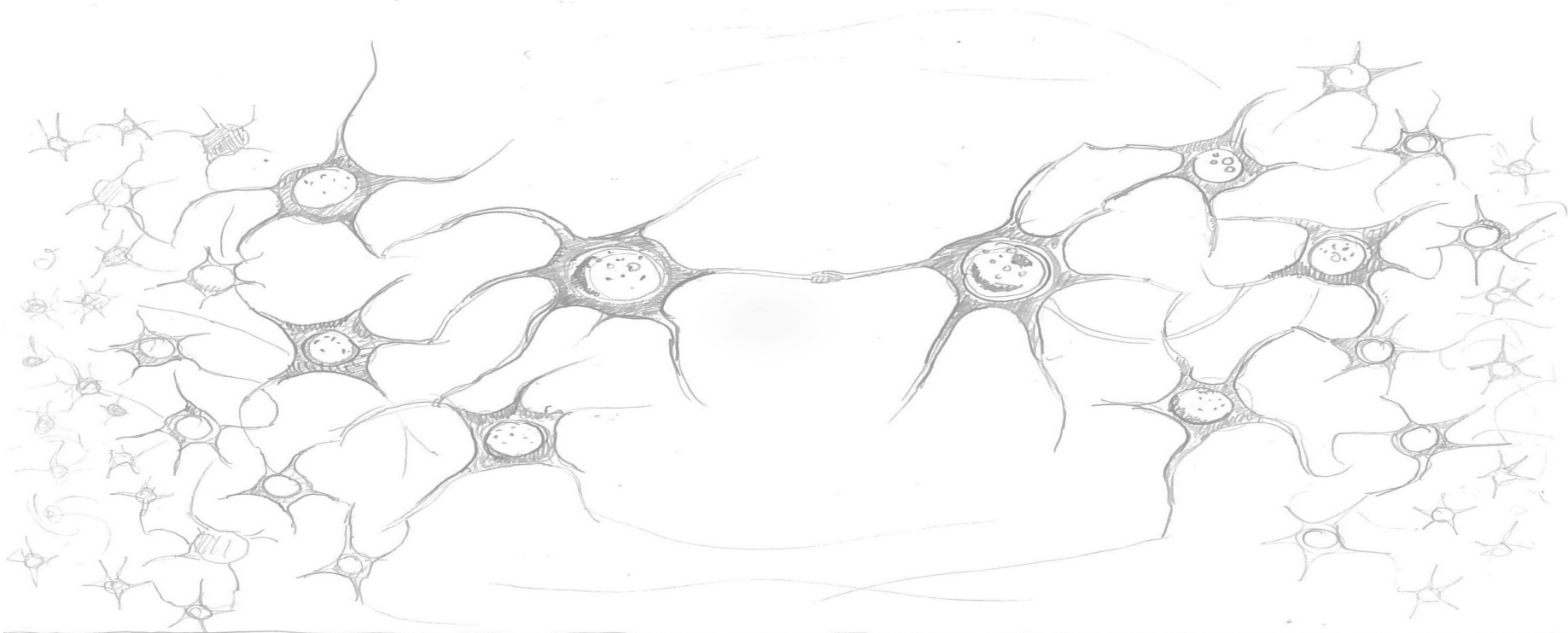


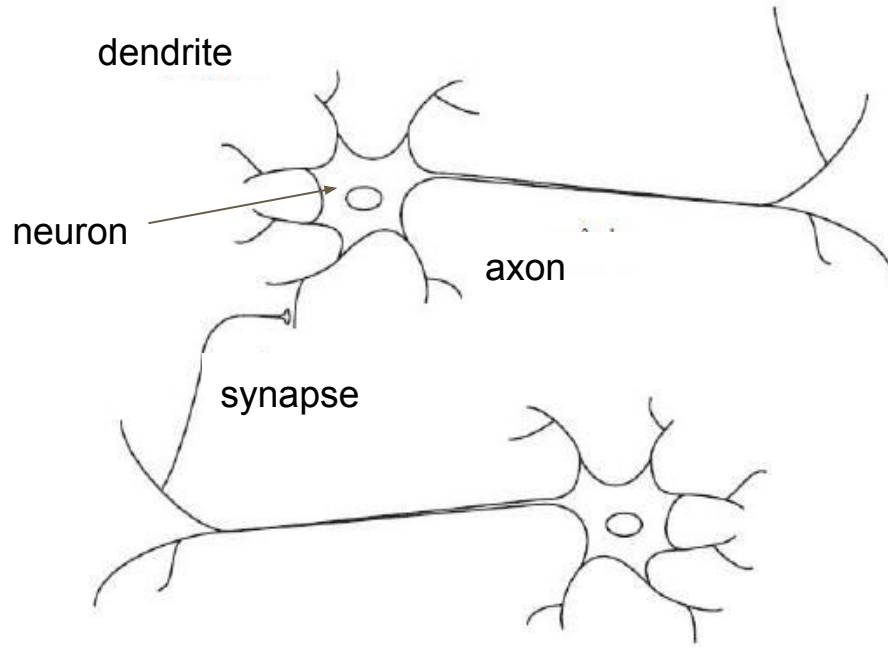
# Navigating the Neural Net Terrain

A 45 min. Tour



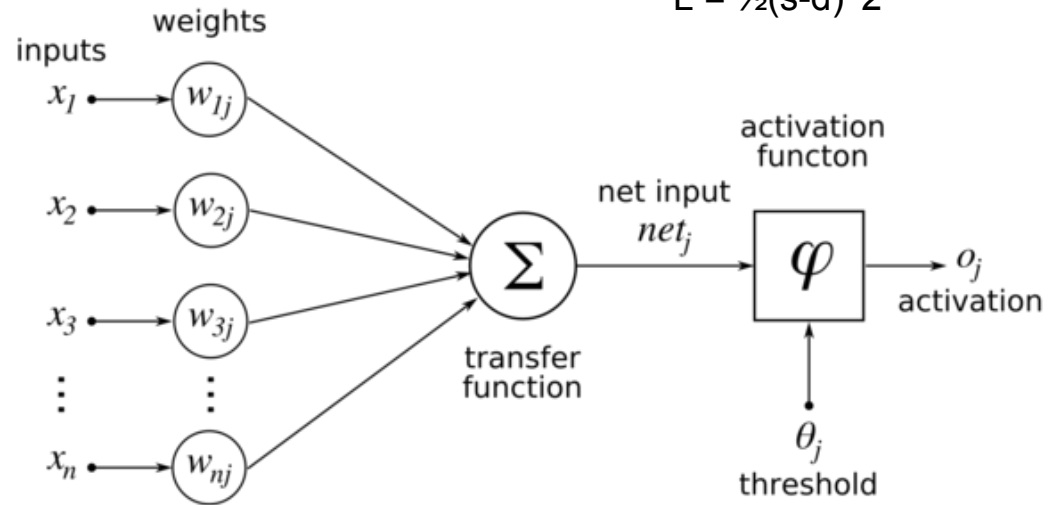
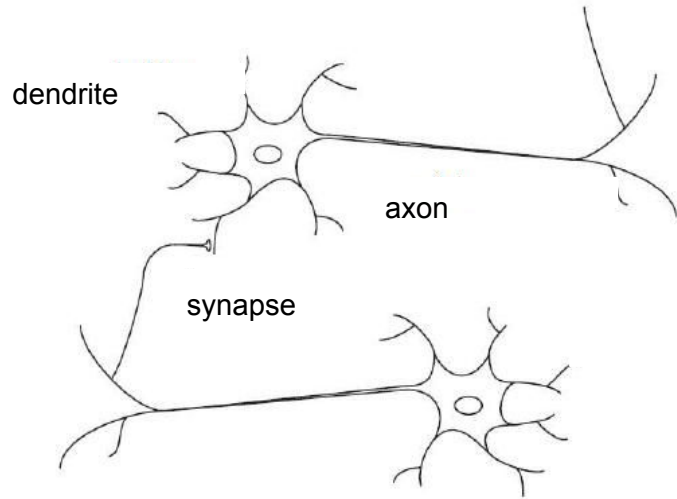
# The Brain Analogy

(our cartoon neuron)



# The Brain Analogy

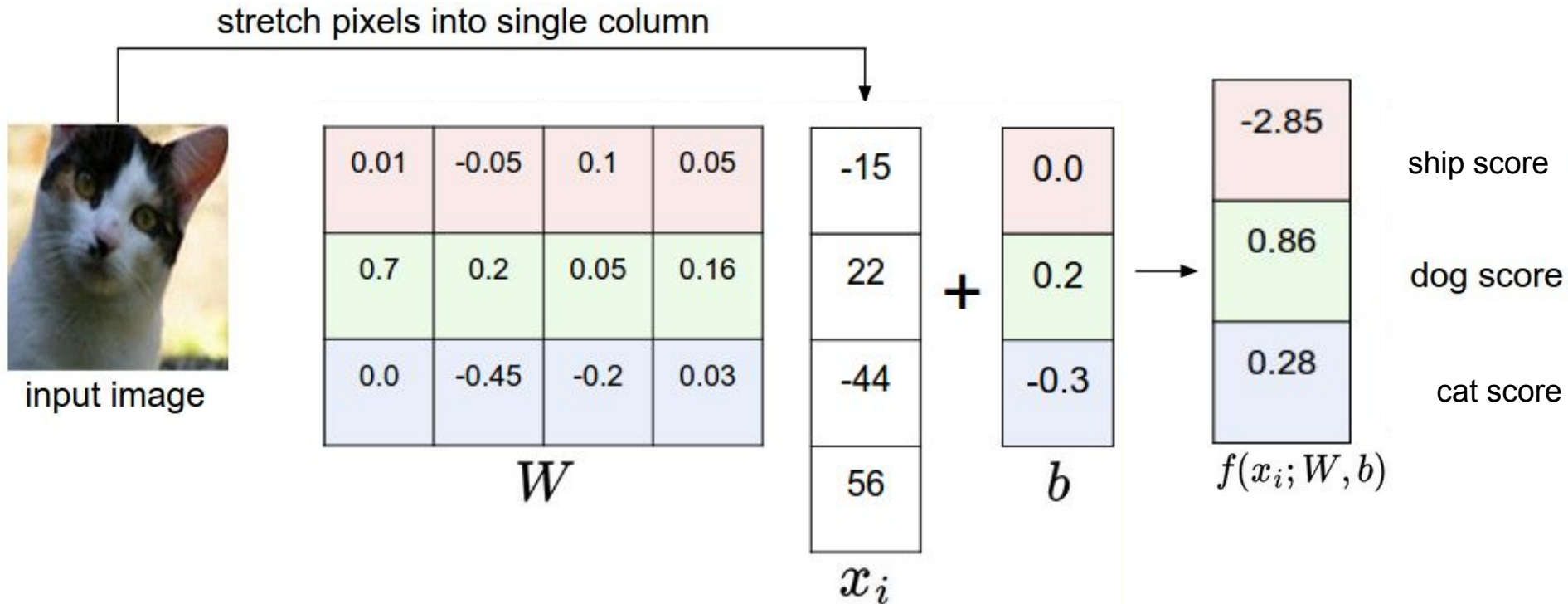
(cartoon neuron & mathematical neuron)



$$s = f(x, w)$$

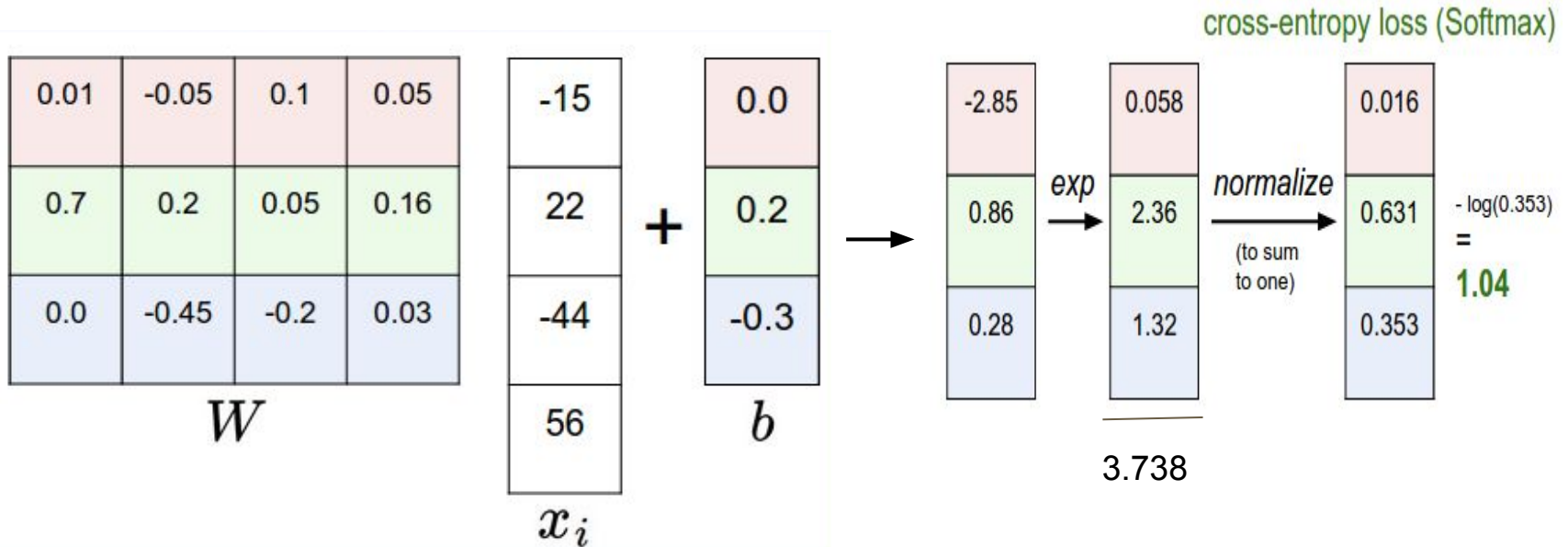
$$L = \frac{1}{2}(s - d)^2$$

# The Linear Classifier Analogy



## Losses:

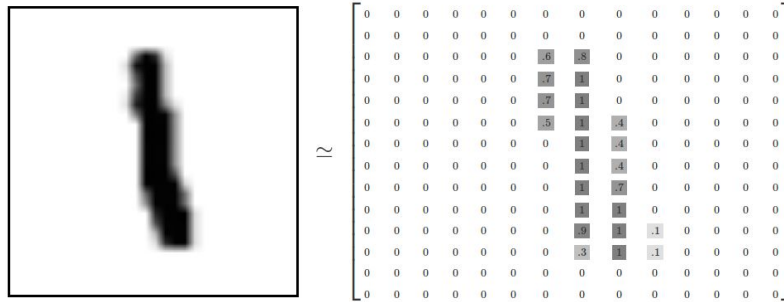
### Softmax (Cross-Entropy) Loss



Softmax:  $f_j(z) = \frac{e^{z_j}}{\sum_k e^{z_k}}$

Cross-Entropy  $Li = -\log\left(\frac{e^{z_j}}{\sum_k e^{z_k}}\right)$

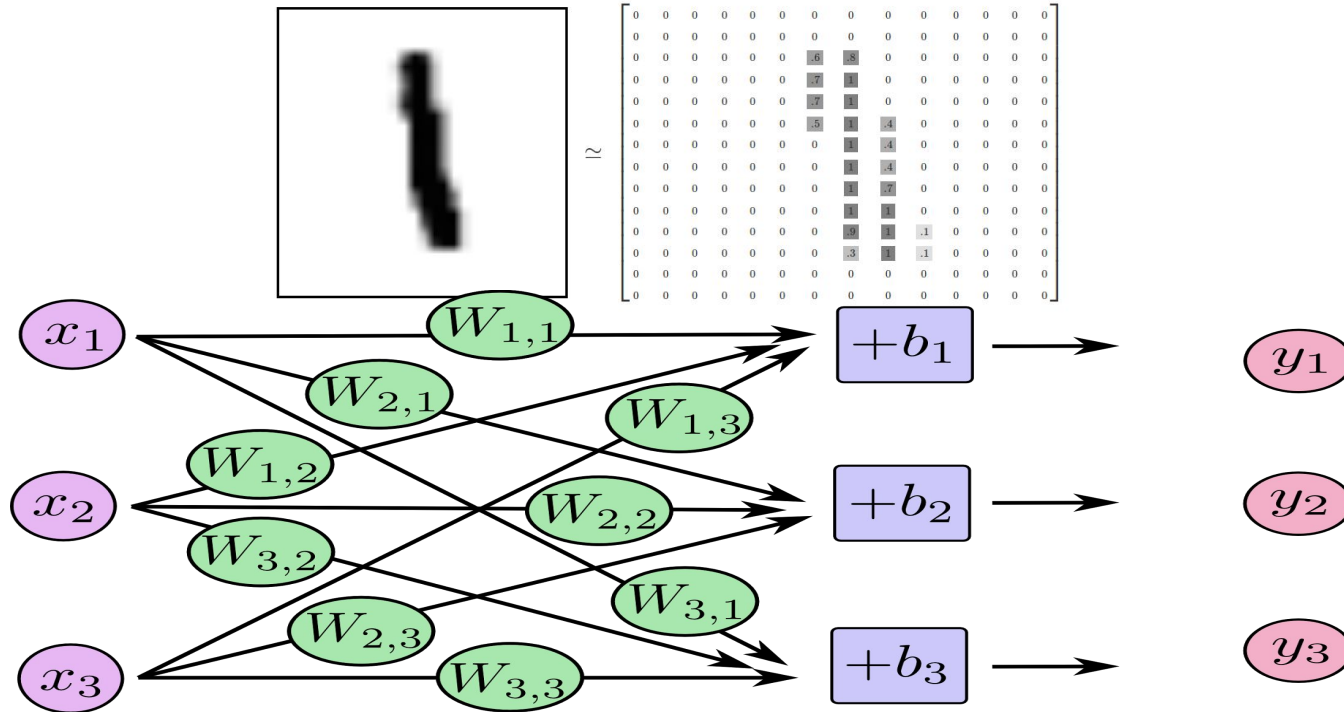
## The Linear Classifier Analogy: MNIST data set



$$\begin{bmatrix} W_{1,1}x_1 + W_{1,2}x_2 + W_{1,3}x_3 + b_1 \\ W_{2,1}x_1 + W_{2,2}x_2 + W_{2,3}x_3 + b_2 \\ W_{3,1}x_1 + W_{3,2}x_2 + W_{3,3}x_3 + b_3 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

1) Add up evidence of input being in a certain class Evidence =  $\sum W_{i,j}x_j + b_i$

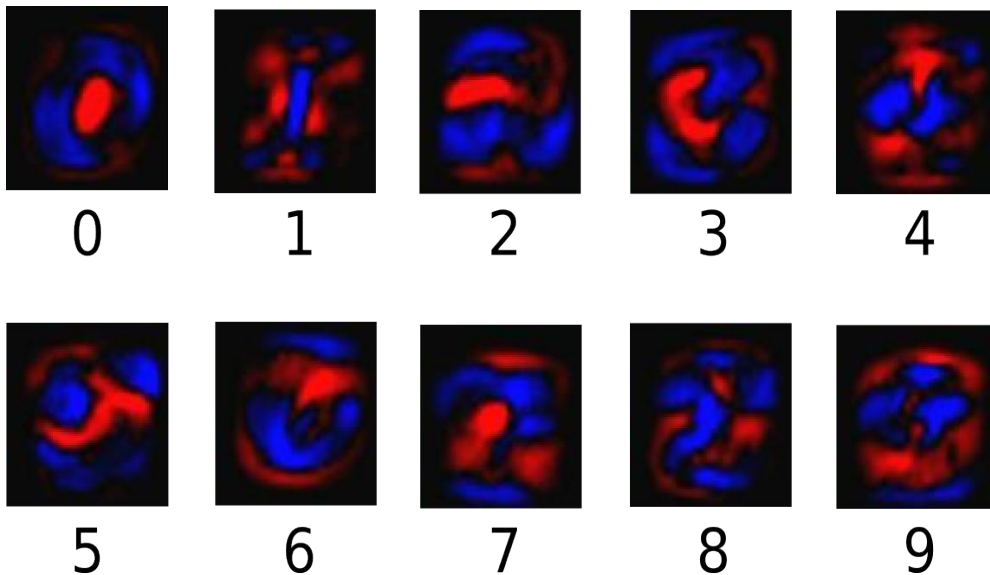
# The Linear Classifier Analogy: MNIST data set



- 1) Add up evidence of input being in a certain class Evidence =  $\sum W_{i,j}x_j + b_i$

# The Linear Classifier Analogy: MNIST data set

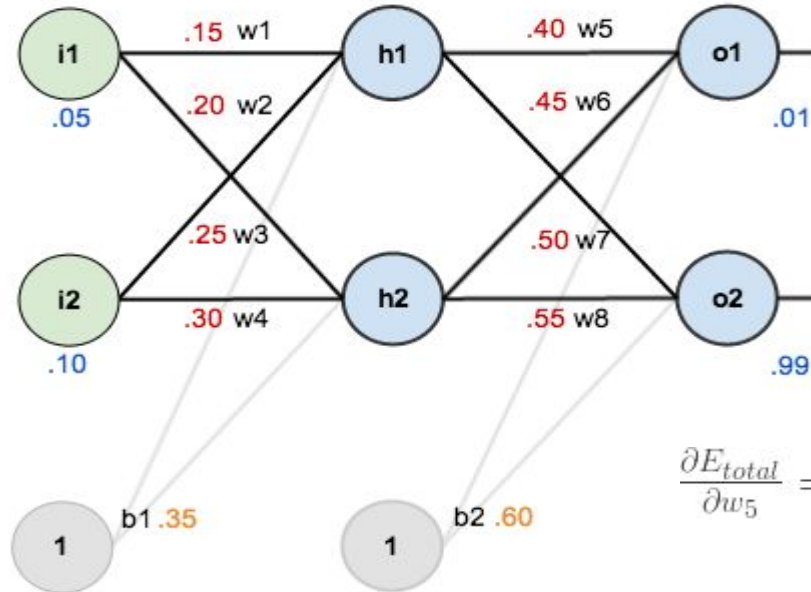
$W \approx$





# BackPropagation

## How do we get there?

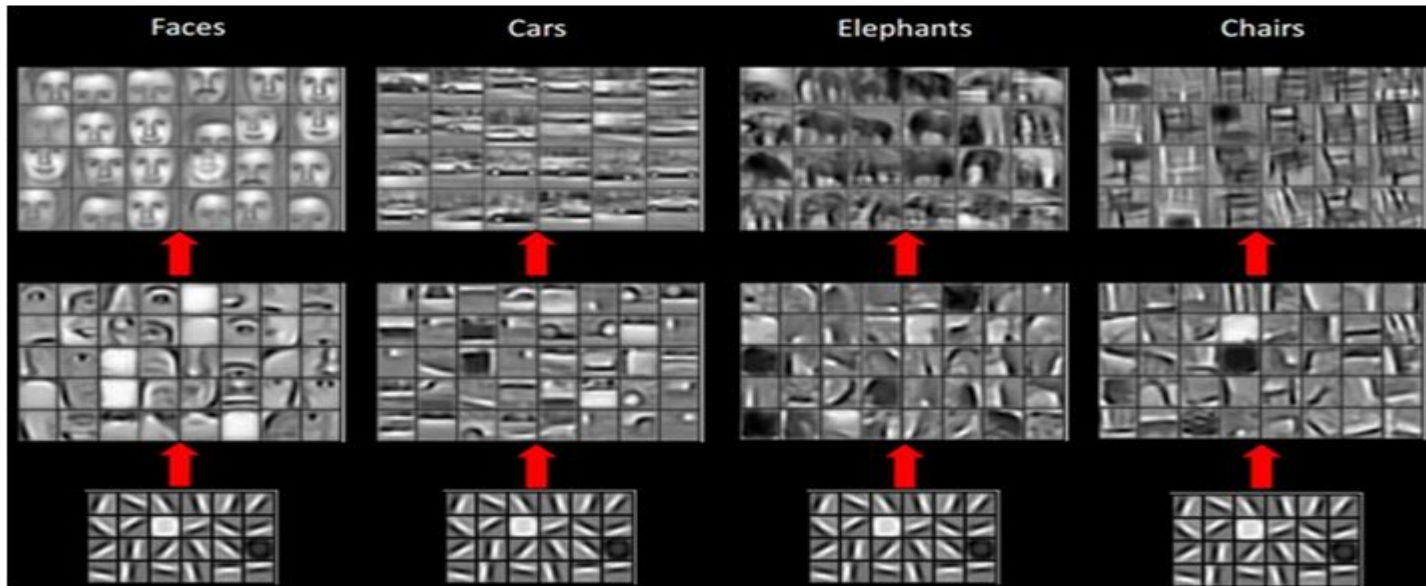


$$\frac{\partial E_{total}}{\partial w_5} = \frac{\partial E_{total}}{\partial out_{o1}} * \frac{\partial out_{o1}}{\partial net_{o1}} * \frac{\partial net_{o1}}{\partial w_5}$$

Chain Rule!

# Convolutional Neural Nets

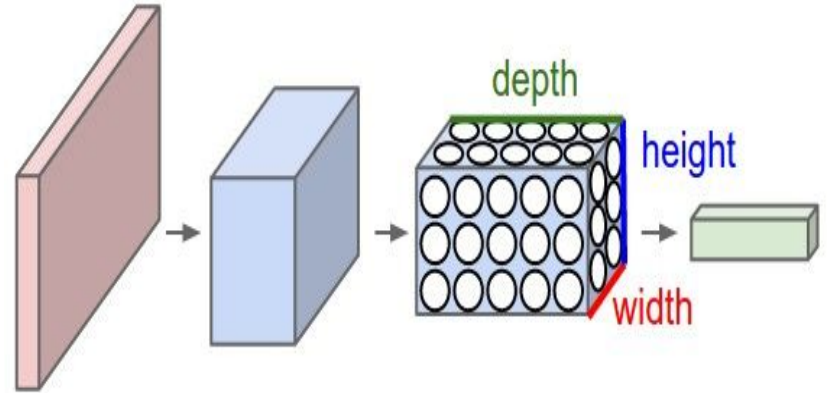
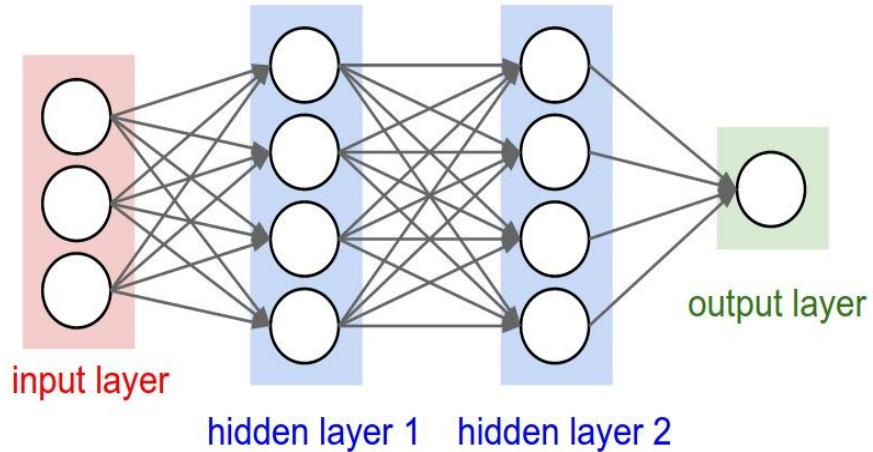
Very similar to Neural Nets.. But how are they different ?



# Convolutional Neural Nets

## Vs. Neural Nets

- Input is an image: Leverage 3D Structure
- Fully Connected ? Not really



# The CNN Family

## Winners of the ILSVRC ImageNet challenges

**AlexNet (2012, Krizhevsky):** Popularized CNNs - 1st to incorporate consecutive convolutional layers

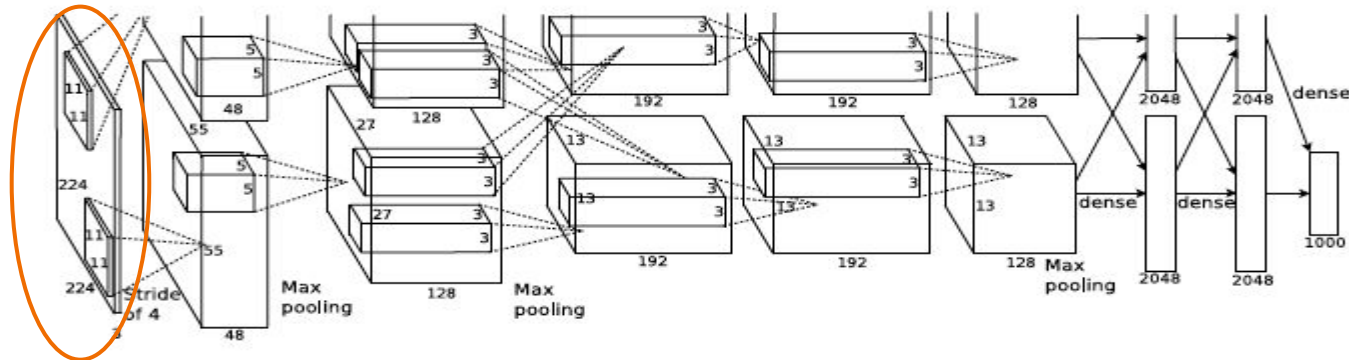
**GoogLeNet / Inception (2014, Szegedy):** Drastically reduced the # of parameters used (from 60 million to 4 million)

**ResNet (2015, Kaiming He):** Residual Network : famous for skip-connections and heavy use of batch-normalization; also removes some fully connected layers (at end of network)



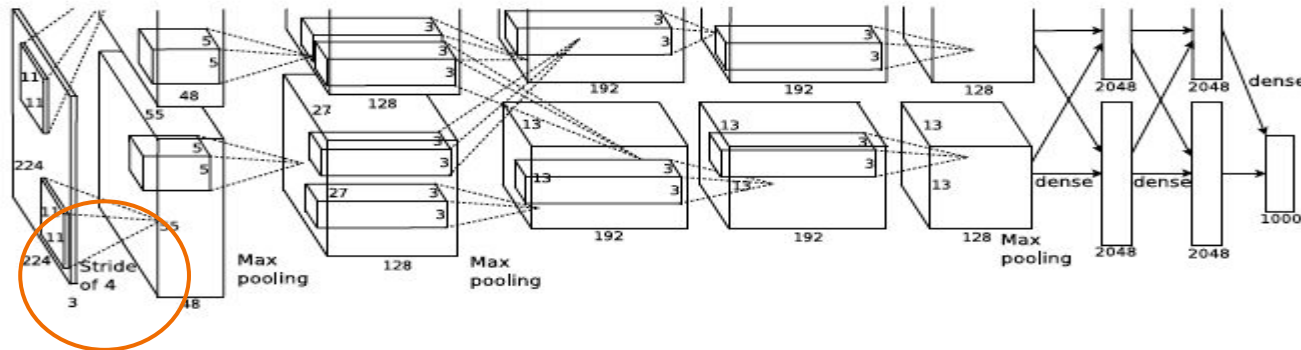
# Convolutional Neural Nets : Architecture

- 1) **Input Layer: Raw pixel values of the image**  
(ex:  $224 \times 224 \times 3$  (3 ~ color channels (RGB)))
- 2) Conv Layer
- 3) Pool Layer
- 4) ReLU Layer
- 5) FC (Fully Connected Layer)



# Convolutional Neural Nets : Architecture

- 1) Input Layer: Raw pixel values of the image
- 2) **Conv Layer: Dot product between weights and the small region of input volume (ex: 11 x 11 x 3 filters)**
- 3) Pool Layer
- 4) ReLU Layer
- 5) FC (Fully Connected Layer)

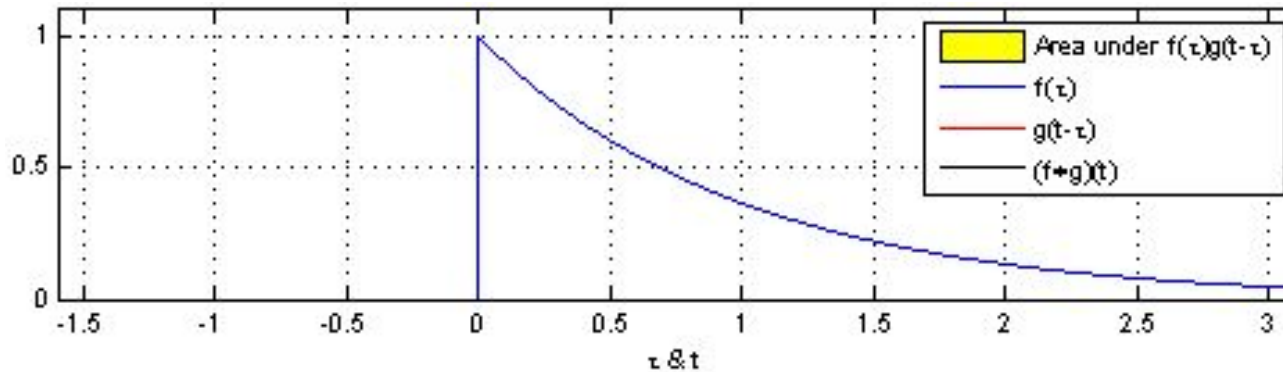




# Convolutional Neural Nets : Architecture

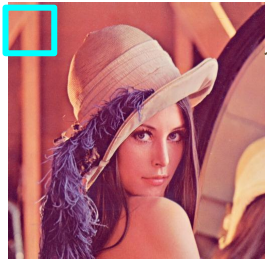
## What is a Convolution?

$$f * g = \int f(t - \tau)g(\tau)d\tau$$



# Convolutional Neural Nets : Architecture

## What is a Convolution?



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

1 1 1  
1 -8 1  
1 1 1

→ 0

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

1 1 1  
1 -8 1  
1 1 1

→ -3



# Convolutional Neural Nets : Architecture

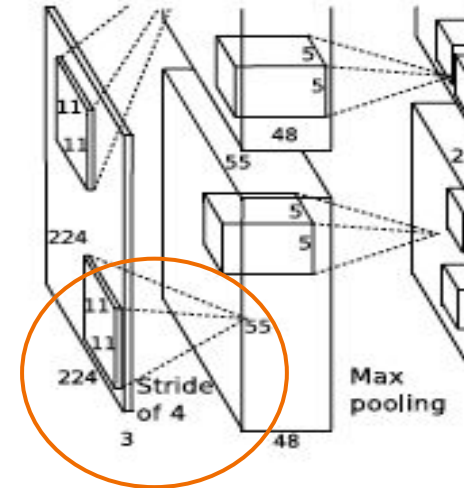
## What is a Convolution?

**Convolutional Layer:**  $(W-F + 2P)/S + 1$

- **W** : Input Volume size
- **F**: Receptive Field size of the Conv Layer Neuron
- **P**: Zero- Padding
- **S**: Stride

$$(224 - 11 + 2(3))/4 + 1 = 55$$

Conv Layer Output ~ 55 x 55 x 96 (ie : 55<sup>2</sup> neurons in each layer)



# Convolutional Neural Nets : Architecture

What is a Convolution?

**Voila. We have 96 filters.**



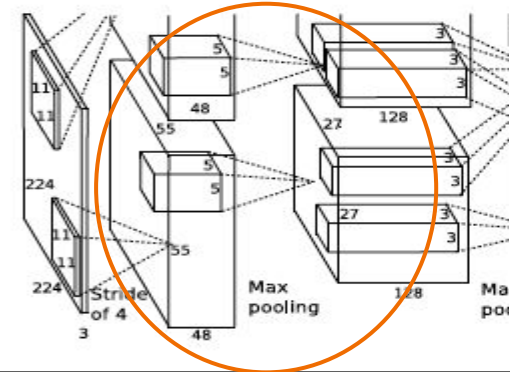
# Convolutional Neural Nets : Architecture

- 1) Input Layer
- 2) Conv Layer
- 3) **Pooling Layer: Performs downsampling operation**
- 4) ReLU Layer
- 5) FC (Fully Connected Layer)

Our Eqn :  $O = (W - F) / S + 1$

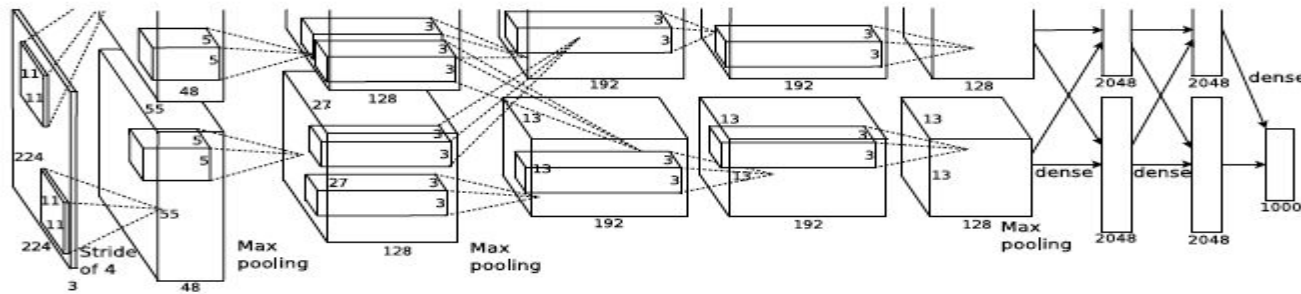
AlexNet: use 3 x 3 MaxPooling w/ stride = 2

$$O = (55 - 3) / 2 + 1 = 27$$



# Convolutional Neural Nets : Architecture

- 1) Input Layer: Raw pixel values of the image
- 2) Conv Layer:
- 3) Pool Layer:
- 4) **ReLU Layer: Apply an elementwise activation function**  
**(ex :  $\max(0,x)$  thresholding output dimension ~ same as input)**
- 5) FC (Fully Connected Layer)



\*The ReLU non-linearity is applied to the output of every convolutional and fully-connected layer.

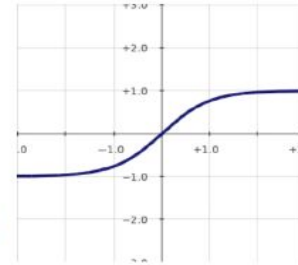
# Convolutional Neural Nets : Architecture

## ReLU Layer:

Traditionally:

$f(x) = \tanh(x)$  or  $fx = (1+e^{-x})^{-1}$  ( Very slow to train)

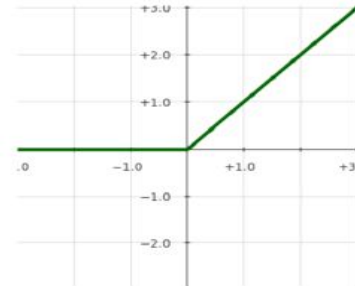
$f(x) = \tanh(x)$



Now:

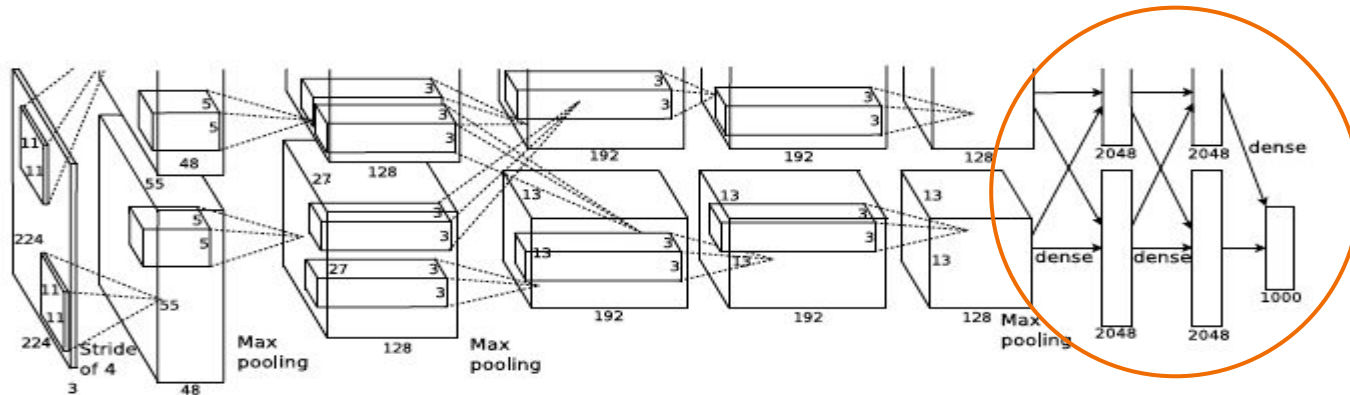
$f(x) = \max(0, x)$  (Faster to train )

$f(x) = \max(0, x)$

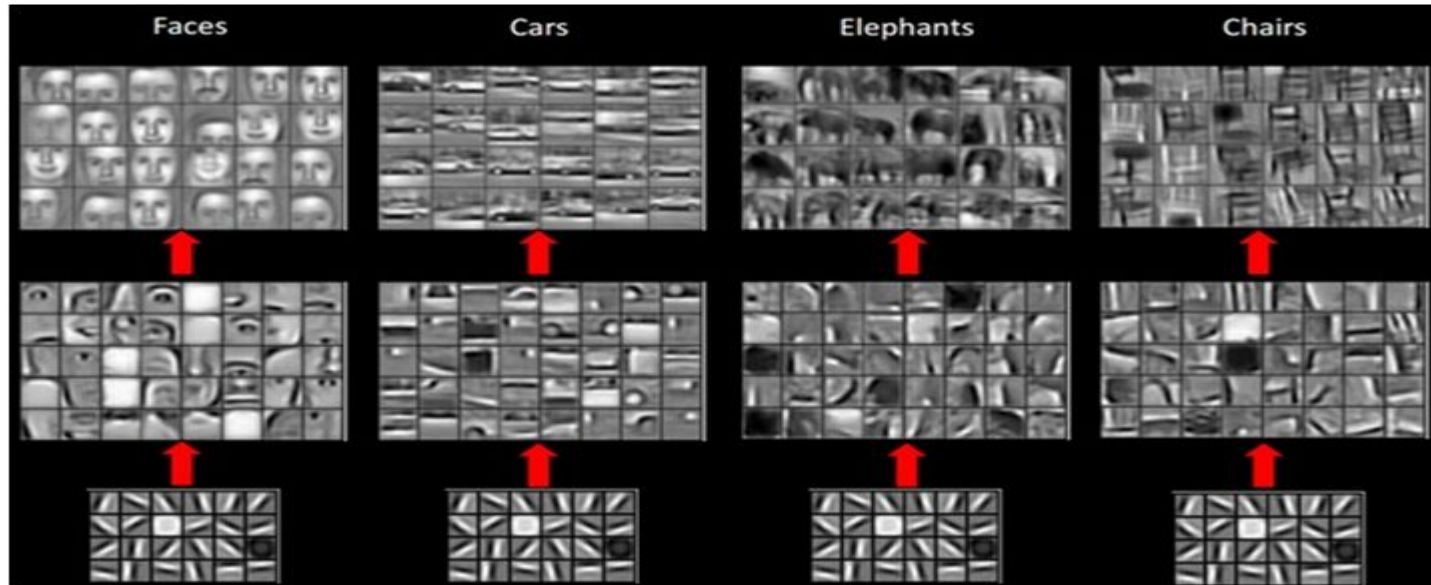


# Convolutional Neural Nets : Architecture

- 1) Input Layer: Raw pixel values of the image
- 2) Conv Layer:
- 3) Pool Layer:
- 4) ReLU Layer:
- 5) **FC (Fully Connected) Layer** : Each neuron will be connected to all activations of the previous volume. The output layer will compute class scores (ex:  $[1 \times 1 \times 1000]$  )



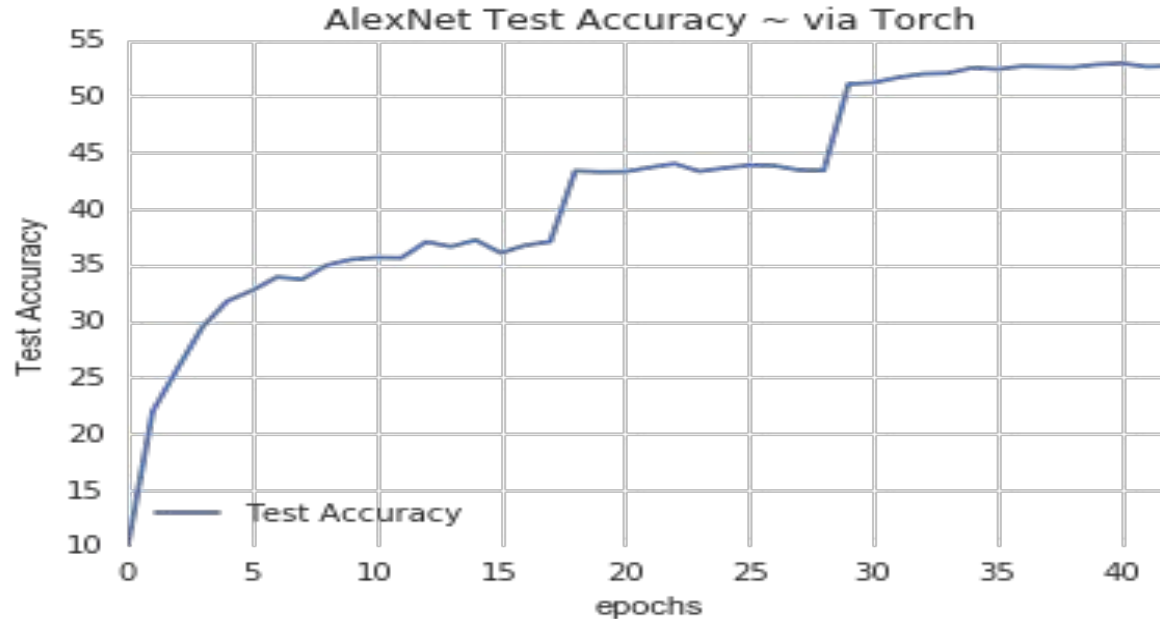
# Convolutional Neural Nets : Architecture



# Working with Behold.ai

*How long does it take to train AlexNet to achieve 50% accuracy?*

***First: via Torch***

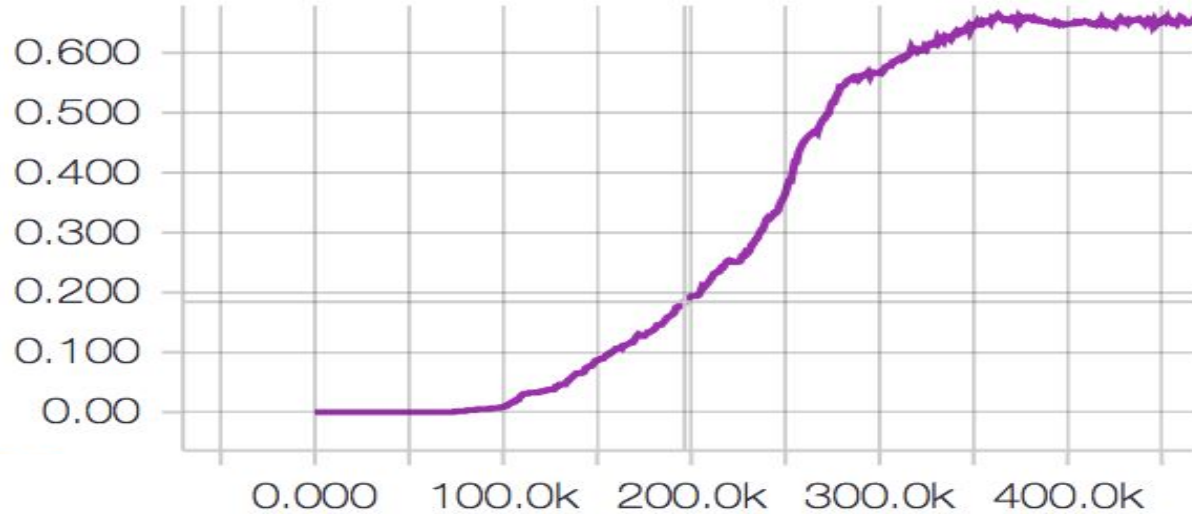




## Working with Behold.ai

*How long does it take to train Inception-V3 to achieve 50% accuracy?*

***Then: via TensorFlow***



# Working with Behold.ai

## *Torch:*

- + Fast. Easy to integrate with GPUs
- + Many modular pieces that are easy to combine

<https://github.com/soumith/imagenet-multiGPU.torch/blob/master/models/alexnet.lua>

- Written in Lua



## *TensorFlow:*

- + Written in python & numpy
- + Tensorboard for visualization
- Latest releases can be buggy (difficult to integrate GPUs)
- Can be many x slower than Torch



<https://console.aws.amazon.com/ec2/v2/home?region=us-east-1#LaunchInstanceWizard>

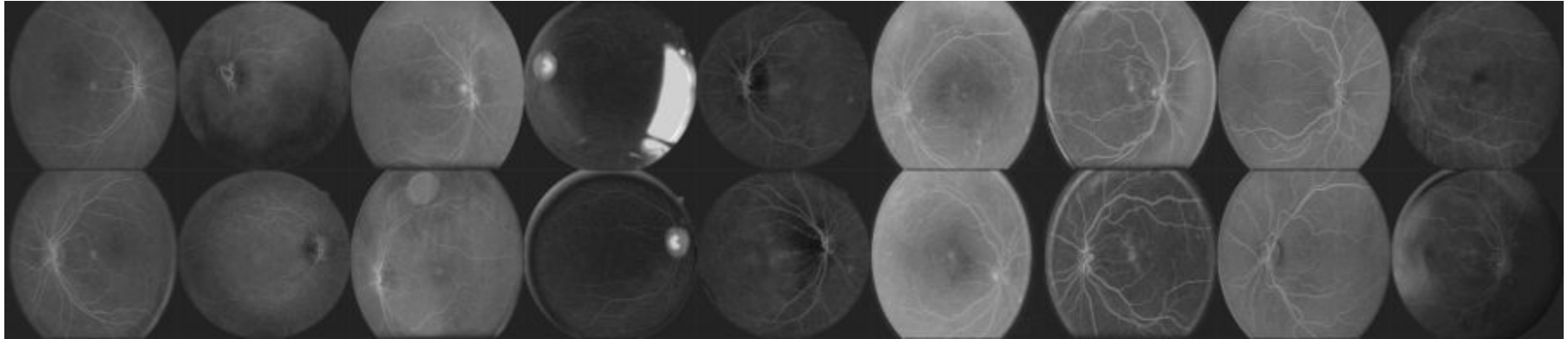
# Working with Behold.ai

*Can I leverage the AlexNet model and retrain it on a new dataset?*

## Train Retinopathy data via AlexNet on Torch

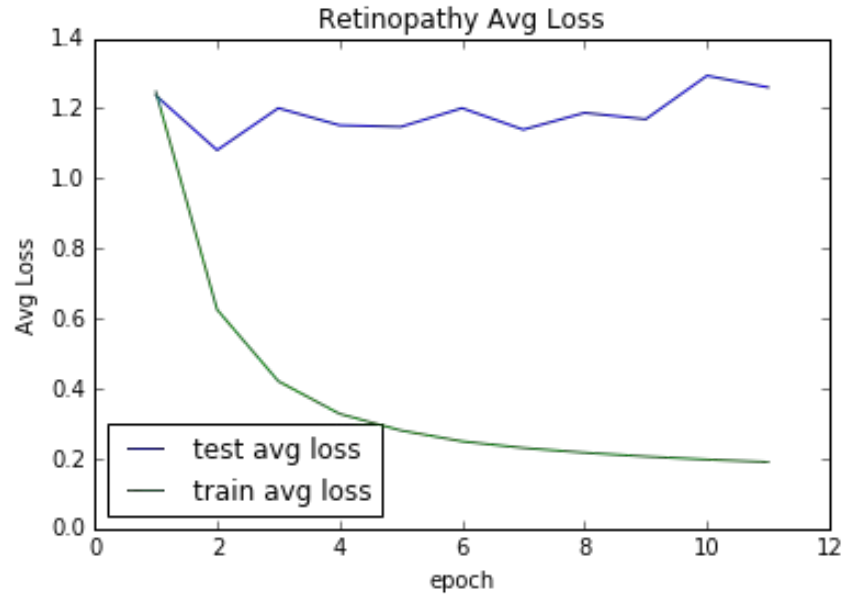
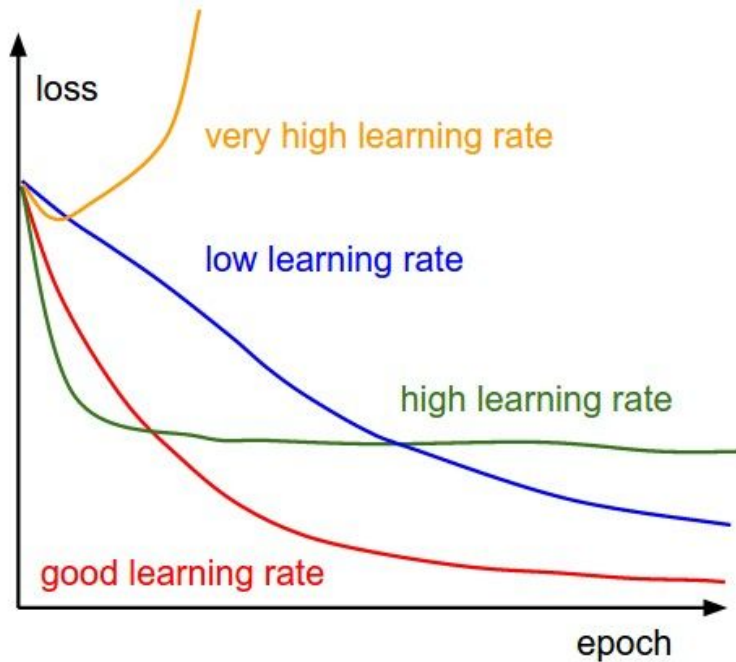
Kaggle Dataset:

**Diabetic Retinopathy Detection**



# Learning from the Learning Process

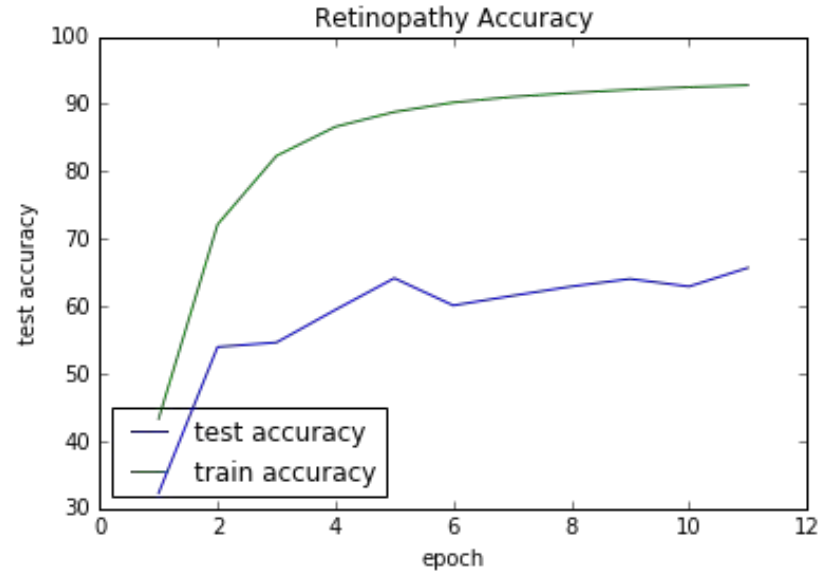
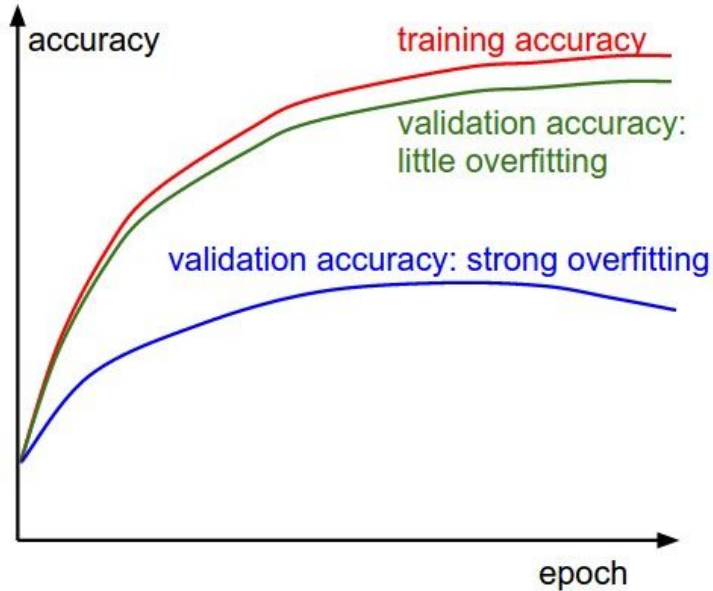
## 1) Loss functions



\* Tip: Change the learning rate!

# Learning from the Learning Process

## 2) Accuracy



\* Tip: Increase L2 weight penalty , Increase Drop-Out, More Data (possibly with jitter) - -try batch norm ?

## Learning from the Learning Process:

### 3) Weight Ratios

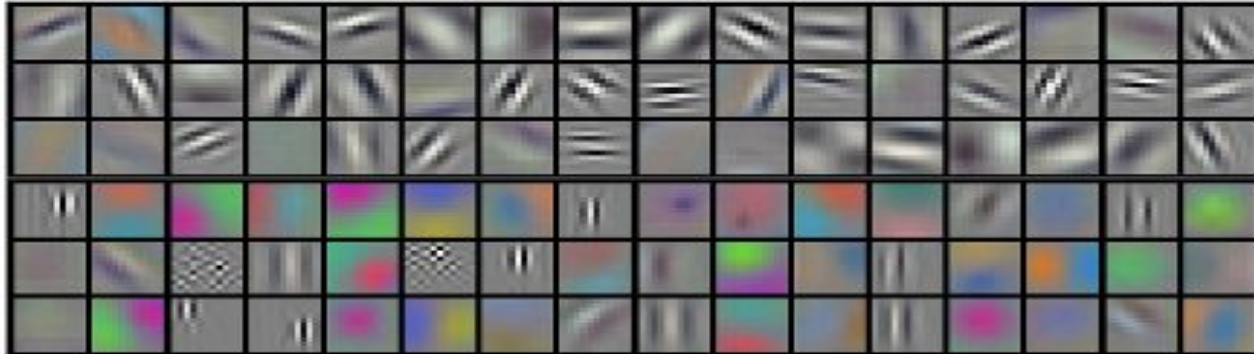
- update / weight ratio : should be roughly about  $1e-3$

(larger  $\sim$  learning rate may be too, too much lower  $\sim$  learning rate may be too low )

### 4) First-layer Visualizations

Visualized weights from the 1st layer of the network:

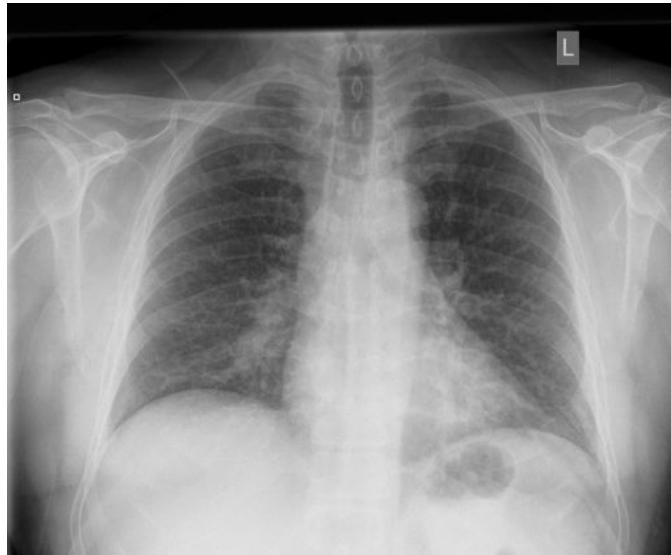
(smooth, diverse features indicate that training is going well)



# Working with Behold.ai

*Can I leverage the Inception model to decipher different diseases via Tensorflow?*

**Train XRAY data via TF's Inception-V3**

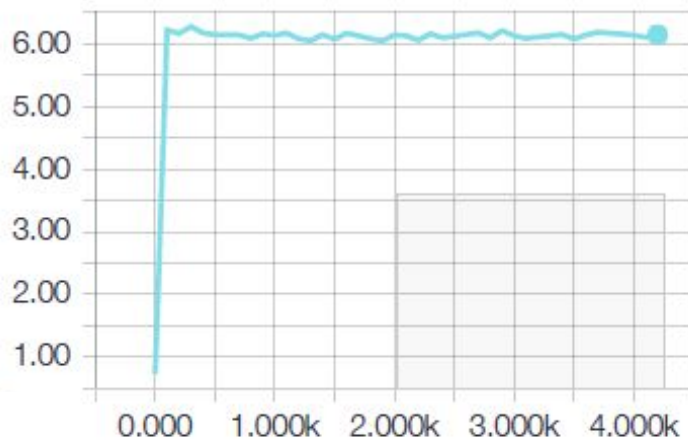


Opacity

# Working with Behold.ai

## Train XRAY data via TF's Inception-V3

total\_loss

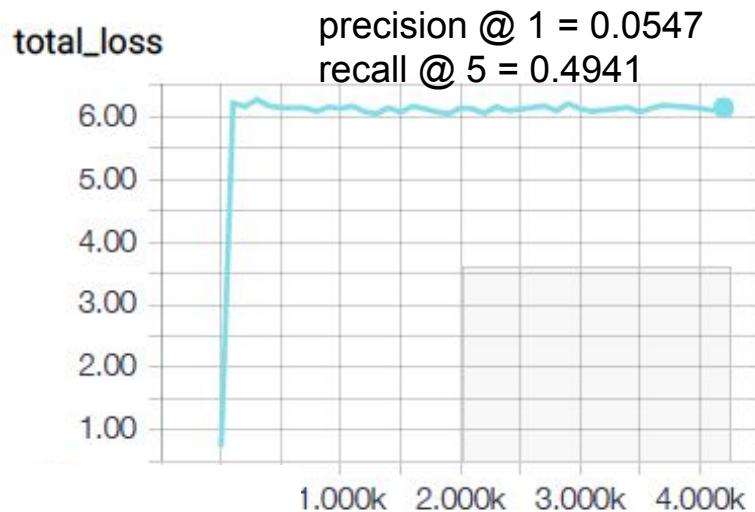


precision @ 1 = 0.0547  
recall @ 5 = 0.4941

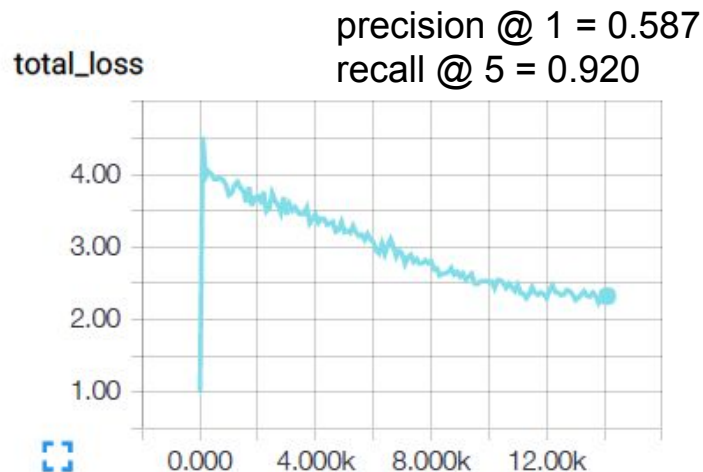


# Working with Behold.ai

## Train XRAY data via TF's Inception-V3



Train using Inception-V3 from scratch



Retrain using Inception-V3 from existing model

# Working with Behold.ai

Why did that work so well ???

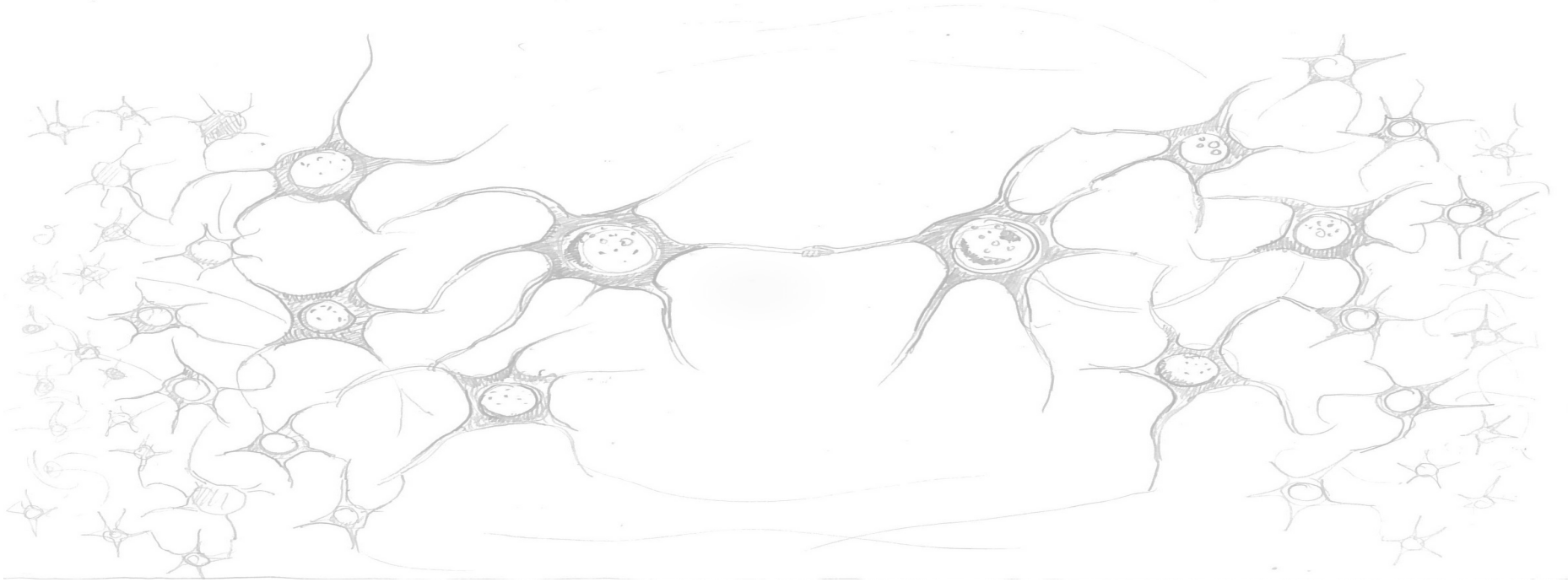


# A quick quick look at TensorFlow

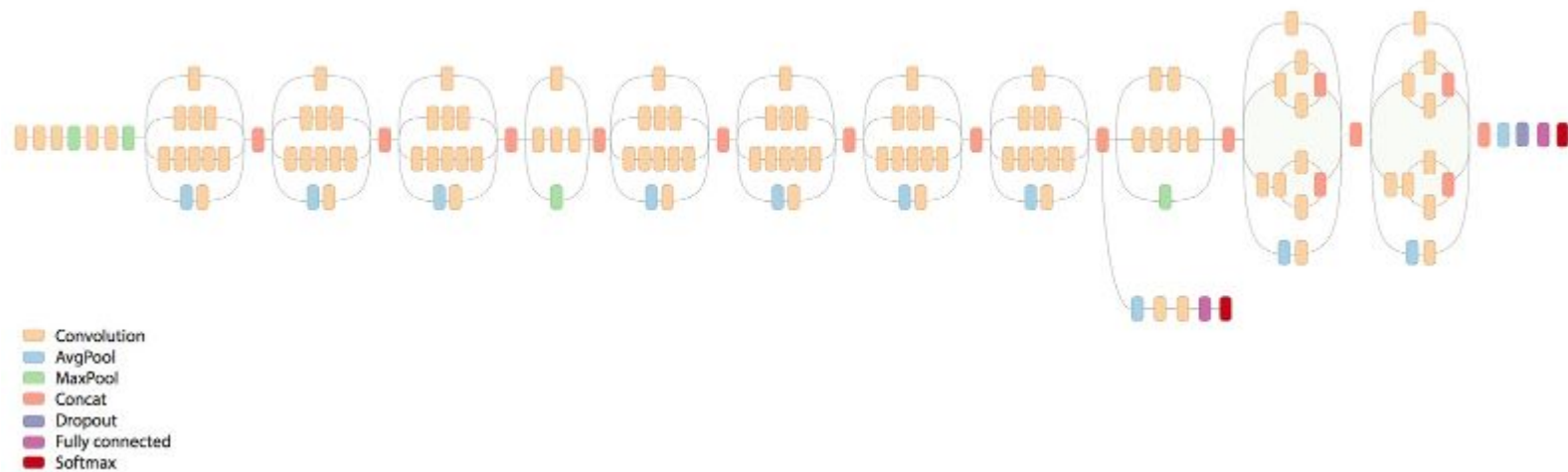
- Tensorflow is based on the concept of a computational graph with nodes & edges.
- The output of one operation is fed as input into the next operation.
- TF has it's own 'version' of things:  
Ex: `input=tf.constant(5)`, why ?

[http://localhost:8888/notebooks/tensorflow\\_final.ipynb](http://localhost:8888/notebooks/tensorflow_final.ipynb)

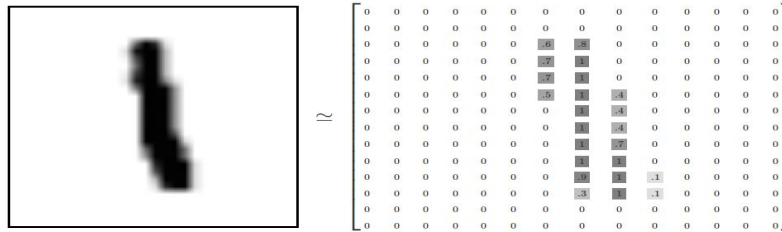
# Thank you!



## Appendix



# The Linear Classifier Analogy: MNIST data set



$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \text{softmax} \left( \begin{bmatrix} W_{1,1}x_1 + W_{1,2}x_2 + W_{1,3}x_3 + b_1 \\ W_{2,1}x_1 + W_{2,2}x_2 + W_{2,3}x_3 + b_2 \\ W_{3,1}x_1 + W_{3,2}x_2 + W_{3,3}x_3 + b_3 \end{bmatrix} \right)$$

- 1) Add up evidence of input being in a certain class Evidence =  $\sum_i W_{i,j}x_j + b_i$
- 2) Convert evidence into probabilities using softmax (illustrate on board)

Softmax:  $f_j(z) = \frac{e^{z_j}}{\sum_k e^{z_k}}$       Cross-Entropy       $Li = -\log\left(\frac{e^{z_j}}{\sum_k e^{z_k}}\right)$