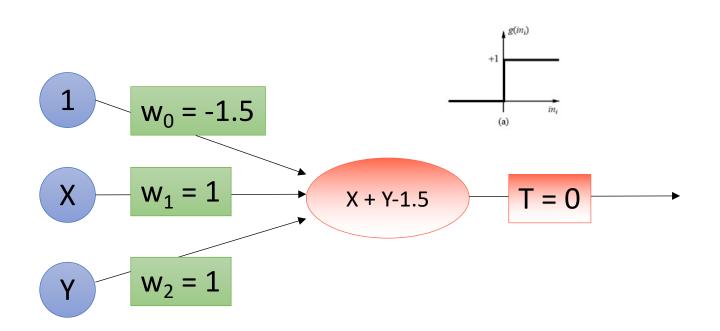
• A Neuron:

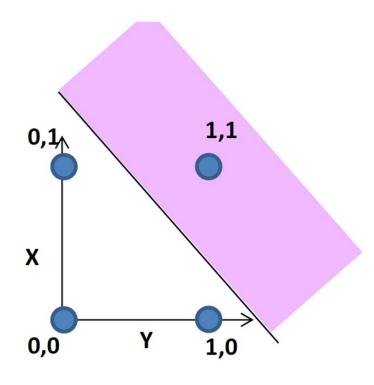


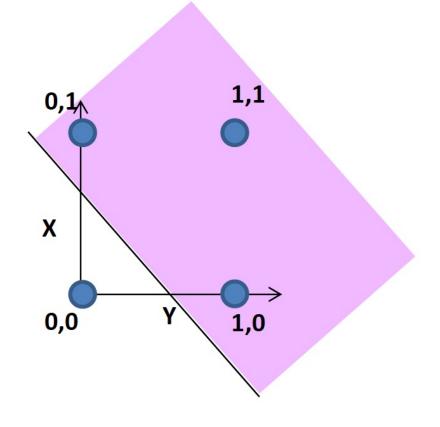
If two neurons consistently fire simultaneously, synaptic connection is increased, (if firing at different time, strength is reduced)

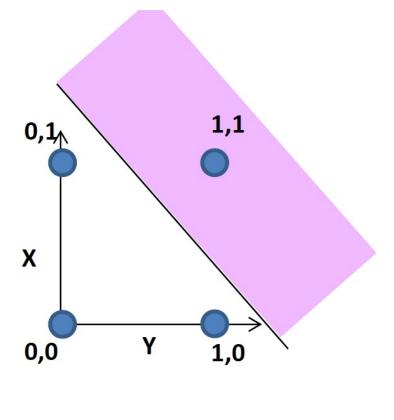


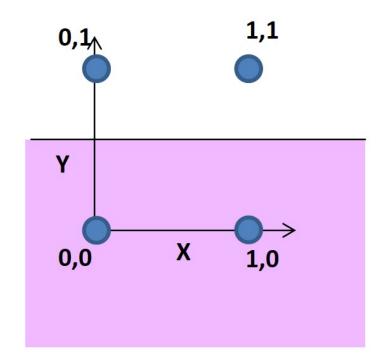






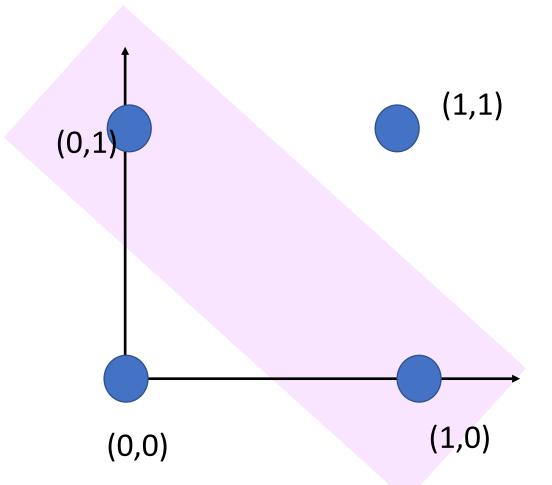




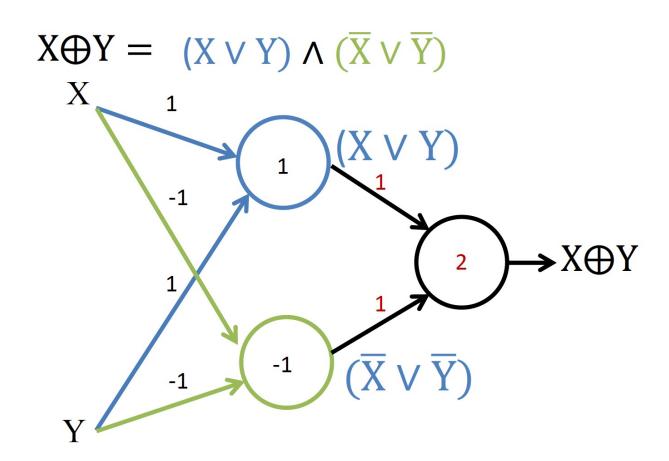


Neuron - Perceptron

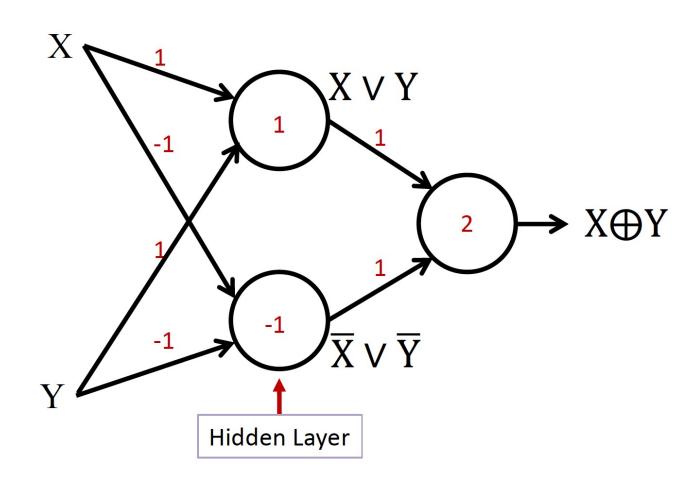
x_1	x_2	$x_1 \text{ XOR } x_2$
0	0	0
0	1	1
1	0	1
1	1	0



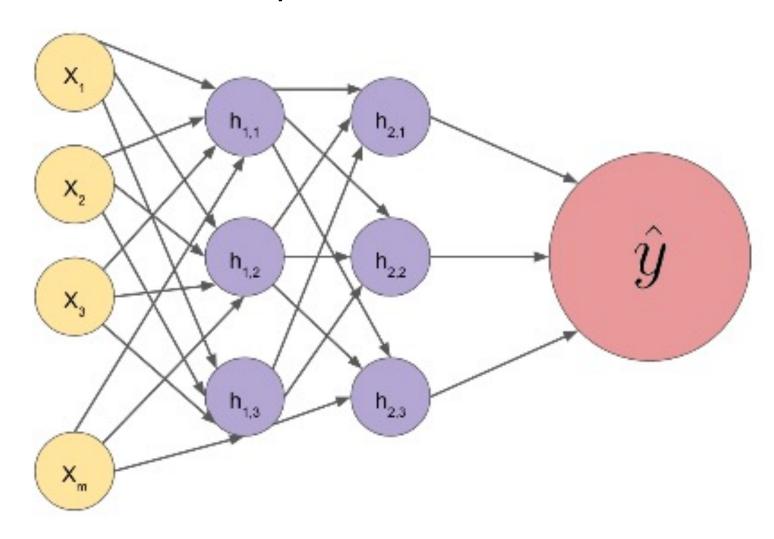
Multilayer Perceptron (MLP)



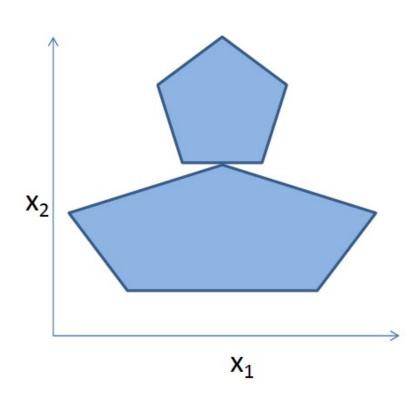
Multilayer Perceptron (MLP)

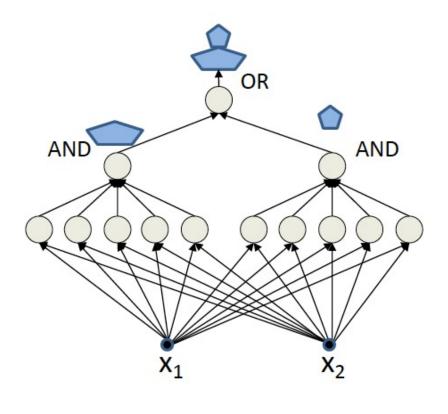


Neuron with Hidden Layers

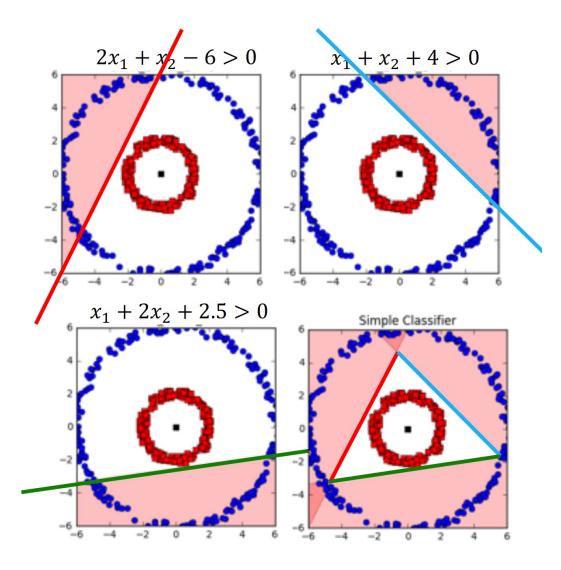


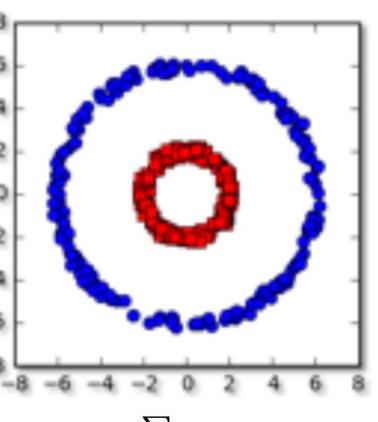
Neuron with Hidden Layers

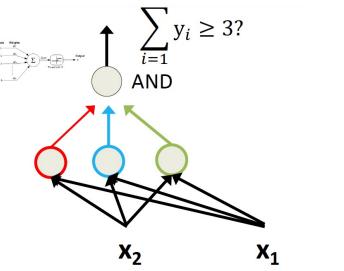




MLP for Classification



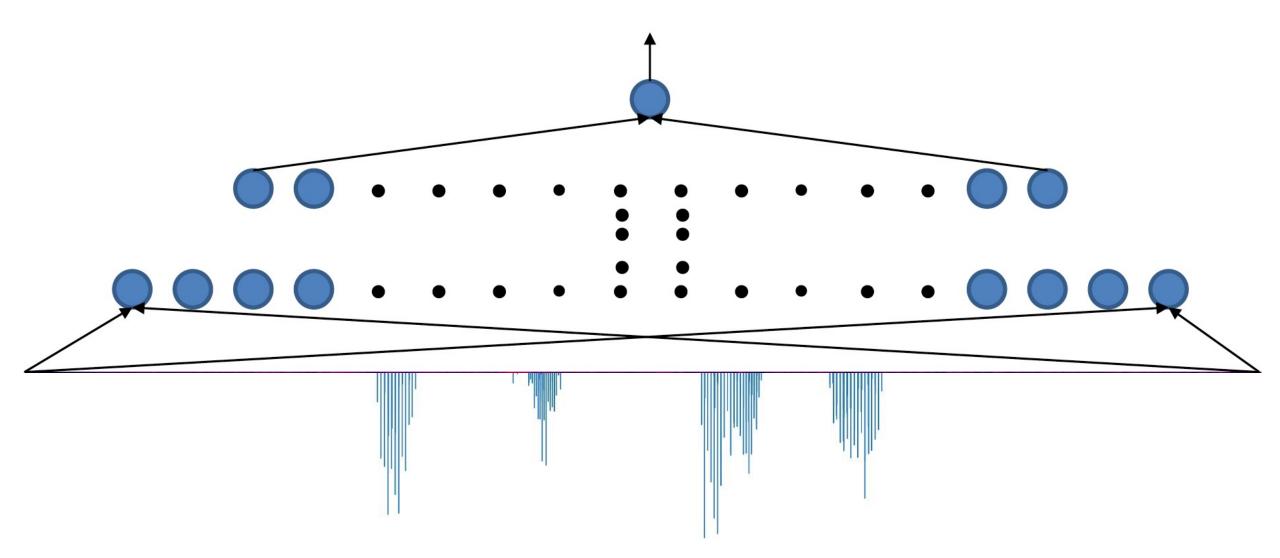






Using MLP to answer:

- Does this signal contain the word "Machine Learning"?
- If yes, where is the word "Machine Learning"?

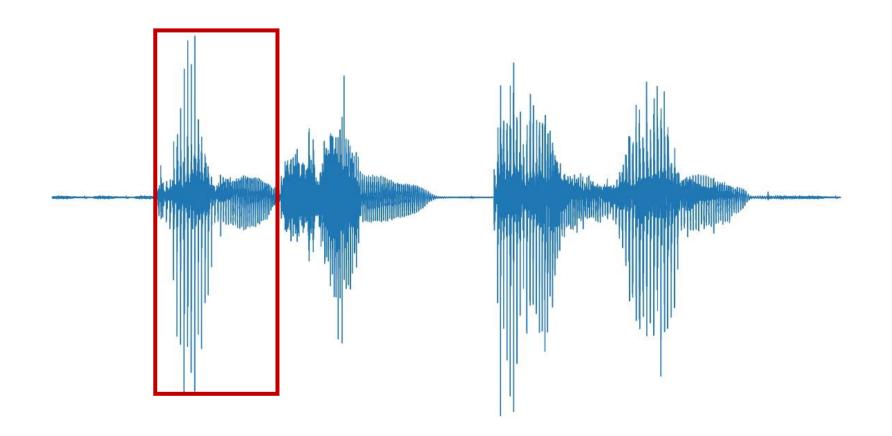


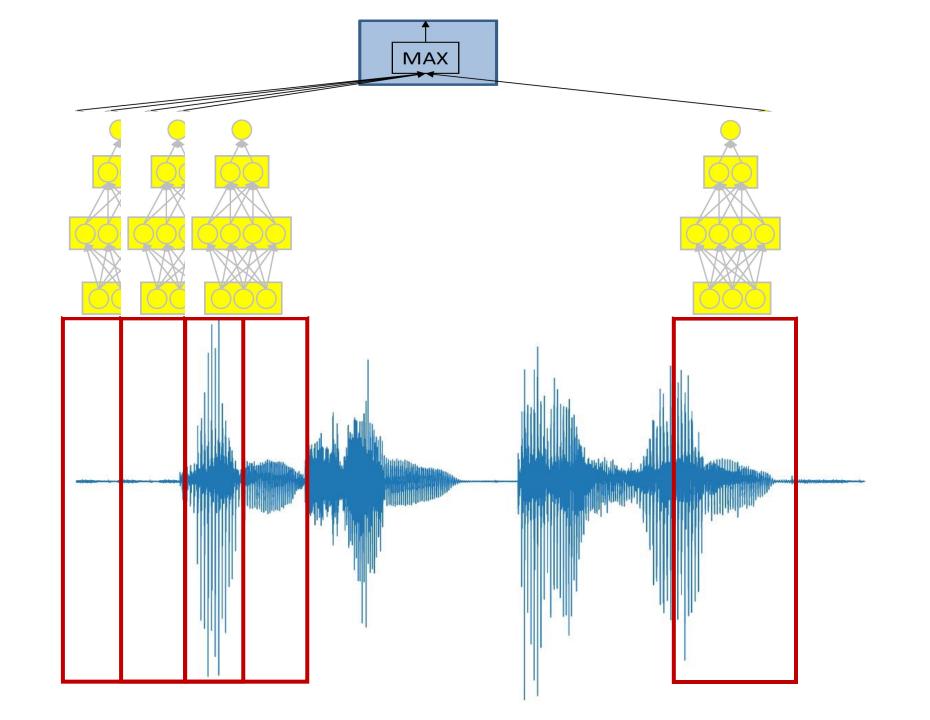
Search Dattorn

Search Pattern with MLP

Problems?

Scanning



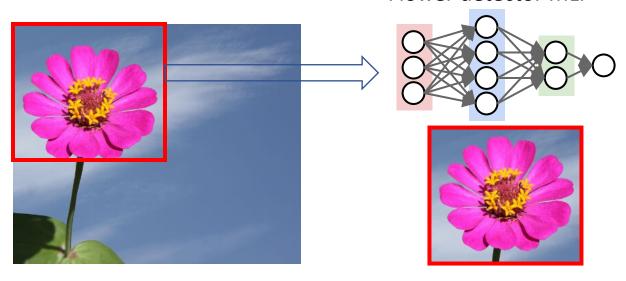


"Look" for the target object at each position

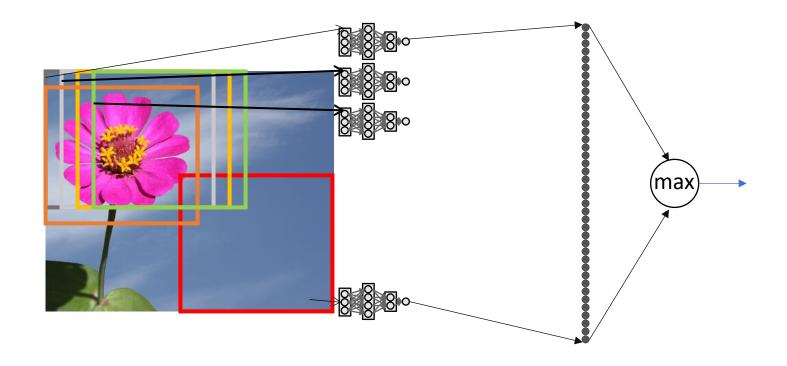




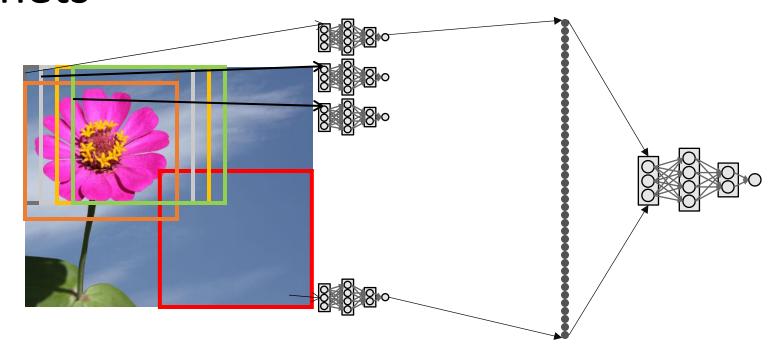
"Look" for the target object at each eposition

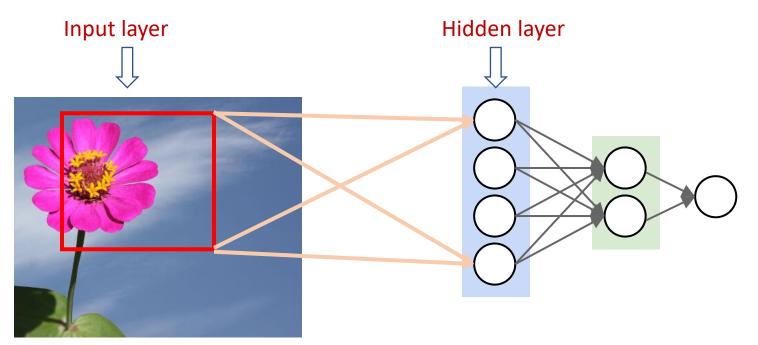


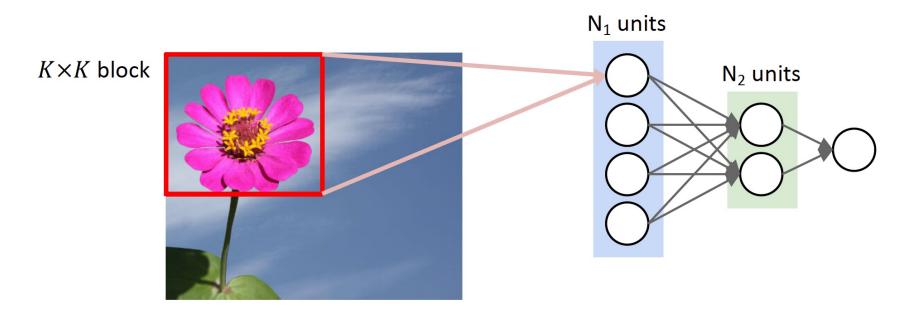
"Look" for the target object at each position

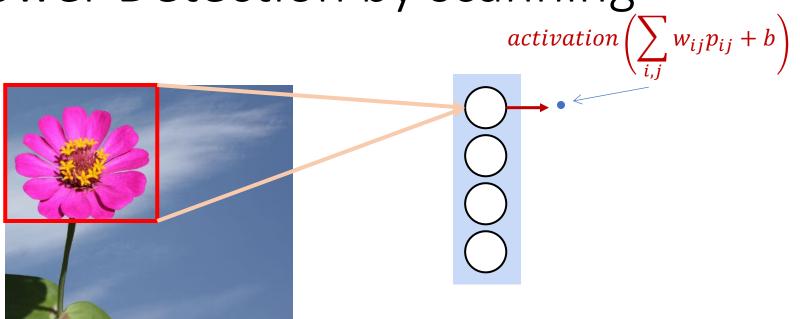


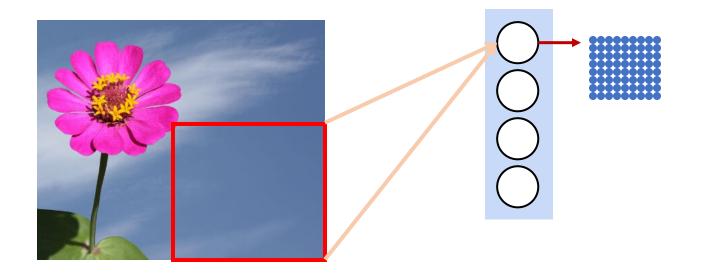
Its just a giant network with common subnets

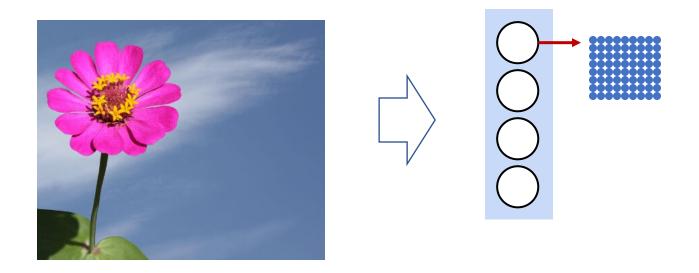


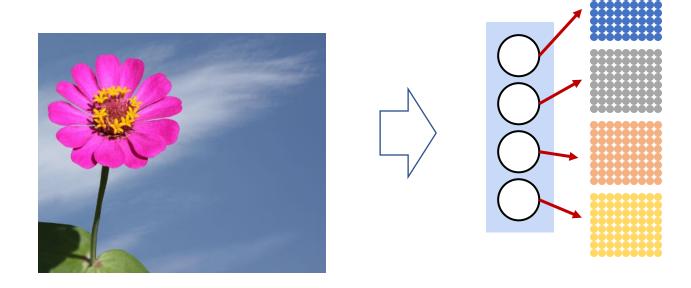


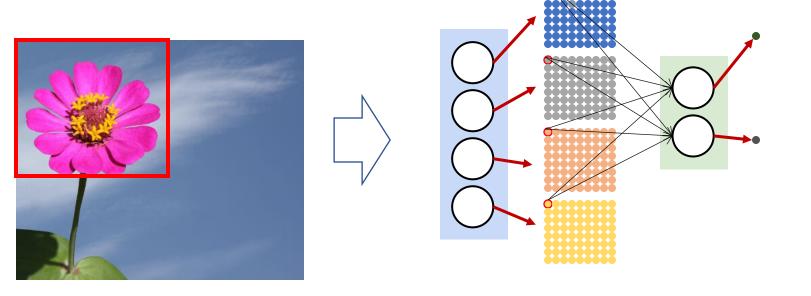


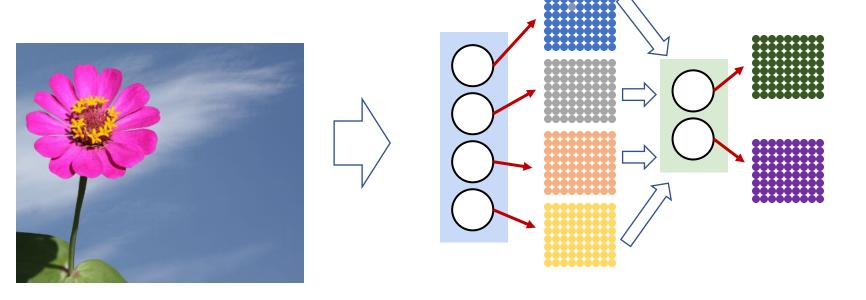


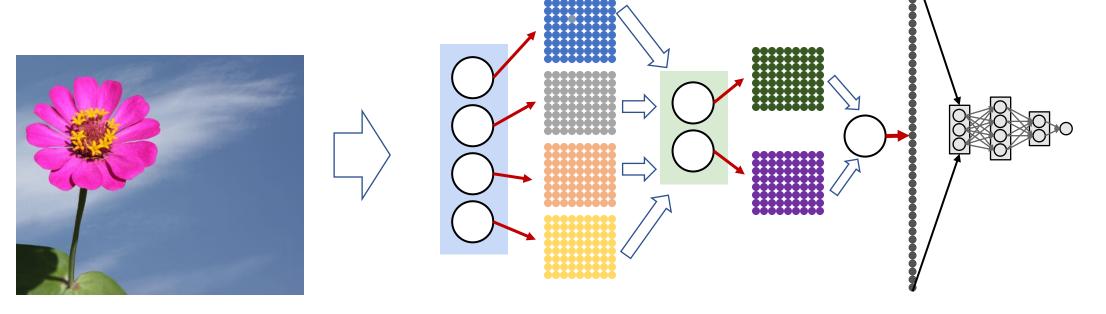


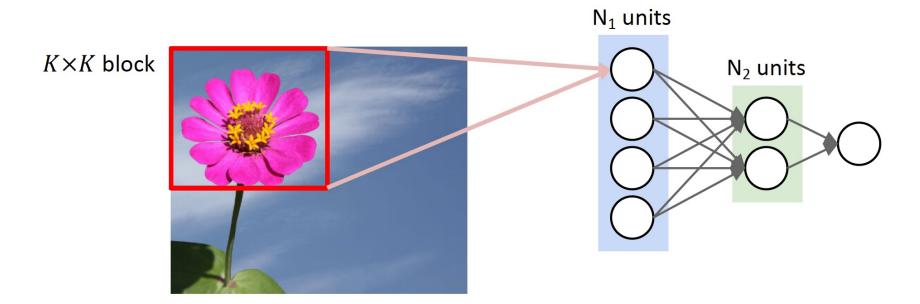












 $(K^2+1)N_1$ weights in first layer $(N_1+1)N_2$ weights in second layer $(N_{i-1}+1)N_i$ weights in subsequent ith layer

Total parameters:

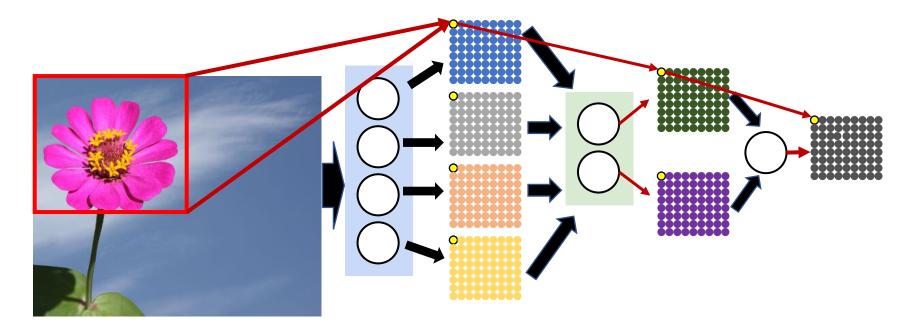
$$O(K^2N_1 + N_1N_2 + N_2N_3 \dots)$$

Example

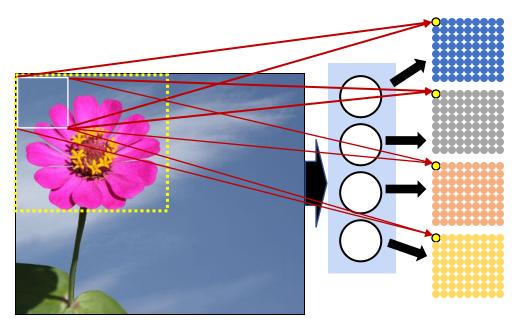
For this example, let K = 16, $N_1 = 4$, $N_2 = 2$, $N_3 = 1$

Total 1034 weights

Scanning with Distribution



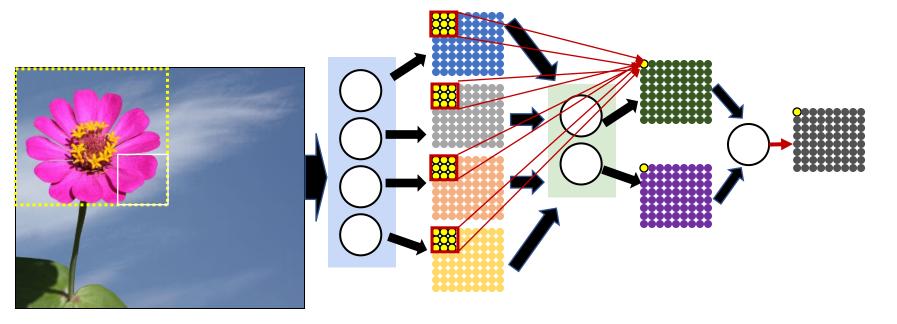
Flower Detection: Distributing the scan



The first layer evaluates smaller blocks of pixels

We can distribute the pattern matching over more (two) layers and still achieve the same block analysis at the second layer

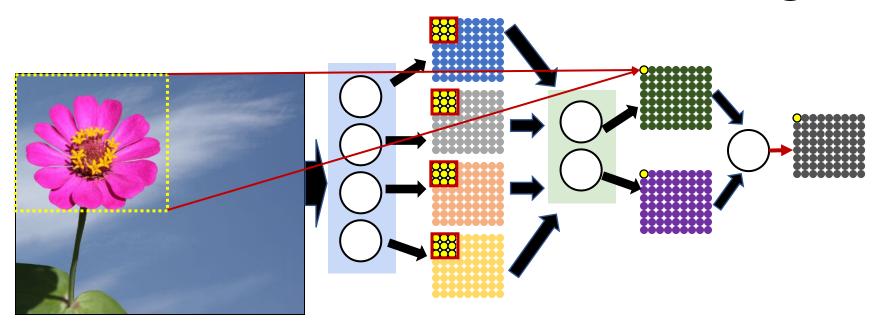
Flower Detection: Distributing the scan



The first layer evaluates smaller blocks of pixels

The next layer evaluates blocks of outputs from the first layer

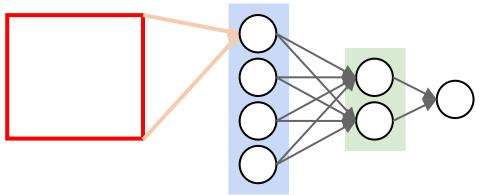
Flower Detection: Distributing the scan



The first layer evaluates smaller blocks of pixels

The next layer evaluates blocks of outputs from the first layer

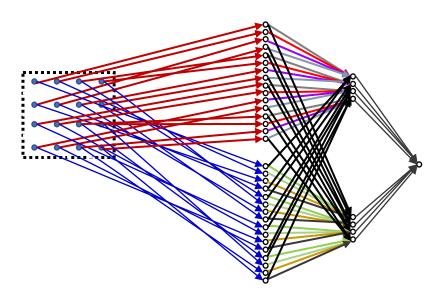
Conventional MLP, not distributed



- $\mathcal{O}(K^2N_1 + N_1N_2 + N_2N_3 \dots)$
- For this example, let K = 16, $N_1 = 4$, $N_2 = 2$, $N_3 = 1$

Total 1034 weights

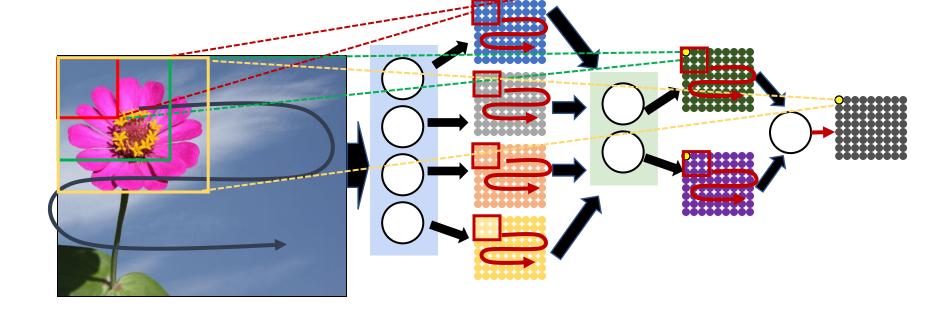
Distributed (3 layers)



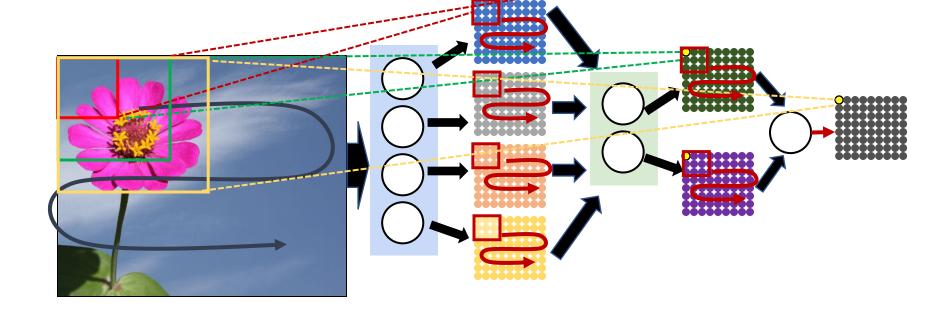
•
$$\mathcal{O}\left(L_1^2N_1 + L_2^2N_1N_2 + \left(\frac{K}{L_1L_2}\right)^2N_2N_3 + \cdot\right)$$

• Here, let
$$K=16$$
, $L_1=4$, $L_2=4$, $N_1=4$, $N_2=2$, $N_3=1$

• Total 64+128+8 = 160 weights



Convolutional Neural Networks

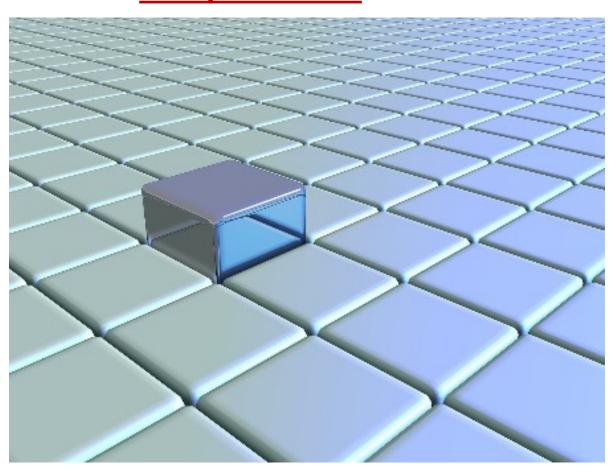


Each of the scanning neurons is generally called a "<u>filter</u>"

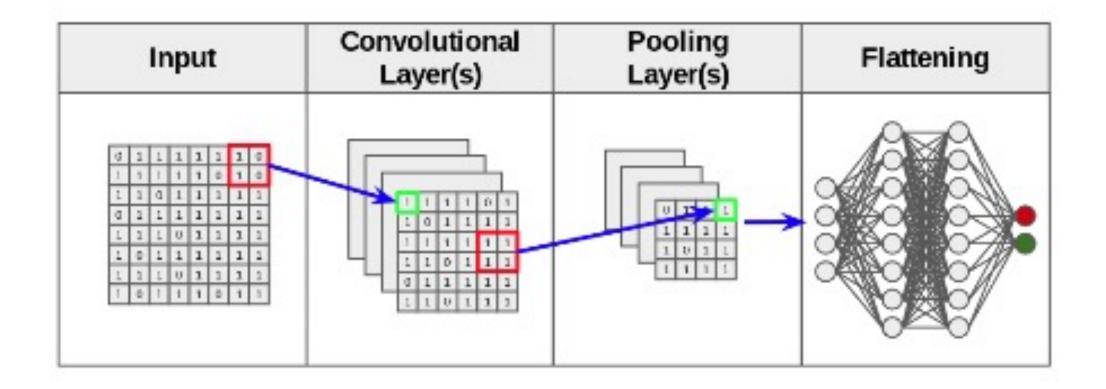
Its really a correlation filter as we saw earlier

Each filter scans for a pattern in the map it operates on

For a given neuron, the visual space that affects whether or not that neuron will fire is known as its "receptive field."



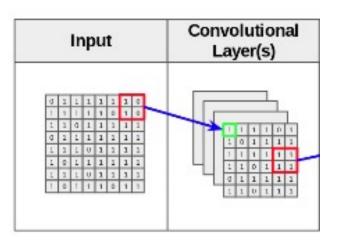
Convolutional Neural Networks



Convolutional Neural Networks: Convolution

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

1	0	1
0	1	0
1	0	1



Input

Filter

Bias: 0

Convolutional Neural Networks: Convolution

1	0	1
0	1	0
1	0	1

Filter

1,	1,0	1,	0	0
O _{×0}	1,	1,0	1	0
0 _{×1}	0 _{×0}	1,	1	1
0	0	1	1	0
0	1	1	0	0

Input Map

4	

Input

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0



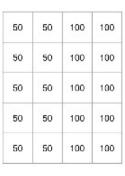
1	0	1
0	1	0
1	0	1

1 1, 1, 0, 0	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		1 1 1 0 0
$0 \ 1_{x_0} \ 1_{x_1} \ 1_{x_0} \ 0$	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$	4 3 4	$0_{x_1} \ 1_{x_0} \ 1_{x_1} \ 1 \ 0$
0 0, 1, 1, 1	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$		0, 0, 1, 1
0 0 1 1 0	0 0 1 1 0		$0_{x_1} 0_{x_0} 1_{x_1} 1 0$
0 1 1 0 0	0 1 1 0 0		0 1 1 0 0
1 1 1 0 0	1 1 1 0 0		1 1 1 0 0
0 1, 1, 0	4 3 4 0 1 1 _{x1} 1 _{x0} 0 _{x1}	4 3 4	0 1 1 1 0
$0 \ \ 0_{x_0} \ \ 1_{x_1} \ \ 1_{x_0} \ \ 1$	2 4 0 0 1 1 1 1	2 4 3	0, 0, 1, 1 1
$0 \ \ 0_{x_1} \ \ 1_{x_0} \ \ 1_{x_1} \ \ 0$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		0, 0, 1, 0
0 1 1 0 0	0 1 1 0 0		0, 1, 0 0
1 1 1 0 0			
0 1 1 1 0	4 3 4 0 1 1 1 0	4 3 4	
0 0, 1, 1, 1	2 4 3 0 0 1 _{x1} 1 _{x0} 1 _{x1}	2 4 3	
0 0, 1, 1, 0	$\begin{bmatrix} 2 & 3 & 0 & 0 & 1_{x_0} & 1_{x_1} & 0_{x_0} \end{bmatrix}$	2 3 4	
0 1 1 0 0	0 1 1 0 0		

Blurring

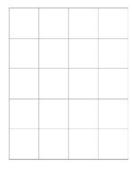
1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

Blurring



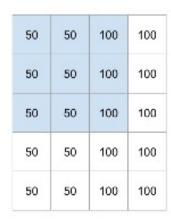
1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

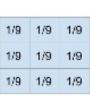
9 1/9 1 Kernel Mask Filter



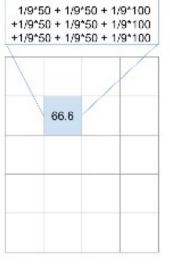
Image

New Image

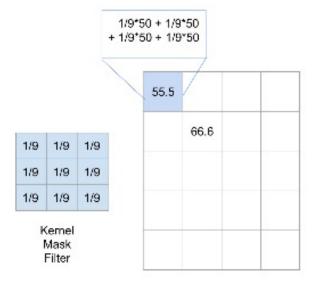




Kernel Mask Filter



50	100	100
50	100	100
50	100	100
50	100	100
50	100	100
	50 50 50	50 100 50 100 50 100



Image

New Image

Image

New Image

Edge Detection

$$G_{x} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

Measures changes in x-direction (i.e. detects vertical lines)

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

Measures changes in y-direction (i.e. detects horizontal lines)

Edge Detection

50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100



50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100

$$G_{x} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

0	

50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100

D	200	

50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100

$$G_{x} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

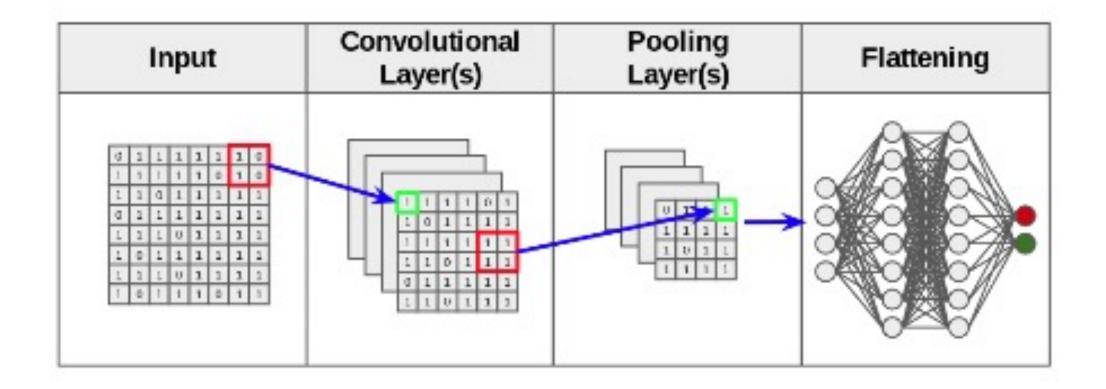
0	200 /9	300 /9	

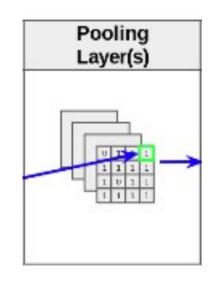
			***	400	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100

$$G_{x} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

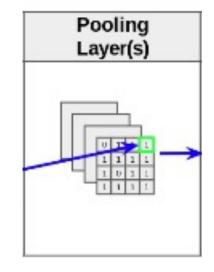
0	200 /9	300 /9	0	

Convolutional Neural Networks





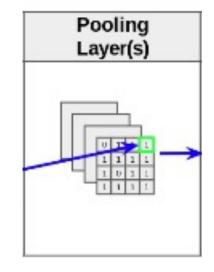
Pooling is a type of downsampling that often occurs after convolution. The goal is, without losing much information, to reduce the size of the training data before it goes into the fully connected network.



- 1. Pick a window size
- 2. Pick a strike
- 3. Move your window across each of the filtered image
- 4. Take maximum/minimum, average value in each window

29	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

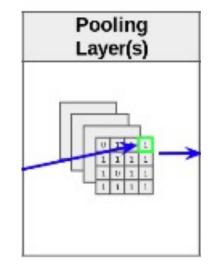
29	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6



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0	100	70	38
12	12	7	2
12	12	45	6

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0	100	70	38
12	12	7	2
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29	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

29	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

	29	15	28	184	29
	0	100	70	38	0
'	12	12	7	2	12
	12	12	45	6	12

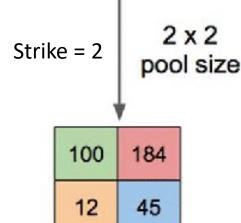
			i
29	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

ling

Pooling Layer(s)

Max Poo	ling
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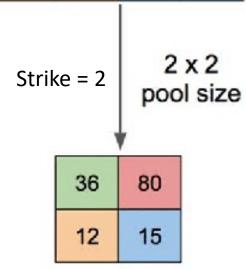
29	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6
		2	v 2



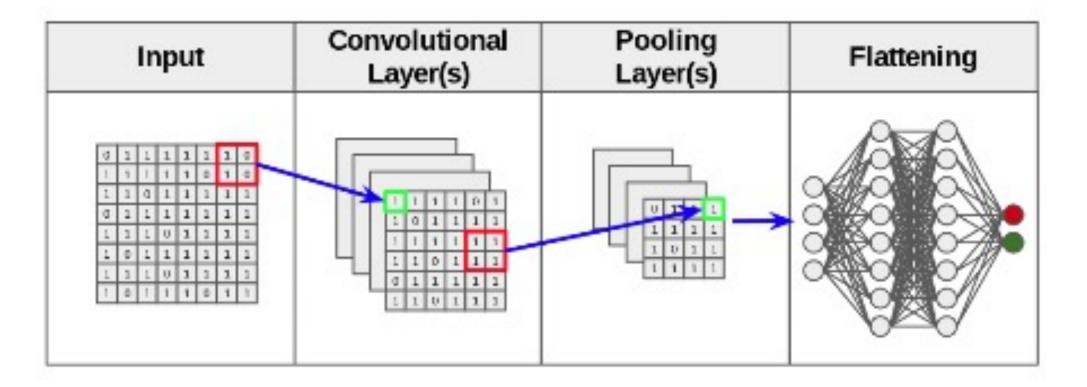
Pooling Layer(s)

Average Po	oling
------------	-------

31	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6



Hyperparameters



How many of each layers and in what orders

Hyperparameters

- Convolution Layer
 - Number of filters
 - Size of filters
- Pooling Layers
 - Window size
 - Strike
- Fully Connected Layers
 - Number of nodes