

# Introduction to Keras: Theory and Examples

IIT PATNA

# OUTLINE

- Introduction to Google Colab
- Keras
  - Introduction
  - Fully Connected Neural Network
  - Convolution Neural Network
  - Working with own data

# Confession

- Introductory (Hello World)
- Internet (sources at the end)

# Part 0: Google Colab

# Introduction to Google Colab

- Product by Google
- Google's free cloud service with GPU support for AI developers
  - CPU  $\Leftrightarrow$  GPU  $\Leftrightarrow$  TPU
  - Python programming language
  - Support to many neural network libraries such as Keras, PyTorch, OpenCV
- Files are stored on Drive

# Introduction to Google Colab

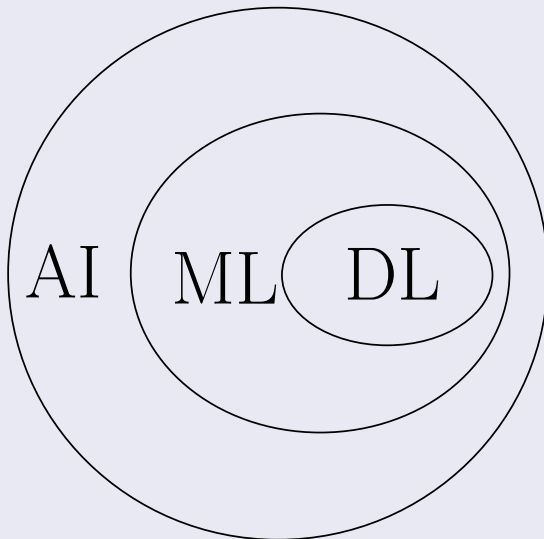
- <https://github.com/nrjcs/swym>
- <https://colab.research.google.com/>

- Notebook: list of cells (code or text)
- can be shared
- collaborated
- GitHub
- Default folder is Colab Notebooks

- [welcome example](#)

# Part I: Regular Neural Network

# Introduction





# Architecture of a Neural Network

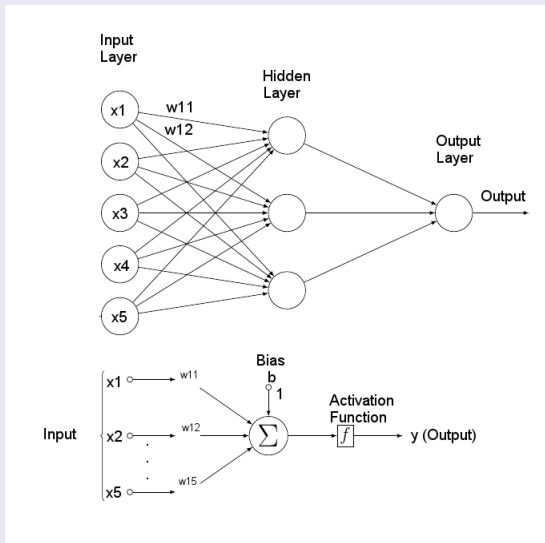


Figure: A Neural Network

# Architecture of a Neural Network

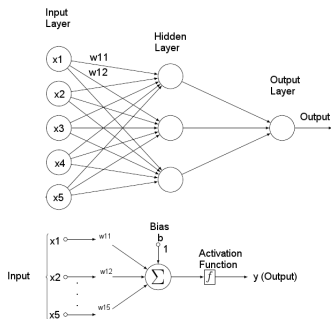


Figure: A Neural Network

## Learning Steps (Decisions to be made):

- 1 Application (Problem)
- 2 Type of model
- 3 No. of layers
- 4 No. of nodes
- 5 Initialization of weights
- 6 Activation Function
- 7 Optimization Function
- 8 Evaluation Metrics
- 9 Dataset
- 10 Testing and Training Data
- 11 Batch size
- 12 Epoch

- NN: development (implementation and experimentation) is difficult.

## Keras is

- high-level neural networks library
- written in Python
- capable of running on top of
  - TensorFlow (open source software library for numerical computation)
  - Theano (numerical computation library for Python)
  - CNTK (Microsoft Cognitive Toolkit): Deep learning framework
- developed with a focus on enabling fast experimentation (through user friendliness, modularity, and extensibility)
- and much more [visit](#)

# Guiding principles

- Modularity
  - configurable modules
    - neural layers, cost functions, optimizers, initialization schemes, activation functions, regularization schemes are all standalone modules that you can combine to create new models
- Minimalism
  - Each module should be kept short and simple
- Easy extensibility
  - New modules are simple to add (as new classes and functions)
  - suitable for advanced research
- Work with Python
  - Models are described in Python code, which is compact, easier to debug, and allows for ease of extensibility
- User friendliness

# Installation and Dependencies

- No worries
  - Google Colab
- You may visit Keras Installation Page @ [keras.io](https://keras.io)

## What is in the toolbox ?

- Models
- Layers
- Preprocessing
- Metrics
- Optimizers
- Activations
- Datasets
- Constraints
- Initializers
- Loss (Objective) Function
- and many more...

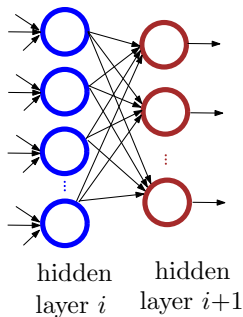
- Model
  - core data structure of Keras
  - a way to organize layers
- Two types:
  - Sequential
  - Model class API
- Sequential Model: a linear stack of layers
- functional API: for defining complex models, such as models with shared layers

- Core Layers
  - Dense
  - Activation
  - Dropout
  - Flatten
  - many more ...
- Convolutional Layers
- Pooling Layers
- Recurrent Layers
- Your own Keras layers
- and many more ...



## Dense

- fully connected NN layer: connection to all activations from previous layer



# Core Layers

## Activation

- Applies an activation function
  - detailed next

## Dropout

- Applies Dropout to the input
- randomly setting a fraction  $p$  of input units to 0
- prevent overfitting

## Flatten

- Flattens the input
- many more

# Activation Function: Sigmoid

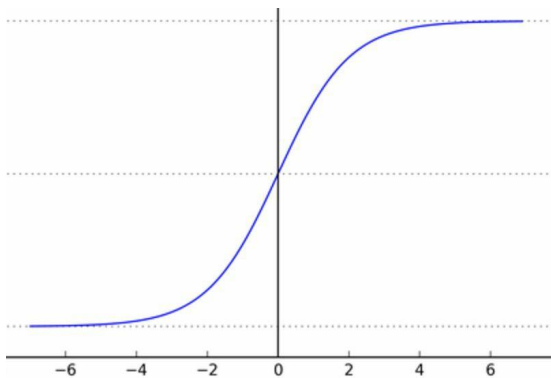


Figure: Sigmoid Function

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (1)$$

# Activation Function: ReLU (rectified linear unit)



Figure: ReLU

$$f(x) = \max(0, x) \quad (2)$$

# Activation Function: softmax

- usually used on the output layer to turn the outputs into probability-like values
- Sigmoid: two class
- softmax: multiclass

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} \quad (3)$$

for  $i=1$  to  $K$  and  $K$  is number of output units in output layer

# Activation Function

linear

$$f(x) = x \quad (4)$$

- and many more...

# Keras provides

## Optimizer

- the specific algorithm used to update weights while we train our model
- such as *sgd* (Stochastic gradient descent optimizer)

## Objective function or loss function

- used by the optimizer to navigate the space of weights
- such as *mse* (mean squared error)

## Metrics

- used to judge the performance of your model
- such as *accuracy*

- Keras provides nice API
- documentation
  - A tour of <https://keras.io>



# Building a Simple Deep Learning Network Using Keras

## Steps

- Import libraries and modules
- Load image data
- Pre-process data
- Define model architecture
- Compile model
- Fit and evaluate Model
- Improvements

- Fully Connected Neural Network with MNIST dataset

# Sample Output

```
temp : bash - Konsole
File Edit View Bookmarks Settings Help
niraj@niraj-Veriton-M200-Q87:~/temp$ python 1.py
Using Theano backend.
(60000, 28, 28)
(60000,)

Layer (type)                Output Shape              Param #                   Connected to
-----
dense_1 (Dense)             (None, 784)               615440                    dense_input_1[0][0]
dense_2 (Dense)             (None, 10)                7850                      dense_1[0][0]
-----
Total params: 623,290
Trainable params: 623,290
Non-trainable params: 0

None
Train on 60000 samples, validate on 10000 samples
Epoch 1/2
60000/60000 [=====] - 4s - loss: 0.2744 - acc: 0.9221 - val_loss: 0.1356 - val_acc: 0.9601
Epoch 2/2
60000/60000 [=====] - 4s - loss: 0.1078 - acc: 0.9688 - val_loss: 0.0957 - val_acc: 0.9707
 9600/10000 [=====>...] - ETA: 0s Error: 2.93%
niraj@niraj-Veriton-M200-Q87:~/temp$
```

# Improving Performance of Simple Network: additional hidden layers

```
temp : bash - Konsole
File Edit View Bookmarks Settings Help
niraj@niraj-Veriton-M200-Q87:~/temp$ python 1.py
Using Theano backend.
(60000, 28, 28)
(60000,)

=====
Layer (type)                Output Shape      Param #           Connected to
=====
dense_1 (Dense)             (None, 784)       615440            dense_input_1[0][0]
=====
dense_2 (Dense)             (None, 784)       615440            dense_1[0][0]
=====
dense_3 (Dense)             (None, 10)        7850              dense_2[0][0]
=====

Total params: 1,238,730
Trainable params: 1,238,730
Non-trainable params: 0

None
Train on 60000 samples, validate on 10000 samples
Epoch 1/2
60000/60000 [=====] - 8s - loss: 0.2184 - acc: 0.9354 - val_loss: 0.1094 - val_acc: 0.9639
Epoch 2/2
60000/60000 [=====] - 8s - loss: 0.0755 - acc: 0.9767 - val_loss: 0.0852 - val_acc: 0.9720
 9824/10000 [=====>.] - ETA: 0s Error: 2.80%
niraj@niraj-Veriton-M200-Q87:~/temp$
```

# Improving Performance of Simple Network: additional hidden layers

```
temp : bash - Konsole
File Edit View Bookmarks Settings Help
niraj@niraj-Veriton-M200-Q87:~/temp$ python 1.py
Using Theano backend.
(60000, 28, 28)
(60000,)

=====
Layer (type)                Output Shape      Param #   Connected to
=====
dense_1 (Dense)             (None, 784)      615440    dense_input_1[0][0]
=====
dense_2 (Dense)             (None, 784)      615440    dense_1[0][0]
=====
dense_3 (Dense)             (None, 784)      615440    dense_2[0][0]
=====
dense_4 (Dense)             (None, 10)       7850     dense_3[0][0]
=====

Total params: 1,854,170
Trainable params: 1,854,170
Non-trainable params: 0

None
Train on 60000 samples, validate on 10000 samples
Epoch 1/2
60000/60000 [=====] - 11s - loss: 0.1999 - acc: 0.9388 - val_loss: 0.0950 - val_acc: 0.9712
Epoch 2/2
60000/60000 [=====] - 12s - loss: 0.0751 - acc: 0.9770 - val_loss: 0.0914 - val_acc: 0.9738
9920/10000 [=====>.] - ETA: 0s Error: 2.62%
niraj@niraj-Veriton-M200-Q87:~/temp$
```

# Improving Performance of Simple Network: introducing dropout layer

```
temp : bash - Konsole
File Edit View Bookmarks Settings Help
niraj@niraj-Veriton-M200-Q87:~/temp$ python 1.py
Using Theano backend.
(60000, 28, 28)
(60000,)

=====
Layer (type)                Output Shape      Param #    Connected to
=====
dense_1 (Dense)             (None, 784)      615440    dense_input_1[0][0]
=====
dense_2 (Dense)             (None, 784)      615440    dense_1[0][0]
=====
dense_3 (Dense)             (None, 784)      615440    dense_2[0][0]
=====
dropout_1 (Dropout)         (None, 784)      0         dense_3[0][0]
=====
dense_4 (Dense)             (None, 10)       7850     dropout_1[0][0]
=====
Total params: 1,854,170
Trainable params: 1,854,170
Non-trainable params: 0

None
Train on 60000 samples, validate on 10000 samples
Epoch 1/2
60000/60000 [=====] - 13s - loss: 0.2014 - acc: 0.9386 - val_loss: 0.1017 - val_acc: 0.9697
Epoch 2/2
60000/60000 [=====] - 14s - loss: 0.0771 - acc: 0.9760 - val_loss: 0.0811 - val_acc: 0.9740
10000/10000 [=====] - 1s
Error: 2.60%
niraj@niraj-Veriton-M200-Q87:~/temp$
```

# Improving Performance of Simple Network: using different optimizers

```
temp : bash - Konsole
File Edit View Bookmarks Settings Help
niraj@niraj-Veriton-M200-Q87:~/temp$ python 1.py
Using Theano backend.
(60000, 28, 28)
(60000,)

=====
Layer (type)                Output Shape      Param #           Connected to
=====
dense_1 (Dense)             (None, 784)      615440            dense_input_1[0][0]
=====
dense_2 (Dense)             (None, 784)      615440            dense_1[0][0]
=====
dense_3 (Dense)             (None, 784)      615440            dense_2[0][0]
=====
dropout_1 (Dropout)         (None, 784)      0                 dense_3[0][0]
=====
dense_4 (Dense)             (None, 10)       7850              dropout_1[0][0]
=====
Total params: 1,854,170
Trainable params: 1,854,170
Non-trainable params: 0

None
Train on 60000 samples, validate on 10000 samples
Epoch 1/2
60000/60000 [=====] - 9s - loss: 1.0352 - acc: 0.7382 - val_loss: 0.4882 - val_acc: 0.8791
Epoch 2/2
60000/60000 [=====] - 10s - loss: 0.4422 - acc: 0.8784 - val_loss: 0.3497 - val_acc: 0.9051
 9984/10000 [=====>.] - ETA: 0s Error: 9.49%
niraj@niraj-Veriton-M200-Q87:~/temp$
```

# Improving Performance of Simple Network: training for more number of epochs

```
temp : bash - Konsole
File Edit View Bookmarks Settings Help
niraj@niraj-Veriton-M200-Q87:~/temp$ python 1.py
Using Theano backend.
(60000, 28, 28)
(60000,)
```

Layer (type)	Output Shape	Param #	Connected to
dense_1 (Dense)	(None, 784)	615440	dense_input_1[0][0]
dense_2 (Dense)	(None, 784)	615440	dense_1[0][0]
dense_3 (Dense)	(None, 784)	615440	dense_2[0][0]
dropout_1 (Dropout)	(None, 784)	0	dense_3[0][0]
dense_4 (Dense)	(None, 10)	7850	dropout_1[0][0]

```
=====  
Total params: 1,854,170  
Trainable params: 1,854,170  
Non-trainable params: 0  
=====  
None  
Train on 60000 samples, validate on 10000 samples  
Epoch 1/20  
60000/60000 [=====] - 10s - loss: 1.0537 - acc: 0.7378 - val_loss: 0.4933 - val_acc: 0.8815  
Epoch 2/20  
60000/60000 [=====] - 9s - loss: 0.4407 - acc: 0.8813 - val_loss: 0.3505 - val_acc: 0.9054  
Epoch 3/20  
60000/60000 [=====] - 10s - loss: 0.3512 - acc: 0.9016 - val_loss: 0.3008 - val_acc: 0.9187  
Epoch 4/20
```

```
temp : bash
```



# Improving Performance of Simple Network: training for more number of epochs

```
temp : bash - Konsole
File Edit View Bookmarks Settings Help
60000/60000 [=====] - 9s - loss: 0.2415 - acc: 0.9314 - val_loss: 0.2227 - val_acc: 0.9377
Epoch 8/20
60000/60000 [=====] - 10s - loss: 0.2280 - acc: 0.9348 - val_loss: 0.2114 - val_acc: 0.9404
Epoch 9/20
60000/60000 [=====] - 9s - loss: 0.2150 - acc: 0.9386 - val_loss: 0.2007 - val_acc: 0.9428
Epoch 10/20
60000/60000 [=====] - 9s - loss: 0.2036 - acc: 0.9420 - val_loss: 0.1931 - val_acc: 0.9454
Epoch 11/20
60000/60000 [=====] - 10s - loss: 0.1934 - acc: 0.9446 - val_loss: 0.1835 - val_acc: 0.9477
Epoch 12/20
60000/60000 [=====] - 10s - loss: 0.1845 - acc: 0.9476 - val_loss: 0.1775 - val_acc: 0.9497
Epoch 13/20
60000/60000 [=====] - 10s - loss: 0.1757 - acc: 0.9500 - val_loss: 0.1714 - val_acc: 0.9508
Epoch 14/20
60000/60000 [=====] - 9s - loss: 0.1689 - acc: 0.9516 - val_loss: 0.1649 - val_acc: 0.9525
Epoch 15/20
60000/60000 [=====] - 10s - loss: 0.1614 - acc: 0.9541 - val_loss: 0.1584 - val_acc: 0.9532
Epoch 16/20
60000/60000 [=====] - 10s - loss: 0.1546 - acc: 0.9556 - val_loss: 0.1549 - val_acc: 0.9547
Epoch 17/20
60000/60000 [=====] - 9s - loss: 0.1484 - acc: 0.9583 - val_loss: 0.1491 - val_acc: 0.9564
Epoch 18/20
60000/60000 [=====] - 10s - loss: 0.1429 - acc: 0.9593 - val_loss: 0.1455 - val_acc: 0.9565
Epoch 19/20
60000/60000 [=====] - 10s - loss: 0.1373 - acc: 0.9611 - val_loss: 0.1412 - val_acc: 0.9579
Epoch 20/20
60000/60000 [=====] - 10s - loss: 0.1324 - acc: 0.9623 - val_loss: 0.1381 - val_acc: 0.9583
10000/10000 [=====] - 1s
Error: 4.17%
niraj@niraj-Veriton-M200-Q87:~/temp$
```

# Improving Performance of Simple Network

## other options to explore

- additional hidden layers
- dropout
- different optimizers
- more number of epochs
- optimizer learning rate
- number of internal hidden neurons
- batch size

# Part II: Convolution Neural Network

# Let's take a break from NN concepts

## Convolution

- among the most important operations in signal and image processing
- it is the core concept behind the convolution neural network
- convolution operation:  $(f * g) \triangleq \int_{-\infty}^{\infty} f(\tau)g(t - \tau)d\tau$
- produces a third function which represents how functions are correlated

# Convolution

- the two functions in context of images are:
  - input image
  - kernel (filter/feature detector)
- output is some feature
- important for images due to the property of being stationary  $\Rightarrow$  same feature detector for whole image

# 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

Image Source: Internet

# Convolution Example

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

Image

4	3	

Convolved  
Feature

Image Source: Internet

# Convolution Example

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

Image

4	3	4

Convolved  
Feature

Image Source: Internet



# Convolution Example

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

Image

4	3	4
2		

Convolved  
Feature

Image Source: Internet

# Convolution Example

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

Image

4	3	4
2	4	

Convolved  
Feature

Image Source: Internet

# Convolution Example

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

Image

4	3	4
2	4	3

Convolved  
Feature

Image Source: Internet

# Convolution Example

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

Image

4	3	4
2	4	3
2		

Convolved  
Feature

Image Source: Internet

# Convolution Example

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

Image

4	3	4
2	4	3
2	3	

Convolved  
Feature

Image Source: Internet

# Convolution Example

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

Image

4	3	4
2	4	3
2	3	4

Convolved  
Feature

Image Source: Internet

# Convolution Example






Operation	Kernel $\omega$	Image result $g(x,y)$
<b>Identity</b>	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
<b>Edge detection</b>	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
<b>Sharpen</b>	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	

Image Source: Internet

# Convolution Example





<b>Box blur</b> (normalized)	$\frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
<b>Gaussian blur 3 x 3</b> (approximation)	$\frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	
<b>Gaussian blur 5 x 5</b> (approximation)	$\frac{1}{256} \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$	
<b>Unsharp masking 5 x 5</b> Based on Gaussian blur with amount as 1 and threshold as 0 (with no image mask)	$\frac{-1}{256} \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & -476 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$	

Image Source: Internet



Switching back . . .

# Issue with the Fully Connected Neural Network

- number of parameters
  - a 32X32X3 image  $\Rightarrow$  3072 (on input layer)
  - a 720X720X3 image  $\Rightarrow$  15,55,200 (on input layer)
  - for large images, depending on number of hidden layers and the neurons in each layer, for fully connected neural network, number of parameters may be in *millions*
  - resource requirement
  - overfitting

# Convolution Neural Network (ConvNet)

## in many way similar to regular Neural Networks

- *neurons* organized to form *layers*
- weights to be learnt
- biases
- neurons receive inputs, performs a dot product followed by some activation function
- have a loss function ...

## in addition

- assume that input are images  $\Rightarrow$  thus, many things follows
- utilize spatial structure
  - regular network  $\Rightarrow$  image processed as a flat vector
- number of parameters is input independent

# ConvNet

- well suited for classifying images
  - being applied to other problems as well such as text, speech, video ...
- 
- network architecture more appropriate
  - layers of a ConvNet have neurons arranged in 3 dimensions: width, height, depth
  - each layer transforms an input 3D volume to an output 3D volume

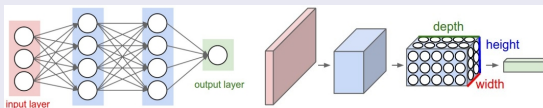


Image Source: <http://cs231n.github.io/convolutional-networks/>

# Convolution Example

## Recall convolution operation

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

Image

4	3	4
2	4	3
2	3	

Convolved  
Feature

Image Source: Internet

# Padding

## Issue

- pixels on the side are ignored
- in addition, padding helps in controlling image size

0	0	0	0	0	0	0	0
0	18	54	51	239	244	188	0
0	55	121	75	78	95	88	0
0	35	24	204	113	109	221	0
0	3	154	104	235	25	130	0
0	15	253	225	159	78	233	0
0	68	85	180	214	245	0	0
0	0	0	0	0	0	0	0

Image Source: Internet

# Padding

## No padding

- Input:  $n \times n$
- Filter size:  $f \times f$
- Output:  $(n-f+1) \times (n-f+1)$

## with padding

- Input:  $n \times n$
- Padding:  $p$
- Filter size:  $f \times f$
- Output:  $(n+2p-f+1) \times (n+2p-f+1)$

## Two common choices for padding

- valid: no padding
- same: output size is same as input
  - $n+2p-f+1 = n \Rightarrow p = (f-1)/2$

# Stride

- number of steps during convolution
- Input:  $n \times n$
- Padding:  $p$
- Stride:  $s$
- Filter size:  $f \times f$
- Output:  $\lfloor (n+2p-f)/s+1 \rfloor \times \lfloor (n+2p-f)/s+1 \rfloor$
- reduces the size of the image



# Filters and Depth

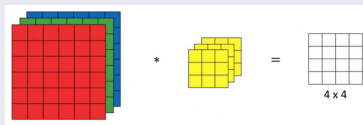


Image Source: Internet

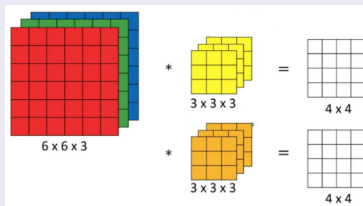


Image Source: Internet

# ConvNet Architecture

- Stack of layers: each layer transform the image volume (w,h,d) to an output volume
- Commonly used layers: Convolutional Layer, Pooling Layer, Fully-Connected Layer, ReLU
- a layer may (such as convolution layer) or may not (such as ReLU) have parameters
- a layer (such as convolution layer) may or may not (such as ReLU) have additional hyper-parameters (number of filters, stride, zero padding)

# Convolutional Layer

- core building block of a ConvNet
- perform convolution with the three hyper-parameters: depth, stride and padding
- incoming example

# Pooling

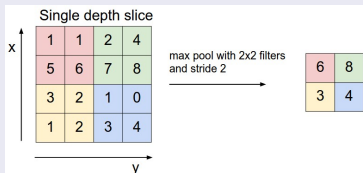


Image Source: Internet

## Pooling Layer

- reduces size  $\Rightarrow$  number of parameters and computation also decreases
- helps avoiding overfitting

## Findings

- Smaller stride is better (1)
- padding improves performance
- average pooling

- MNIST Example

## Additional

- Working with own data

# Constructing the Right Network

## steps to follow to make an efficient image classifier?

- lot of experimentation and testing to get the optimal structure and parameters
- A pre-trained model

## Links

- 1 Keras Official Documentation Page
- 2 Keras official github
- 3 Another GitHub Page
- 4 GitHub Page MNIST example
- 5 Keras Tutorial
- 6 An Example
- 7 Another Example
- 8 Deep Learning with Keras (Book)



The End