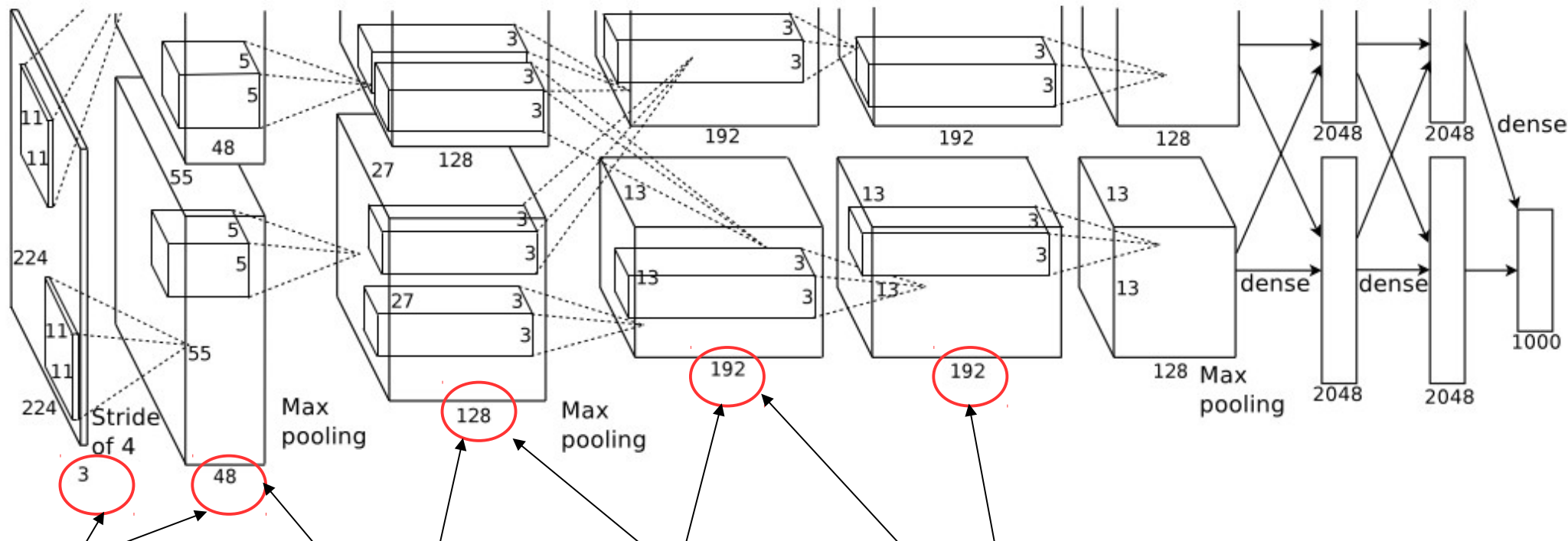




Reference: Alex Net

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

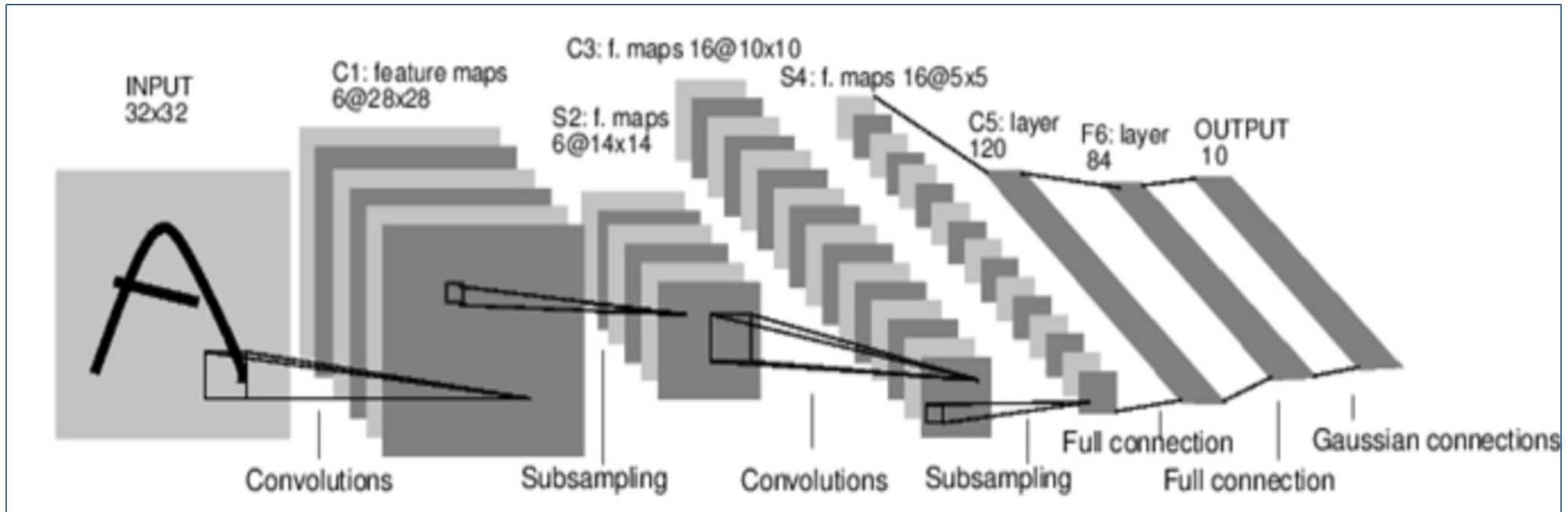
Example 3: 192 kernels,
the depth of the kernel
is 128

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



Reference 1: LeNet

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

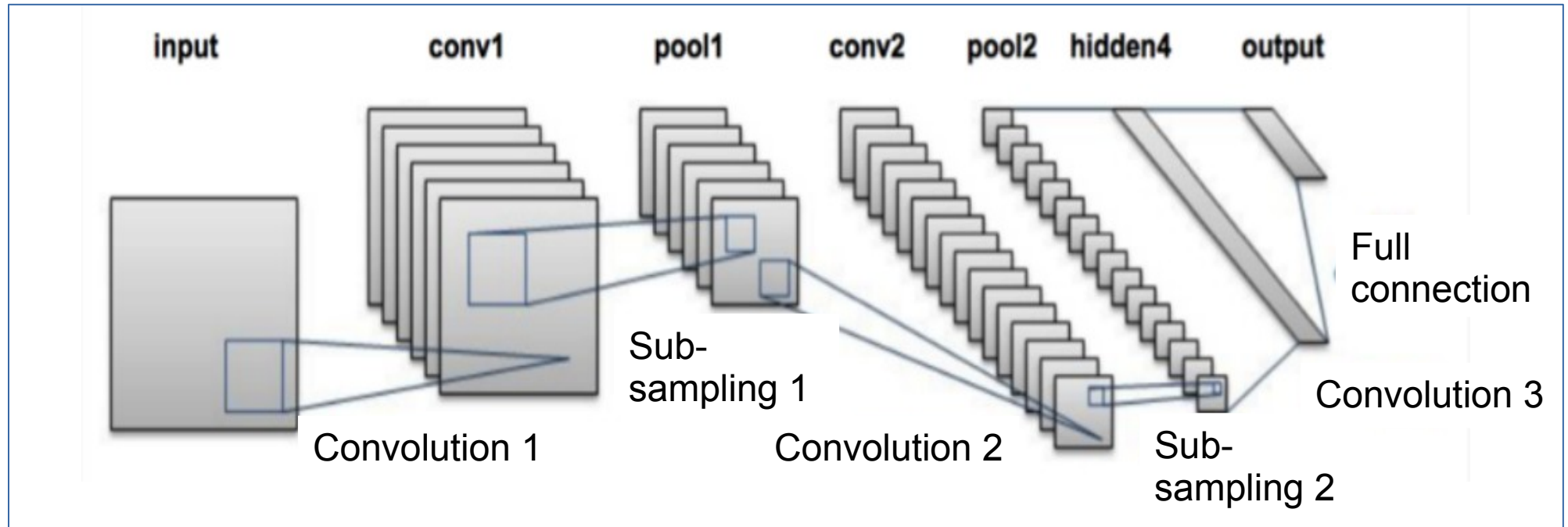


Convolution 1	Sub-sampling 1	Convolution 2	Sub-sampling 2	Full Conn 1	Full Conn2	Gau
C1	S2	C3	S4	Con5	F6	
Layer1	Layer2	Layer3	Layer4	Layer5	Layer6	output



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	

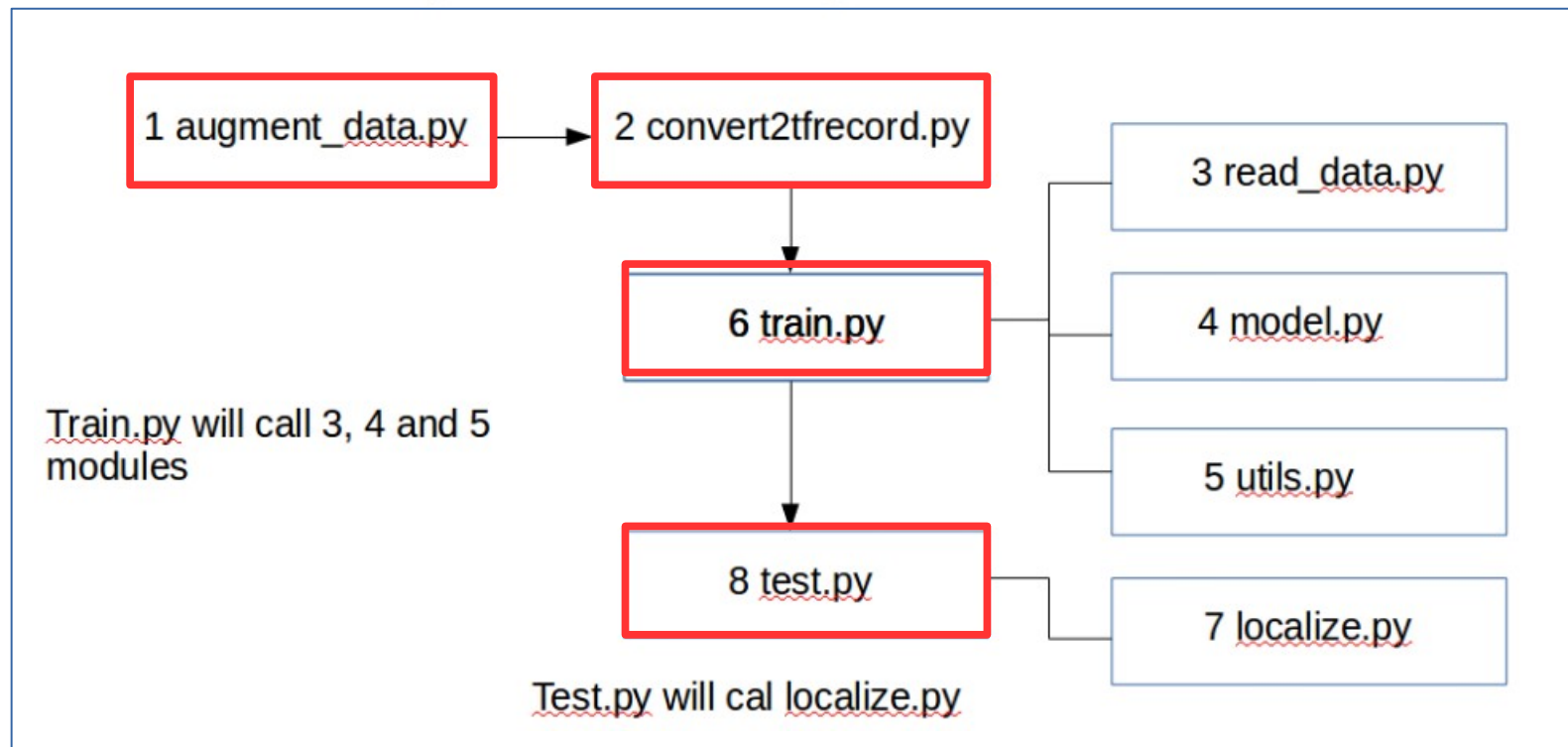


CTI One Production Code: TDAT

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

Architecture of the TDAT

Deep Learning Modules



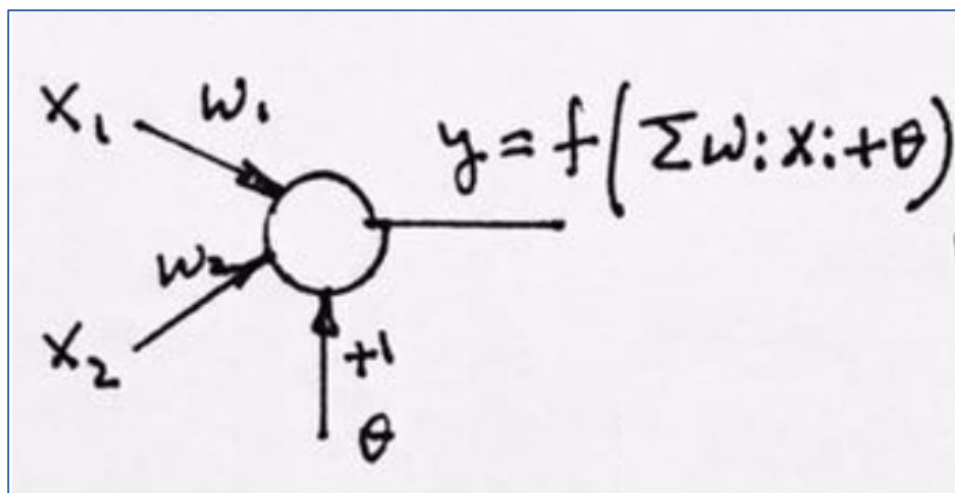


CTI One Production Sample Code

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>

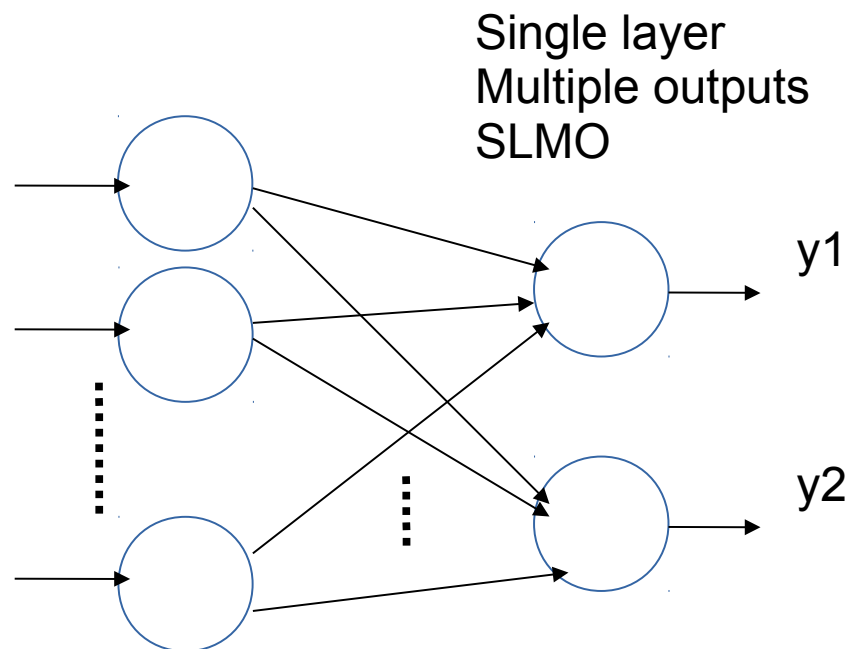
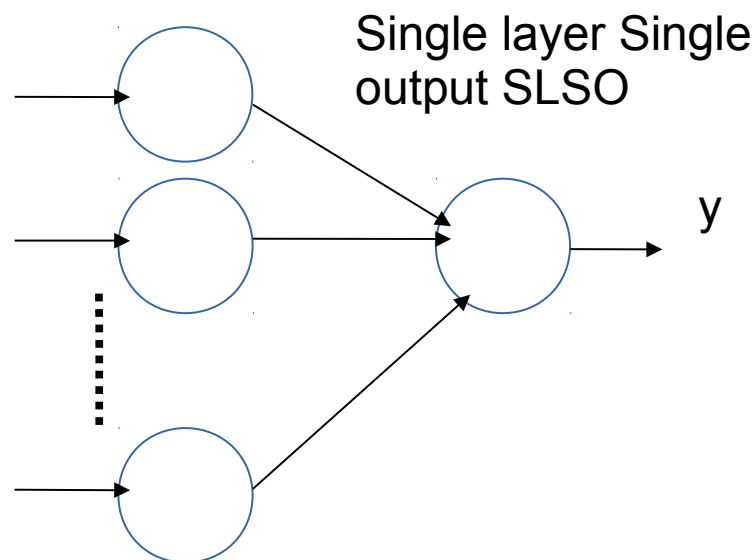
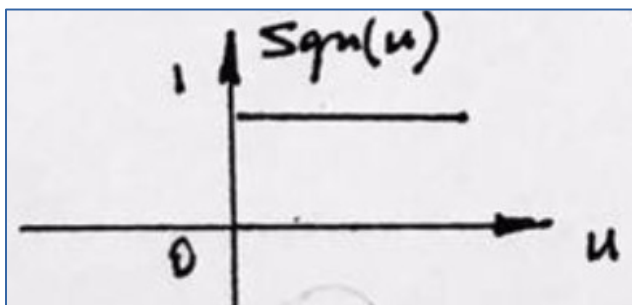
Road Map to LeNet (1)



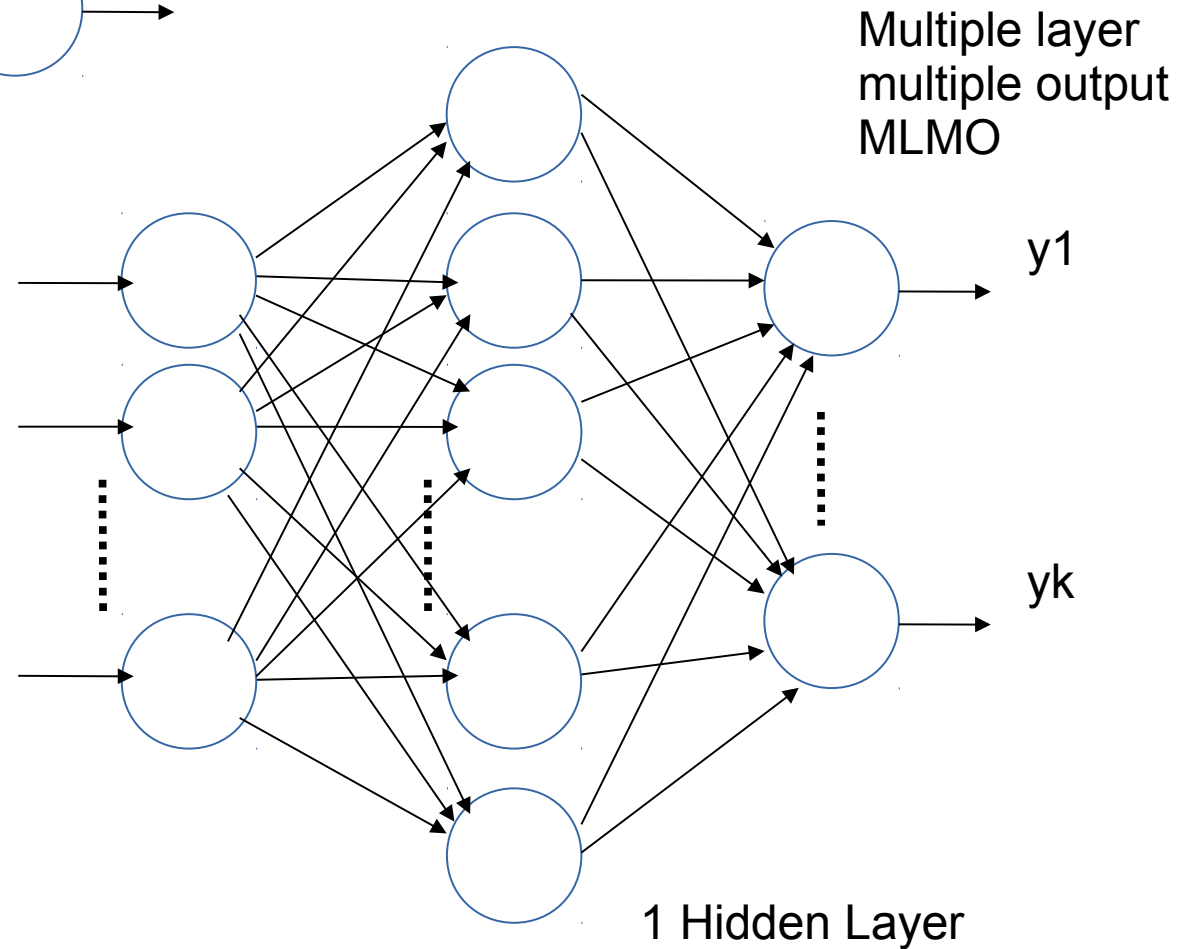
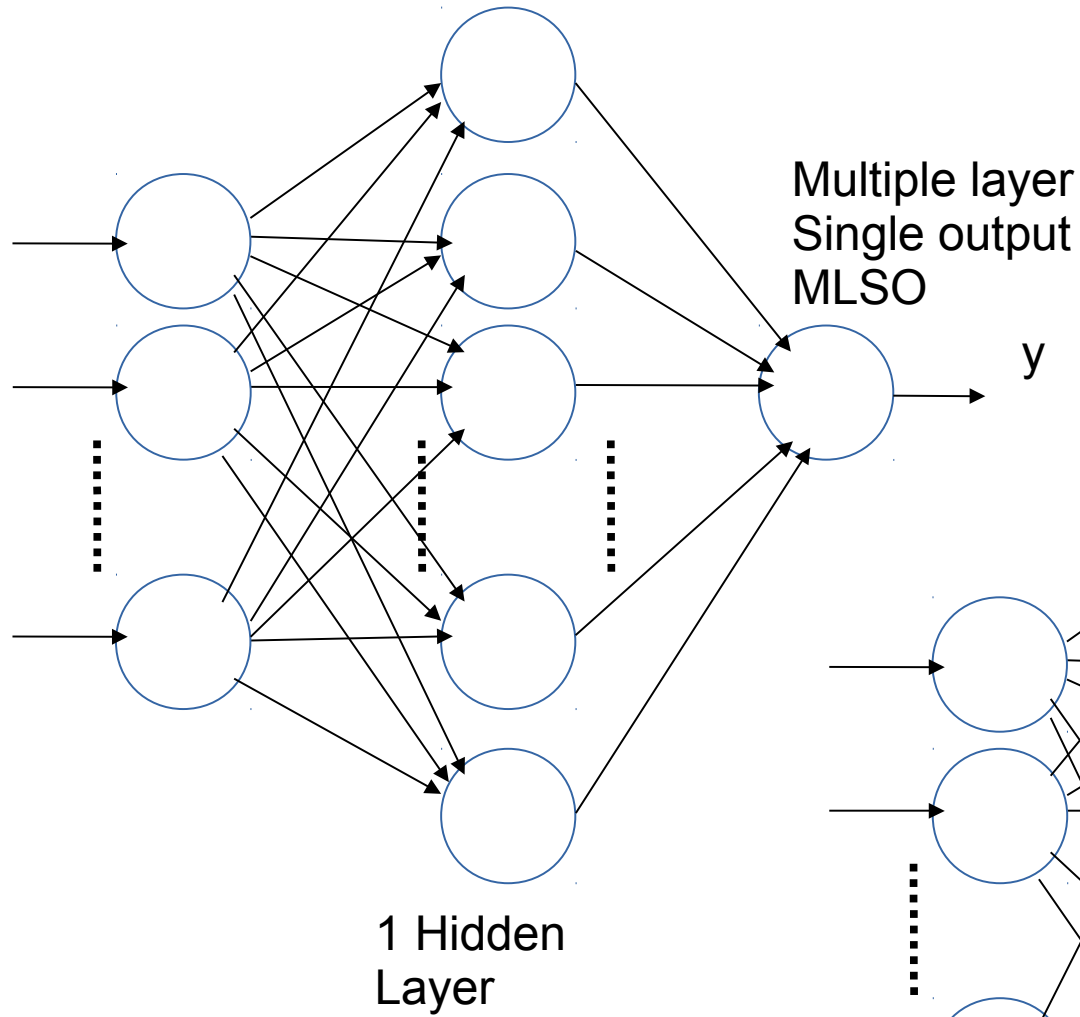
$$y = f(\sum w_i x_i + \theta) \quad \dots (1)$$

Where

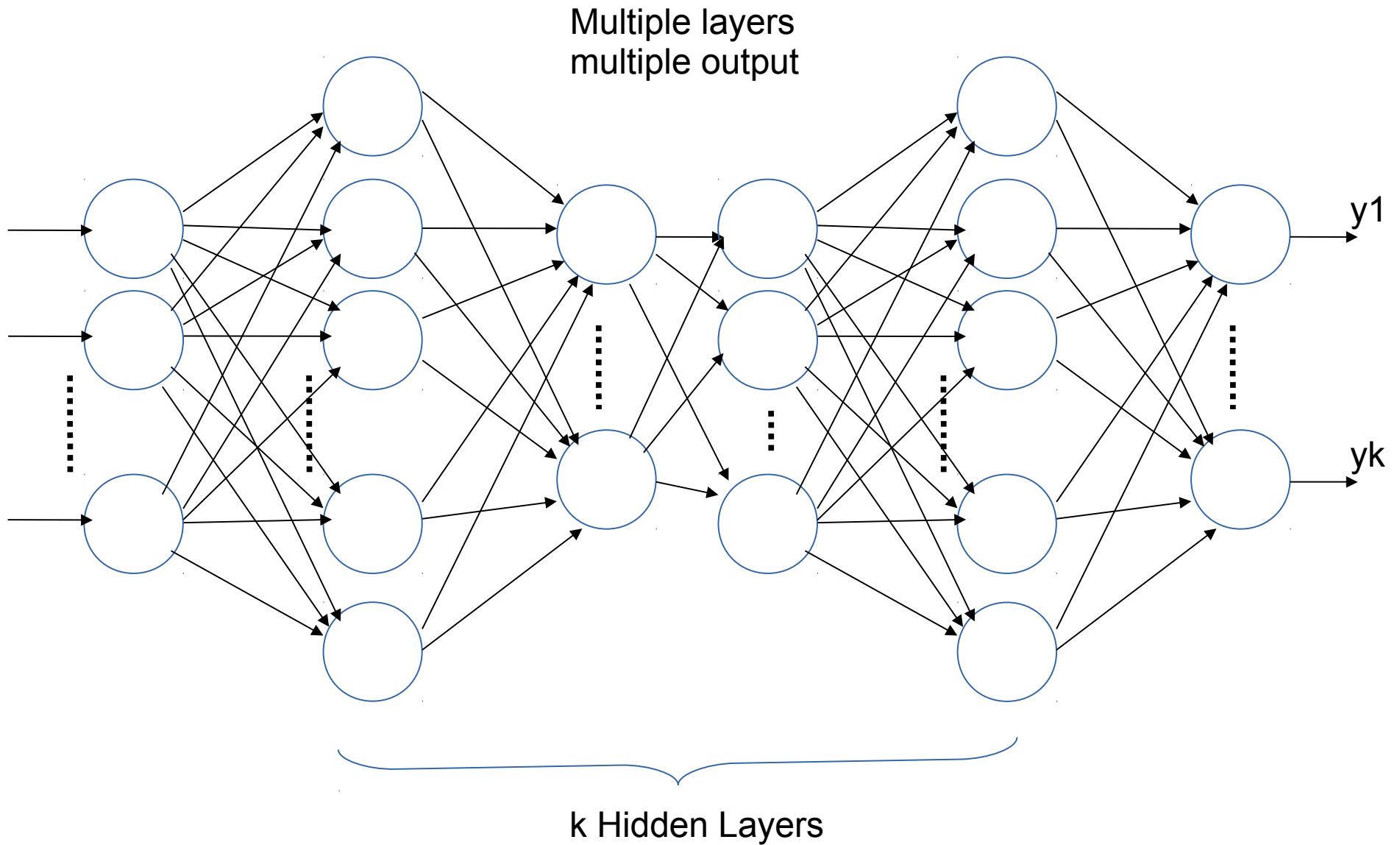
$$y = f(\cdot) \text{ as } \text{sgn}(\cdot) \quad \dots (2)$$



Road Map to LeNet (2)



Road Map to LeNet (3)





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

$k(x,y)$

-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

$I_4(x,y)$

	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

$O_4(x,y)$

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



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 .

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

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

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

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

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

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 .

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

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

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

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

$I_7(x,y)$

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

$k(x,y)$

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

$O_7(x,y)$

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

$I_8(x,y)$

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

$k(x,y)$

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

$O_8(x,y)$

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

Note: $I_7(x,y)$ and $I_8(x,y)$ are the same. Typo.



2D Convolution (5)

Diagram showing the input image $I_9(x,y)$ for a 2D convolution operation. The x and y axes are indicated by arrows pointing right and down respectively.

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

Diagram showing the kernel $k(x,y)$ for a 2D convolution operation. The x and y axes are indicated by arrows pointing right and down respectively.

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

Diagram showing the output image $O_9(x,y)$ for a 2D convolution operation. The x and y axes are indicated by arrows pointing right and down respectively.

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

Diagram showing the input image $I_{10}(x,y)$ for a 2D convolution operation. The x and y axes are indicated by arrows pointing right and down respectively.

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

Diagram showing the kernel $k(x,y)$ for a 2D convolution operation. The x and y axes are indicated by arrows pointing right and down respectively.

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

Diagram showing the output image $O_{10}(x,y)$ for a 2D convolution operation. The x and y axes are indicated by arrows pointing right and down respectively.

100	100	-100	-100
100	100	-100	-100
100	100	-100	-100
100	100	-100	-100



Kernel Coefficients to Neural Nets

Version 2.0; Nov. 3rd, 2017

One Image Plane

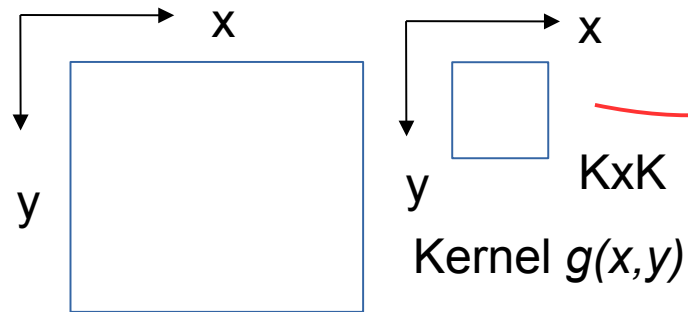
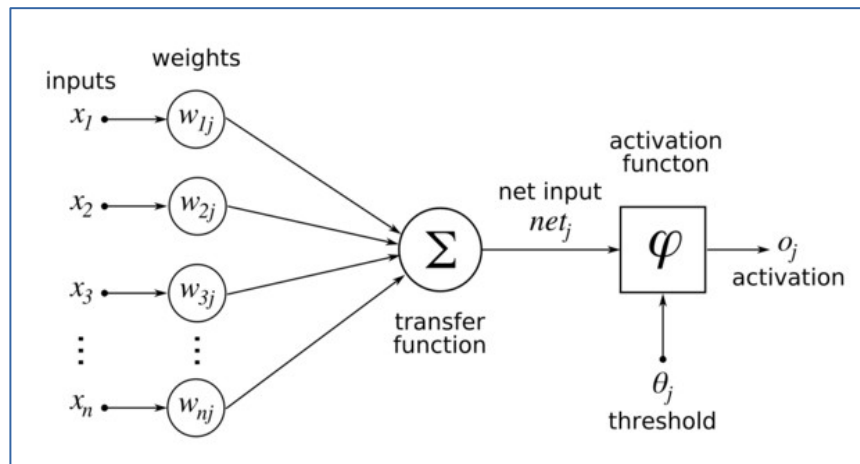


Image $f(x,y)$ (N-1,M-1)

w_{11}	w_{12}	w_{13}
w_{21}	w_{22}	w_{23}
w_{31}	w_{32}	w_{33}



Input from image $I(x,y)$	weight	Output $O(x,y)$
x_{11}	w_{11}	} $O(x,y)$ at w_{22} location
x_{12}	w_{12}	
x_{13}	w_{13}	
x_{21}	w_{21}	
x_{22}	w_{22}	
x_{23}	w_{23}	
x_{31}	w_{31}	
x_{32}	w_{32}	
x_{33}	w_{33}	

Modify The SLSO (1)

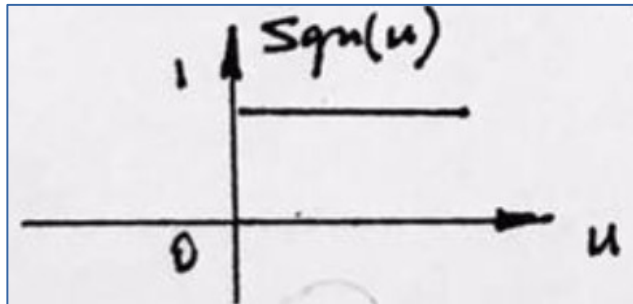
Version 2.0; Nov. 3rd, 2017

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

Hence, for the following

Where

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



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

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

(1,1), y = 0; (1,2), y=1; (1,3), y=1; (1,4), y=0
 (2,1), y = 0; (2,2), y=1; (2,3), y=1; (2,4), y=0
 (3,1), y = 0; (3,2), y=1; (3,3), y=1; (3,4), y=0
 (4,1), y = 0; (4,2), y=1; (4,3), y=1; (4,4), y=0

Previously,

Group 1, C1, as those from edge pixels

Group 2, C2, as those from non-edge pixels

Change to

Group 1, C1, from +100 edge pixel

Group 2, C2, from -100 edge,

Group 3, C3 from non-edge pixels

Changed to:

(1,1), y1y2: 00; (1,2), 01; (1,3), 01; (1,4), 00
 (2,1), 00; (2,2), 01; (2,3), 01; (2,4), 00
 (3,1), 00; (3,2), 01; (3,3), 01; (3,4), 00
 (4,1), 00; (4,2), 01; (4,3), 01; (4,4), 00



Change SLSO to SLMO

From the following,

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

100	100	-100	-100
100	100	-100	-100
100	100	-100	-100
100	100	-100	-100

(1,1), y = 1; (1,2), y=1; (1,3), y=1; (1,4), y=1
(2,1), y = 1; (2,2), y=1; (2,3), y=1; (2,4), y=1
(3,1), y = 1; (3,2), y=1; (3,3), y=1; (3,4), y=1
(4,1), y = 1; (4,2), y=1; (4,3), y=1; (4,4), y=1

The training algorithm:

$$w_i^+ = w_i^- + \eta (d - y) x_i$$

where

η is gain.
 d : desired the output.
 y : actual output.

SLSO

SLMO

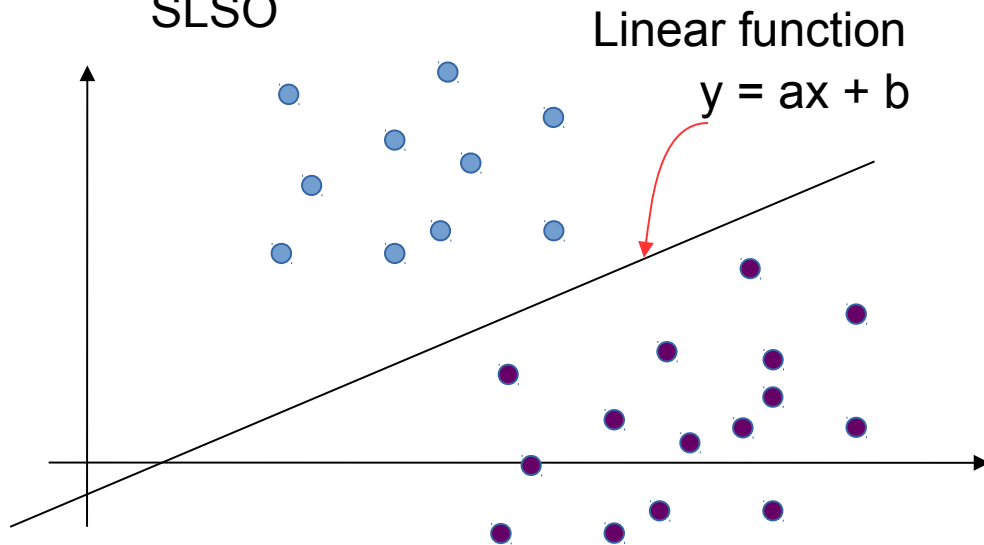
(1,1), 01; (1,2), 01; (1,3), 10; (1,4), 10
(2,1), 01; (2,2), 01; (2,3), 10; (2,4), 10
(3,1), 01; (3,2), 01; (3,3), 10; (3,4), 10
(4,1), 01; (4,2), 01; (4,3), 10; (4,4), 10



SLSO vs. SLMO

Linear Decision Function

SLSO



Remark 1: The single layer neural network decision making function is a linear function.

Versification: remember equation (1) from the previous section, we have

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

Clearly,

$$\sum w_i x_i + \theta$$

Is a linear function (line, plane or in higher dimension), while $f(\)$ an activation function plays a role of moving the linear function up or down.

SLMO

