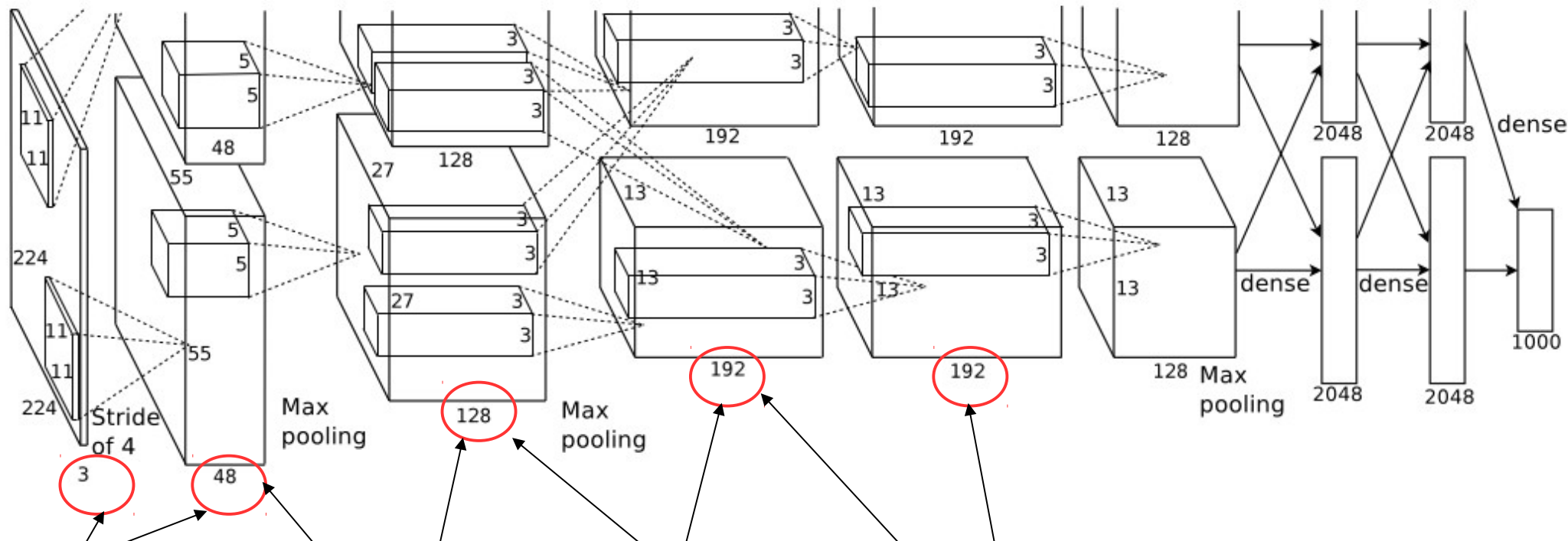




Reference: Alex Net

Reference: The 9 Deep Learning Papers You Need To Know About (Understanding CNNs Part 3)

<https://adeshpande3.github.io/adeshpande3.github.io/The-9-Deep-Learning-Papers-You-Need-To-Know-About.html>



Example 1: 48 kernels,
the depth of the kernel
is 3

Example 2: 128 kernels,
the depth of the kernel
is 48

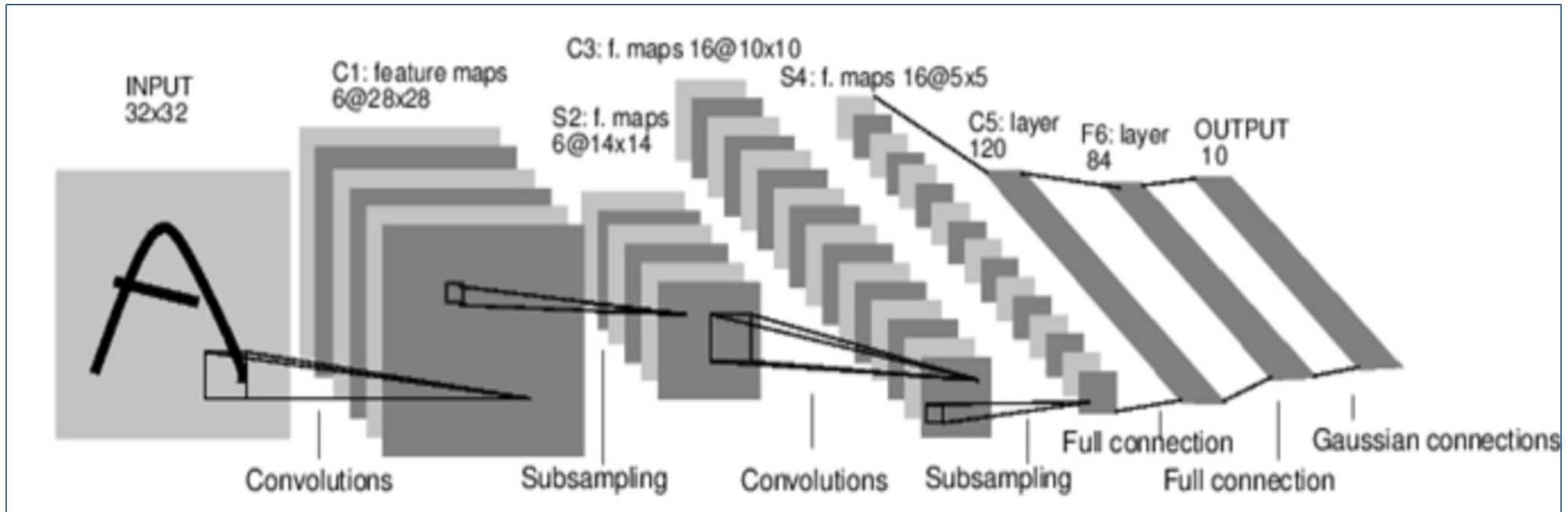
Example 3: 192 kernels,
the depth of the kernel
is 128

Example 4: 192 kernels,
the depth of the kernel
is 192



Reference 1: LeNet

<http://timdettmers.com/2015/03/26/convolution-deep-learning/>

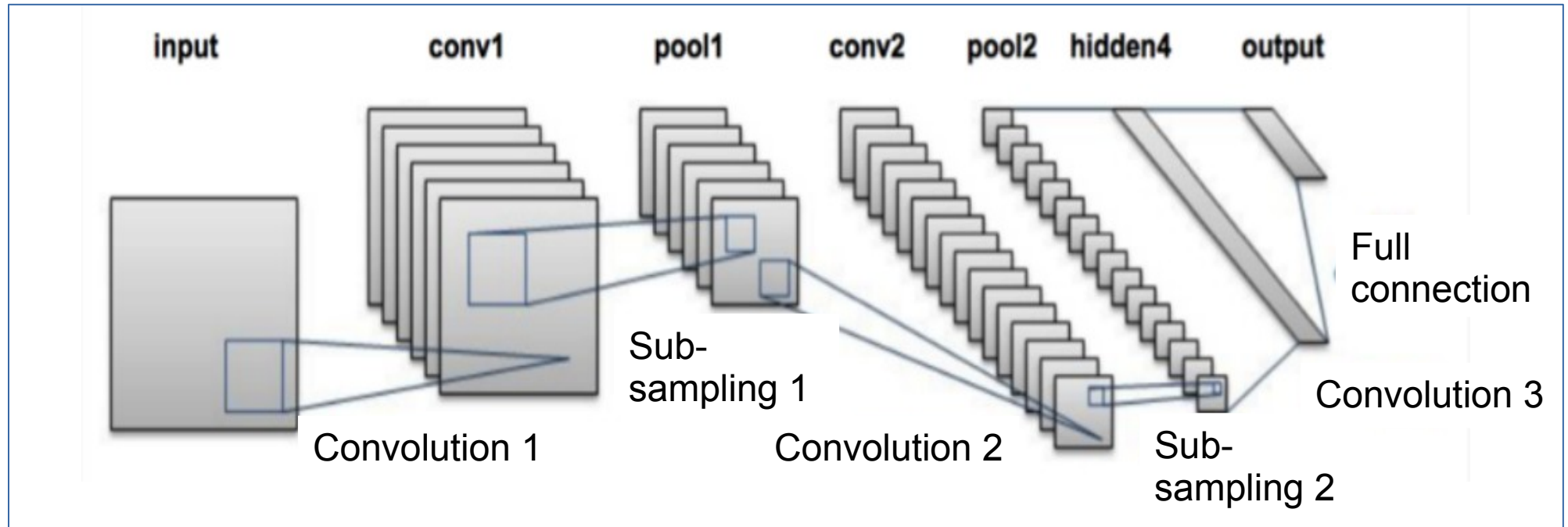


Convolution 1	Sub-sampling 1	Convolution 2	Sub-sampling 2	Full Conn 1	Full Conn2	Gau
C1	S2	C3	S4	Con5	F6	
Layer1	Layer2	Layer3	Layer4	Layer5	Layer6	output



Reference 2: LeNet

<https://www.pyimagesearch.com/2016/08/01/lenet-convolutional-neural-network-in-python/>



Convolution 1	Sub-sampling 1	Convolution 2	Sub-sampling 2	Convolution 3	Full connection
Conv1	pool1	Conv2	pool2	Hidden 4	Output
Layer1	Layer2	Layer3	Layer4	Layer5	

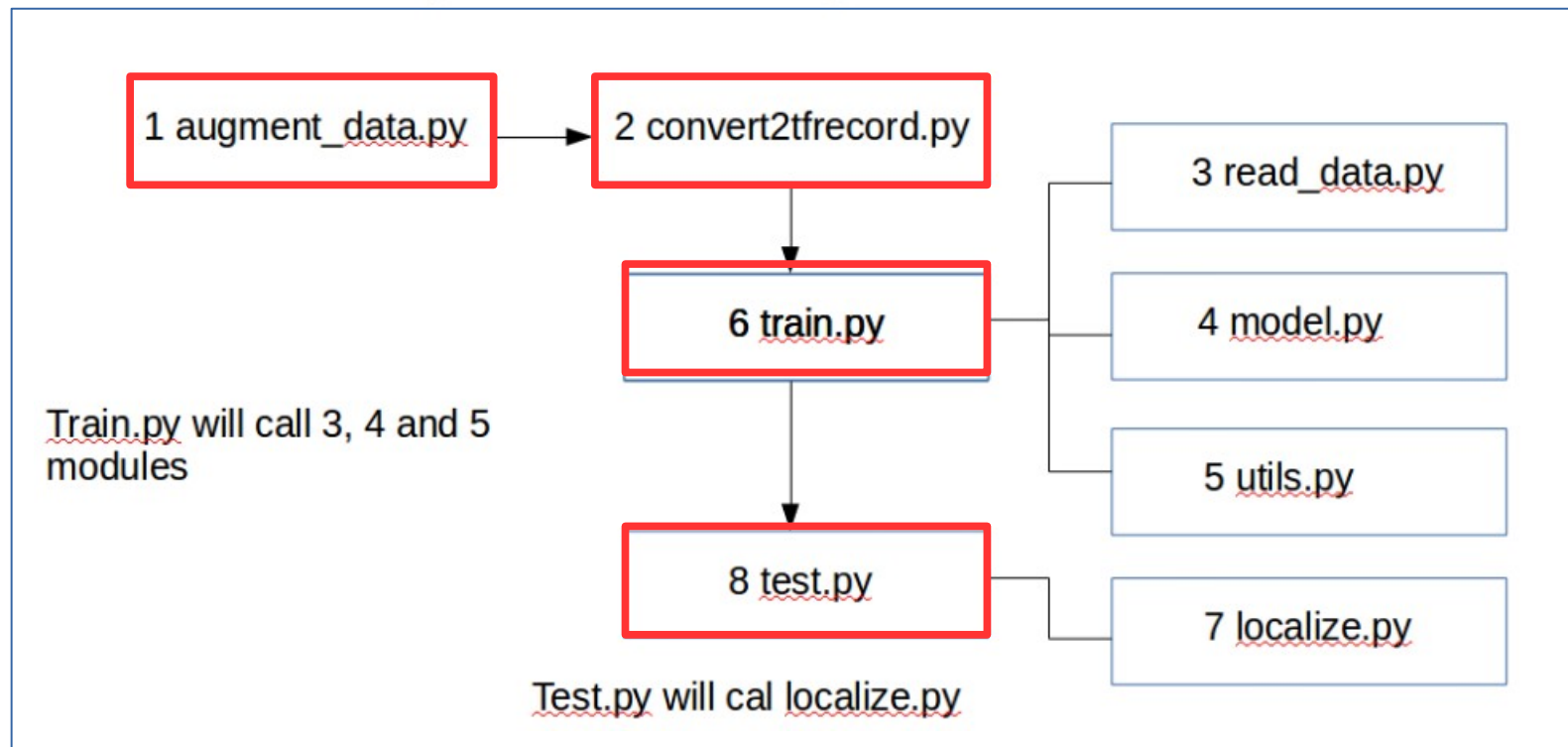


CTI One Production Code: TDAT

1. Code name: TDAT for (Tensor flow based, Deep Learning enabled, AGV4000 Toolkit)

Architecture of the TDAT

Deep Learning Modules



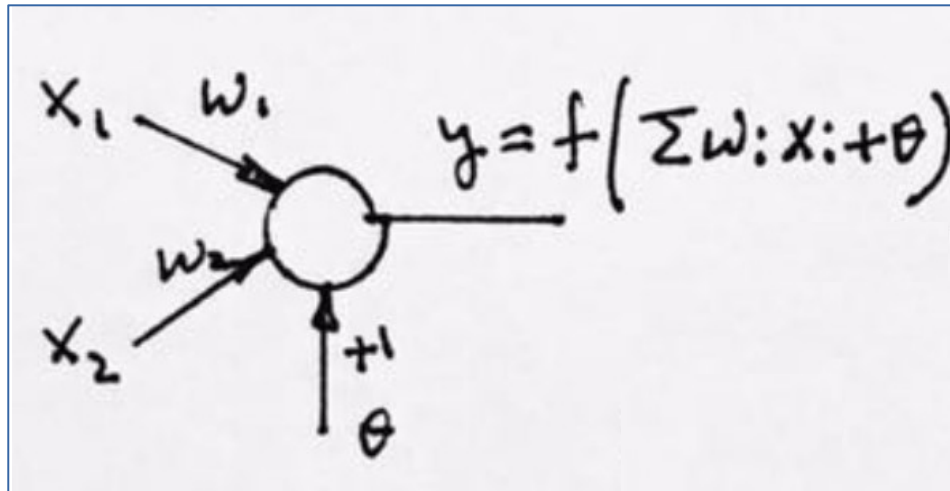


CTI One Production Sample Code

Table 1. Deep Learning Function Module Testing

Name of Module	Description	Execution and Application
1 <u>augment_data.py</u>	Augment cropped raw image data including Gaussian blur, motion blur, and Rotation to produce 20 new images.	\$ python <u>augment_data.py</u> Note: raw data set directory path can be changed in program
2 <u>convert2tfrecord.py</u>	Convert image data set to <u>tfrecord</u> file.	\$ python <u>convert2tfrecord.py</u>
3 <u>read_data.py</u>	Function of read data from <u>tfrecord</u> .	Called by <u>train.py</u>
4 <u>model.py</u>	3 models in <u>model.py</u> , <u>lenet_advanced</u> is used to train in this project.	Called by <u>train.py</u>
5 <u>utils.py</u>	Function of calculating loss and accuracy of training set	Called by <u>train.py</u>
6 <u>train.py</u>	Train the model using training data set.	\$ python <u>train.py</u>
7 <u>localize.py</u>	Localize the traffic signs by <u>pre-trained</u> model.	Called by <u>test.py</u>
8 <u>test.py</u>	Deploy and test our trained model by reading image from real <u>enviornment</u> .	\$ python <u>test.py</u>

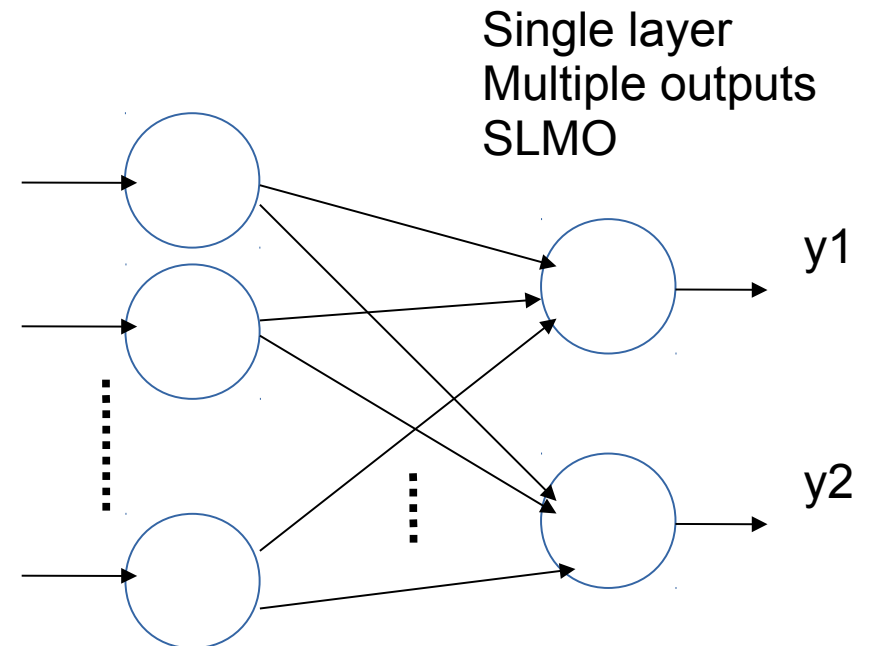
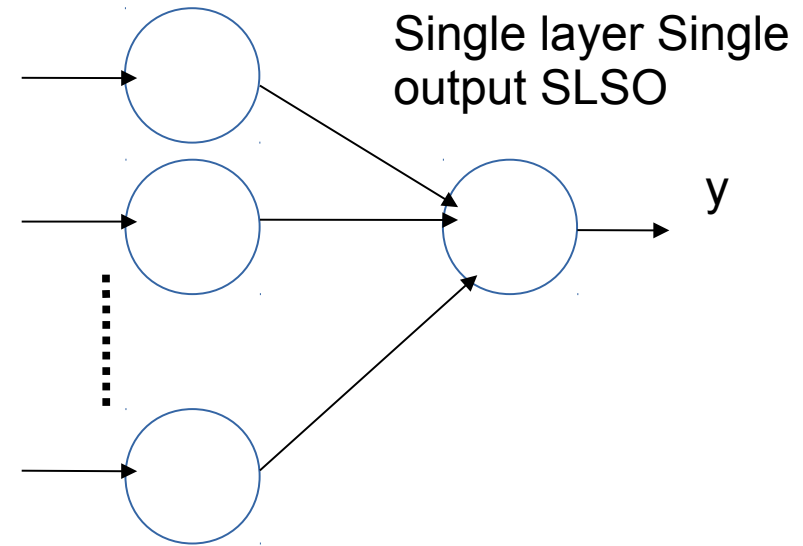
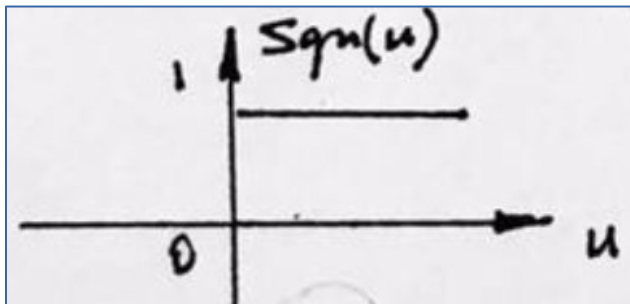
Road Map to LeNet (1)



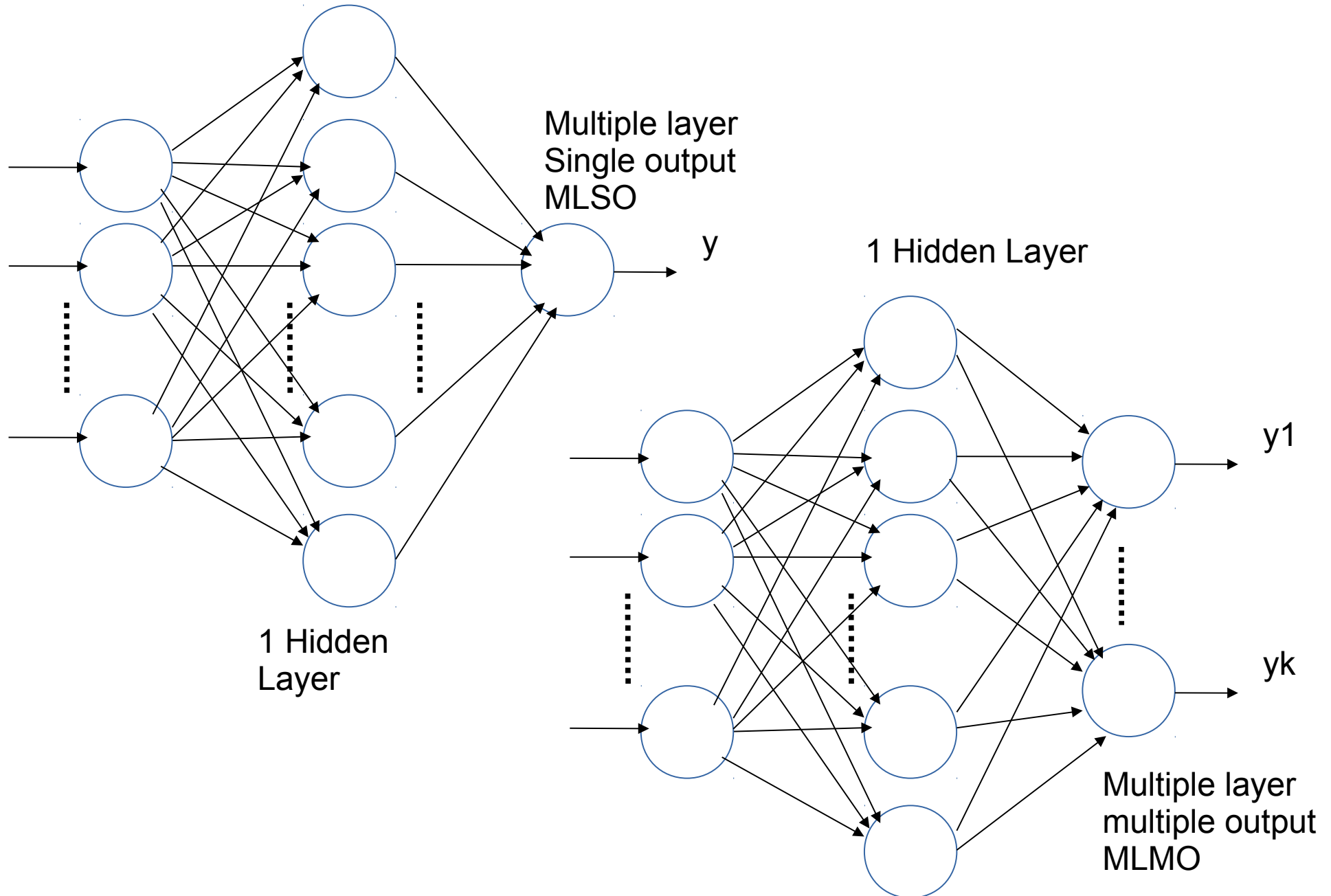
$$y = f(\sum w_i x_i + \theta) \quad \dots (1)$$

Where

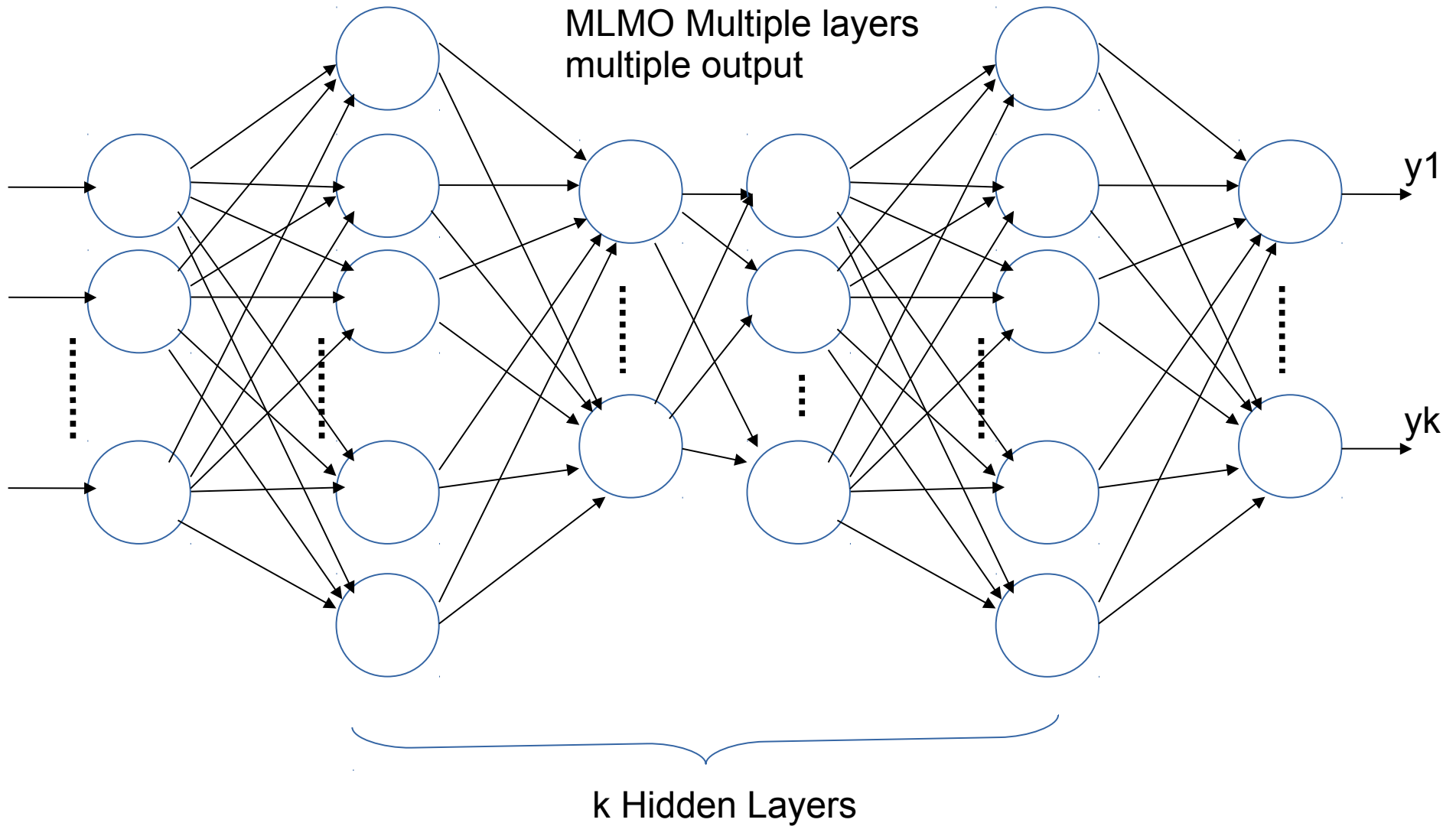
$$y = f(\cdot) \text{ as } \text{sgn}(\cdot) \quad \dots (2)$$



Road Map to LeNet (2)



Road Map to LeNet (3)





Python Implementation with numpy

```
#-----#  
# Program: 106-pytest86-edgefinder4.py;      #  
# Coded by: Tony Xu;          Date: Nov. 3rd, 2017;      #  
# Network Designed by: Harry Li, Ph.D. CTI One Corp.      #  
# Version: x01.0;      #  
# Status: Tested.      #  
# Note: Set output image pixel value 100, -100 and 0, as 1, #  
#       -1 and 0, so the output is 2 nodes, and this model  #  
#       converges.      #  
#-----#
```

1

Always starts your program with a well structured header like the one.

```
import numpy as np
```

2

```
learning_rate = 0.001  
momentum = 0.9
```

Define learning rate and momentum. See the updating formula next page

```
epochs = 10000 # Number of iterations  
stopError = 0.001
```

3

```
#define layout of network.
```

```
inputLayerSize, hiddenLayerSize, outputLayerSize = 27, 200, 2
```

4

```
imageSize = 4  
kernelSize = 3  
expandSize = 6 #imageSize + 2 * (kernelSize/2)
```

Define MLMO architecture



Python Code

2

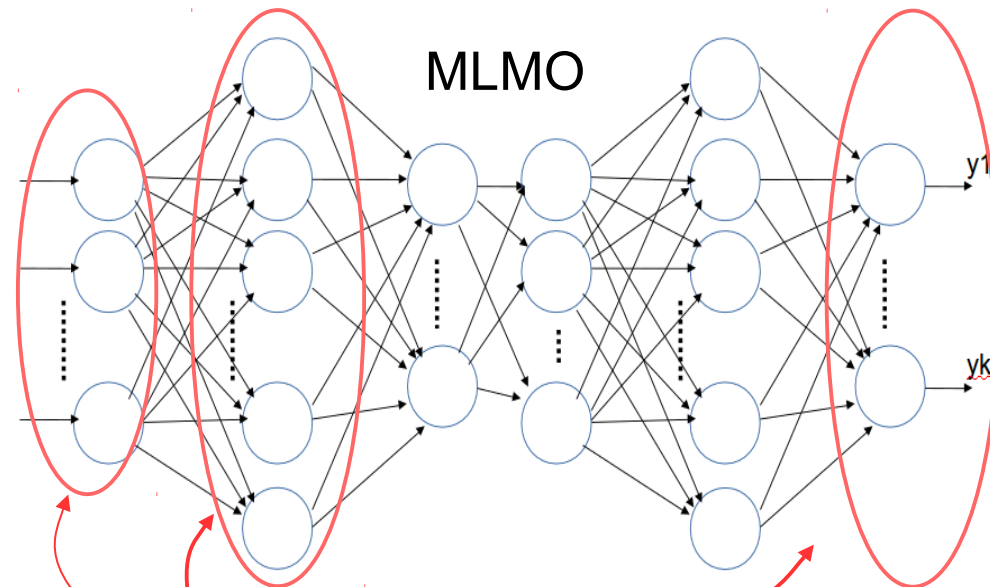
NumPy is a library for the Python programming language: (1) adding support for large, multi-dimensional arrays and matrices, and (2) large collection of high-level mathematical functions. BSD-new license [Stable release](#): 1.13.3 (September 2017); [Initial release](#): As Numeric, 1995; as NumPy, 2006.



<https://docs.scipy.org/doc/numpy-1.13.0/index.html> **Numpy C-API**
<https://docs.scipy.org/doc/numpy-1.13.0/reference/c-api.html>

3

Define MLMO architecture as:



inputLayerSize, hiddenLayerSize, outputLayerSize = 27, 200, 2



Connecting to Our Image Data

4

imageSize = 4
kernelSize = 3
expandSize = 6 $\#imageSize + 2 * (kernelSize - 1)/2$

	100	100	0	0
	100	100	0	0
	100	100	0	0
	100	100	0	0

Expand for
convolution

		x	$I_1(x,y)$	
	y		100	100
			100	100
			100	100
			100	100

Image

		$k(x,y)$	
		-1	0
		-1	0
		-1	0

Kernel



Python Code Defines Test Image Data

5

```
inputImagelist = [  
    [100,100,0,0, 100,100,0,0, 100,100,0,0, 100,100,0,0],  
    [100,100,100,0, 100,100,0,0, 100,100,0,0, 100,100,0,0],  
    [100,100,100,0, 100,100,100,0, 100,100,0,0, 100,100,0,0],  
    [100,100,100,0, 100,100,100,0, 100,100,100,0, 100,100,0,0],  
    [100,100,100,0, 100,100,100,0, 100,100,100,0, 100,100,100,0],  
    [0,100,100,0, 100,100,100,0, 100,100,100,0, 100,100,100,0],  
    [0,100,100,0, 0,100,100,0, 100,100,100,0, 100,100,100,0],  
    [0,100,100,0, 0,100,100,0, 0,100,100,0, 100,100,100,0],  
    [0,100,100,0, 0,100,100,0, 0,100,100,0, 0,100,100,0]  
]
```

```
desiredValues = [  
    [0,-1,-1,0, 0,-1,-1,0, 0,-1,-1,0, 0,-1,-1,0],  
    [0,0,-1,-1, 0,-1,-1,0, 0,-1,-1,0, 0,-1,-1,0],  
    [0,0,-1,-1, 0,0,-1,-1, 0,-1,-1,0, 0,-1,-1,0],  
    [0,0,-1,-1, 0,0,-1,-1, 0,0,-1,-1, 0,-1,-1,0],  
    [0,0,-1,-1, 0,0,-1,-1, 0,0,-1,-1, 0,0,-1,-1],  
    [1,1,-1,-1, 0,0,-1,-1, 0,0,-1,-1, 0,0,-1,-1],  
    [1,1,-1,-1, 1,1,-1,-1, 0,0,-1,-1, 0,0,-1,-1],  
    [1,1,-1,-1, 1,1,-1,-1, 1,1,-1,-1, 0,0,-1,-1],  
    [1,1,-1,-1, 1,1,-1,-1, 1,1,-1,-1, 1,1,-1,-1]  
]
```

Diagram illustrating the mapping of input image data to a 4x4 grid labeled $I_1(x,y)$.

	x	$I_1(x,y)$		
y	100	100	0	0
100	100	100	0	0
100	100	100	0	0
100	100	100	0	0

Diagram illustrating the mapping of desired values to a 4x4 grid.

0	-100	-100	0
0	-100	-100	0
0	-100	-100	0
0	-100	-100	0



Python Code Function Definition

```
def getsubImage(image, px, py):
    myElements = []
    startPosition = expandSize * py + px
    for i in range(kernelSize):
        for j in range(kernelSize):
            myElements.append(image[startPosition + i * expandSize + j])
    return myElements
```

		x		$I_1(x,y)$
y		100	100	0 0
		100	100	0 0
		100	100	0 0
		100	100	0 0

Syntax of Function Definition for Python

```
def function_name(parameters):
    """docstring"""
    statement(s)
```

<https://www.programiz.com/python-programming/function>

```
def functionName():
```

```
    ... .. ←
    ... ..
```

```
    ... ..
    ... ..
```

```
functionName();
```

```
    ... ..
    ... ..
```

Note: (1) def Keyword marks the start of function header.

(2) Parameters (arguments) if any;

(3) A colon (:) to mark the end of function header.

(4) Optional documentation string (docstring) to describe the function.

(5) Valid python statements make up the function body with same indentation level (usually 4 spaces).

(6) An optional return statement to return a value from the function.



Python Code “for” Loop

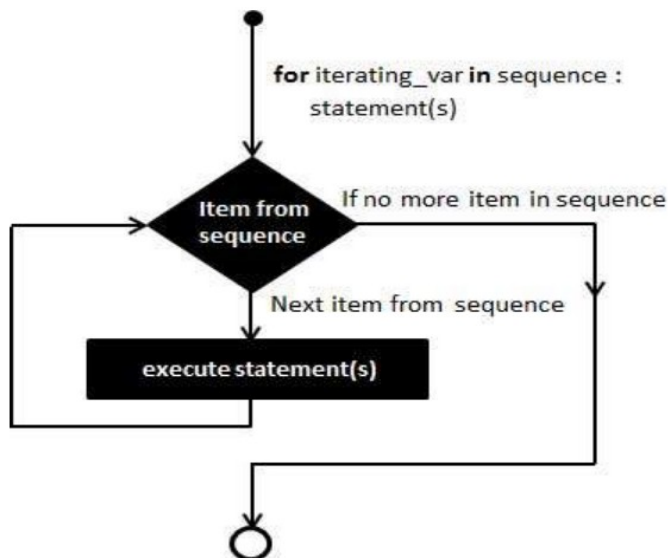
```
def getsubImage(image, px, py):  
    myElements = []  
    startPosition = expandSize * py + px  
    for i in range(kernelSize):  
        for j in range(kernelSize):  
            myElements.append(image[startPosition + i * expandSize + j])  
    return myElements
```

Diagram illustrating the iteration process for the 'for' loop. The grid shows the values of $I_1(x,y)$ for x and y coordinates. The first two columns (x=0,1) contain 100, and the last two columns (x=2,3) contain 0. The y-axis ranges from 0 to 3.

	x=0	x=1	x=2	x=3
y=0	100	100	0	0
y=1	100	100	0	0
y=2	100	100	0	0
y=3	100	100	0	0

Syntax

```
for iterating_var in sequence:  
    statements(s)
```



Note:

- (1) A sequence, e.g., an expression list is evaluated. Then, the first item in the sequence is assigned to the iterating variable.
- (2) then the statements block is executed.
- (3) Each item in the list is assigned to iterating_var, and the statement(s) block is executed until the entire sequence is exhausted.



Python Code Define Function

```
def expandImage(image):
    operationalInput = []
    inputImage = []
    #expand right and left intensity column
    for i in range(imageSize):
        for j in range(imageSize):
            if j == 0:
                operationalInput.append(image[i * imageSize + j])
            if j == imageSize - 1:
                operationalInput.append(image[i * imageSize + j])
            operationalInput.append(image[i * imageSize + j])

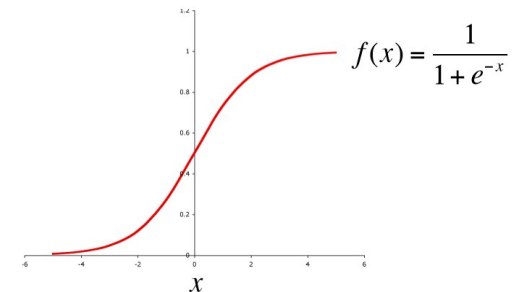
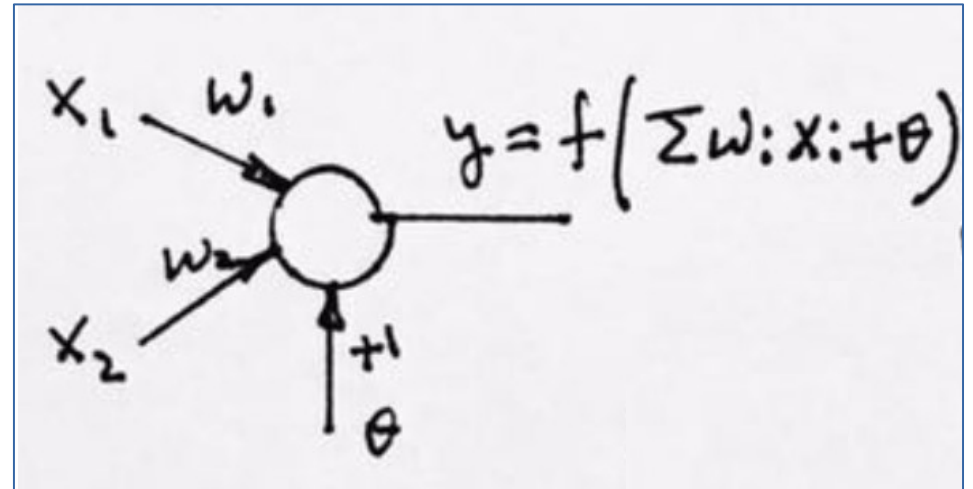
    #expand first intensity row
    for i in range(expandSize):
        inputImage.append(operationalInput[i])
    #keep middle rows
    for i in range(imageSize):
        for j in range(expandSize):
            inputImage.append(operationalInput[i * expandSize + j])
    #add last row
    for i in range(expandSize):
        inputImage.append(operationalInput[(imageSize-1) * expandSize + i])
    return inputImage
```




Python Code for Sigmoid Function

```
#activation function sigmoid
def sigmoid (x):
    return 1/(1 + np.exp(-x))
```

```
# derivative of sigmoid
def sigmoid_derivative(x):
    return x * (1 - x)
```



Python Code for Weights Init

```
#init weights and old weights
Weights_i_h = np.random.uniform(-1, 1, size=(inputLayerSize, hiddenLayerSize))
lastdeltaWeights_i_h = np.zeros(shape=(inputLayerSize, hiddenLayerSize))

Weightsh_o = np.random.uniform(-1, 1, size=(hiddenLayerSize, outputLayerSize))
lastdeltaWeightsh_o = np.zeros(shape=(hiddenLayerSize, outputLayerSize))
```



np.random.uniform and np.zeros

```
#init weights and old weights
Weights_i_h = np.random.uniform(-1, 1, size=(inputLayerSize, hiddenLayerSize))
lastdeltaWeights_i_h = np.zeros(shape=(inputLayerSize, hiddenLayerSize))
```

`numpy.random.` **uniform** (*low=0.0, high=1.0, size=None*)



Samples are uniformly distributed over the half-open interval [low, high) (includes low, but excludes high).

Note:

`size=(inputLayerSize, hiddenLayerSize)`

`size` : int or tuple of ints

`numpy.` **zeros** (*shape, dtype=float, order='C'*)

`shape` : int or
sequence of ints

Return a new array of given shape and type, filled with zeros.



Back Prop

```
for i in range(epochs):
    #forward path
    hiddenLayerOutput = sigmoid(np.dot(X, Weightsi_h))
    outputLayerOutput = sigmoid(np.dot(hiddenLayerOutput, Weightsh_o))
    #error (delta error) /cost /loss
    E = D - outputLayerOutput
    #determine if we have reached desired accuracy
    currentError = np.sum(np.square(E)) /float(len(X))
    if (currentError < stopError):
        print ("Reach to desired accuracy at epoch:", i)
        break
    #step 1, output layer's error
    dEatoutputLayer = E * sigmoid_derivative(outputLayerOutput)
    #step 2, determine delta weights between hidden layer and output layer
    dWeightsh_o = learning_rate * hiddenLayerOutput.T.dot(dEatoutputLayer) + momentum *
lastdeltaWeightsh_o
    #save current to be old
    lastdeltaWeightsh_o = dWeightsh_o
    #step 3, caculate delta E for hidden layers
    dEathiddenLayer = dEatoutputLayer.dot(Weightsh_o.T) * sigmoid_derivative(hiddenLayerOutput)
    #determine delta weights between hidden layer and input layer
    dWeightsi_h = learning_rate * X.T.dot(dEathiddenLayer) + momentum * lastdeltaWeightsi_h
    lastdeltaWeightsi_h = dWeightsi_h
    #update output and hidden layer weights
    Weightsh_o += dWeightsh_o
    Weightsi_h += dWeightsi_h
```

6

7

8



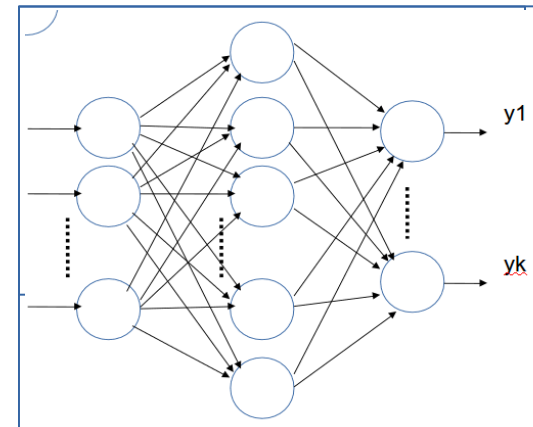
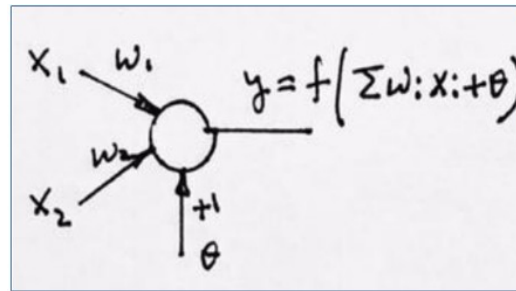
np.dot & np.sum & np.square

`numpy.dot(a, b, out=None)`

Dot product of two arrays.

For 2-D arrays it is equivalent to matrix multiplication, and for 1-D arrays to inner product of vectors (without complex conjugation). For N dimensions it is a sum product over the last axis of a and the second-to-last of b:

Example:
`np.dot(X, Weightsi_h)`



```
dWeightsh_o = learning_rate *  
hiddenLayerOutput.T.dot(dEaoutputLayer) + momentum *  
lastdeltaWeightsh_o
```

$$W(t+1) = W(t) + \Delta W \quad \dots (3)$$

$$\Delta W = - \eta * \partial E / \partial w \quad \dots (3.1)$$



Quiz (1)

1. what is NumPy? What language is it written for? What is the current release version?
2. How do you import numpy?
3. write one line of Python code to define MLMO feed-forward Neural Network architecture? Suppose there is one hidden layer and there are 100 nodes of the hidden layer? Input nodes = 20, and output nodes = 10?
4. How do you use def to define a function? Define a simple calculator function that is input arguments of 2 operand and 1 operator, such as addition, subtraction, multiplication, or division, and return the computed the result?
5. How is the for loop defined? Write a simple double for loop to read K by K image one pixel at time from left to right, top to bottom?
6. How would you call C function from python or from C call python?
7. How do you use np. to compute exp() function? Any other functions?
8. np.random.normal(), np.zeros(), and np.exp() etc.



Example: 2D Convolution (1)

$I_1(x,y)$

	x			
y	↓			
	100	100	0	0
	100	100	0	0
	100	100	0	0
	100	100	0	0

$I_2(x,y)$

	x			
y	↓			
	100	100	100	0
	100	100	0	0
	100	100	0	0
	100	100	0	0

$k(x,y)$

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

$O_1(x,y)$

	x			
y	↓			
	0	-100	-100	0
	0	-100	-100	0
	0	-100	-100	0
	0	-100	-100	0

$O_2(x,y)$

	x			
y	↓			
	0	0	-100	-100
	0	-100	-100	0
	0	-100	-100	0
	0	-100	-100	0

Verify this output by trained NN



2D Convolution (2)

$I_3(x,y)$

	x			
y	100	100	100	0
	100	100	100	0
	100	100	0	0
	100	100	0	0

$I_4(x,y)$

	x			
y	100	100	100	0
	100	100	100	0
	100	100	100	0
	100	100	0	0

$k(x,y)$

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

$O_3(x,y)$

	x			
y	0	0	-100	-100
	0	0	-100	-100
	0	-100	-100	0
	0	-100	-100	0

$O_4(x,y)$

	x			
y	0	0	-100	-100
	0	0	-100	-100
	0	0	-100	-100
	0	-100	-100	0

Verify this output by trained NN



2D Convolution (3)

Diagram showing the input image $I_5(x,y)$ for the first convolution operation. The image is a 4x4 grid with axes x and y .

	x	$I_5(x,y)$			
y		100	100	100	0
		100	100	100	0
		100	100	100	0
		100	100	100	0

Diagram showing the output image $O_5(x,y)$ for the first convolution operation. The image is a 4x4 grid with axes x and y .

	x	$O_5(x,y)$			
y		0	0	-100	-100
		0	0	-100	-100
		0	0	-100	-100
		0	0	-100	-100

Diagram showing the kernel $k(x,y)$ used for the convolution operation. The kernel is a 3x3 grid.

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

Diagram showing the input image $I_6(x,y)$ for the second convolution operation. The image is a 4x4 grid with axes x and y .

	x	$I_6(x,y)$			
y		0	100	100	0
		100	100	100	0
		100	100	100	0
		100	100	100	0

Diagram showing the output image $O_6(x,y)$ for the second convolution operation. The image is a 4x4 grid with axes x and y .

	x	$O_6(x,y)$			
y		100	100	-100	-100
		0	0	-100	-100
		0	0	-100	-100
		0	0	-100	-100



2D Convolution (4)

Version 2.0; Nov. 3rd, 2017

Diagram showing the input image $I_7(x,y)$ with axes x and y .

0	100	100	0
0	100	100	0
100	100	100	0
100	100	100	0

Diagram showing the kernel $k(x,y)$.

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

Diagram showing the output image $O_7(x,y)$ with axes x and y .

100	100	-100	-100
100	100	-100	-100
0	0	-100	-100
0	0	-100	-100

Verify this output by trained NN



2D Convolution (5)

$I_9(x,y)$

	x			
y	0	100	100	0
	0	100	100	0
	0	100	100	0
	100	100	100	0

$O_9(x,y)$

	x			
y	100	100	-100	-100
	100	100	-100	-100
	100	100	-100	-100
	0	0	-100	-100

$k(x,y)$

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

$I_{10}(x,y)$

	x			
y	0	100	100	0
	0	100	100	0
	0	100	100	0
	0	100	100	0

$O_{10}(x,y)$

	x			
y	100	100	-100	-100
	100	100	-100	-100
	100	100	-100	-100
	100	100	-100	-100