

# Convolutional Neural Networks





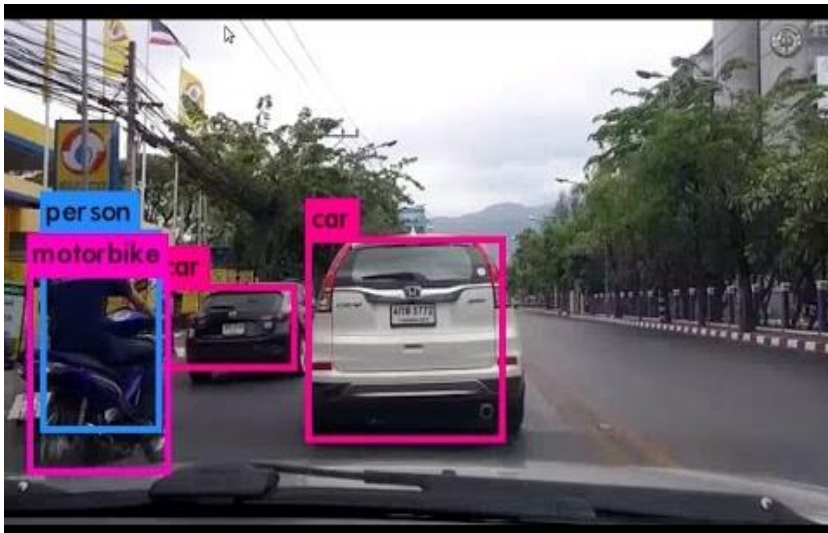
Face Recognition



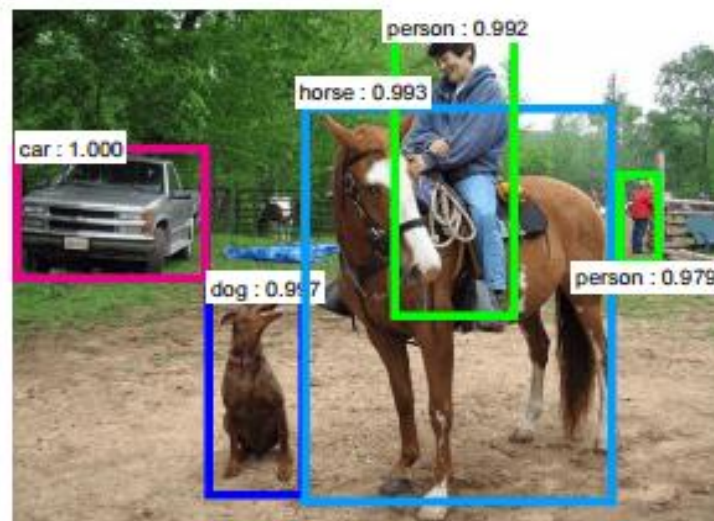
Style Transferring



Image quality enhancement  
Beautification



Object detection (Self driving car)

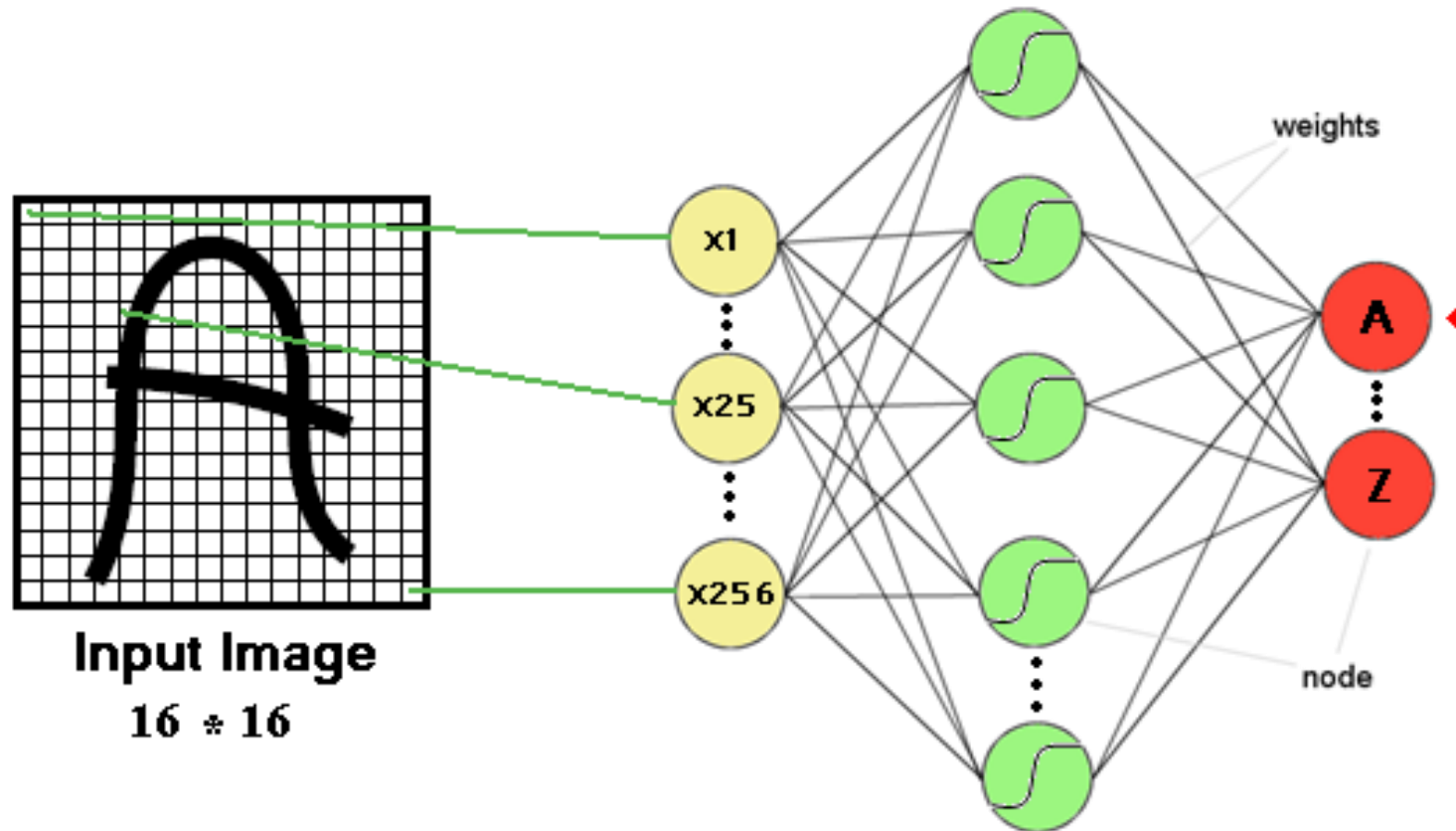


Classification



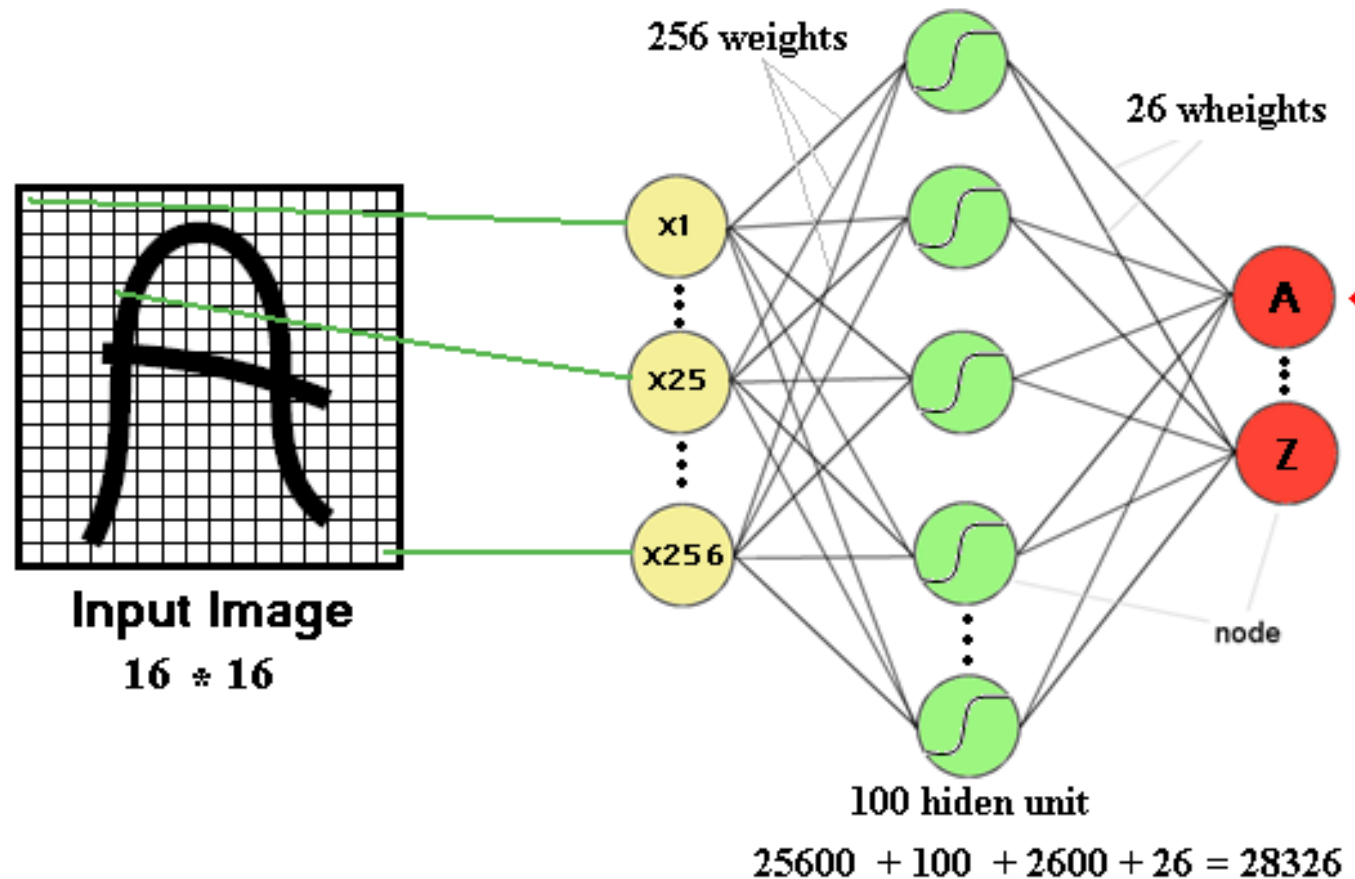
Gesture Recognition

# Multi-layer perceptron and image processing



# Even a simple 16x16 image

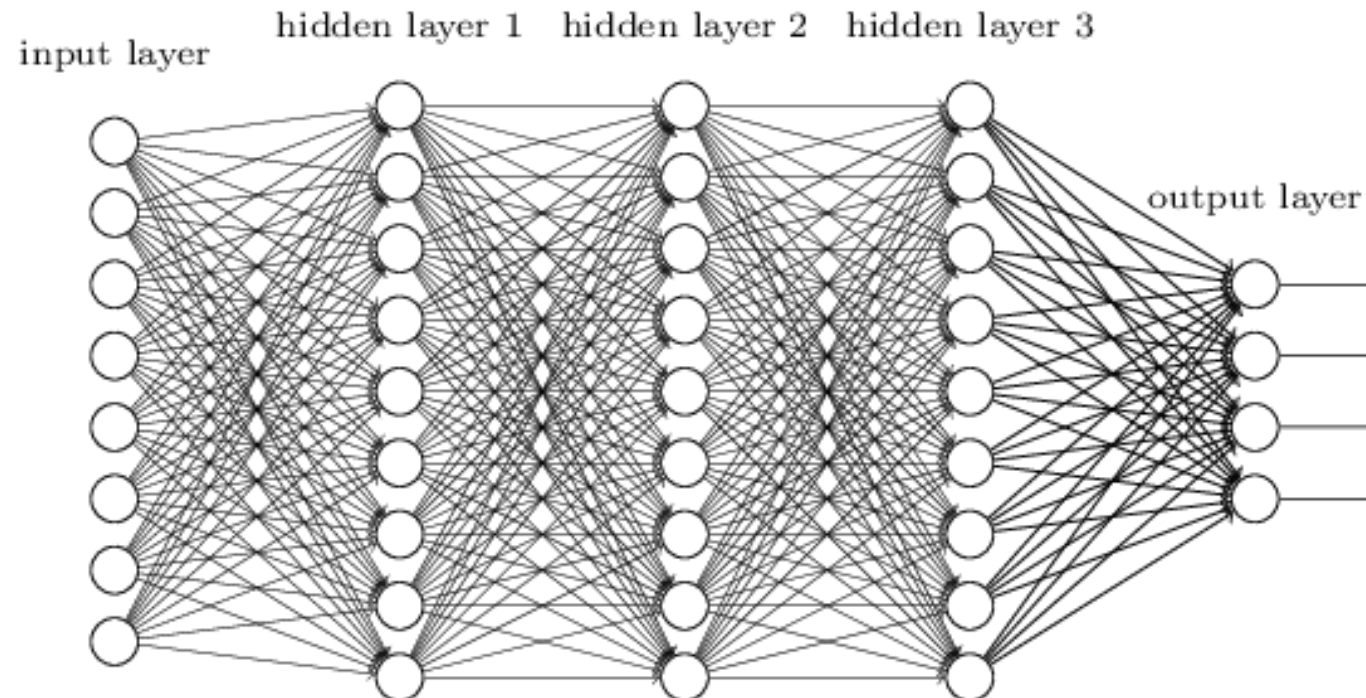
- ☹️  $256 \times 100 + 100 \text{ bias} + 100 \times 26 \text{ output neurons} + 26 \text{ bias} = 28236$
- ☹️ the number of **trainable parameters** becomes extremely large





# ANN: Too many parameters

- We know it is good to learn a small model.
- From this fully connected model, do really need all the edges?
- Can some of these be shared?



# Can we do with less information?

- How much information we can throw away and still recognize the object?



**10%**

**20%**

**50%**

**75%**

- **Subsampling pixels will not change the object**

bird



Subsampling

bird



**We can subsample the pixels to make image smaller**



**fewer parameters to characterize the image**





# CNNs Vs. ANNs

- ANNs suffer from **curse of dimensionality** when it comes to high resolution images
- We use filters (receptive fields) to exploit **spatial locality** by enforcing a local connectivity pattern between neurons of adjacent layers
- **Parameter Sharing**
- **Sparsity of connection**

# Convolution

- Convolution is a pointwise multiplication of two functions to produce a third function.
- Primary purpose of convolution in CNN is to extract features from the input image.
- Matrix formed by sliding the filter over the image and computing the dot product is called the 'Convolved Feature' or 'Activation Map' or the 'Feature Map'.

# Convolution Example

3	0	1	2	7	4
1	5	8	9	3	1
2	7	2	5	1	3
0	1	3	1	7	8
4	2	1	6	2	8
2	4	5	2	3	9

6X6 Matrix (nXn)

Convolution

\*

1	0	-1
1	0	-1
1	0	-1

3X3 Filter (fXf)

=

-5	-4	0	8

(n-f+1)X(n-f+1)

# Convolution Example

3	0 1	1 0	2 -1	7	4
1	5 1	8 0	9 -1	3	1
2	7 1	2 0	5 -1	1	3
0	1	3	1	7	8
4	2	1	6	2	8
2	4	5	2	3	9

6X6 Matrix (nXn)

Convolution

\*

1	0	-1
1	0	-1
1	0	-1

3X3 Filter (fXf)

=

-5	-4	0	8

(n-f+1)X(n-f+1)

# Convolution Example

1 <sub>x1</sub>	1 <sub>x0</sub>	1 <sub>x1</sub>	0	0
0 <sub>x0</sub>	1 <sub>x1</sub>	1 <sub>x0</sub>	1	0
0 <sub>x1</sub>	0 <sub>x0</sub>	1 <sub>x1</sub>	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved  
Feature



# Detecting Vertical edges

$6*6 = 36$

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0



\*

1	0	-1
1	0	-1
1	0	-1



$4*4=16$

0	30	30	0
0	30	30	0
0	30	30	0
0	30	30	0



# Filter Weights

1	1	1
0	0	0
-1	-1	-1

Horizontal Filter

1	0	-1
2	0	-2
1	0	-1

Sobel Filter

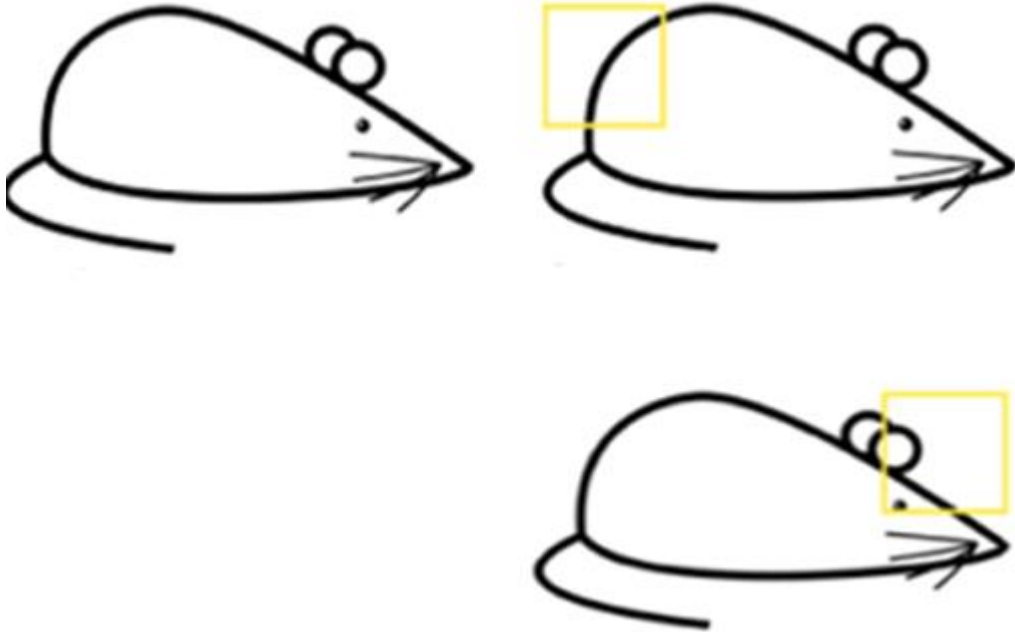
3	0	-3
10	0	-10
3	0	-3

Schorr Filter

$w_1$	$w_2$	$w_3$
$w_4$	$w_5$	$w_6$
$w_7$	$w_8$	$w_9$

Convolutional Neural Networks  
automatically estimates the  
weights of the filter

# More Intuition



0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

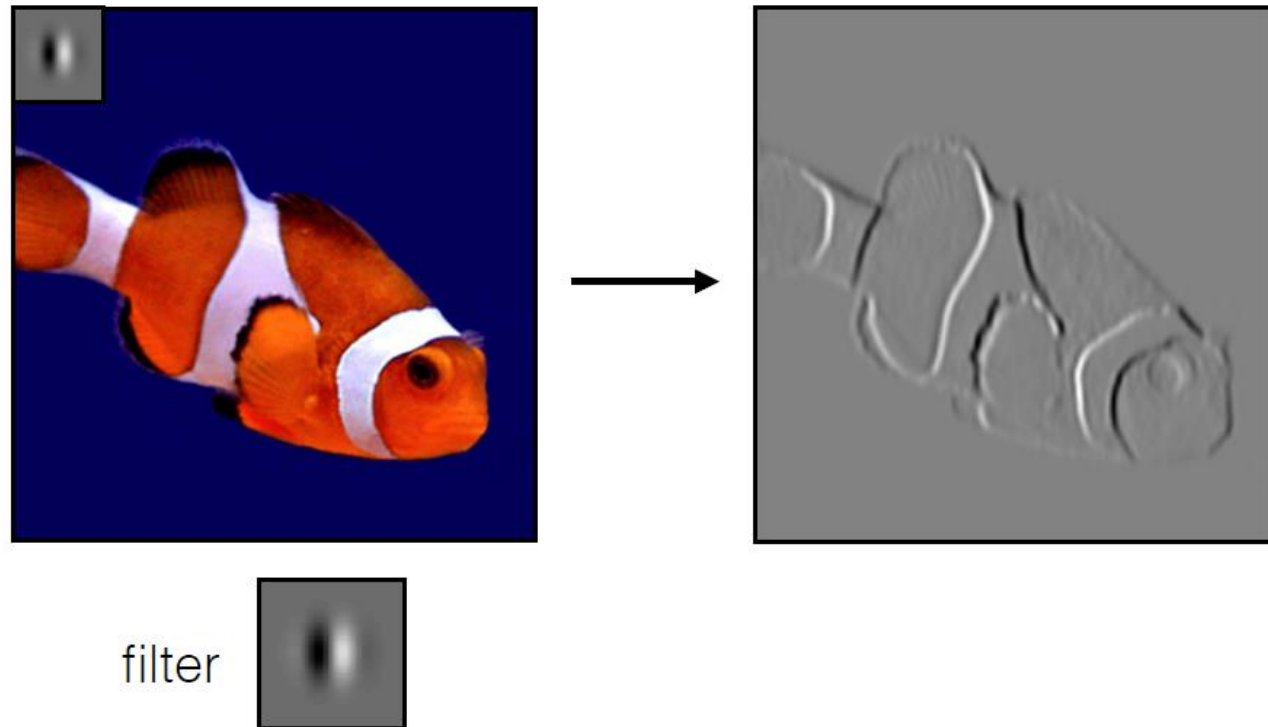


Visualization of a curve detector filter

# Interpretation

Convolution is just another way of computing  $W^T X$

In CNN, **input** is **image**, **kernel** is **convolution filter** to be learned, **response** is the **feature map**



# Padding

Padding is used to preserve the original dimensions of the input

Zeros are added to outside of the input

Number of zero layers depend upon the size of the kernel

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

5X5 (with padding)

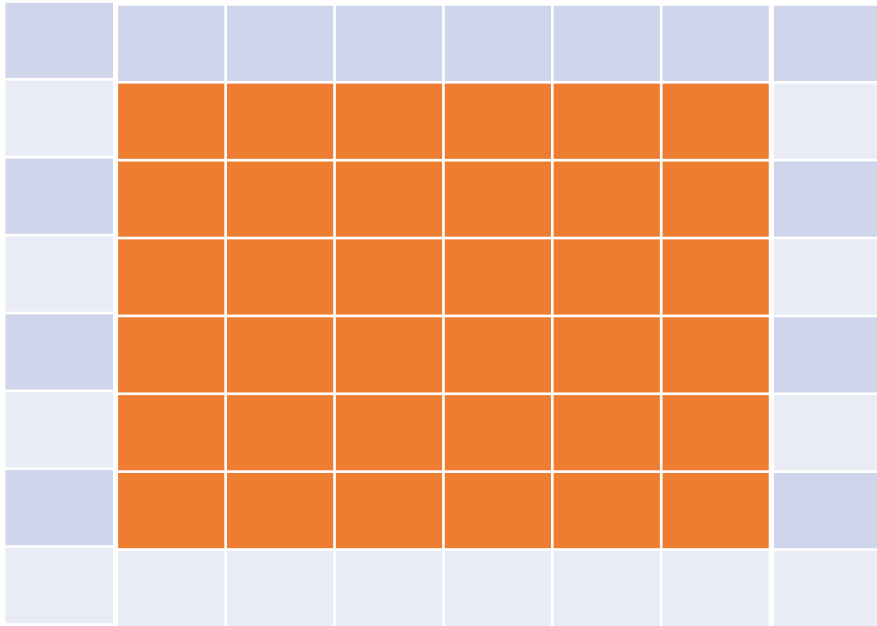
x1	x0	x1
x0	x1	x0
x1	x0	x1

2	2	3	1	1
1	4	3	4	1
2	2	4	3	3
1	2	3	4	1
1	2	3	1	1

5X5

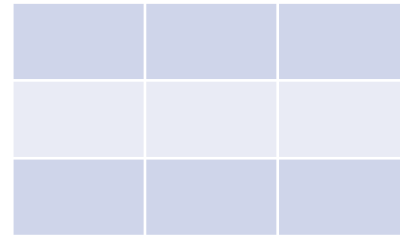


# Padding



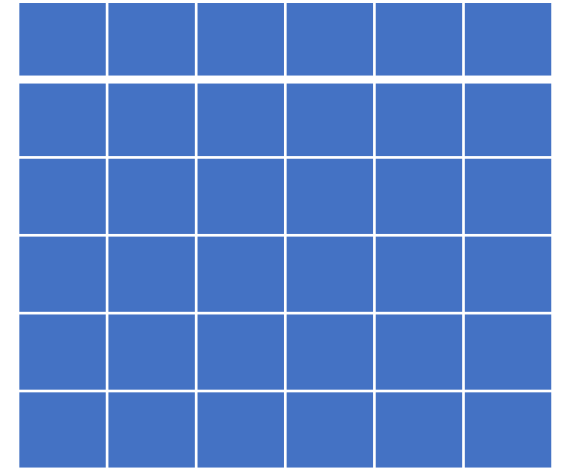
$n \times n$  6X6 to 8X8 Padding=1

\*



$f$  3X3

=



$(n-f+1) \times (n-f+1)$  to  $(n+2p-f+1) \times (n+2p-f+1)$

# Stride

3	0	1	2	7	4
1	5	8	9	3	1
2	7	2	5	1	3
0	1	3	1	7	8
4	2	1	6	2	8
2	4	5	2	3	9

6X6 Matrix

Stride=s (3 Here)  $\text{Floor}(\frac{n+2p-f}{s} + 1) \times \text{Floor}(\frac{n+2p-f}{s} + 1)$

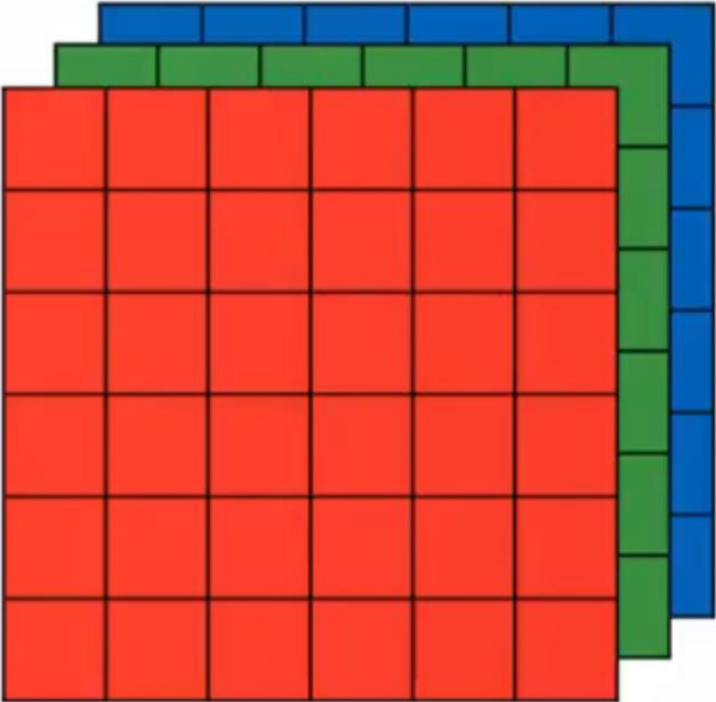
1	0	-1
1	0	-1
1	0	-1

3X3 Filter

-5	8
-3	-16

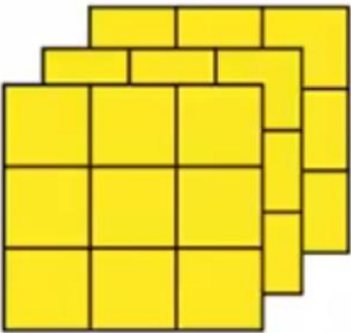
2X2

# Channels



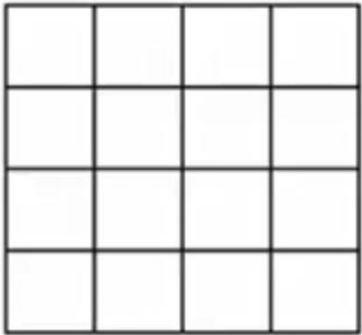
6X6 Matrix

\*



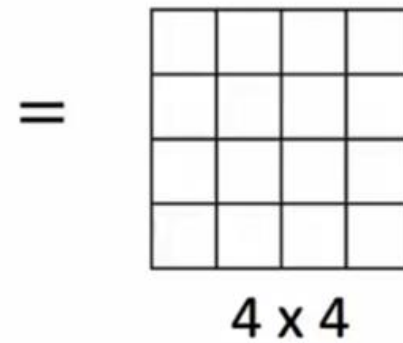
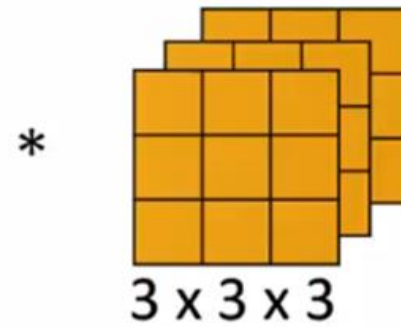
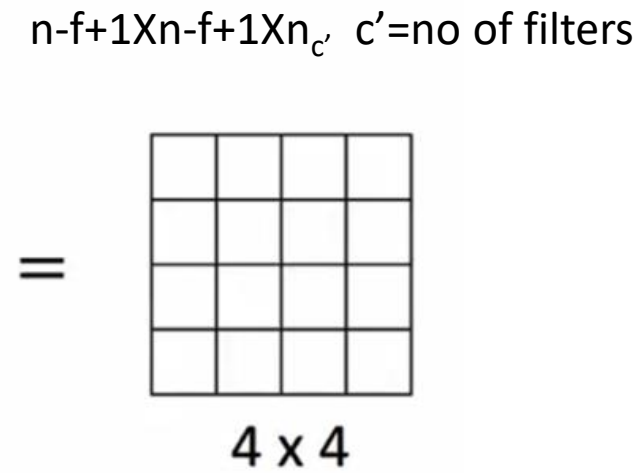
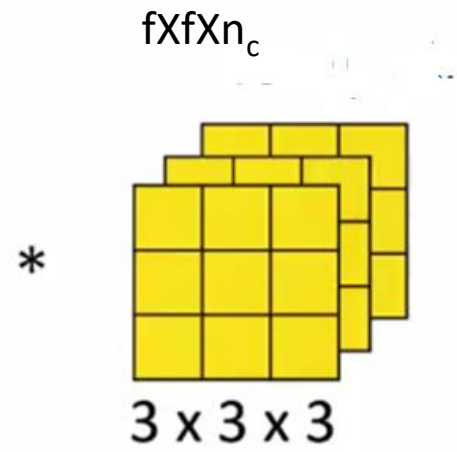
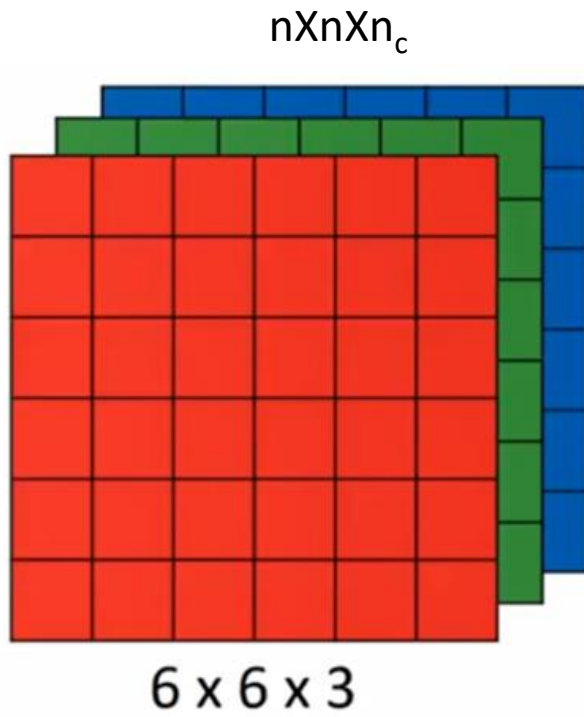
3X3 Filter

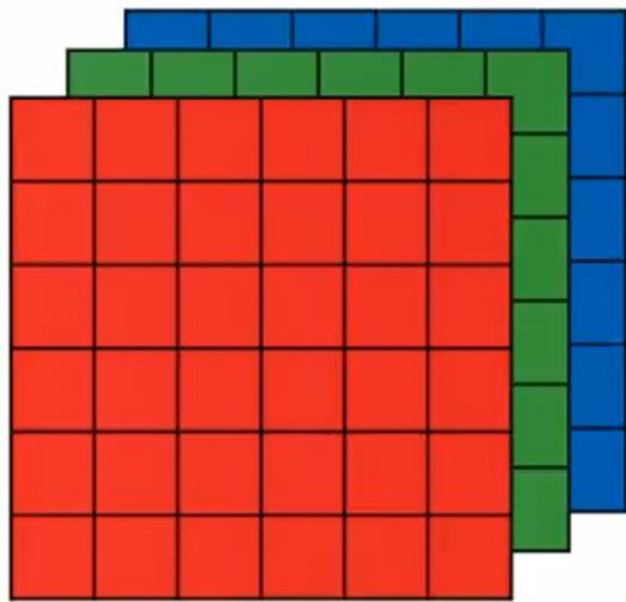
=



4 x 4

Padding =0 Stride=1

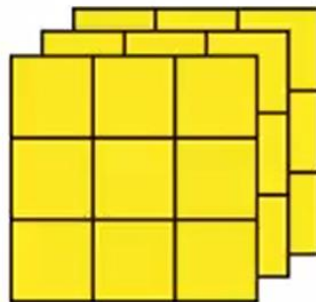




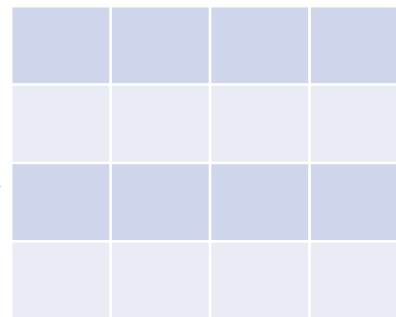
$6 \times 6 \times 3$

$a^{[0]}$

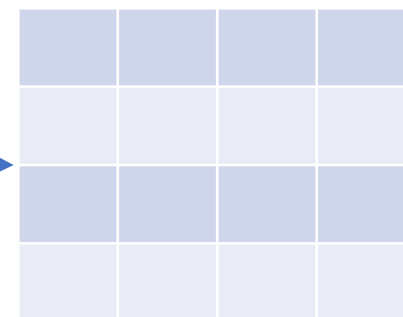
\*



$3 \times 3 \times 3$



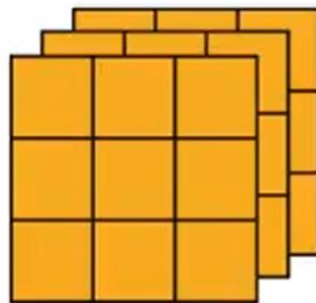
+b1



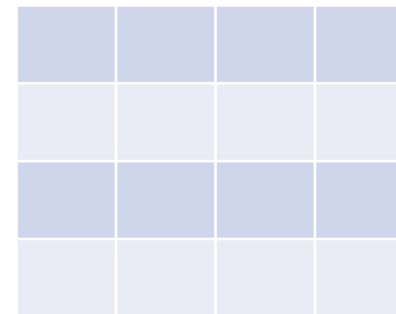
ReLU

ReLU

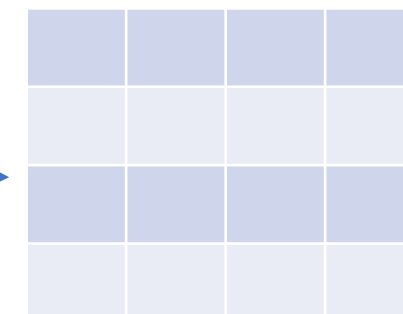
\*



$3 \times 3 \times 3$



+b2



$w^{[1]} a^{[0]}$

$a^{[1]} 4 \times 4 \times 2$

$w^{[1]}$  2 filters means two units here



# Pooling

1	4	6	3
1	8	9	7
2	9	1	2
3	4	4	3

8	9
9	4

Max Pooling : One example of pooling layer

$f=2$

$s=2$  4X4 converted to 2X2

Function of Pooling is to progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network.

# Pooling

1	4	6	3
1	8	9	7
2	9	1	2
3	4	4	3

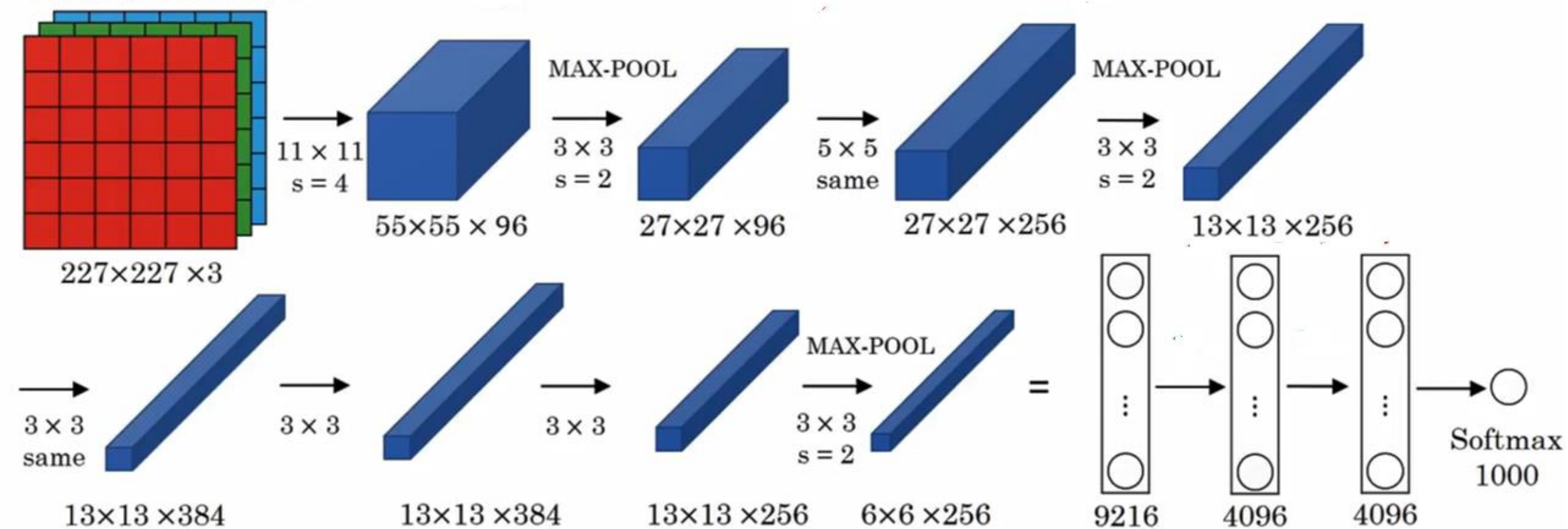
3.5	6.25
4.5	2.5

Average Pooling : Another example of pooling layer

$f=2$

$s=2$  4X4 converted to 2X2

# AlexNet



# Famous CNN Models

LeNet - 1990

AlexNet - 2012

ZFNet - 2013

GoogLeNet - 2014

VGGNet - 2014

ResNet - 2015

Inception v3 - 2016

MobileNet – 2017

Squeezenet - 2017

# Open Source Implementations

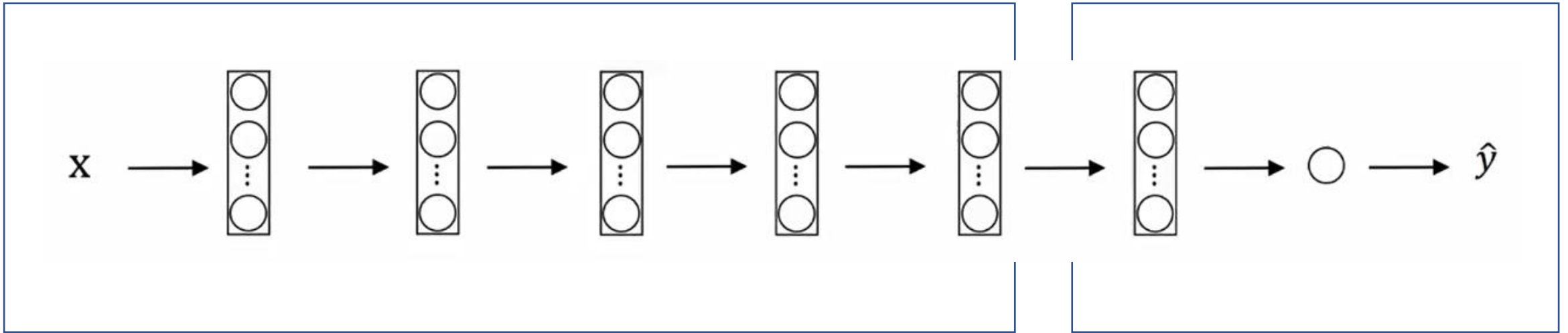
- Developers has spent months in developing some good open source networks
- Many of them have access to high-speed GPUs and have the capacity to do lot of experimentation for months
- It is always good to start with a known open source implementation
- Search <name of the network> Github
- you will get few links pointing you to Github profiles of individuals who have put these network models along with the learned weights online
- Download or clone these network depending upon whether you are working on the your machine or remotely on a notebook
- Use this trained model fully or partially depending upon your requirements



# Transfer Learning

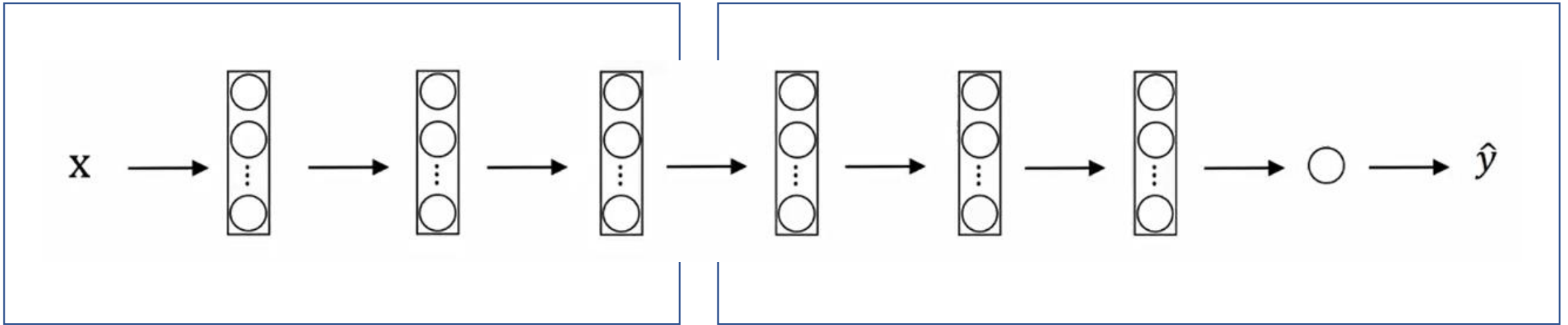
- Sharing the Knowledge gained solving one problem and applying to a different but related problem
- Transfer Learning is next popular driver of deep learning after supervised learning
- The feature spaces of the source and target domain are different, e.g. the documents are written in two different languages.
- The marginal probability distributions of source and target domain are different, e.g. the documents discuss different topics.
- Simulation training is becoming a hot area within the sphere of Deep Learning. Few labs have also started using AR/VR Technologies to be integrated for making advance learning models for some of the critical problems area

# Transfer Learning – Small Data



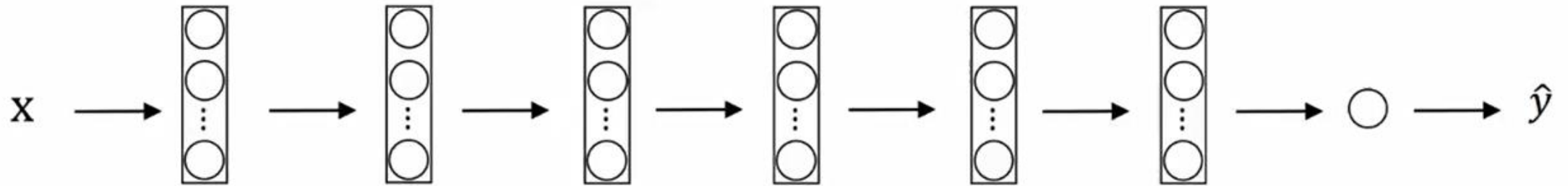
- \*Finding a Bengal Cat or British Cat where you have small dataset of these categories of cats
- \*You can download a cat classifier and train last few layers on your data specifically
- \*In Popular Deep Learning platforms, now you have good support for transfer learning
- \* Functions like `Trainable_Parameters` and Freezing specific layers are available

# Transfer Learning-Mid Size Data



In this category we use initial set of layers from the open source model and use the trained weight values. For the remaining layers there are two ways to handle: a) either we can train the layers from start or b) we can start the weight optimization from the existing set of weights that we have received from the open source model

# Transfer Learning- Enough Data



In scenarios, where we have enough data to train our new model, open source model may still be useful. We can use the pre-trained weights of the model from the same domain and consider that as a starting point for our model. It may be much easier and faster to adapt these model for new set of data that we want to train upon.