國立雲林科技大學
電子工程系
Department of Electronic Engineering
教育部補助AI應用領域系列課程-
人工智慧計算晶片設計和應用人才培育

AGC Edge-AI教育訓練

第二周 CNN & LeNet

國立雲林科技大學
王斯弘 助理教授 / 前瞻學位學士學程

2021, Fall Semester

Outline

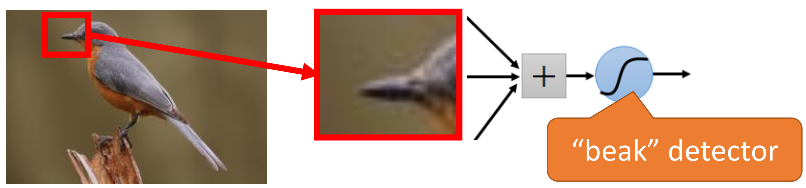
- **CNN**
- LeNet

Why CNN for Image

- Some patterns are much smaller than the whole image

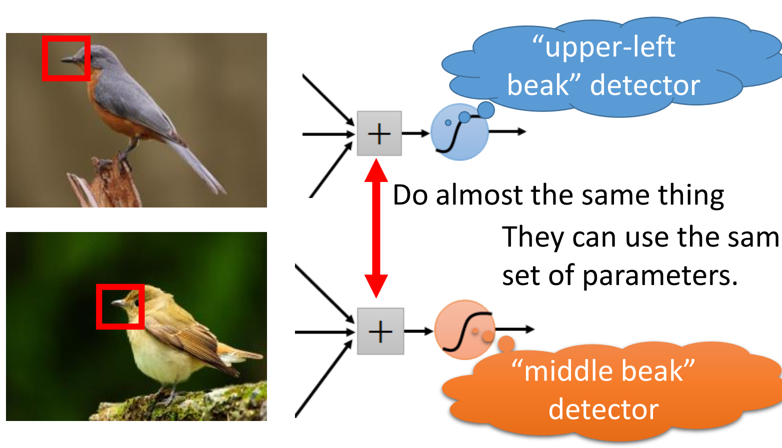
A neuron does not have to see the whole image to discover the pattern.

Connecting to small region with less parameters



Why CNN for Image

- The same patterns appear in different regions.



Why CNN for Image

- Subsampling the pixels will not change the object

bird

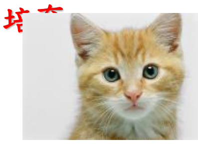
subsampling

bird

We can subsample the pixels to make image smaller

→ Less parameters for the network to process the image

The whole CNN



Convolution

Max Pooling

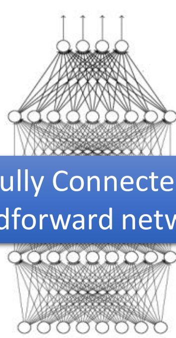
Convolution

Max Pooling

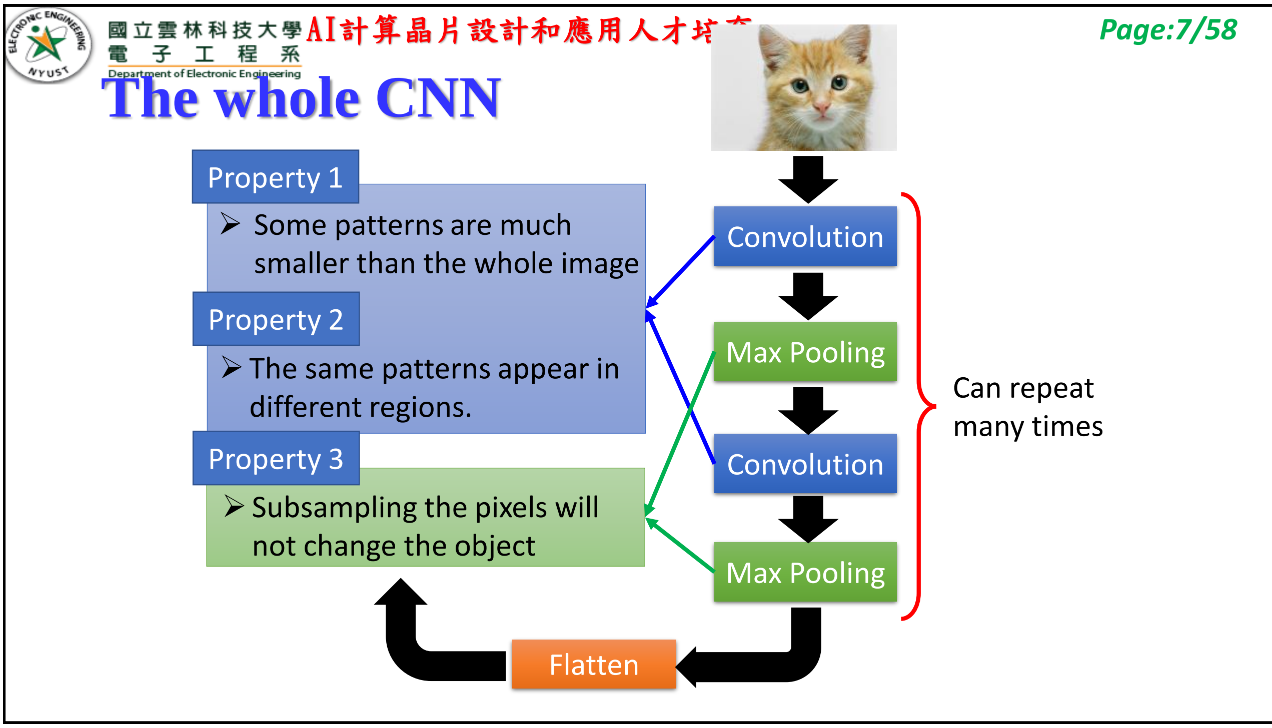
Can repeat many times

Flatten

Fully Connected Feedforward network



cat dog ......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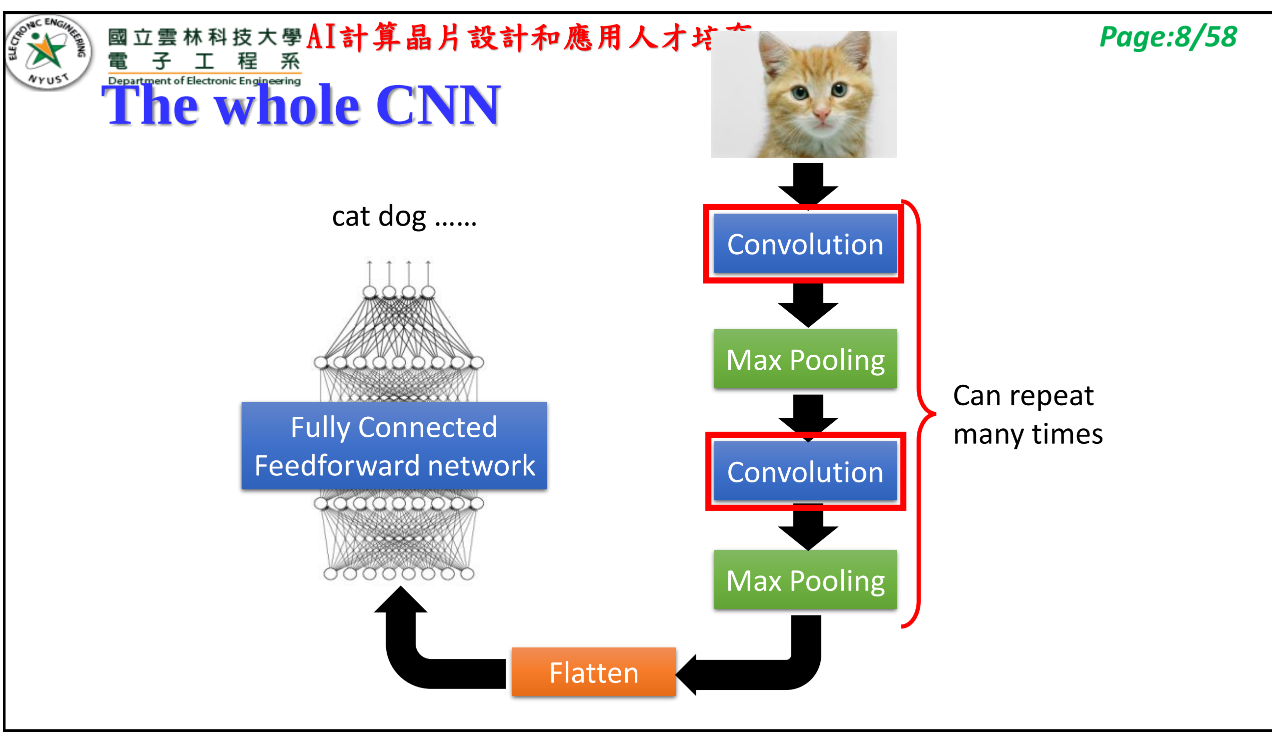
The whole CNN
Property 1
Some patterns are much smaller than the whole image
Property 2
The same patterns appear in different regions.
Property 3
Subsampling the pixels will not change the object
Convolution
Max Pooling
Convolution
Max Pooling
Can repeat many times
Flatten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The whole CNN
cat dog ......
Fully Connected Feedforward network
Convolution
Max Pooling
Convolution
Max Pooling
Can repeat many times
Flatten

CNN – Convolution

Those are the network parameters to be learned.

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

6 x 6 image

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

Filter 1 Matrix

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

Filter 2 Matrix

⋮

Property 1 Each filter detects a small pattern (3 x 3).

CNN – Convolution

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

Filter 1

stride=1

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

6 x 6 image

3 -1

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CNN – Convolution

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

Filter 1

If stride=2

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

6 x 6 image

3	-3

We set stride=1 below

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CNN – Convolution

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

Filter 1

stride=1

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

6 x 6 image

3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	-1

Property 2

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CNN – Convolution

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

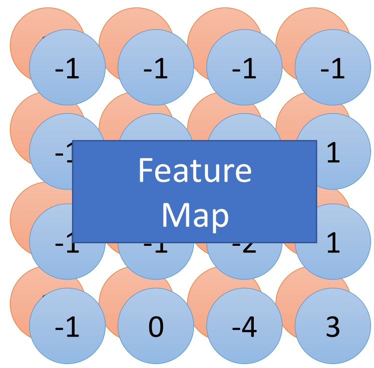
Filter 2

stride=1

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

6 x 6 image

Do the same process for every filter



4 x 4 image

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CNN – Colorful image

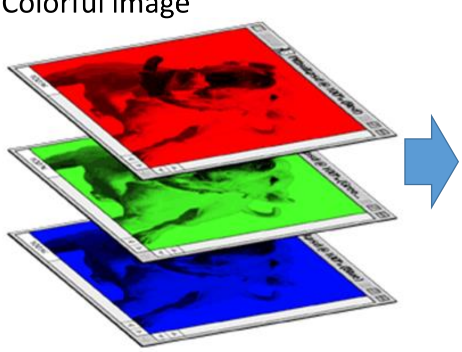
1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

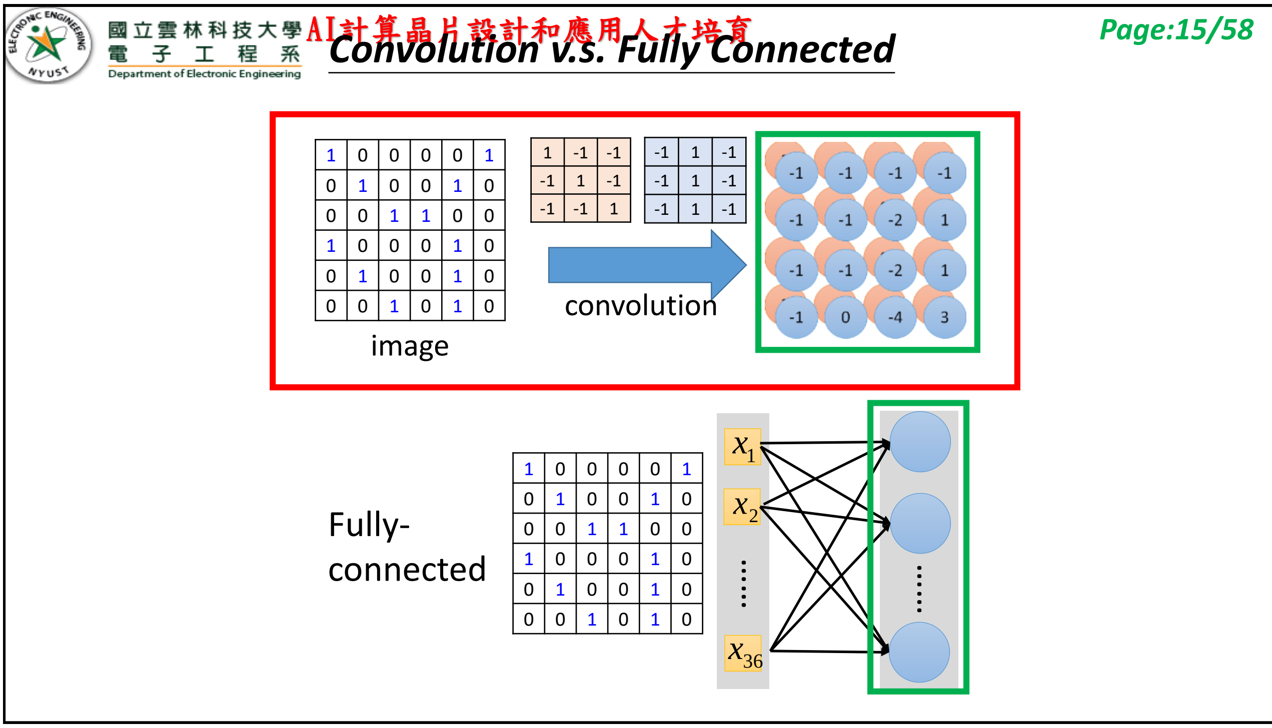
-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

Colorful image



1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0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Convolution v.s. Fully Connected
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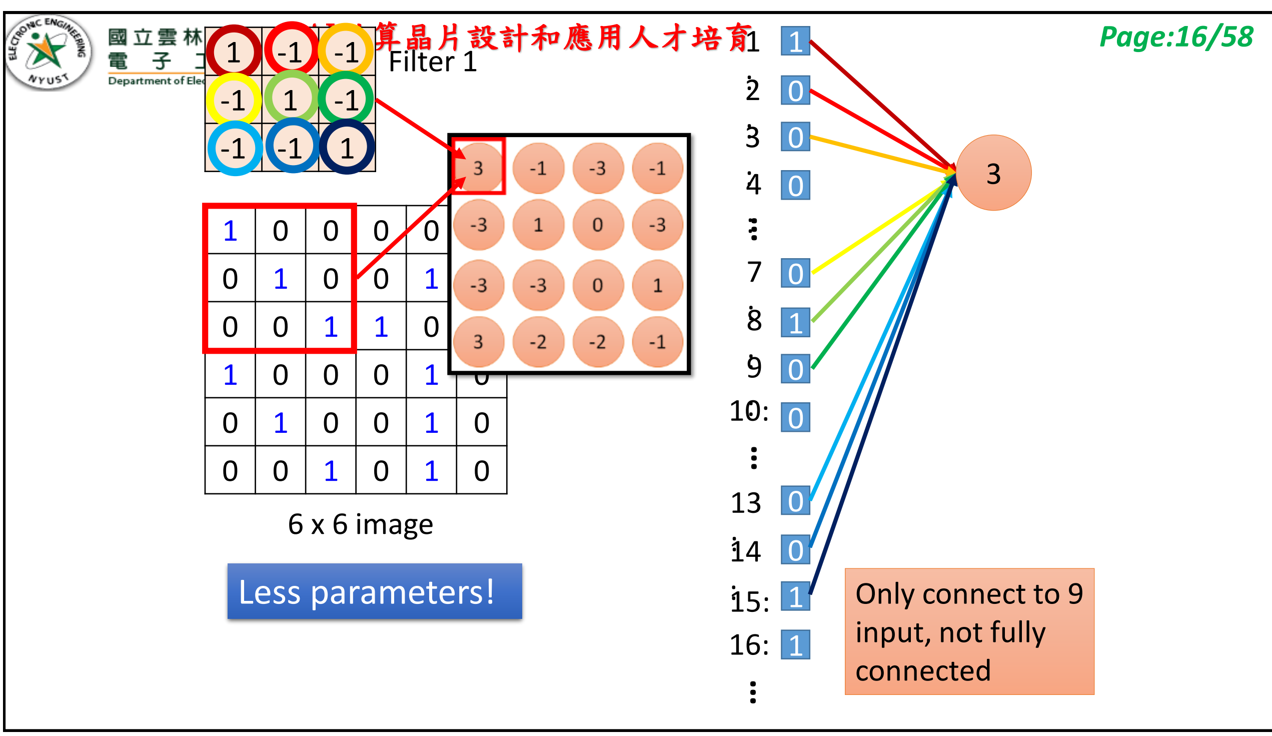
image
convolution
Fully-connected
x_1
x_2
x_{36}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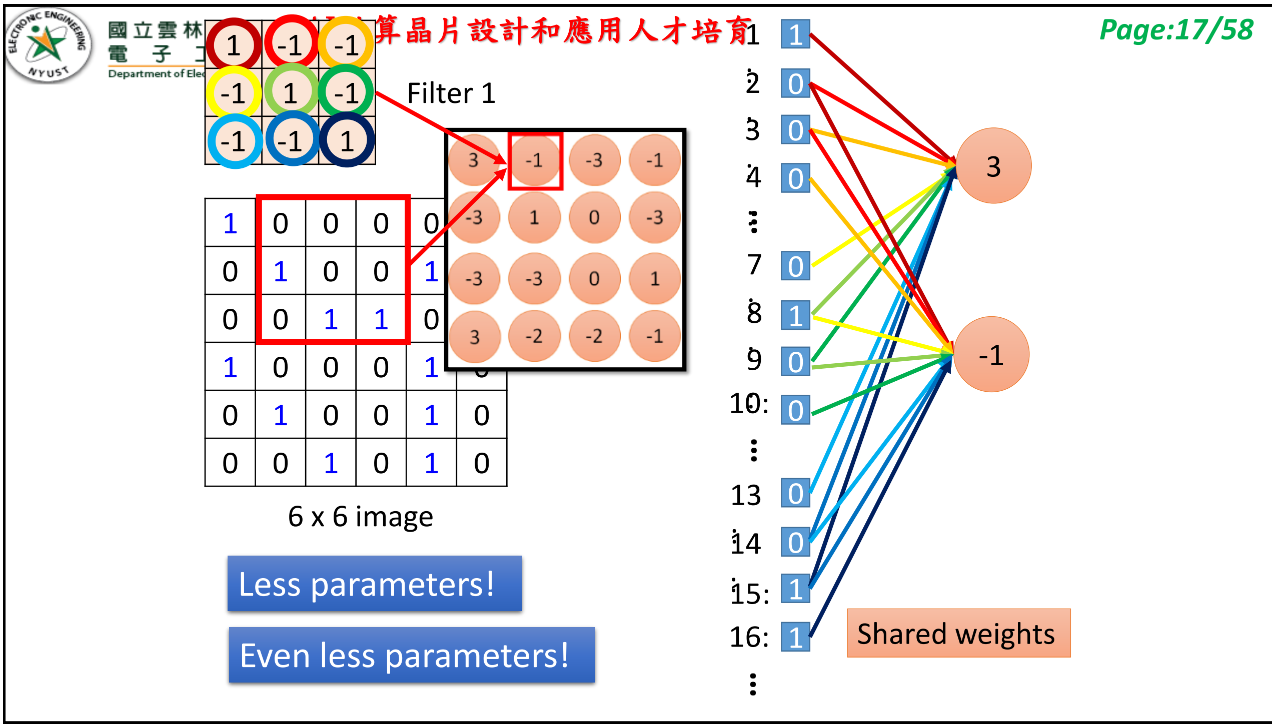
Filter 1
6 x 6 image
Less parameters!
Only connect to 9 input, not fully connected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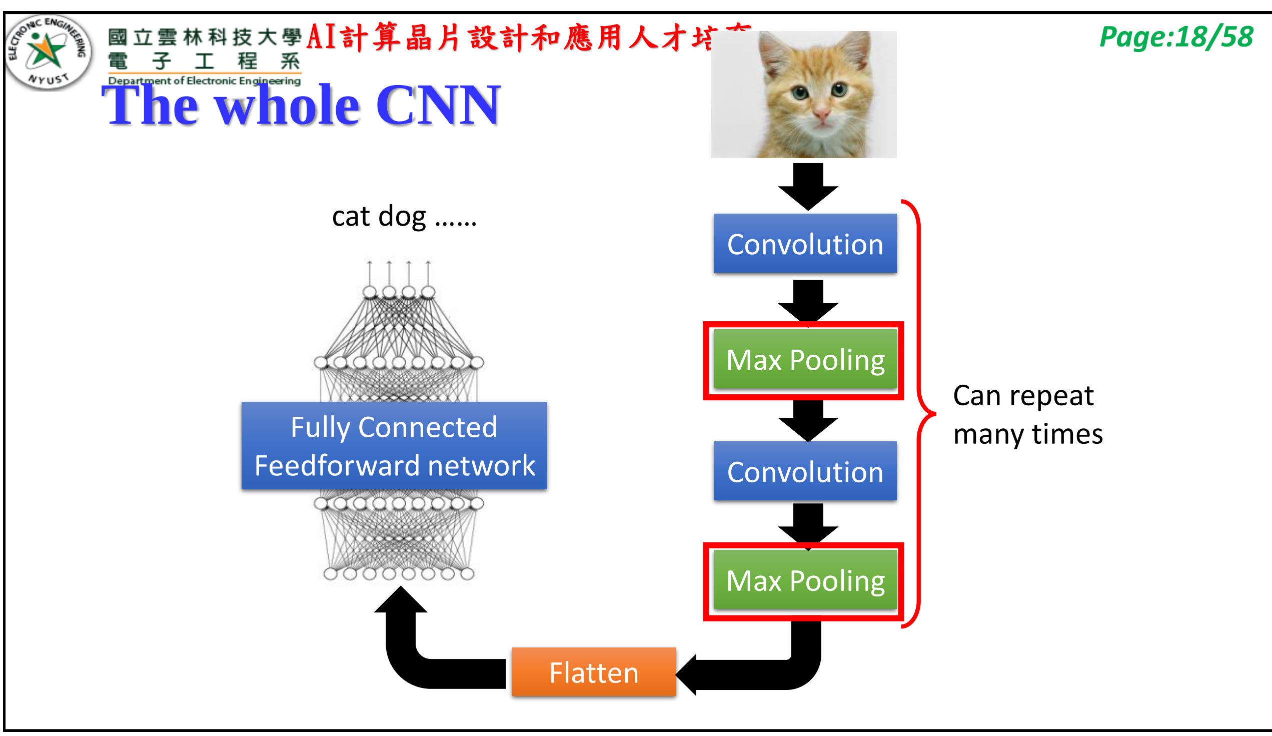
Filter 1
6 x 6 image
Less parameters!
Even less parameters!
Shared weights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The whole CNN
cat dog ......
Fully Connected
Feedforward network
Convolution
Max Pooling
Convolution
Max Pooling
Can repeat
many times
Flatten

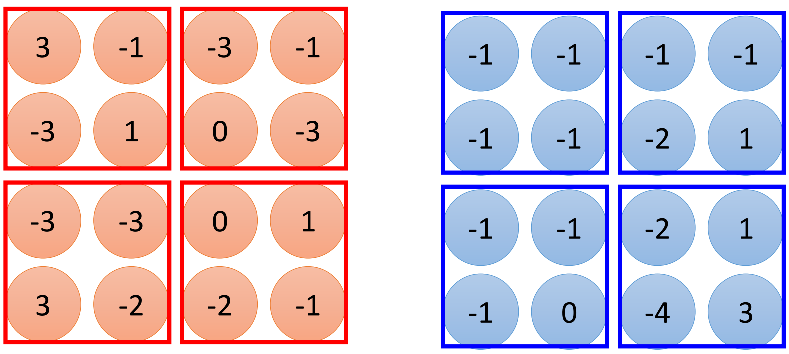
CNN – Max Pooling

Filter 1

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

Filter 2

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

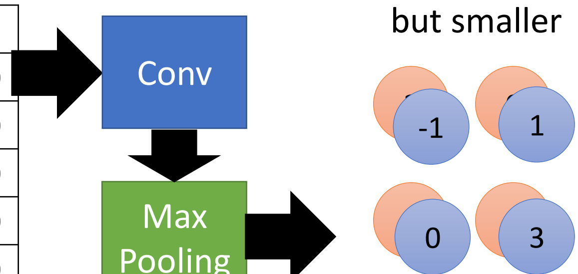


CNN – Max Pooling

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

6 x 6 image

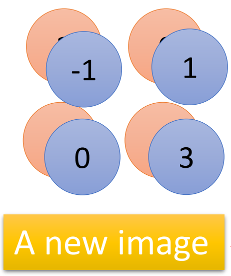
New image but smaller

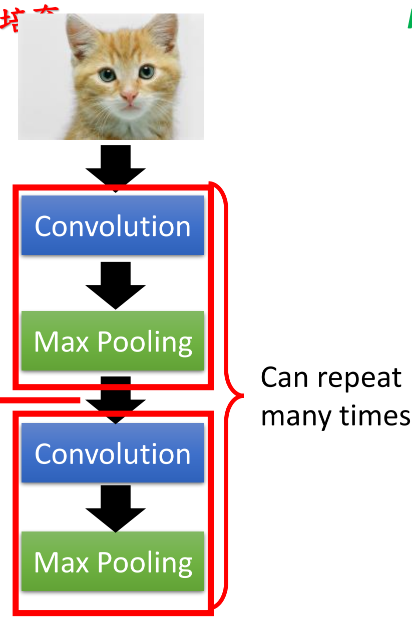


2 x 2 image

Each filter is a channel

The whole CNN

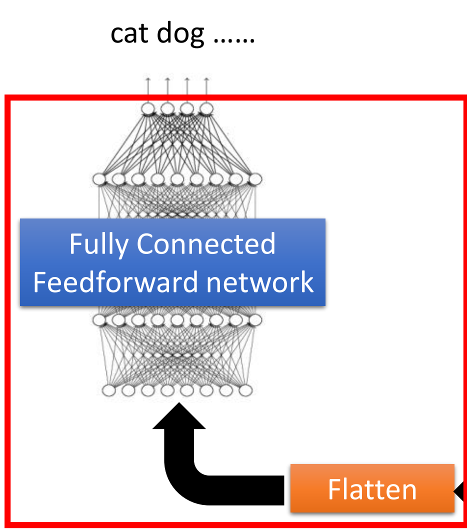


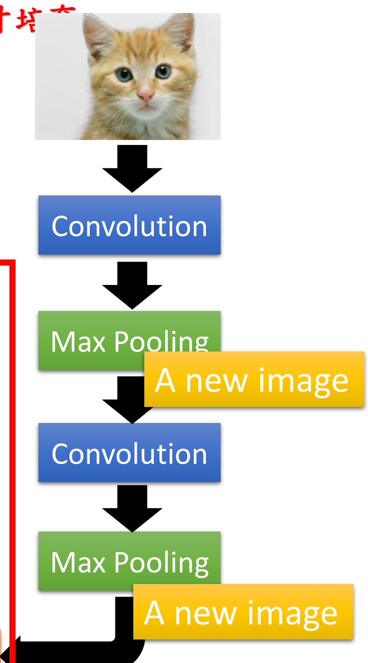


Smaller than the original image

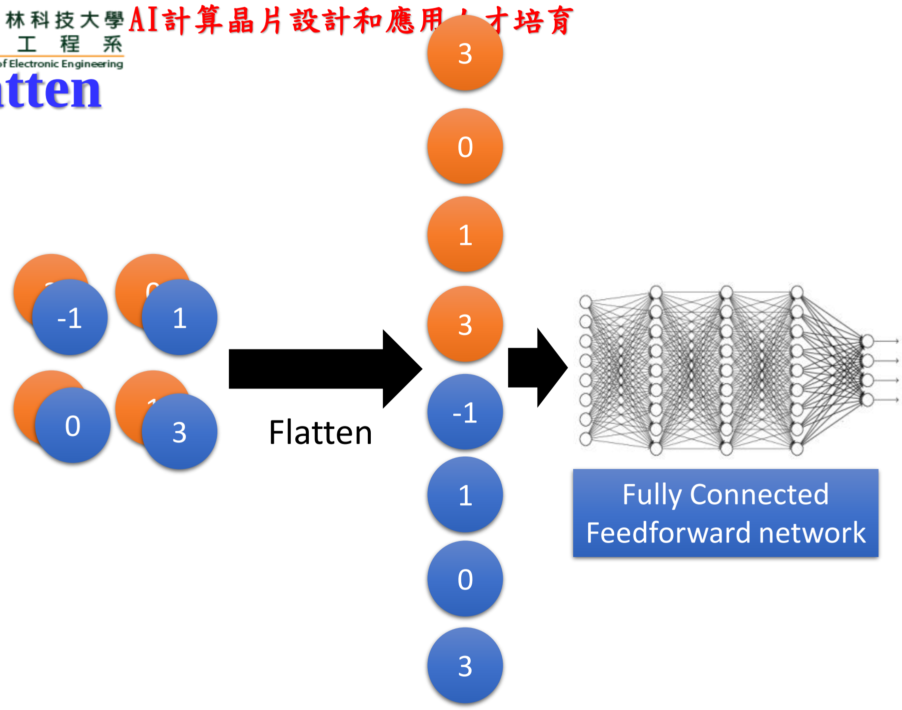
The number of the channel is the number of filters

The whole CNN





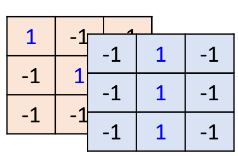
Flatten



CNN in Keras

Only modified the ***network structure*** and ***input format (vector -> 3-D tensor)***

```
model2.add( Convolution2D( 25,3,3,
            input_shape=(28,28,1)) )
```

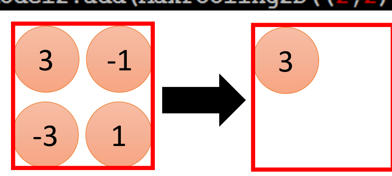


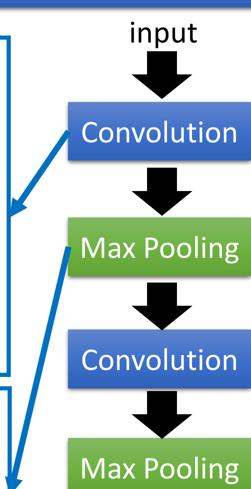
...... There are 25 3x3 filters.

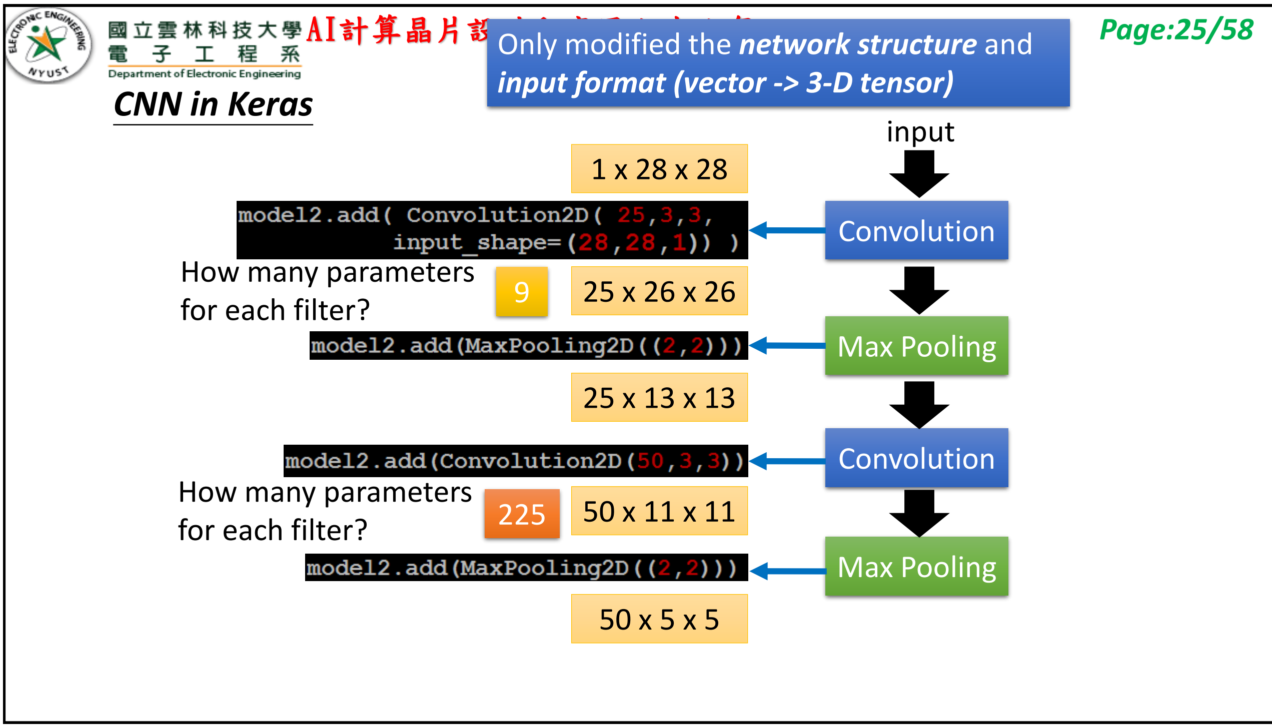
Input_shape = (28 , 28 , 1)

28 x 28 pixels   1: black/white, 3: RGB

```
model2.add(MaxPooling2D((2,2)))
```



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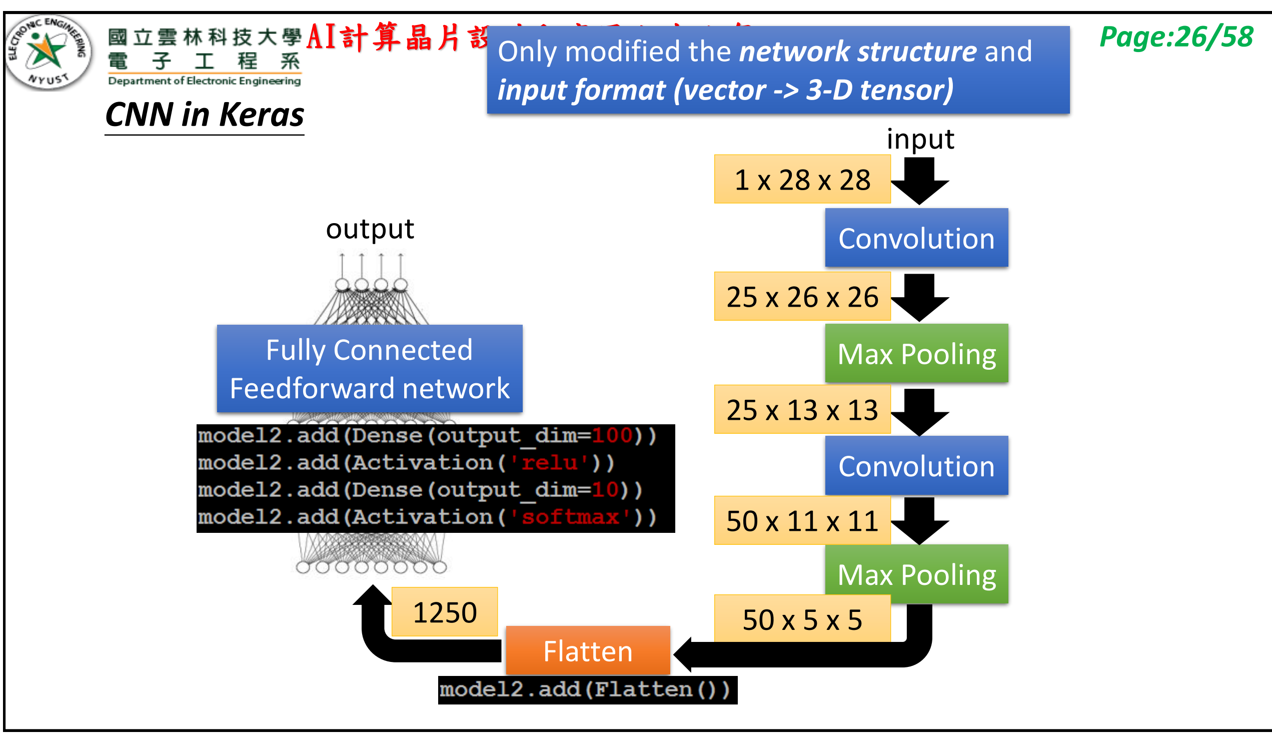
CNN in Keras
Only modified the network structure and input format (vector -> 3-D tensor)
input
1 x 28 x 28
model2.add(Convolution2D(25,3,3,
input_shape=(28,28,1)))
Convolution
How many parameters for each filter?
9
25 x 26 x 26
model2.add(MaxPooling2D((2,2)))
Max Pooling
25 x 13 x 13
model2.add(Convolution2D(50,3,3))
Convolution
How many parameters for each filter?
225
50 x 11 x 11
model2.add(MaxPooling2D((2,2)))
Max Pooling
50 x 5 x 5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CNN in Keras
Only modified the network structure and input format (vector -> 3-D tensor)
input
1 x 28 x 28
Convolution
25 x 26 x 26
Max Pooling
25 x 13 x 13
Convolution
50 x 11 x 11
Max Pooling
50 x 5 x 5
output
Fully Connected Feedforward network
model2.add(Dense(output_dim=100))
model2.add(Activation('relu'))
model2.add(Dense(output_dim=10))
model2.add(Activation('softmax'))
1250
Flatten
model2.add(Flatten())

Outline

- CNN
- **LeNet**

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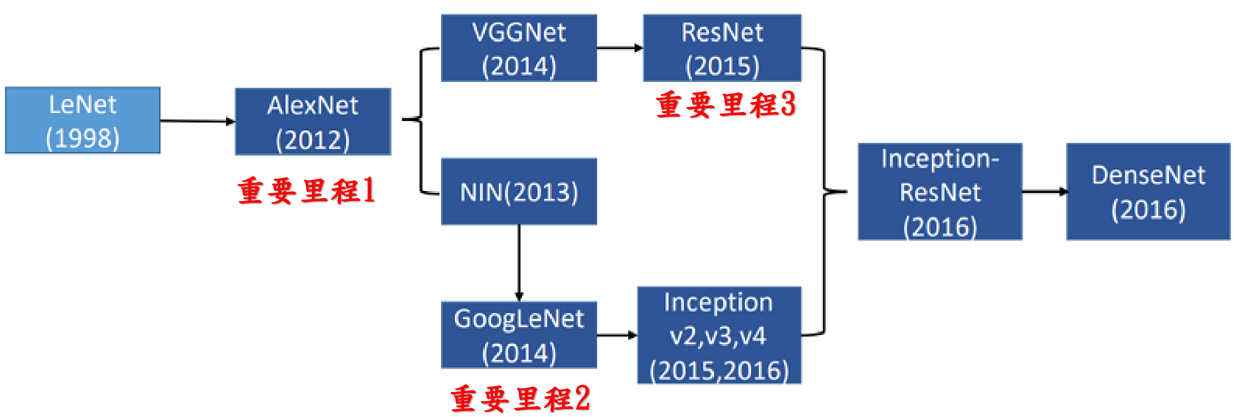
Introduction to CNN



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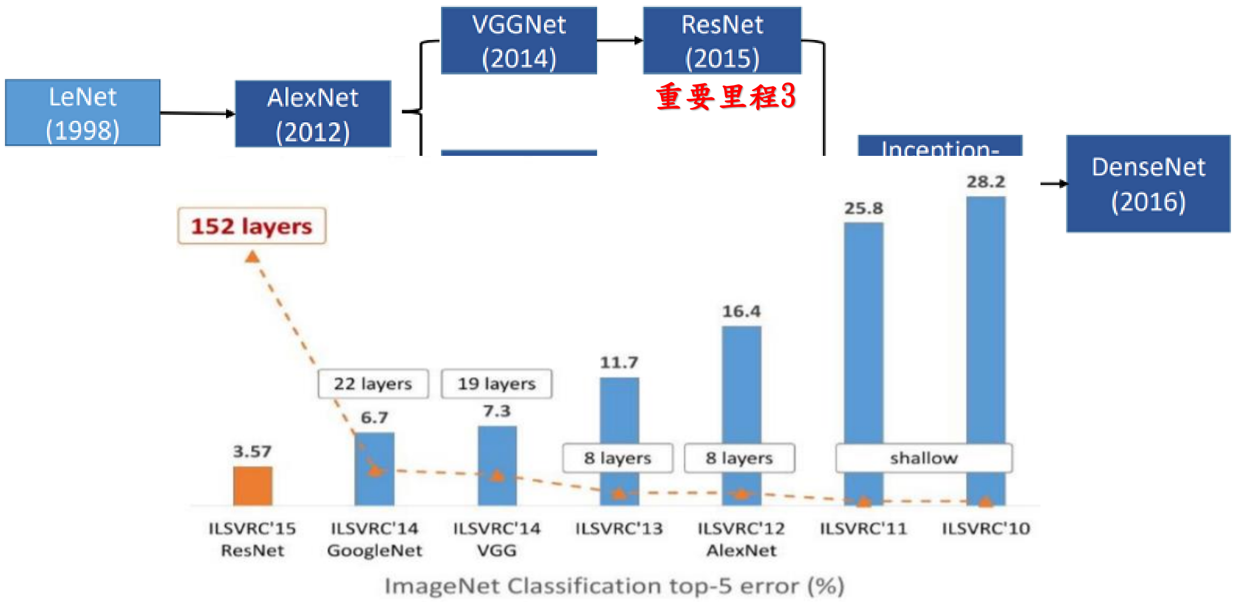
Introduction to CNN



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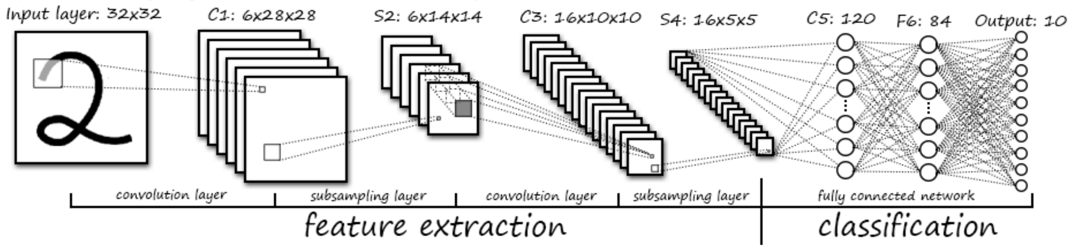
Deep Convolutional Networks

- Compared to standard feed forward neural networks with similarly-sized layers,
  - CNNs have much fewer connections and parameters
  - and so they are easier to train,
  - while their theoretically-best performance is likely to be only slightly worse.

LeNet 5

Y. LeCun, L. Bottou, Y. Bengio and P. Haffner: **Gradient-Based Learning Applied to Document Recognition**, *Proceedings of the IEEE, 86(11):2278-2324, November* ***1998***

LeNet5, LeCun1998



- **Input**:32x32 pixel image. Largest character is 20x20
  (All important info should be in the center of the receptive fields of the highest level feature detectors)
- **Cx**: Convolutional layer (C1, C3, C5)
- **Sx**: Subsample layer (S2, S4)
- **Fx**: Fully connected layer (F6)
- Black and White pixel values are normalized:
  E.g. White = -0.1, Black =1.175 (Mean of pixels = 0, Std of pixels =1)

2-Dimensional Convolution

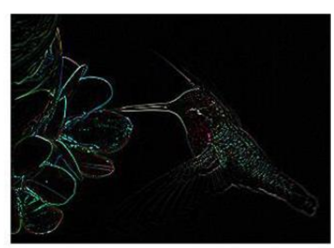
$$f[x,y] * g[x,y] = \sum_{n_1=-\infty}^{\infty} \sum_{n_2=-\infty}^{\infty} f[n_1,n_2] \cdot g[x-n_1, y-n_2]$$

Original

Filter (=kernel)

0.00	0.00	0.00	0.00	0.00
0.00	0.00	-2.00	0.00	0.00
0.00	-2.00	8.00	-2.00	0.00
0.00	0.00	-2.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00

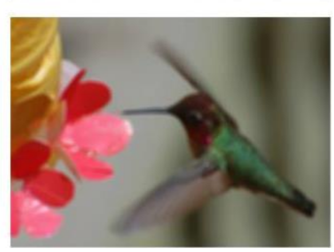
sum(filter) = 0



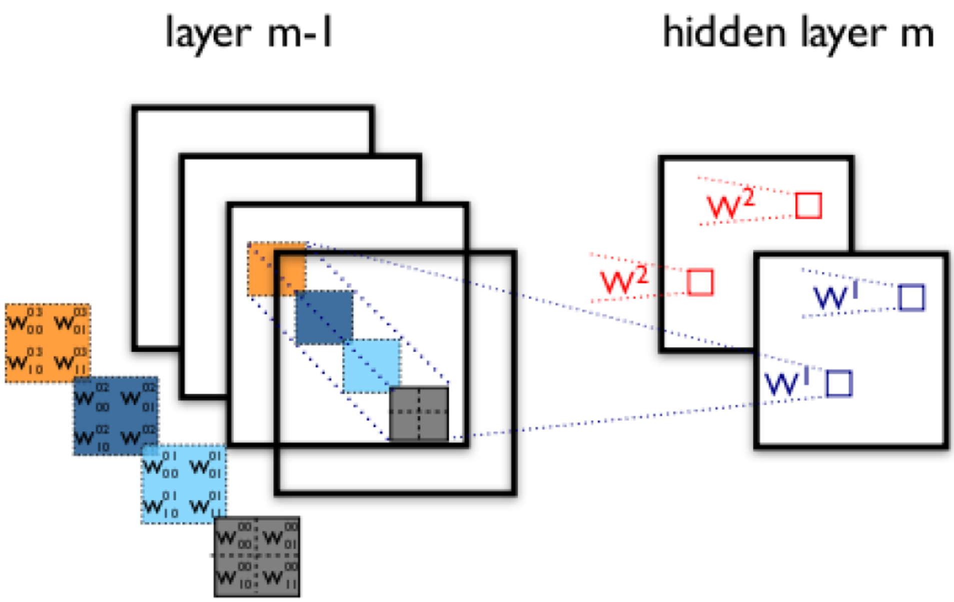
0.04	0.04	0.04	0.04	0.04
0.04	0.04	0.04	0.04	0.04
0.04	0.04	0.04	0.04	0.04
0.04	0.04	0.04	0.04	0.04
0.04	0.04	0.04	0.04	0.04

sum(filter) = 1

1/25 = 0.04



Convolutional Layer



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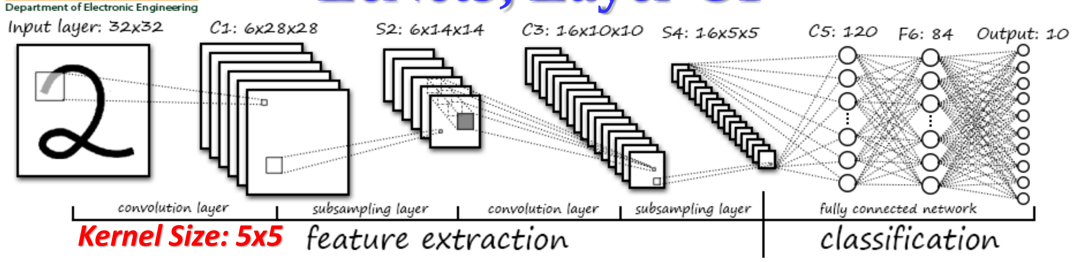
LeNet5, Layer C1



Kernel Size: 5x5

C1: Convolutional layer with 6 feature maps of size 28x28.

Each unit of C1 has a 5x5 receptive field in the input layer. $C1^k,\ k = 1, \ldots, 6.$

- Topological structure
- Sparse connections
- Shared weights

$$C1^k{}_{ij} = \tanh([W^k * x]_{ij} + b_k).$$

$$W_k \in \mathbb{R}^{5\times5}, b_k \in \mathbb{R}, x \in \mathbb{R}^{32\times32}$$

$$k=1,\ldots,6 \quad C1^k \in \mathbb{R}^{28\times28}.$$

(5*5+1)*6 = 156 parameters to learn

Connections: (5*5+1)*28*28*6=122,304

If it was fully connected, we had (32*32+1)*(28*28)*6 parameters = 4,821,600 connections

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LeNet5, Layer S2

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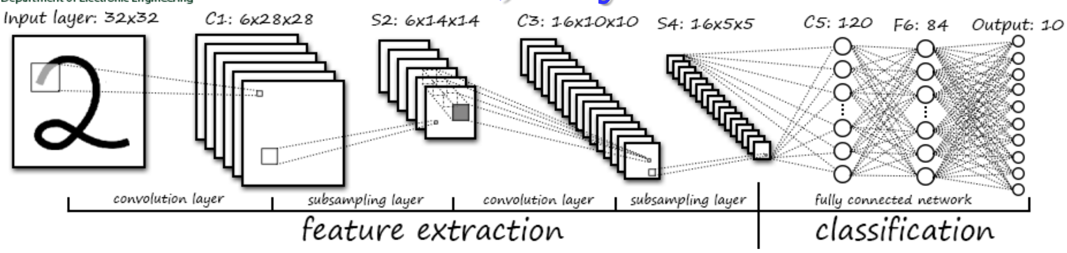

- S2: Subsampling layer with 6 feature maps of size 14x14
- 2x2 non overlapping receptive fields in C1

$$w_1^k, w_2^k \in \mathbb{R}$$

$$S2_{ij}^k = \tanh(w_1^k \sum_{s,t=0}^{1} C1_{2i-s,2j-t}^k + w_2^k).$$

$$k=1,...,6,\ i,j = 1,\dots,14$$

$$S2^k \in \mathbb{R}^{14\times 14}.$$

- Layer S2: 6*2=12 trainable parameters.
- Connections: 14*14*(2*2+1)*6=5880

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LeNet5, Layer C3

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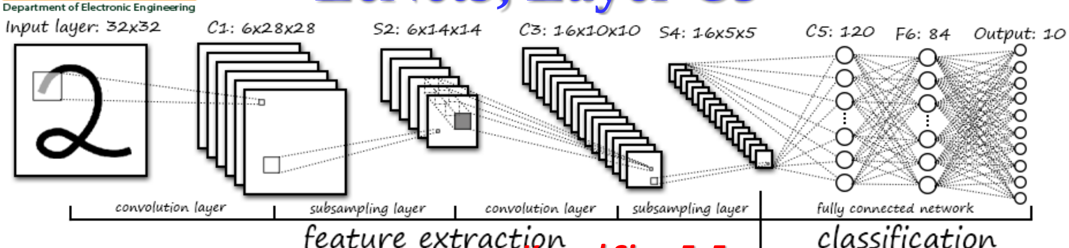


Kernel Size: 5x5

- C3: Convolutional layer with 16 feature maps of size 10x10
- Each unit in C3 is connected to several! 5x5 receptive fields at identical locations in S2

Layer C3: 1516 trainable parameters.

=(3*5*5+1)*6+(4*5*5+1)*9+(6*5*5+1)

Connections: 151600

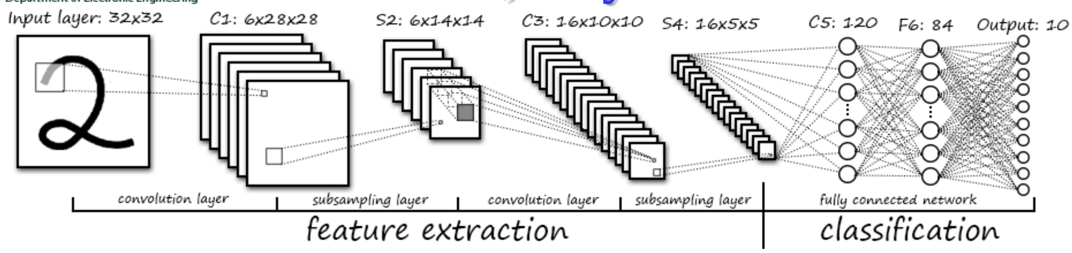
(3*5*5+1)*6*10*10+(4*5*5+1)*9*10*10+(6*5*5+1)*10*10

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	X				X	X	X			X	X	X	X		X	X
1	X	X				X	X	X			X	X	X	X		X
2	X	X	X				X	X	X			X		X	X	X
3		X	X	X			X	X	X	X			X		X	X
4			X	X	X			X	X	X	X		X	X		X
5				X	X	X			X	X	X	X		X	X	X

TABLE I

EACH COLUMN INDICATES WHICH FEATURE MAP IN S2 ARE COMBINED BY THE UNITS IN A PARTICULAR FEATURE MAP OF C3.

LeNet5, Layer S4



- S4: Subsampling layer with 16 feature maps of size 5x5
- Each unit in S4 is connected to the corresponding 2x2 receptive field at C3

$$w_1^k, w_2^k \in \mathbb{R}$$

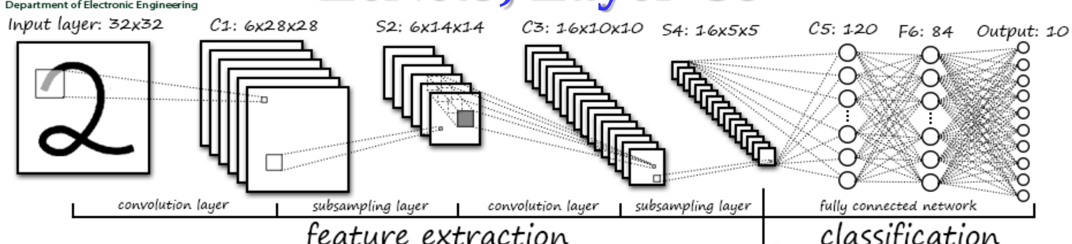
$$S4_{ij}^k = \tanh(w_1^k \sum_{s,t=0}^{1} C1_{2i-s,2j-t}^k + w_2^k).$$

$$k=1,\ldots,16,\ i,j = 1,\ldots,5$$

$$S4^k \in \mathbb{R}^{5\times 5}.$$

Layer S4: **16*2=32** trainable parameters.
Connections: 5*5*(2*2+1)*16=2000

LeNet5, Layer C5

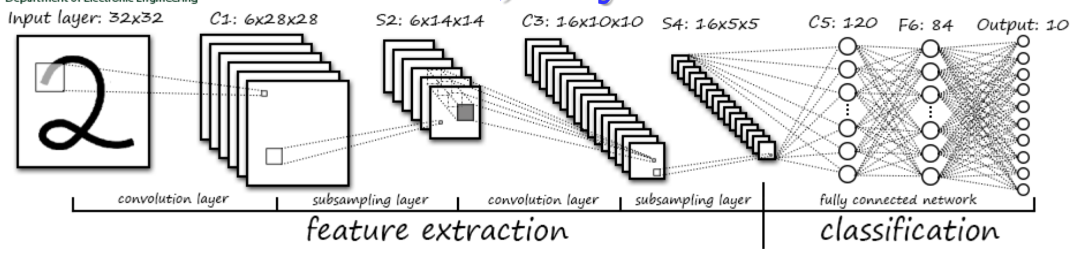


Kernel Size: 5x5

- C5: Convolutional layer with 120 feature maps of size 1x1
- Each unit in C5 is connected to all 16 5x5 receptive fields in S4

Layer C5: 120*(16*25+1) = 48120 trainable parameters and connections (Fully connected)

LeNet5, Layer C5



- **Layer F6**: 84 fully connected units. 84*(120+1)=10164 trainable parameters and connections.
- **Output layer**: 10RBF (One for each digit)

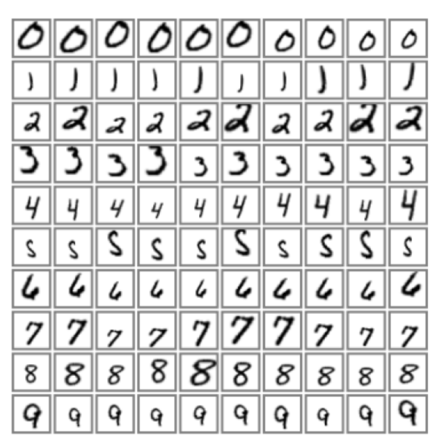
$$y_i = \sum_{j=1}^{84}(x_j - w_{ij})^2,\ i = 1, \ldots, 10.$$

From F6

84=7x12, stylized image.
84 parameters, 84*10 connections
Weight update: Backpropagation

MINIST Dataset

60,000 original datasets
Test error: 0.95%



540,000 artificial distortions
+ 60,000 original
Test error: 0.8%

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Misclassified examples

- True label -> Predicted label

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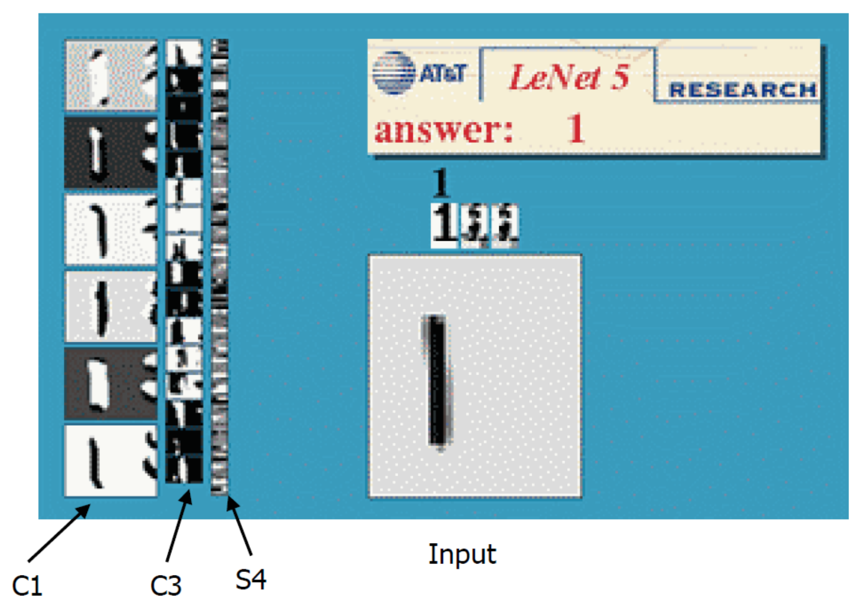
LeNet5 in Action



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LeNet5, Shift invariance

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LeNet5, Rotation invariance

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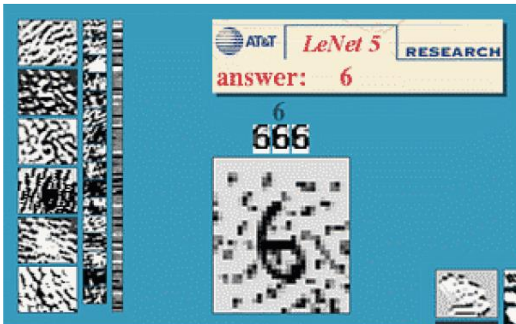
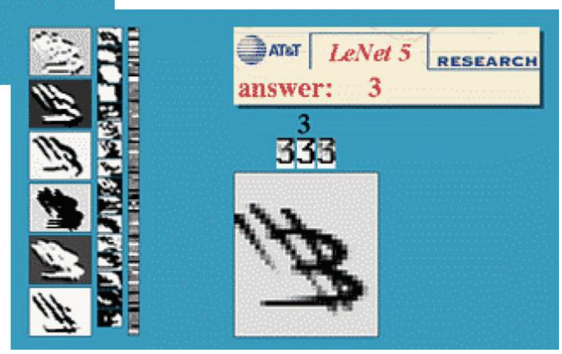
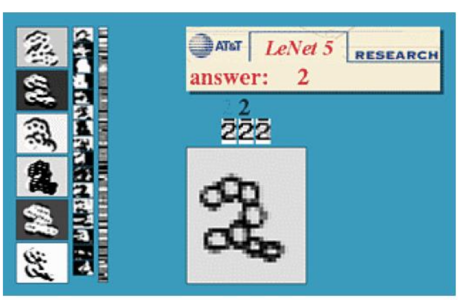
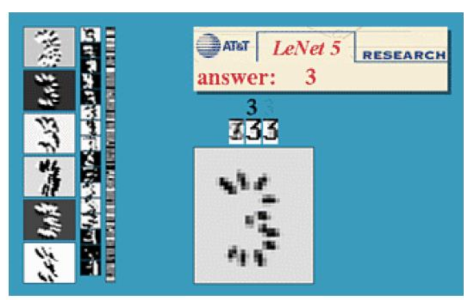
LeNet5, Nosie resistance

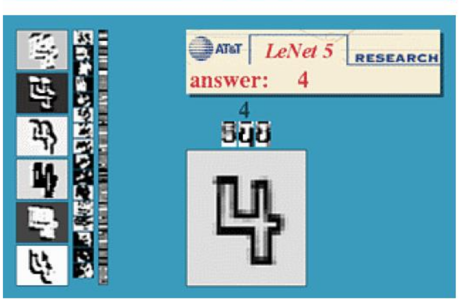


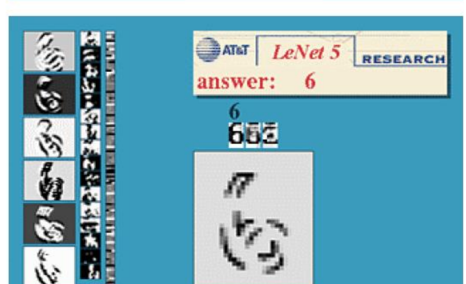


LeNet5, Unusual Patterns

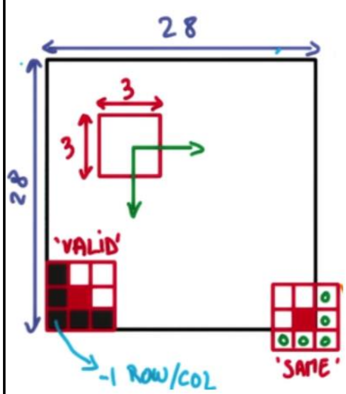






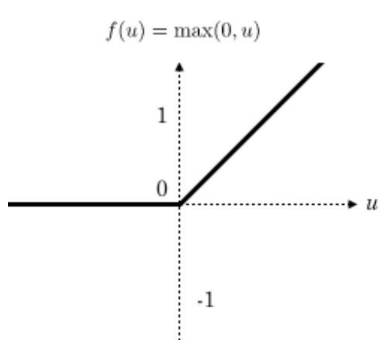


Platform: Tensorflow



- **tf.nn.conv2d**(input, filter, strides, padding, use_cudnn_on_gpu=None, name=None)
- **input**: 輸入影像,格式為[batch，長，寬，通道數]
- **filter**:卷積核，其格式為[長，寬，輸入通道數，輸出通道數]
- **strides** :步長，一般情況下的格式為[1，長上步長，寬上步長，1]
- **padding**: 是卷積核在邊緣處的處理方法，可以取'VALID'或者'SAME'

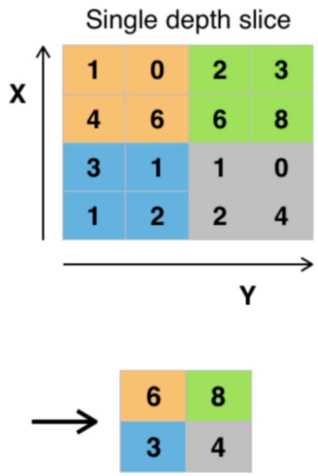
Platform: Tensorflow



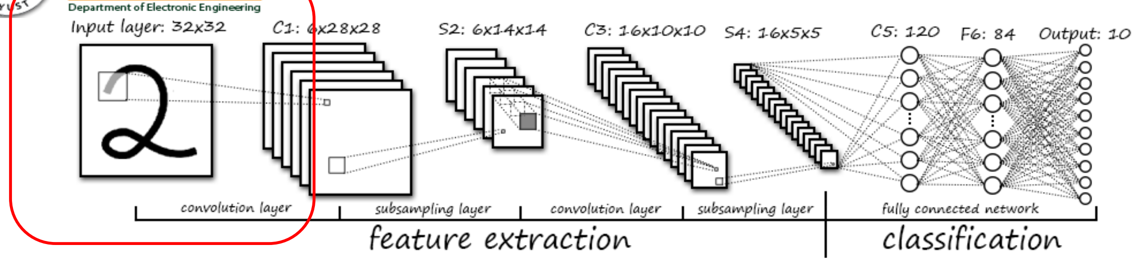
- tf.nn.relu(input_data)
- Example:

  b = tf.nn.relu(a)

Platform: Tensorflow

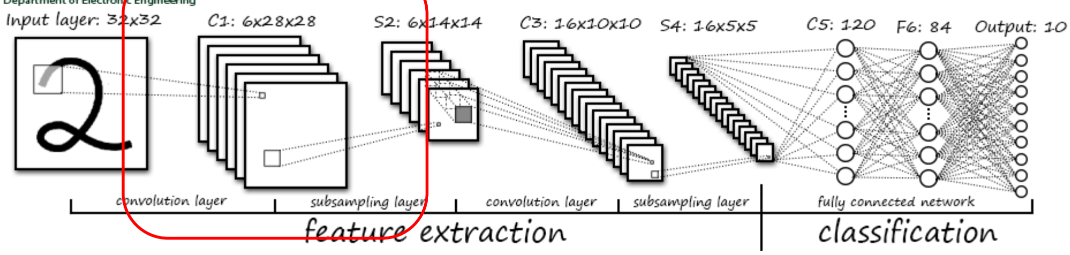


- **tf.nn.max_pool**(value, ksize, strides, padding, name=None)
- **value**：池化的輸入(input feature map)，格式[batch, height, width, channels]
- **ksize**：池化窗口的大小，格式是[1, height, width, 1]
- **strides**：類似卷積，格式是[1, stride,stride, 1]
- **padding**：類似卷積，可以取'VALID'或者'SAME'



reshape imput as [number of examples (m), weight, height, channel]

X_ = tf.reshape(X, [-1, 28, 28, 1]) # num_channel = 1 (gray image)



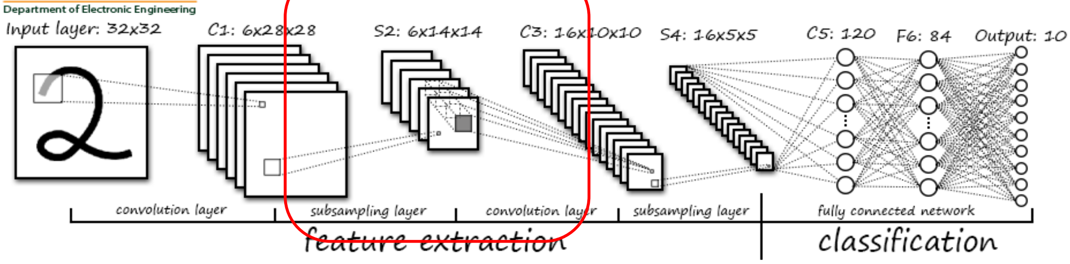
CONV1 (f = 5*5*1, n_f = 6, s = 1, p = 'same')

W_conv1 = weight_variable(shape = [5, 5, 1, 6])

b_conv1 = bias_variable(shape = [6])

shape of A_conv1 ~ [m,28,28,6]

A_conv1 = tf.nn.relu(tf.nn.conv2d(X_, W_conv1, strides = [1, 1, 1, 1], padding = 'SAME') + b_conv1)



MAXPOOL2 (f = 2*2*1, s = 2, p = 'same')

shape of A_pool1 ~ [m,14,14,6]

A_pool1 = tf.nn.max_pool(A_conv1, ksize = [1, 2, 2, 1], strides=[1, 2, 2, 1], padding = 'SAME')

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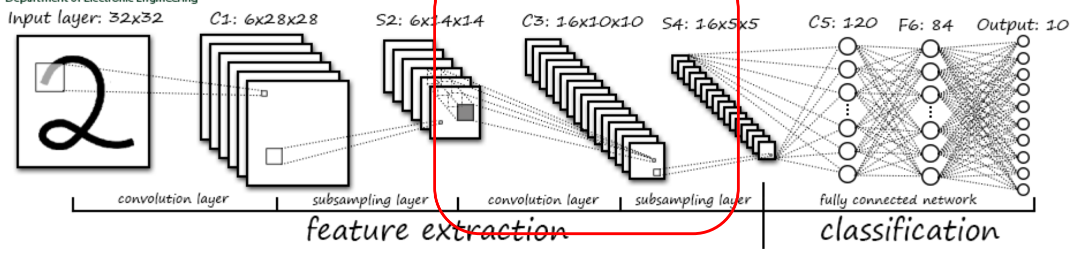

CONV3 (f = 5*5*1, n_f = 16, s = 1, p = 'same')

```
W_conv2 = weight_variable(shape = [5, 5, 6, 16])
b_conv2 = bias_variable(shape = [16])
# shape of A_conv2 ~ [m,10,10,16]
A_conv2 = tf.nn.relu(tf.nn.conv2d(A_pool1, W_conv2, strides = [1, 1, 1, 1], padding = 'VALID') + b_conv2)
```

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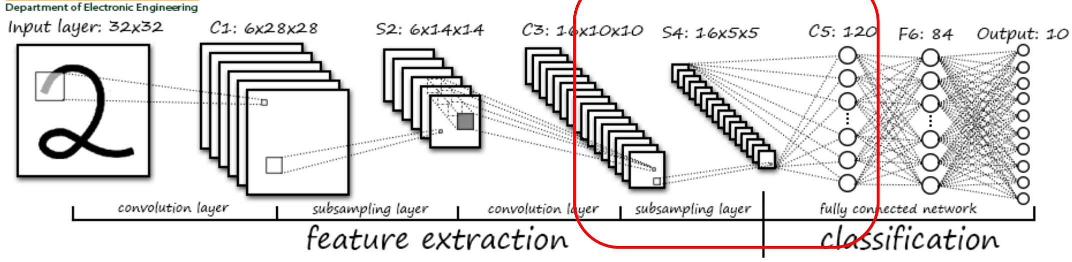
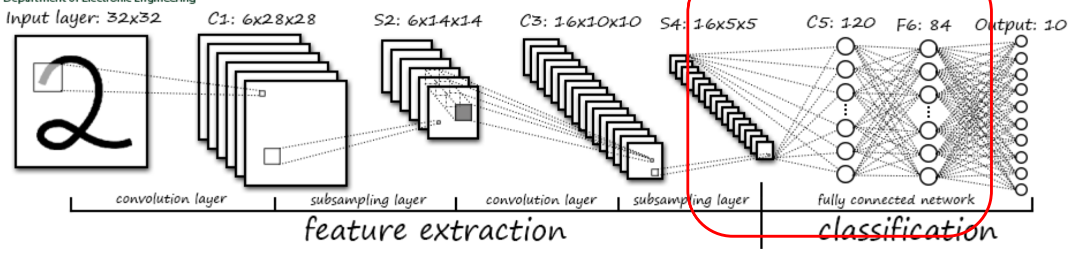
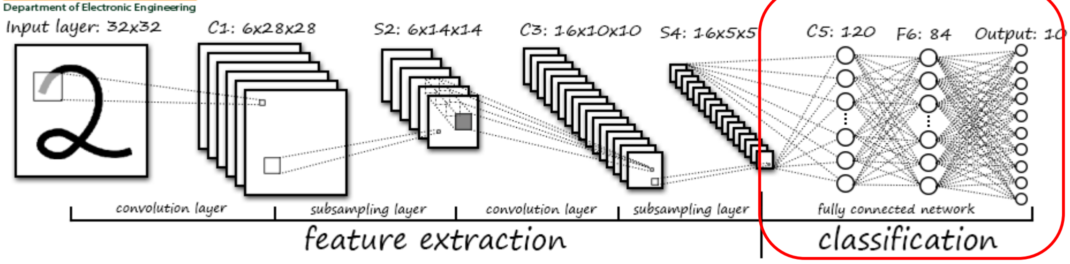


MAXPOOL4 (f = 2*2*1, s = 2, p = 'same')

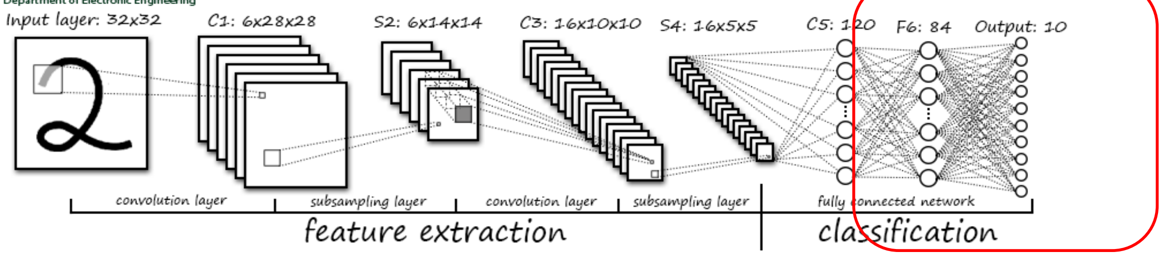
```
# shape of A_pool2~ [m,5,5,16]
A_pool2 = tf.nn.max_pool(A_conv2, ksize = [1, 2, 2, 1], strides=[1, 2, 2, 1], padding = 'SAME')
```




```
### FC5 (n = 120)
  # flatten the volumn to vector
  A_pool2_flat = tf.reshape(A_pool2, [-1, 5*5*16])
  W_fc3 = weight_variable([5*5*16, 120])
  b_fc3 = bias_variable([120])
  # shape of A_fc3 ~ [m,120]
  A_fc3 = tf.nn.relu(tf.matmul(A_pool2_flat, W_fc3) + b_fc3)
```


```
### FC6 (n = 84)
  W_fc4 = weight_variable([120, 84])
  b_fc4 = bias_variable([84])
  # shape of A_fc4 ~ [m, 84]
  A_fc4 = tf.nn.relu(tf.matmul(A_fc3, W_fc4) + b_fc4)
```




```
# Softmax (n = 10)
  W_l = weight_variable([84, 10])
  b_l = bias_variable([10])
  # shape of A_l ~ [m,10]
  A_l=tf.nn.softmax(tf.matmul(A_fc4, W_l) + b_l)
```


Reference

- 台灣大學、電機系、李宏毅, ” Machine Learning”
- CS231n: Convolutional Neural Networks for Visual Recognition, Stanford
- CS230: Deep Learning, Stanford