# Intro to Numpy, Pandas, PyTorch and Keras

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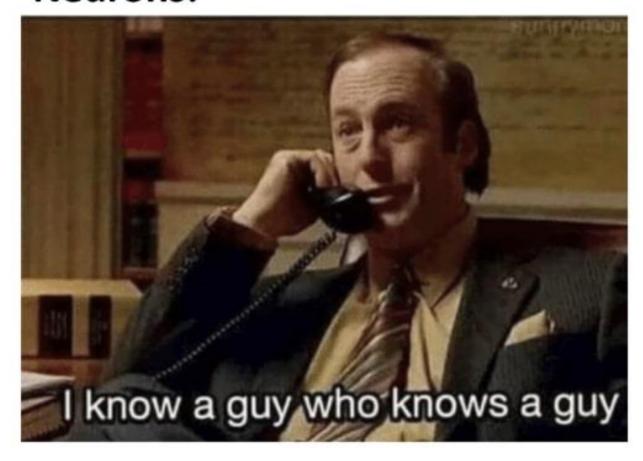
# Agenda

- Numpy & Pandas intro
- Artificial Neural Network
- Implementation with Keras
- What is PyTorch?
- PyTorch and Numpy functions
- Perceptron using numpy/torch
- Autograd
- Multi layer perceptron for MNIST
- Performance difference in CNN



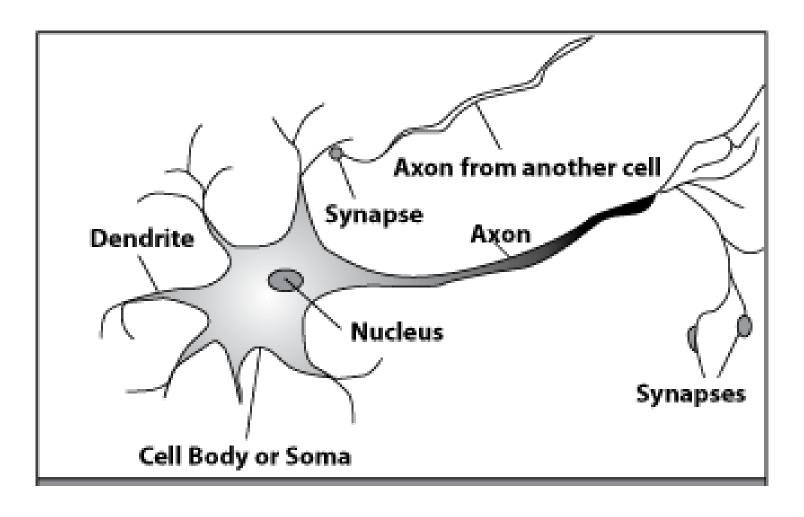
#### **Neural Networks**

# How Neural Networks work? Neurons:





# **Biological Neuron**



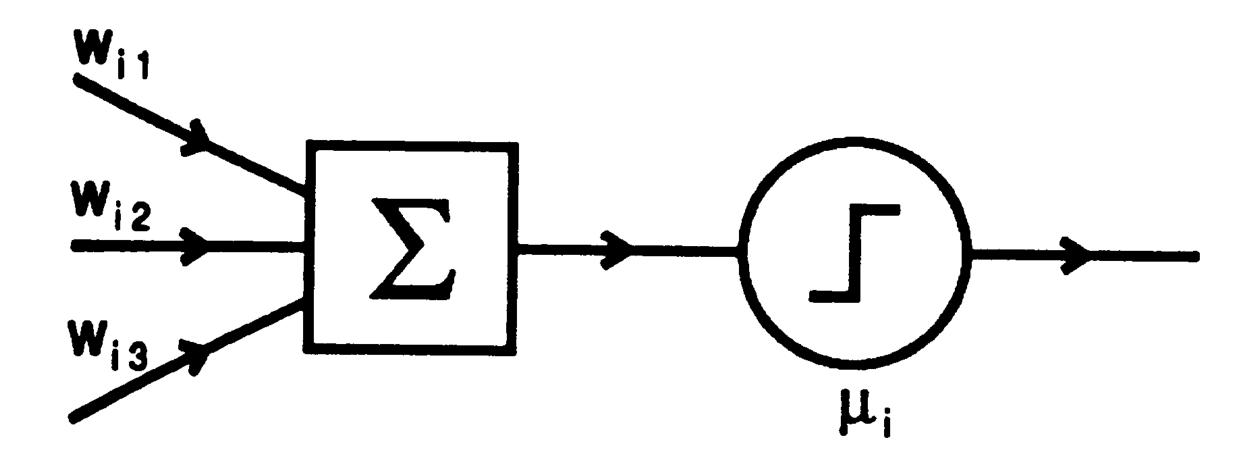


#### **Neurons in brain**

- Although heterogeneous, at a low level, the brain is composed of neurons.
- A neuron receives input from other neurons (generally thousands) from its synapses.
- Inputs are summed up.
- When the input exceeds a threshold, the neuron sends a spike (electrical pulse) that travels to next neuron(s) via axons.



# **McCulloh-Pitts Neuron**





# **Single Layer perceptron**

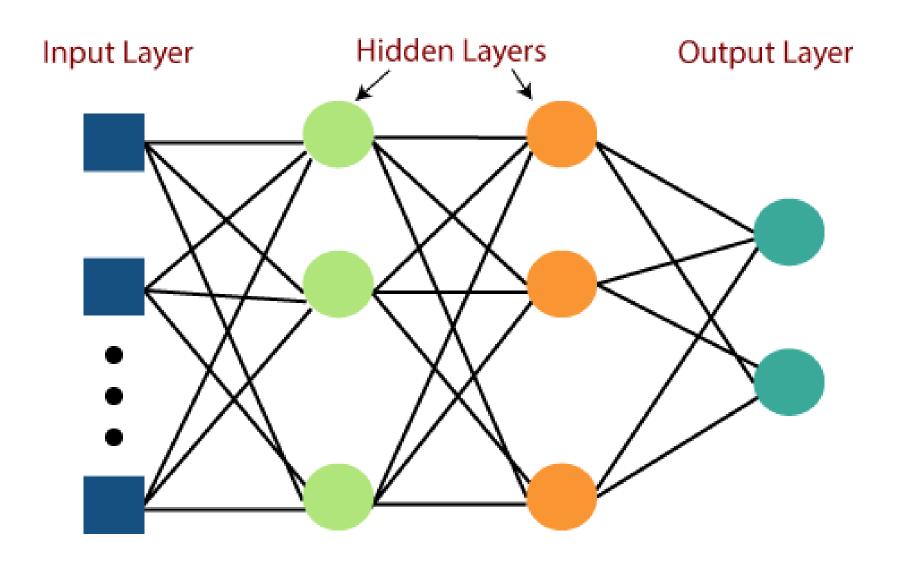
• Initialize w<sub>ij</sub> with random values.

• Repeat until  $w_{ij}$  (t+1)  $\sim = w_{ij}$  (t)

• 
$$\mathbf{w}_{\text{new}} = \mathbf{w}_{\text{old}} - \eta \frac{\partial E}{\partial w}$$



# Multi Layer perceptron



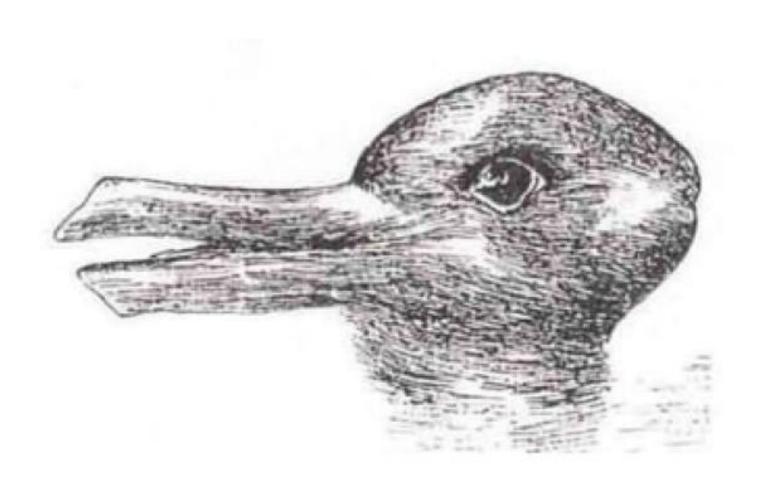












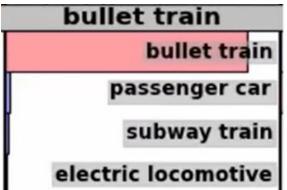


# Examples from the test set (with the network's guesses)

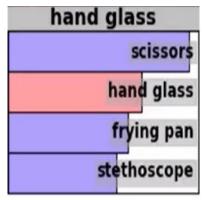






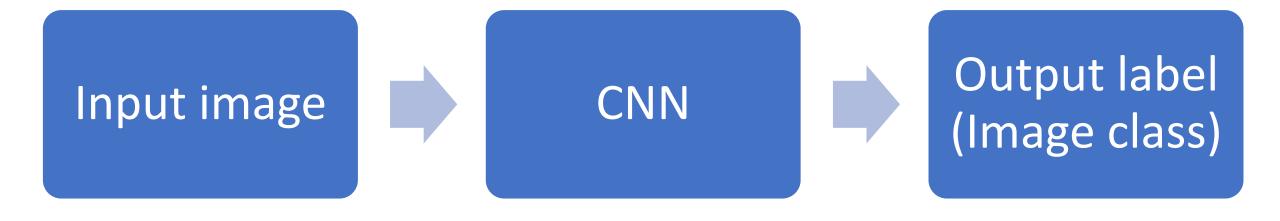








Img source: Geoffrey Hinton

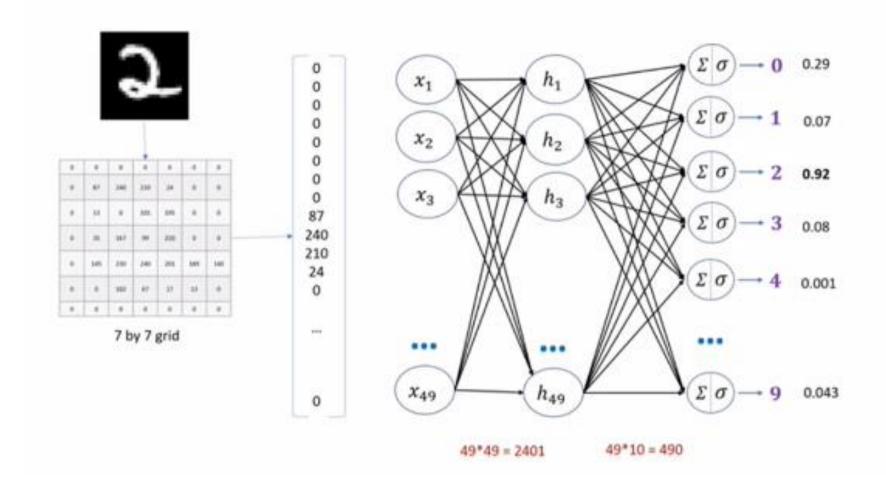




99



# **Digit recognition using ANN**





# What about color images?

- Image size = 1920 \* 1080 \* 3
- First layer neurons = 6 million (approx.)
- Hidden layer neurons = 4 million (approx.)



Image size =  $1920 \times 1080 \times 3$ 

Weights between first layer and hidden layer = 6M \* 4M = 24 millions.



# **Drawbacks of ANN for Image classification**

• Enormous computations

• Treats local pixels same as pixels far apart

• Sensitive to location of an object in an image.

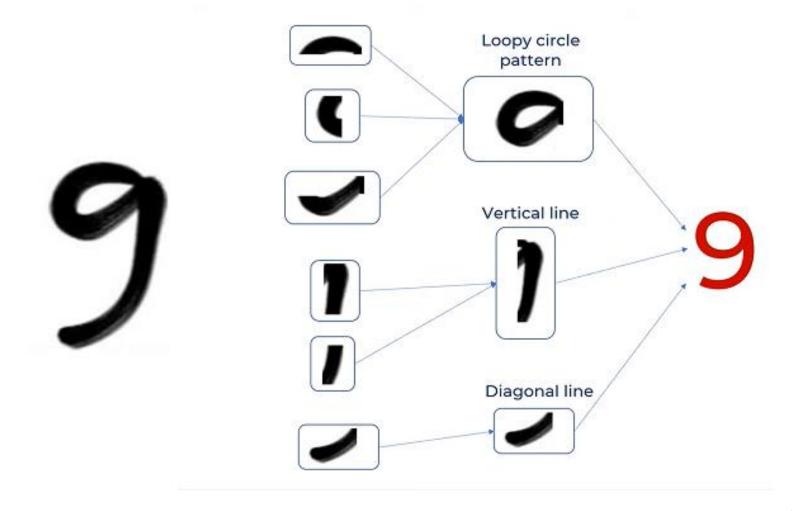


## **CNN** steps

- Convolution operation
  - Generating feature maps
- Pooling layer
- Flattening
- Full connection



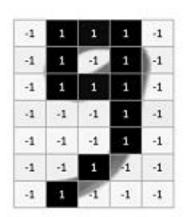
# **CNN** advantage





#### **Feature detection**













Diagonal line filter



-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1

1	1	1
1	-1	1
1	1	1



$$-1+1+1-1-1-1+1+1 = -1 \rightarrow -1/9 = -0.11$$

-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1

1	1	1
1	-1	1
1	1	1

-0.11		



-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1



-0.11	1	-0.11
-0.55	0.11	-0.33



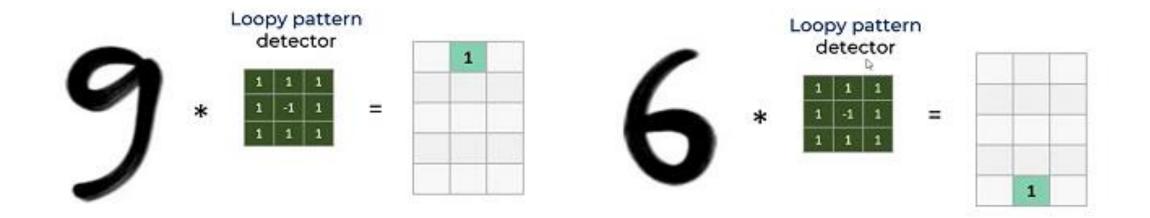
-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1

1	1	1
1	-1	1
1	1	1

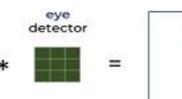
-0.11	1	-0.11
-0.55	0.11	-0.33
-0.33	0.33	-0.33
-0.22	-0.11	-0.22
-0.33	-0.33	-0.33

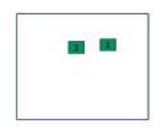
Feature Map



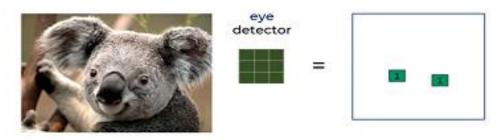


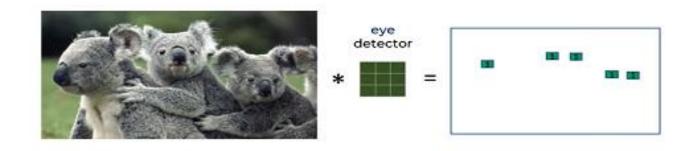




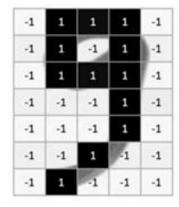


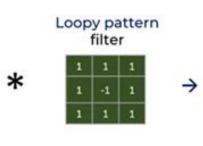
#### Location invariant: It can detect eyes in any location of the image



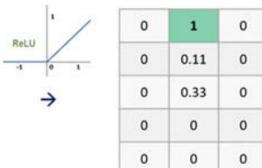




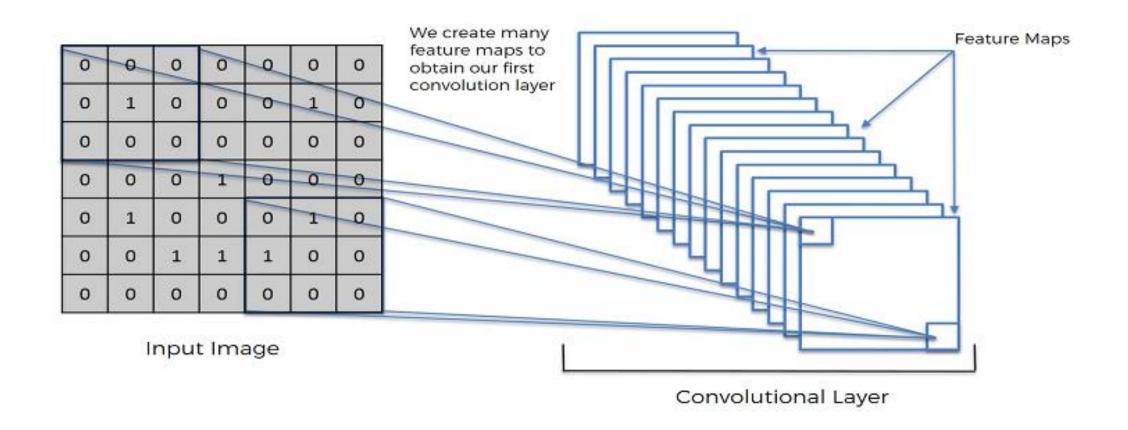








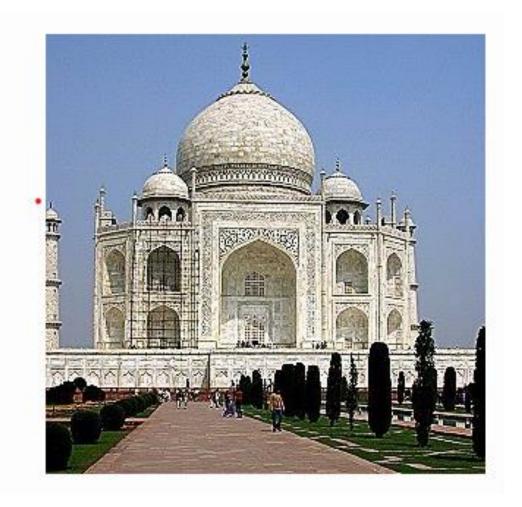






# Sharpen feature

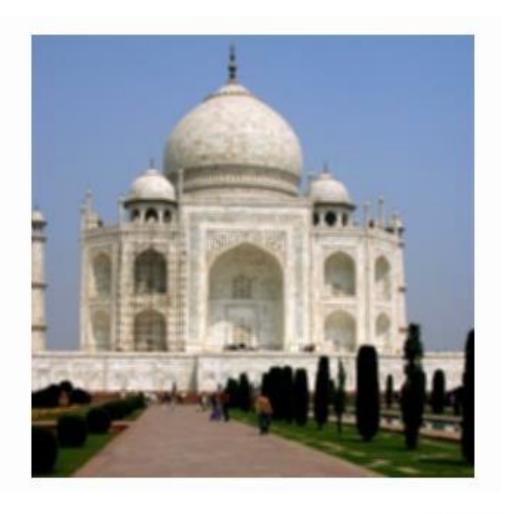
0	0 0 -1 0 0	0	0	0
0	0	-1	0	0
0	-1	5	-1	0
0	0	-1	0	0
0	0	0	0	0





# **Blur feature**

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





# **Edge Detect**

0		1	C
1		4	1
0	)	1	0





# Pooling

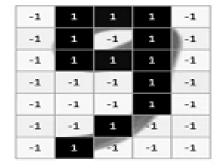
5	1	3	4
8	2	9	2
1	3	О	1
2	2	2	О

8	9
3	2

2 by 2 filter with stride = 2



# Max Pooling

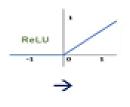




300



-0.11	1	-0.11
-0.55	0.11	-0.33
-0.33	0.33	-0.33
-0.22	-0.11	-0.22
-0.33	-0.33	-0.33



О	1	0
0	0.11	0
О	0.33	0
О	О	0
О	o	О

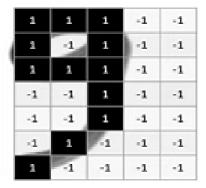
Max pooling

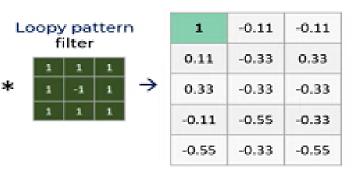
1	1
0.33	0.33
0.33	0.33
О	o

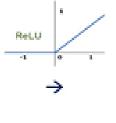


#### **Max Pooling**

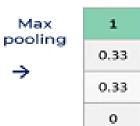
# Shifted 9 at different position







1	0	0
0.11	0	0.33
0.33	0	0
0	0	0
0	О	0





0.33

0.33

0

0

# **Benefits of Pooling**

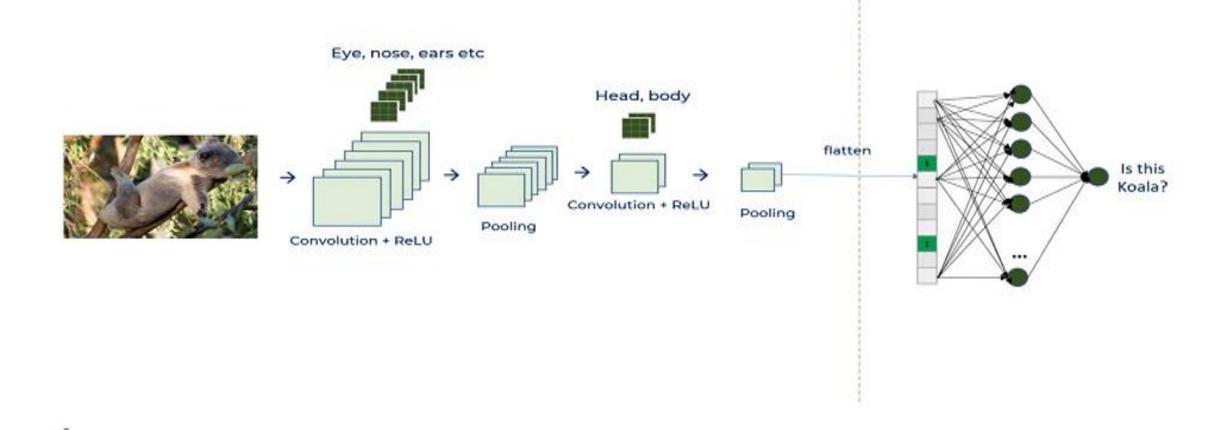
Reduces dimensions & computation

Reduce overfitting as there are less params

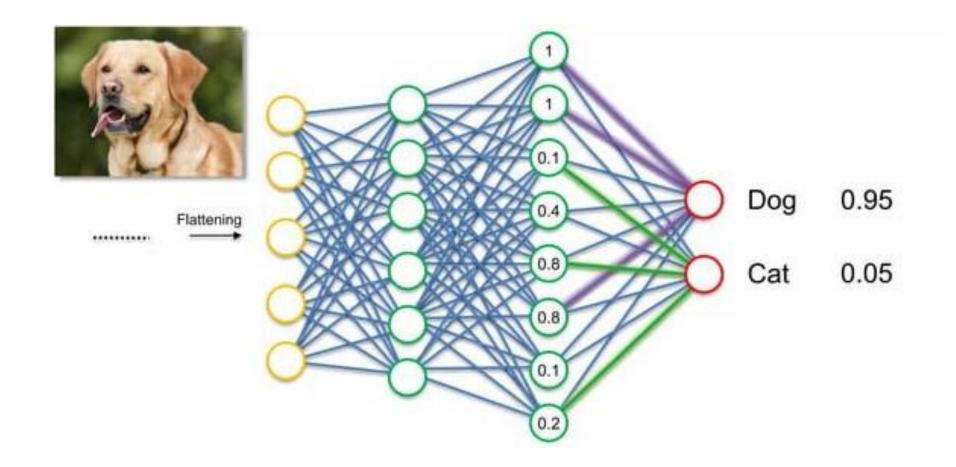
• Model is tolerant towards variations and distortions.



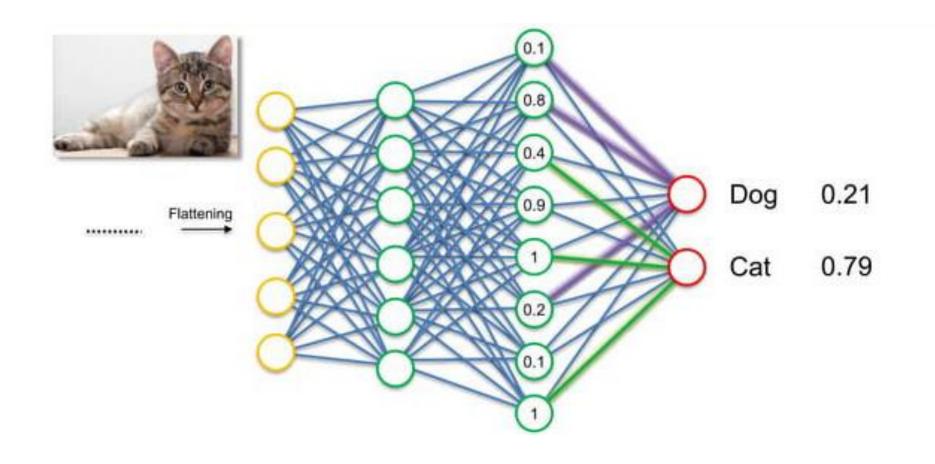
# **Fully connected CNN**













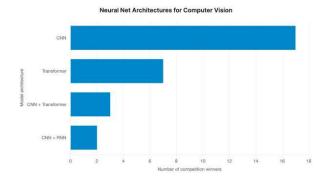
# **PyTorch**

- PyTorch is a deep learning library
- Built by facebook and later made open-source
- Built over torch library (that uses Lua).
- Similar to numpy manipulations, exept that it is called as **Tensors** and has implicit **GPU** computational abilities.

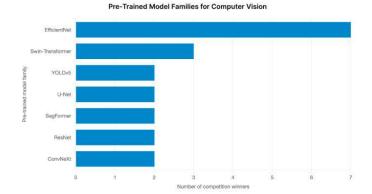


#### **PyTorch**

Convolutional neural networks still dominate computer vision

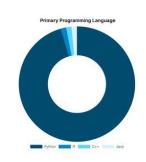


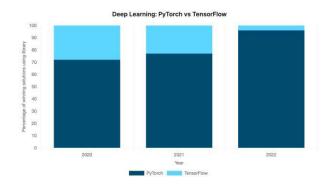
EfficientNet is the most popular pretrained architecture for computer vision



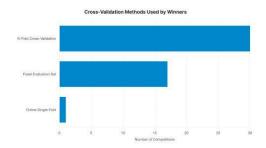
Almost everyone uses Python

Among deep learning practitioners, almost everyone uses PyTorch

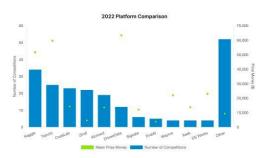




Almost twice as many winning solutions used k-fold CV instead of a fixed validation set



Kaggle remains the most popular competition platform





### **PyTorch vs Numpy**

```
import torch
# Creating tensors
t = torch.tensor([1,2,3])
# Retrieving shape
print(t.shape)
# Accessing type of Data
print(t.dype)
# Changing datatype
t = t.to(torch.float32)
# Random number generation
m = torch.rand(1)
# Tensor with ones zeros
A1 = torch.ones(2,3)
```

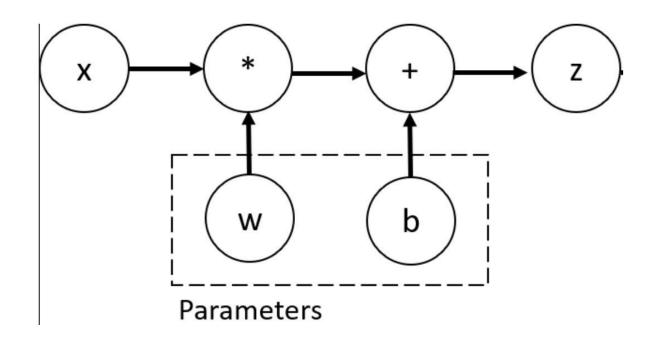
```
import numpy as np
# Creating Arrays
a = np.array([4,5,6])
# Retrieving shape
print(a.shape)
# Accessing type of Data
print(a.dype)
# Changing datatype
a = a.astype('float32')
# Random number generation
n = np.rand(1)
# Array with ones
A2 = np.ones(2,3)
```



#### **AutoGrad**

Autograd is PyTorch's differentiation engine

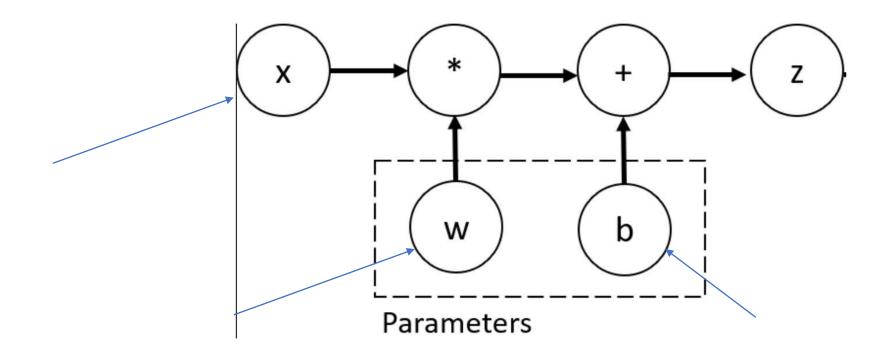
• It achieves the calculation of gradients of each weights by constructing a **Dynamic Directed Acyclic graph** 





#### **AutoGrad**

• Gradients can be obtained only for the leaf nodes of the DAG using .grad attribute





#### **AutoGrad**

• After the forward propagation, i.e calculating the loss, gradients can be calculated with .backward() function.

- During forward propagation
  - Computes output
  - Keeps track of grad\_fn at each node
- During back propagation
  - Gradients are calculated from leaf to root node based on the .grad\_fn at that node
  - Accumulates gradient in .grad attribute of each node

