

Convolutional Neural Network

(Draft)

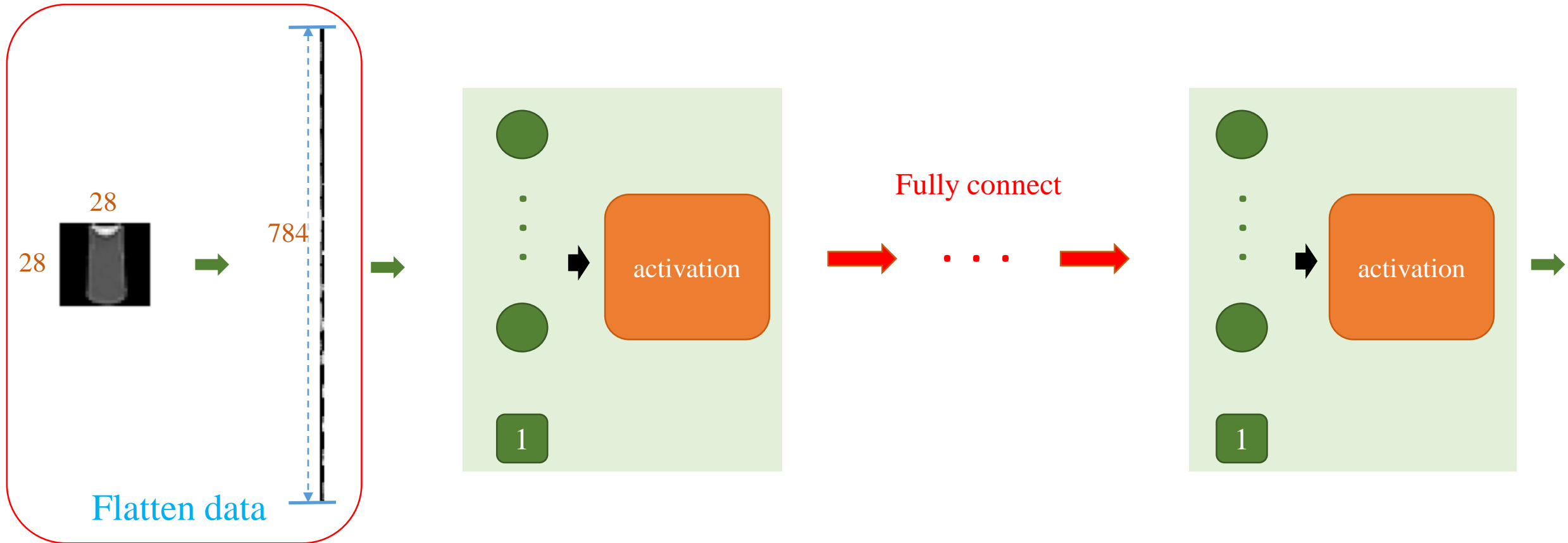
Quang-Vinh Dinh
Ph.D. in Computer Science

Outline

- **From MLP to CNN**
- **Feature Map Down-sampling**
- **Padding**
- **1x1 Convolution**
- **Image classification: Cifar-10 data**

From MLP to CNN

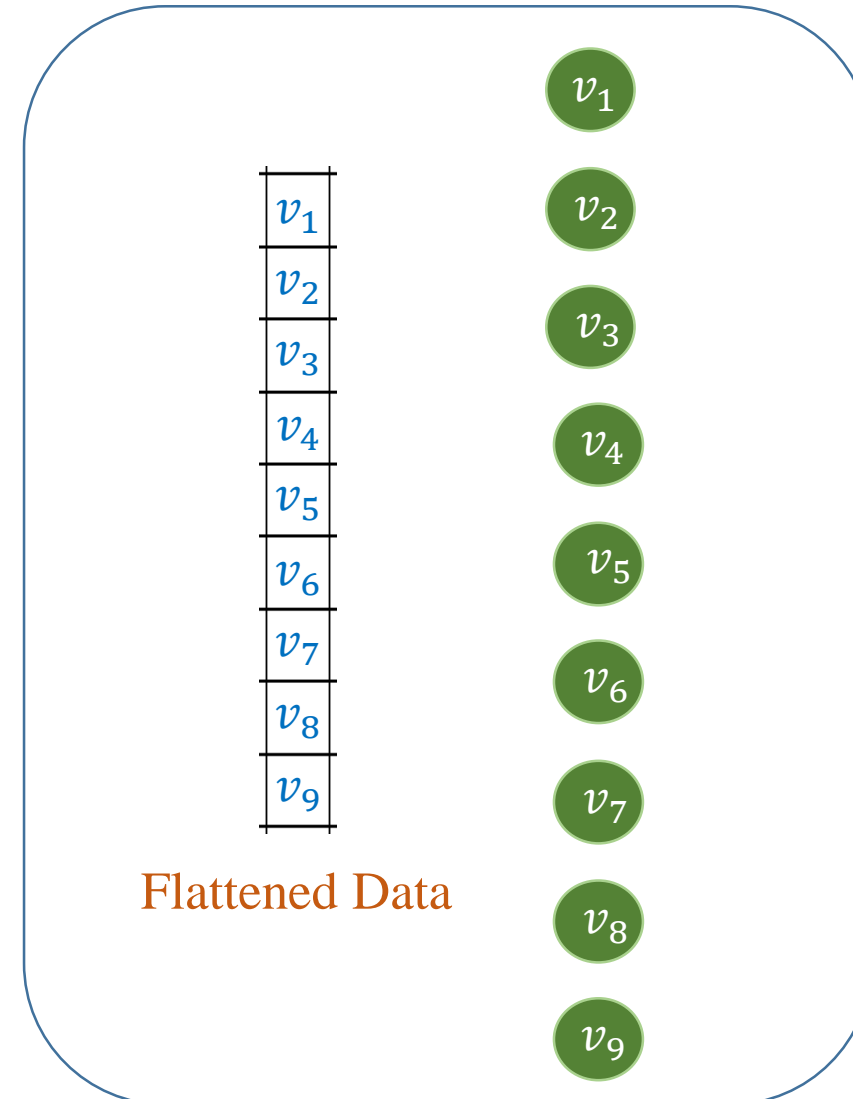
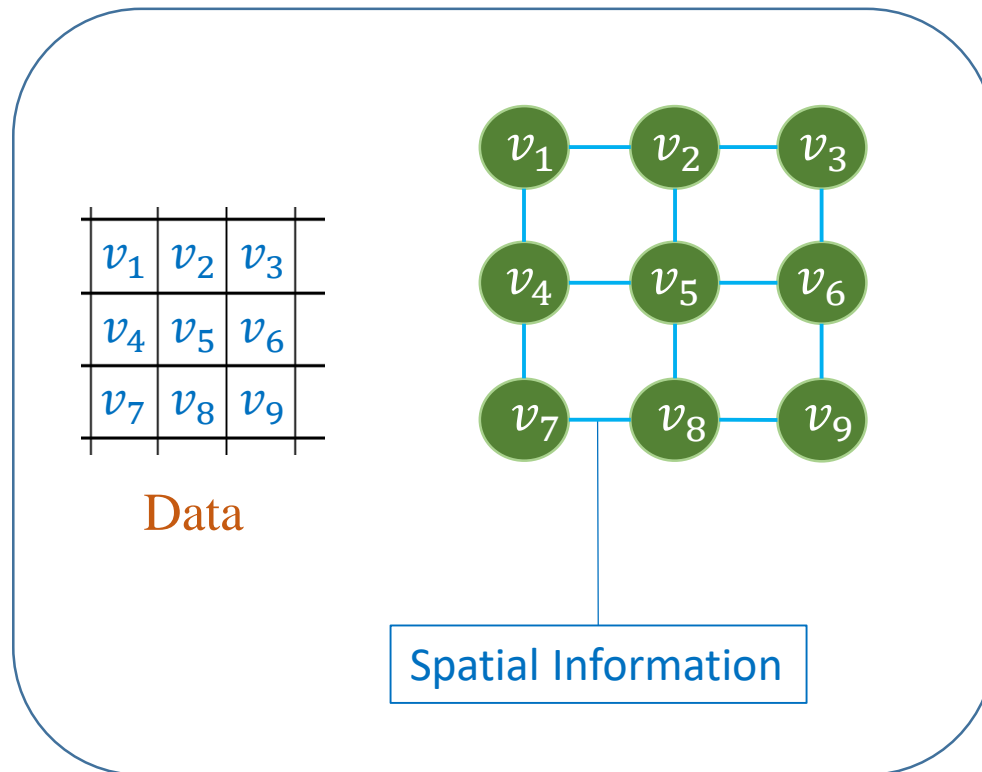
❖ Multi-layer Perceptron



Problem: Remove spatial information of the data
Inefficiently have a large amount of parameters

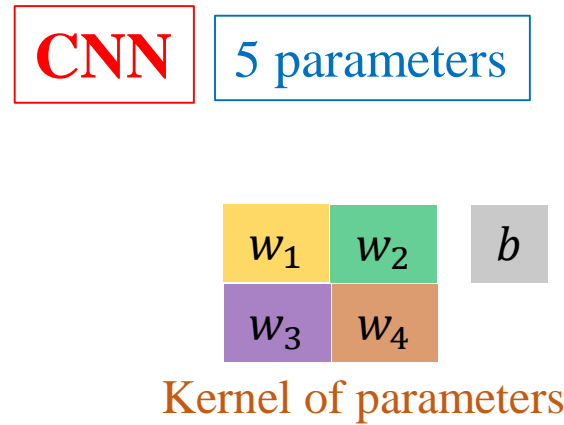
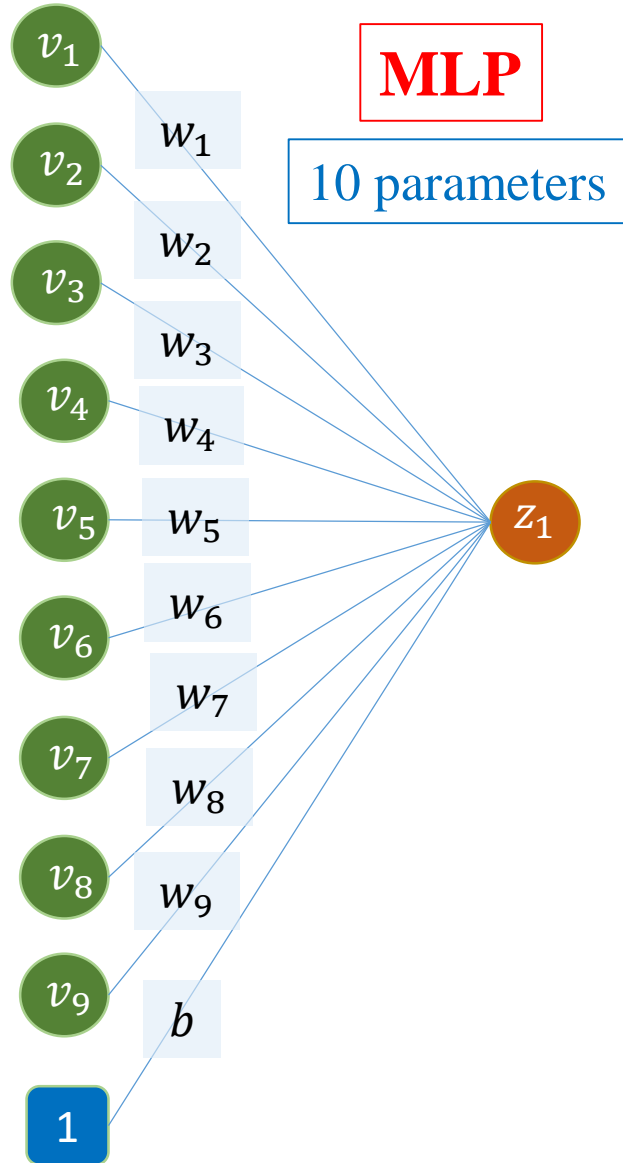
From MLP to CNN

❖ Problem of flattening data

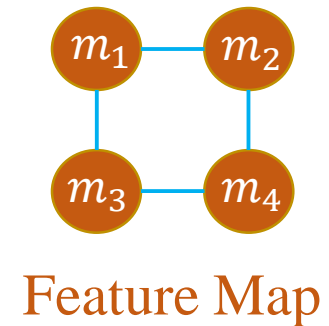
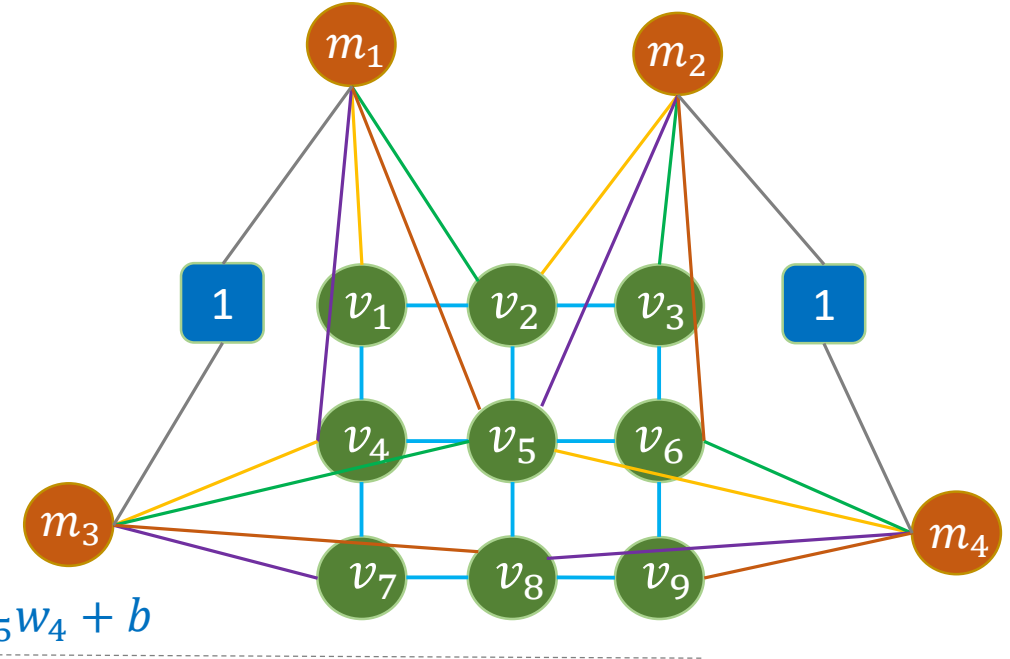
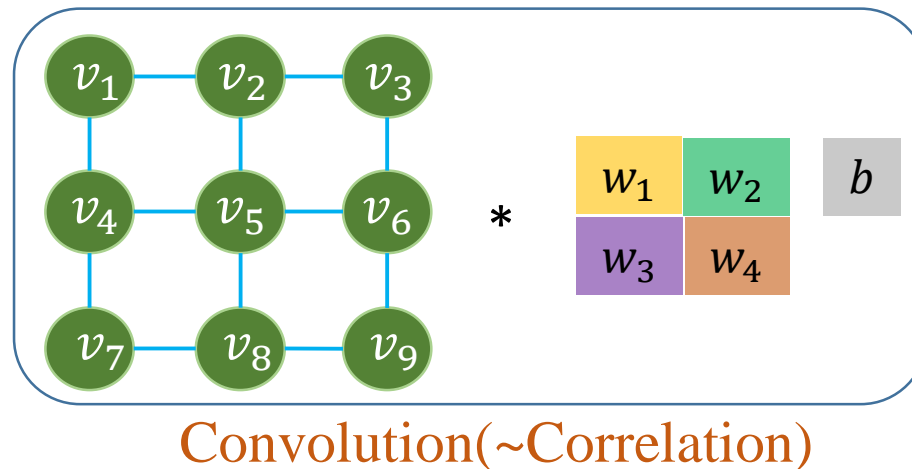


Remove spatial information of the data

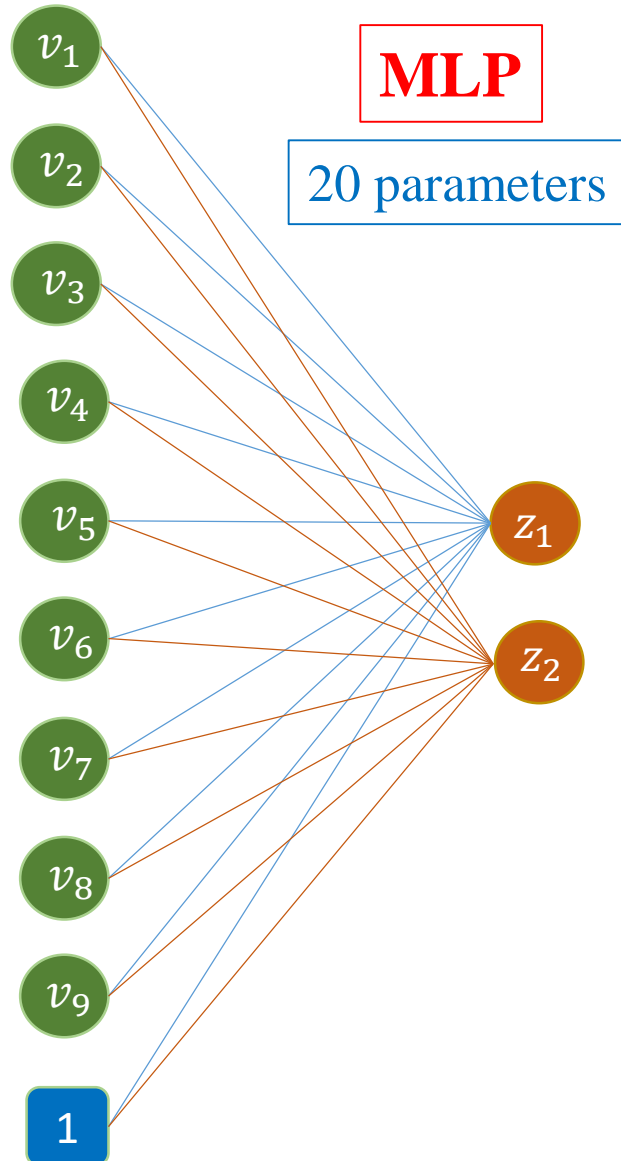
From MLP to CNN



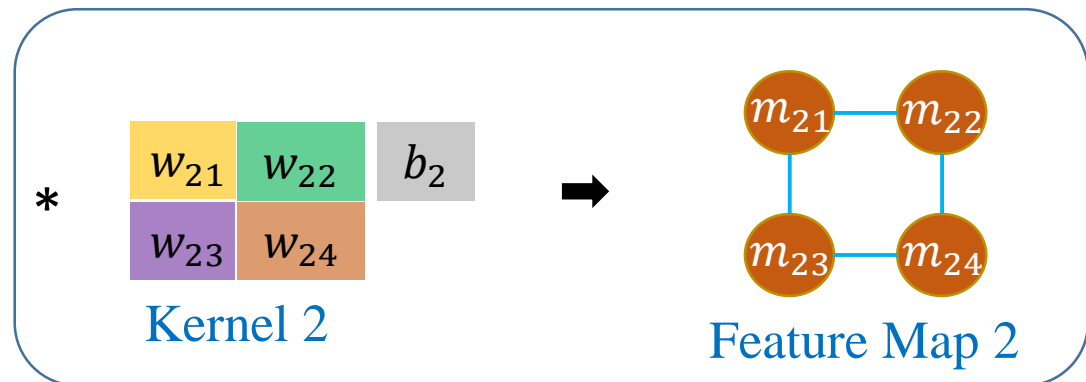
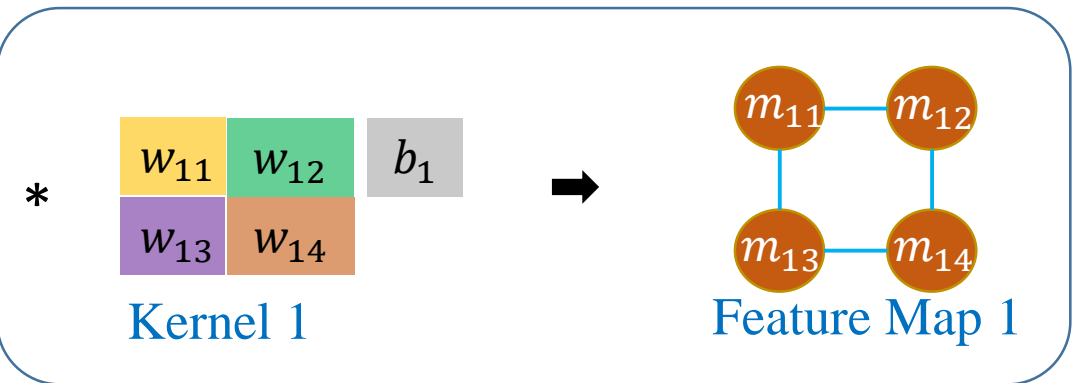
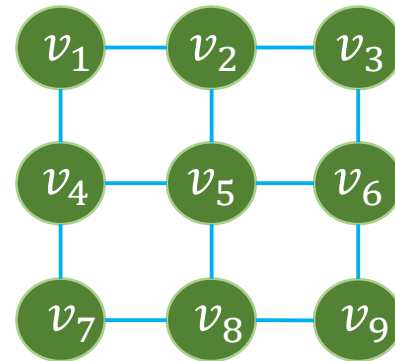
$$m_1 = v_1 w_1 + v_2 w_2 + v_4 w_3 + v_5 w_4 + b$$



From MLP to CNN



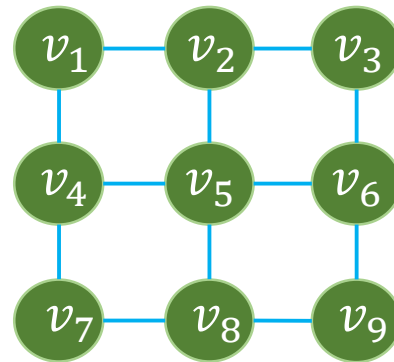
CNN 10 parameters



Kernel 1 \neq Kernel 2

From MLP to CNN

❖ Understand convolution



(Height=3, Width=3, Channel=1)

Shape=(3,3,1)

*



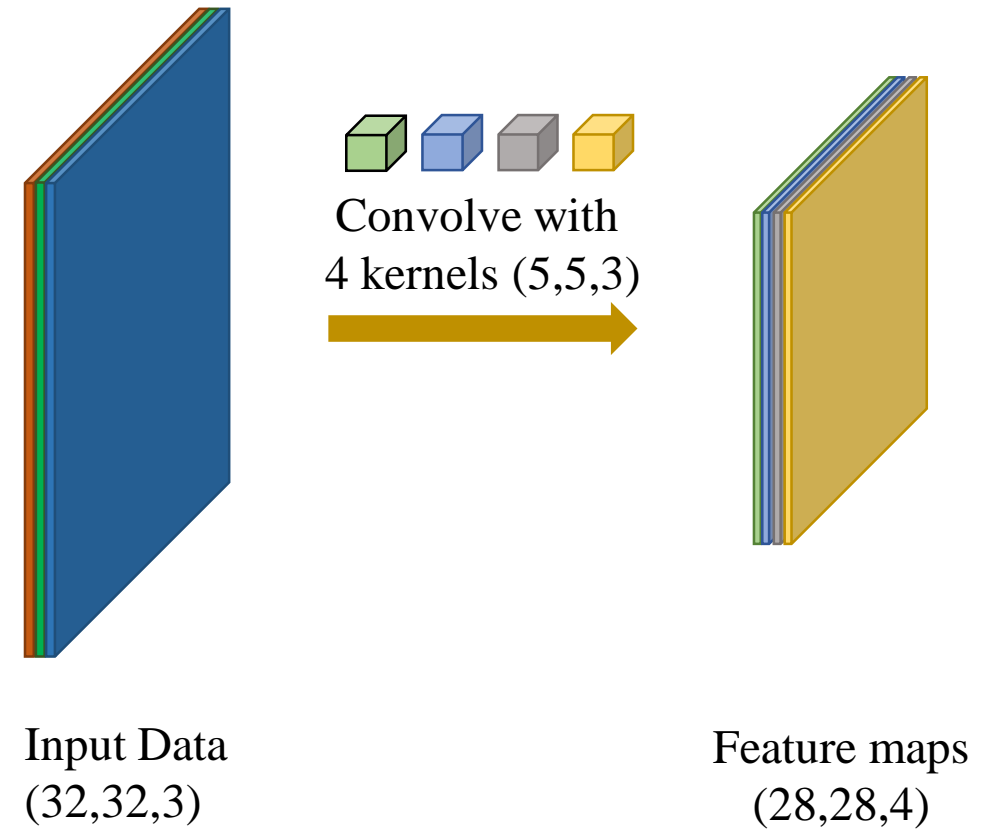
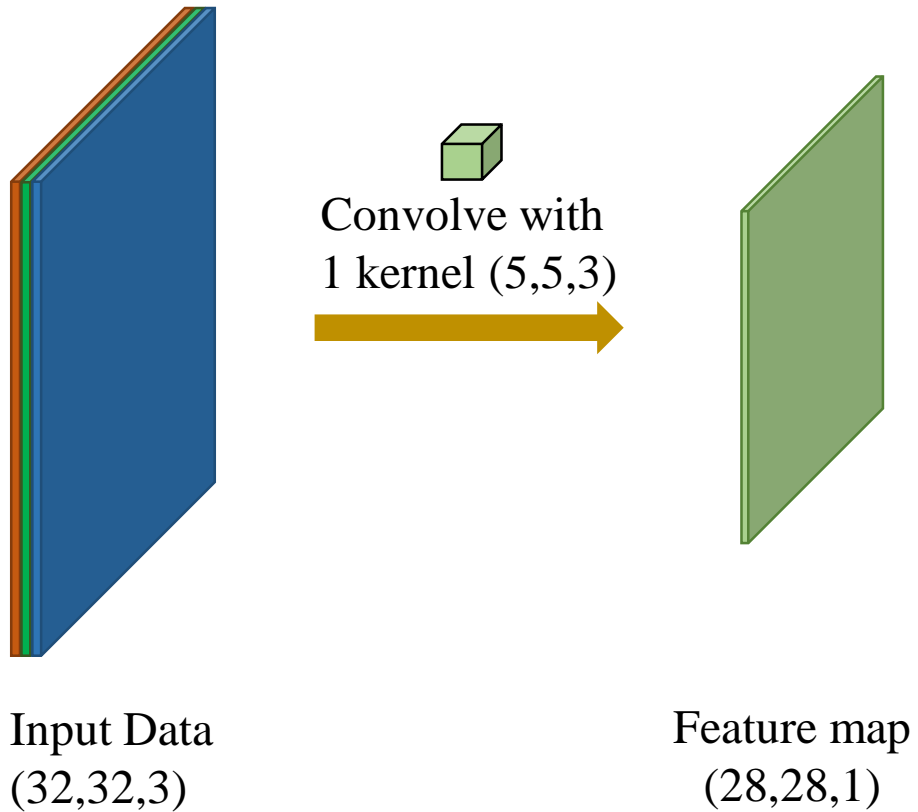
Shape=(2,2,1)

#parameters (including bias) = 5

#channels of data must = #channels of kernel

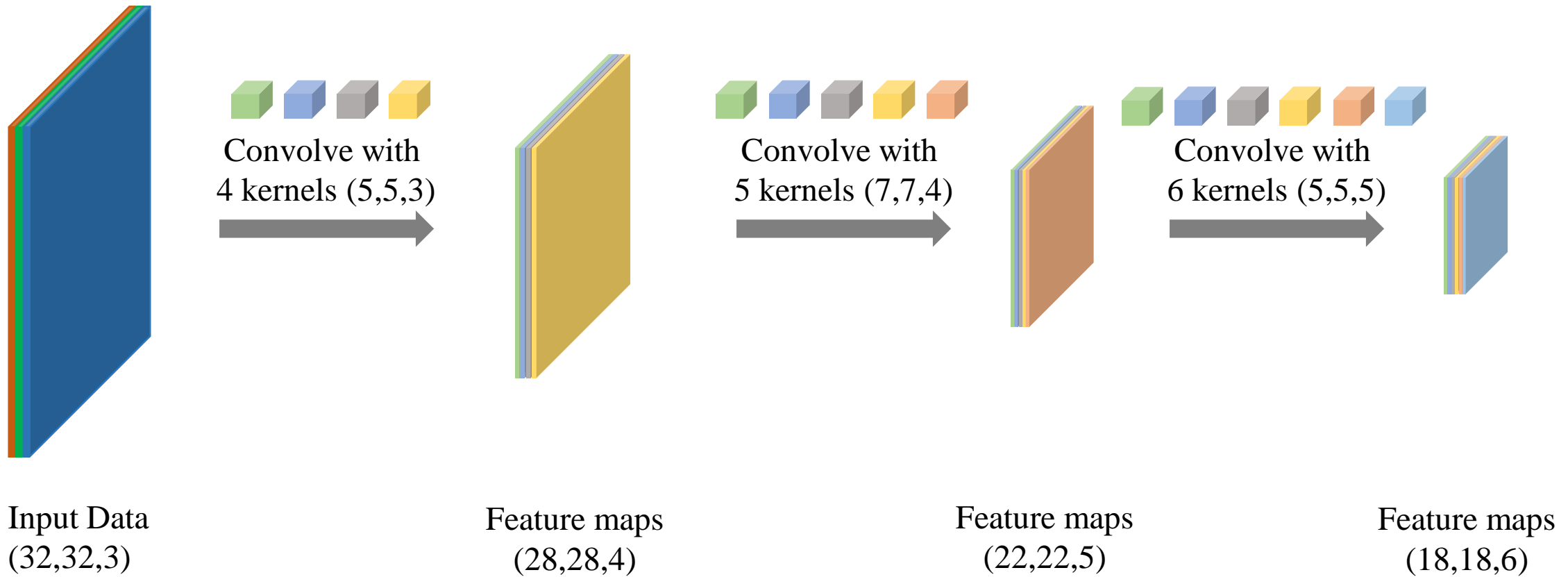
From MLP to CNN

❖ Understand convolution



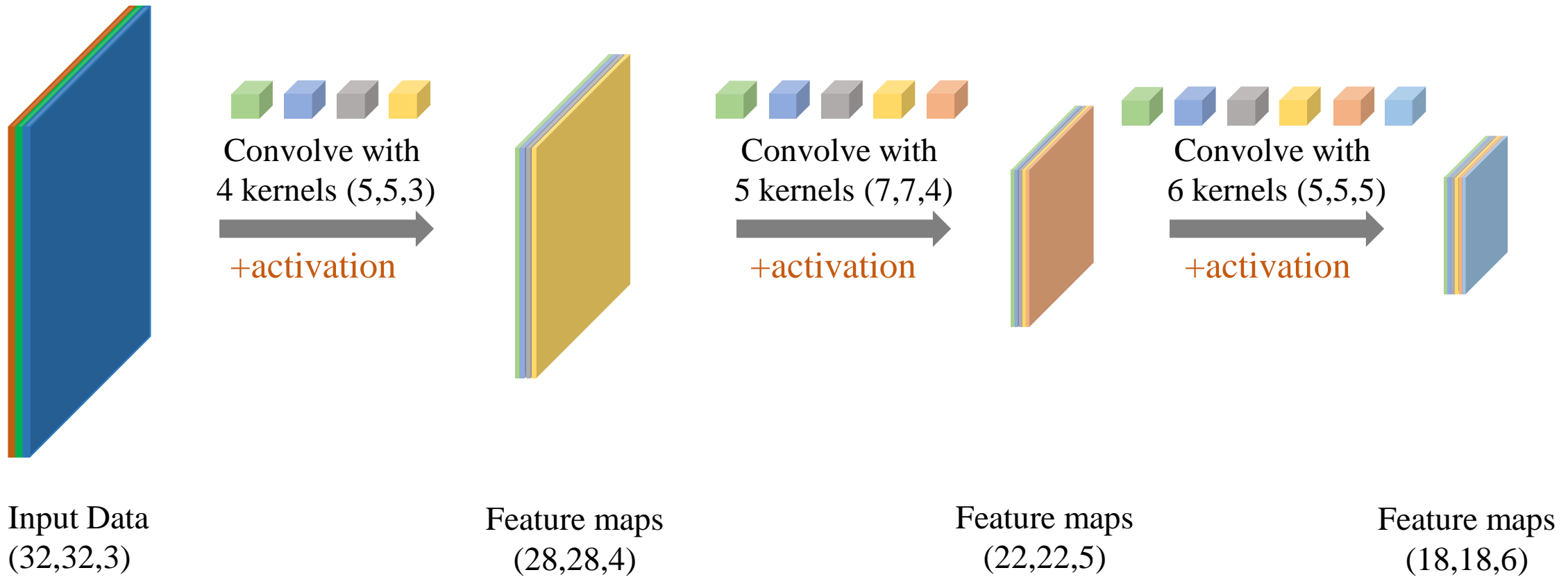
From MLP to CNN

❖ A stack of convolutions



From MLP to CNN

❖ A stack of pairs of convolution+activation



From MLP to CNN

Fashion-MNIST dataset

Grayscale images

Resolution=28x28

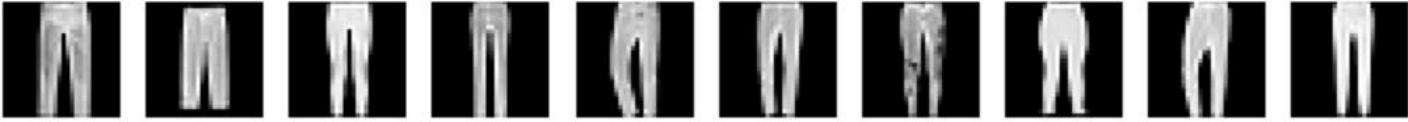
Training set: 60000 samples

Testing set: 10000 samples

T-shirt



Trouser



Pullover



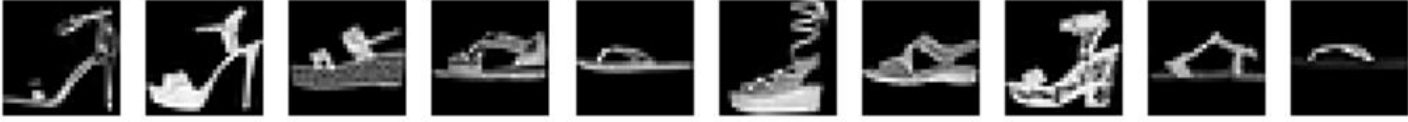
Dress



Coat



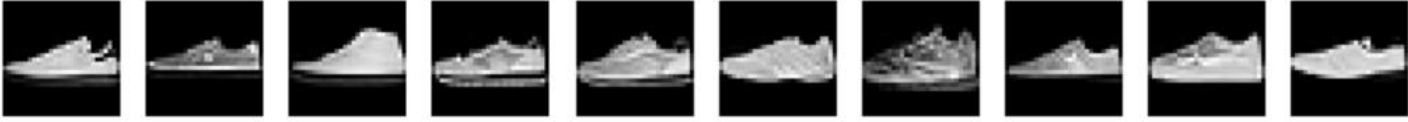
Sandal



Shirt



Sneaker



Bag



Ankle Boot



From MLP to CNN

```
1 # model
2 model = keras.models.Sequential()
3
4 # input is with the shape of (28, 28, 1)
5 model.add(tf.keras.Input(shape=(28, 28, 1)))
6
7 # Convolve with 32 (7x7) kernel; Output: (22x22x32)
8 model.add(keras.layers.Conv2D(32, (7, 7), activation='relu'))
9 # Convolve with 64 (7x7) kernel; Output: (16x16x64)
10 model.add(keras.layers.Conv2D(64, (7, 7), activation='relu'))
11 # Convolve with 128 (7x7) kernel; Output: (10x10x128)
12 model.add(keras.layers.Conv2D(128, (7, 7), activation='relu'))
13 # Convolve with 256 (7x7) kernel; Output: (4x4x256)
14 model.add(keras.layers.Conv2D(256, (7, 7), activation='relu'))
15
16 # flatten
17 model.add(keras.layers.Flatten())
18 model.add(keras.layers.Dense(10, activation='softmax'))
19
20 # compile and train
21 model.compile(optimizer='adam', metrics=['accuracy'],
22               loss='sparse_categorical_crossentropy')
23 model.fit(train_images, train_labels, epochs=10)
24
25 # testing
26 test_loss, test_acc = model.evaluate(test_images,
27                                     test_labels, verbose=2)
28 print('Test accuracy:', test_acc)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 22, 22, 32)	1600
conv2d_1 (Conv2D)	(None, 16, 16, 64)	100416
conv2d_2 (Conv2D)	(None, 10, 10, 128)	401536
conv2d_3 (Conv2D)	(None, 4, 4, 256)	1605888
flatten (Flatten)	(None, 4096)	0
dense (Dense)	(None, 10)	40970

Total params: 2,150,410

Trainable params: 2,150,410

Non-trainable params: 0

Train on 60000 samples

Epoch 1/10

60000/60000 - 577s 10ms/sample - loss: 0.5021 - accuracy: 0.8138

Epoch 2/10

60000/60000 - 578s 10ms/sample - loss: 0.3388 - accuracy: 0.8757

Epoch 3/10

60000/60000 - 567s 9ms/sample - loss: 0.2993 - accuracy: 0.8880

Epoch 4/10

60000/60000 - 545s 9ms/sample - loss: 0.2726 - accuracy: 0.8995

Epoch 5/10

60000/60000 - 1254s 21ms/sample - loss: 0.2475 - accuracy: 0.9083

Epoch 6/10

60000/60000 - 563s 9ms/sample - loss: 0.2201 - accuracy: 0.9172

Epoch 7/10

60000/60000 - 571s 10ms/sample - loss: 0.1983 - accuracy: 0.9254

Epoch 8/10

60000/60000 - 581s 10ms/sample - loss: 0.1806 - accuracy: 0.9340

Epoch 9/10

60000/60000 - 581s 10ms/sample - loss: 0.1517 - accuracy: 0.9431

Epoch 10/10

60000/60000 - 2145s 36ms/sample - loss: 0.1378 - accuracy: 0.9495

10000/1 - 19s - loss: 1.2228 - accuracy: 0.8858

Test accuracy: 0.8858

Outline

- **From MLP to CNN**
- **Feature Map Down-sampling**
- **Padding**
- **1x1 Convolution**
- **Image classification: Cifar-10 data**

Down-sample Feature Map

Max pooling: Features are preserved

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

Data

2x2 max
pooling

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

) =

m_1	m_2
m_3	m_4

$$m_1 = \max(v_1, v_2, v_5, v_6)$$

$$m_2 = \max(v_3, v_4, v_7, v_8)$$

$$m_3 = \max(v_9, v_{10}, v_{13}, v_{14})$$

$$m_4 = \max(v_{11}, v_{12}, v_{15}, v_{16})$$



Feature map (220x220)

max pooling
(2x2)



Feature map
(110x110)

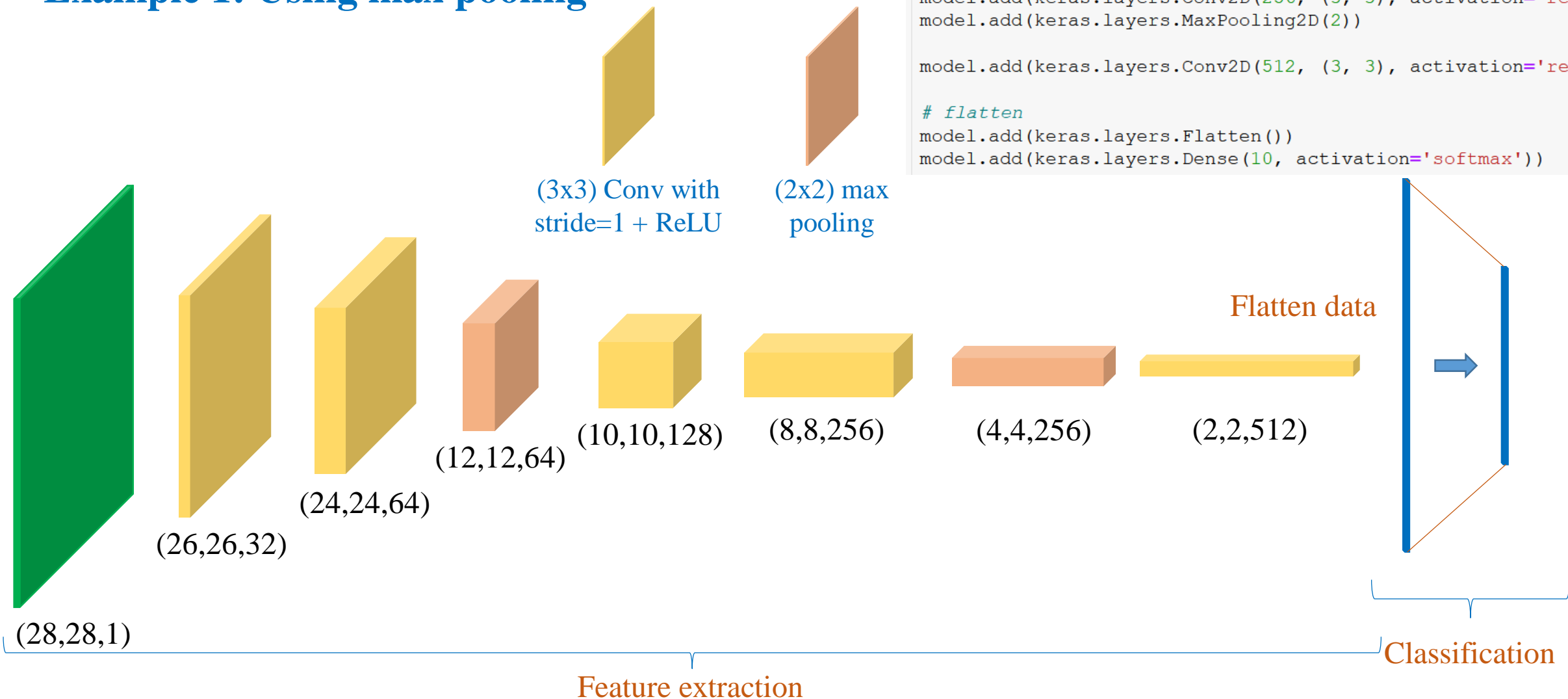
max pooling
(2x2)



Feature map
(55x55)

Down-sample Feature Map

Example 1: Using max pooling



```
# model
model = keras.models.Sequential()
model.add(tf.keras.Input(shape=(28, 28, 1)))

model.add(keras.layers.Conv2D(32, (3, 3), activation='relu'))
model.add(keras.layers.Conv2D(64, (3, 3), activation='relu'))
model.add(keras.layers.MaxPooling2D(2))

model.add(keras.layers.Conv2D(128, (3, 3), activation='relu'))
model.add(keras.layers.Conv2D(256, (3, 3), activation='relu'))
model.add(keras.layers.MaxPooling2D(2))

model.add(keras.layers.Conv2D(512, (3, 3), activation='relu'))

# flatten
model.add(keras.layers.Flatten())
model.add(keras.layers.Dense(10, activation='softmax'))
```


Down-sample Feature Map

❖ Example 1: Using max pooling

```
Epoch 1/10
60000/60000 [=====] - 281s 5ms/sample - loss: 0.4243 - accuracy: 0.8423
Epoch 2/10
60000/60000 [=====] - 295s 5ms/sample - loss: 0.2678 - accuracy: 0.9029
Epoch 3/10
60000/60000 [=====] - 305s 5ms/sample - loss: 0.2200 - accuracy: 0.9199
Epoch 4/10
60000/60000 [=====] - 298s 5ms/sample - loss: 0.1832 - accuracy: 0.9330
Epoch 5/10
60000/60000 [=====] - 298s 5ms/sample - loss: 0.1510 - accuracy: 0.9447
Epoch 6/10
60000/60000 [=====] - 302s 5ms/sample - loss: 0.1245 - accuracy: 0.9540
Epoch 7/10
60000/60000 [=====] - 306s 5ms/sample - loss: 0.0988 - accuracy: 0.9639
Epoch 8/10
60000/60000 [=====] - 292s 5ms/sample - loss: 0.0847 - accuracy: 0.9684
Epoch 9/10
60000/60000 [=====] - 291s 5ms/sample - loss: 0.0709 - accuracy: 0.9741
Epoch 10/10
60000/60000 [=====] - 289s 5ms/sample - loss: 0.0606 - accuracy: 0.9786
10000/1 - 8s - loss: 0.4003 - accuracy: 0.9125
```

Test accuracy: 0.9125

Down-sample Feature Map

❖ Convolve with stride

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

Data **D**

w_1	w_2	b
w_3	w_4	

Kernel of parameters

Convolve **D**
with stride=1

m_1	m_2	m_3
m_4	m_5	m_6
m_7	m_8	m_9

Output

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

Down-sample Feature Map

❖ Convolve with stride

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

Data D

w_1	w_2	b
w_3	w_4	

Kernel of parameters

Convolve D
with stride=2

m_1	m_2
m_3	m_4

Output

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

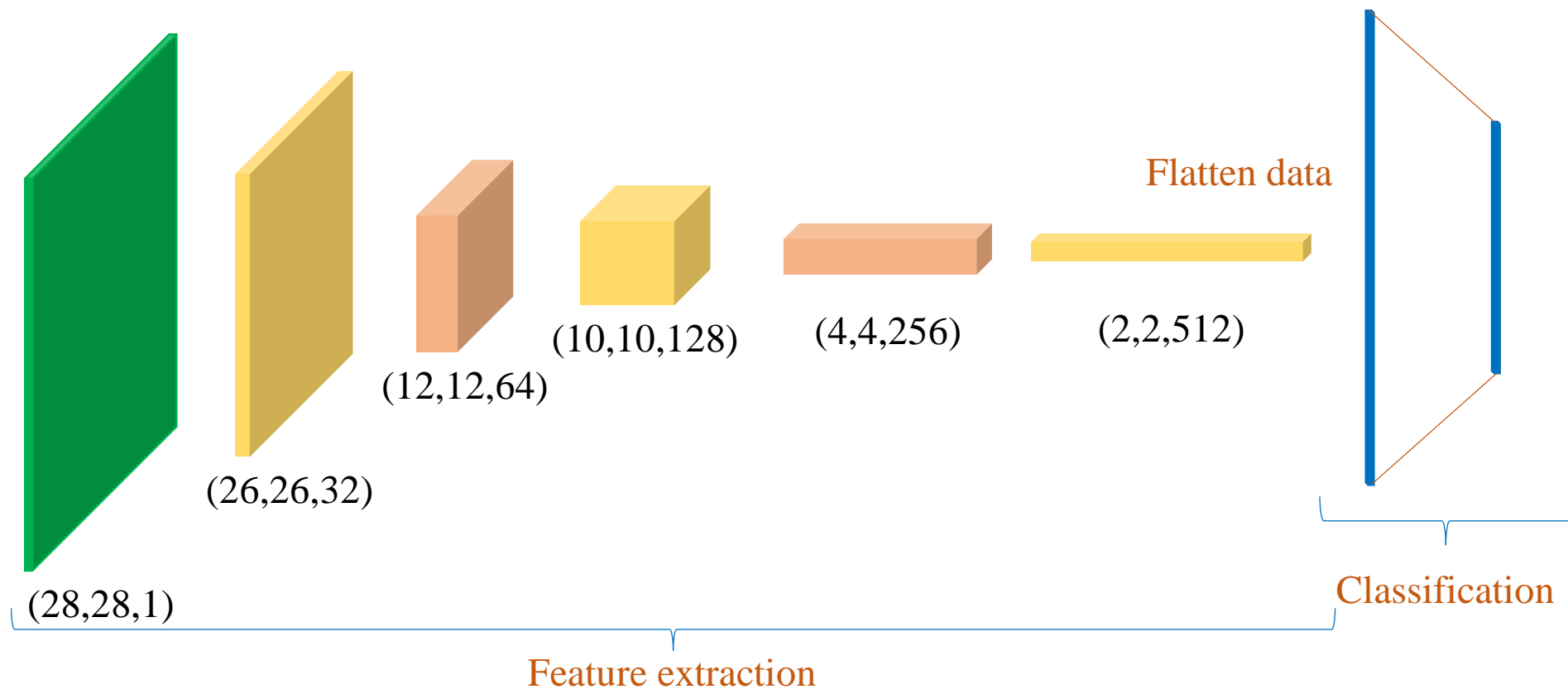
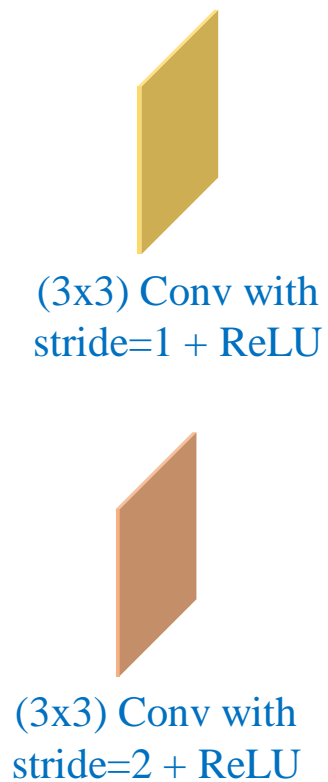
v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

Down-sample Feature Map

Example 2: Using Conv with strides



```
# model
model = keras.models.Sequential()
model.add(tf.keras.Input(shape=(28, 28, 1)))

model.add(keras.layers.Conv2D(32, (3, 3), strides=1, activation='relu'))
model.add(keras.layers.Conv2D(64, (3, 3), strides=2, activation='relu'))
model.add(keras.layers.Conv2D(128, (3, 3), strides=1, activation='relu'))
model.add(keras.layers.Conv2D(256, (3, 3), strides=2, activation='relu'))
model.add(keras.layers.Conv2D(512, (3, 3), strides=1, activation='relu'))

# flatten
model.add(keras.layers.Flatten())
model.add(keras.layers.Dense(10, activation='softmax'))
```

Down-sample Feature Map

❖ Example 2: Using Conv with strides

```
Epoch 1/10
60000/60000 [=====] - 276s 5ms/sample - loss: 0.4500 - accuracy: 0.8350
Epoch 2/10
60000/60000 [=====] - 268s 4ms/sample - loss: 0.2934 - accuracy: 0.8922
Epoch 3/10
60000/60000 [=====] - 285s 5ms/sample - loss: 0.2376 - accuracy: 0.9108
Epoch 4/10
60000/60000 [=====] - 291s 5ms/sample - loss: 0.1942 - accuracy: 0.9283
Epoch 5/10
60000/60000 [=====] - 288s 5ms/sample - loss: 0.1536 - accuracy: 0.9420
Epoch 6/10
60000/60000 [=====] - 288s 5ms/sample - loss: 0.1198 - accuracy: 0.9548
Epoch 7/10
60000/60000 [=====] - 289s 5ms/sample - loss: 0.0934 - accuracy: 0.9653
Epoch 8/10
60000/60000 [=====] - 199s 3ms/sample - loss: 0.0746 - accuracy: 0.9730
Epoch 9/10
60000/60000 [=====] - 200s 3ms/sample - loss: 0.0625 - accuracy: 0.9772
Epoch 10/10
60000/60000 [=====] - 199s 3ms/sample - loss: 0.0566 - accuracy: 0.9797
10000/1 - 5s - loss: 0.3381 - accuracy: 0.9055
```

Test accuracy: 0.9055

Outline

- **From MLP to CNN**
- **Feature Map Down-sampling**
- **Padding**
- **1x1 Convolution**
- **Image classification: Cifar-10 data**

Padding

Goal: Keep resolution
of feature map

v_1	v_2	v_3	v_4
v_5	v_6	v_7	v_8
v_9	v_{10}	v_{11}	v_{12}
v_{13}	v_{14}	v_{15}	v_{16}

Data D
(4x4)

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

Kernel of parameters

b

Without using padding
or padding=0

Convolve
with stride=1 (D) =

m_1	m_2
m_4	m_5

Output
(2x2)

Padding = 1

v	v	v	v	v	v
v	v_1	v_2	v_3	v_4	v
v	v_5	v_6	v_7	v_8	v
v	v_9	v_{10}	v_{11}	v_{12}	v
v	v_{13}	v_{14}	v_{15}	v_{16}	v
v	v	v	v	v	v

Data D_p

Convolve
with stride=1 (D_p) =

m_1	m_2	m_3	m_4
m_5	m_6	m_7	m_8
m_9	m_{10}	m_{11}	m_{12}
m_{13}	m_{14}	m_{15}	m_{16}

Output
(4x4)

Padding

Example

```
# model
model = keras.models.Sequential()
model.add(tf.keras.Input(shape=(28, 28, 1)))

model.add(keras.layers.Conv2D(32, (3, 3), strides=1, padding='same', activation='relu'))
model.add(keras.layers.Conv2D(64, (3, 3), strides=2, padding='same', activation='relu'))

model.add(keras.layers.Conv2D(128, (3, 3), strides=1, padding='same', activation='relu'))
model.add(keras.layers.Conv2D(256, (3, 3), strides=2, padding='same', activation='relu'))

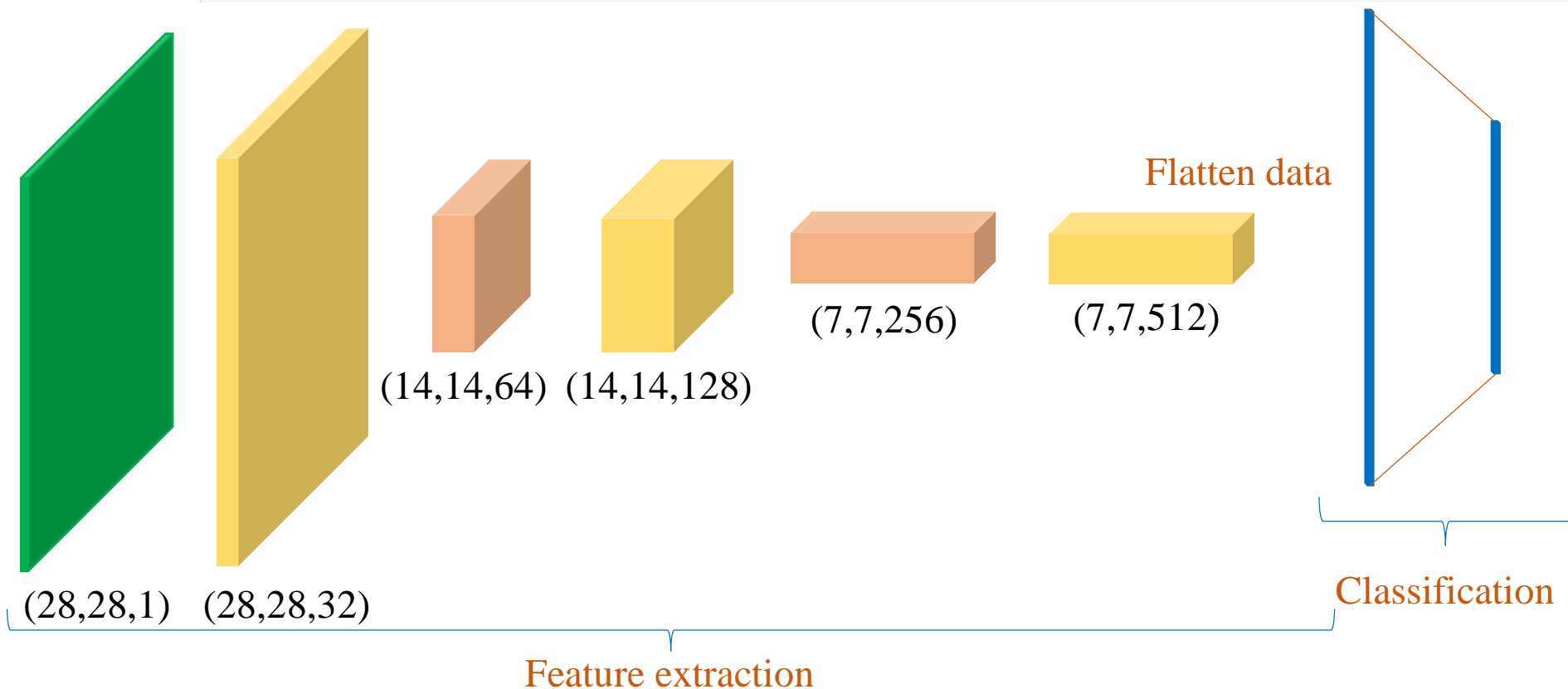
model.add(keras.layers.Conv2D(512, (3, 3), strides=1, padding='same', activation='relu'))

# flatten
model.add(keras.layers.Flatten())
model.add(keras.layers.Dense(10, activation='softmax'))
```

(3x3) Conv with stride=1,
padding='same' + ReLU

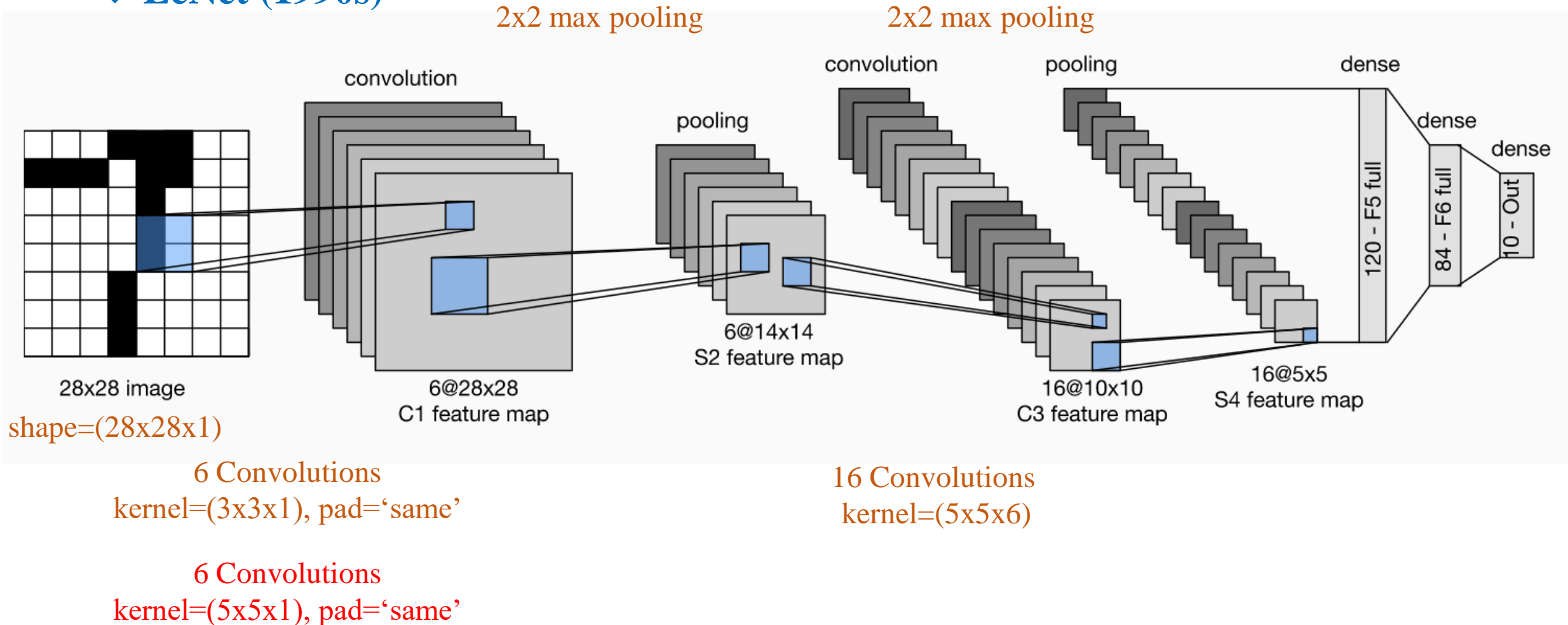


(3x3) Conv with stride=2,
padding='same' + ReLU



Padding

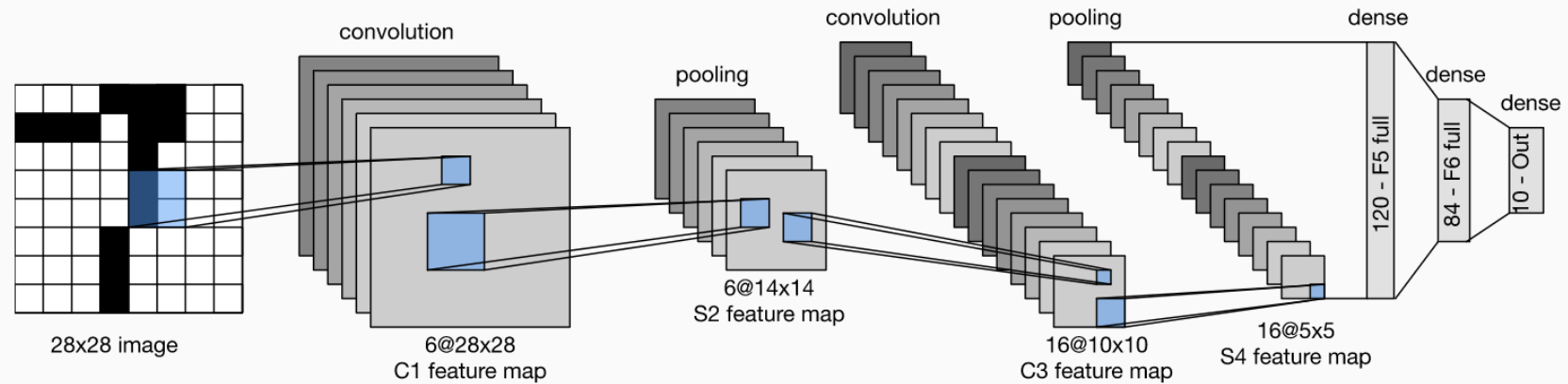
❖ LeNet (1990s)



Padding

❖ LeNet (1990s)

https://d2l.ai/chapter_convolutional-neural-networks/lenet.html



```
# model architecture
model = tf.keras.Sequential()
# input shape (28,28,1)
model.add(tf.keras.Input(shape=(28, 28, 1)))

# convolution 1 and max pooling 1
model.add(tf.keras.layers.Conv2D(6, (5,5), padding='same', activation='relu'))
model.add(tf.keras.layers.MaxPooling2D(pool_size=2))

# convolution 2 and max pooling 2
model.add(tf.keras.layers.Conv2D(filters=16, kernel_size=5, activation='relu'))
model.add(tf.keras.layers.MaxPooling2D(pool_size=2))

# Flatten
model.add(tf.keras.layers.Flatten())

# fully connected
model.add(tf.keras.layers.Dense(120, activation='relu'))
model.add(tf.keras.layers.Dense(84, activation='relu'))
model.add(tf.keras.layers.Dense(10, activation='softmax'))
```

Outline

- **From MLP to CNN**
- **Feature Map Down-sampling**
- **Padding**
- **1x1 Convolution**
- **Image classification: Cifar-10 data**

1x1 Convolution

❖ Why 1x1 Convolution

❖ Flexible input size



Yann LeCun

April 7, 2015 · 🌐



In Convolutional Nets, there is no such thing as "fully-connected layers". There are only convolution layers with 1x1 convolution kernels and a full connection table.

It's a too-rarely-understood fact that ConvNets don't need to have a fixed-size input. You can train them on inputs that happen to produce a single output vector (with no spatial extent), and then apply them to larger images. Instead of a single output vector, you then get a spatial map of output vectors. Each vector sees input windows at different locations on the input. In that scenario, the "fully connected layers" really act as 1x1 convolutions.

Yann LeCun



Yann LeCun in 2018

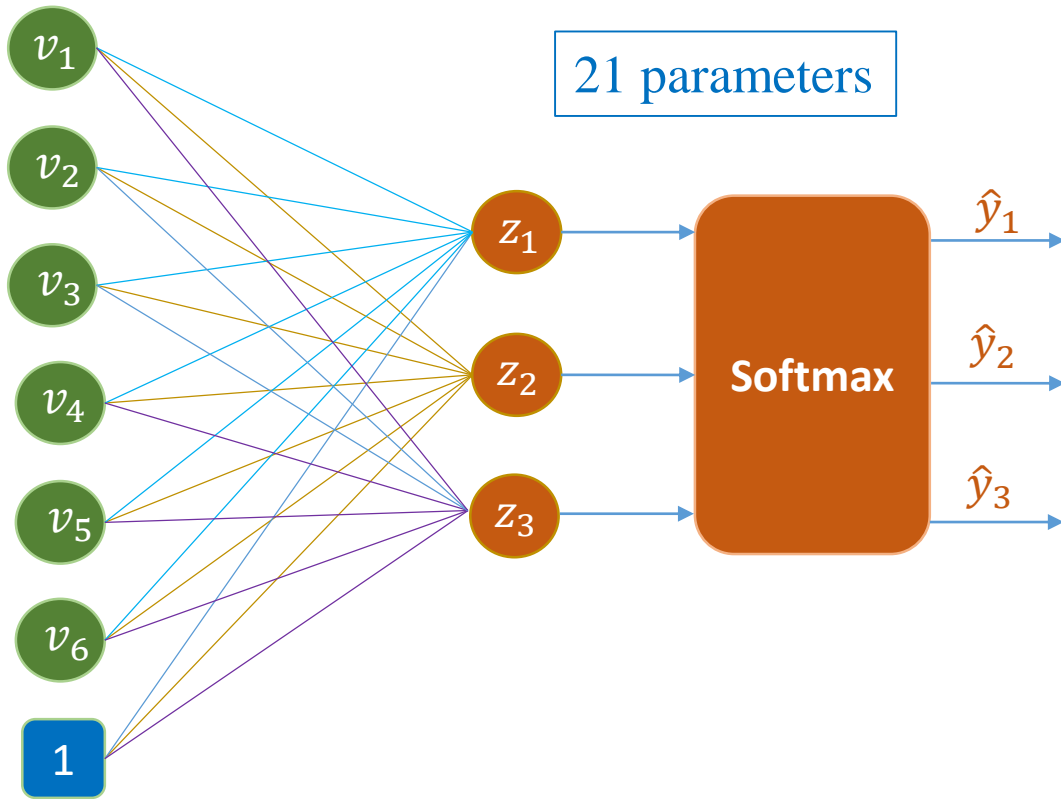
Born	July 8, 1960 (age 60) Soisy-sous-Montmorency, France
Alma mater	ESIEE Paris (MSc) Pierre and Marie Curie University (PhD)
Known for	Deep learning
Awards	Turing Award (2018) AAAI Fellow (2019) Legion of Honour (2020)
Scientific career	
Institutions	Bell Labs (1988-1996) New York University Facebook
Thesis	<i>Modèles connexionnistes de l'apprentissage (connectionist learning models)</i> (1987a)
Doctoral advisor	Maurice Milgram
Website	yann.lecun.com

1x1 Convolution

❖ Comparison

Fully connected layer

21 parameters



CNN

21 parameters

Feature map
(1x1x6)

Convolve with
3 kernels (1,1)
+ softmax activation

\hat{y}_1
 \hat{y}_2
 \hat{y}_3

1x1 Convolution

Replace FC by 1x1 Conv

```
# model
```

```
model = keras.models.Sequential()
```

```
model.add(tf.keras.Input(shape=(28, 28, 1)))
```

```
model.add(keras.layers.Conv2D(32, (3, 3), strides=1, padding='same', activation='relu'))
```

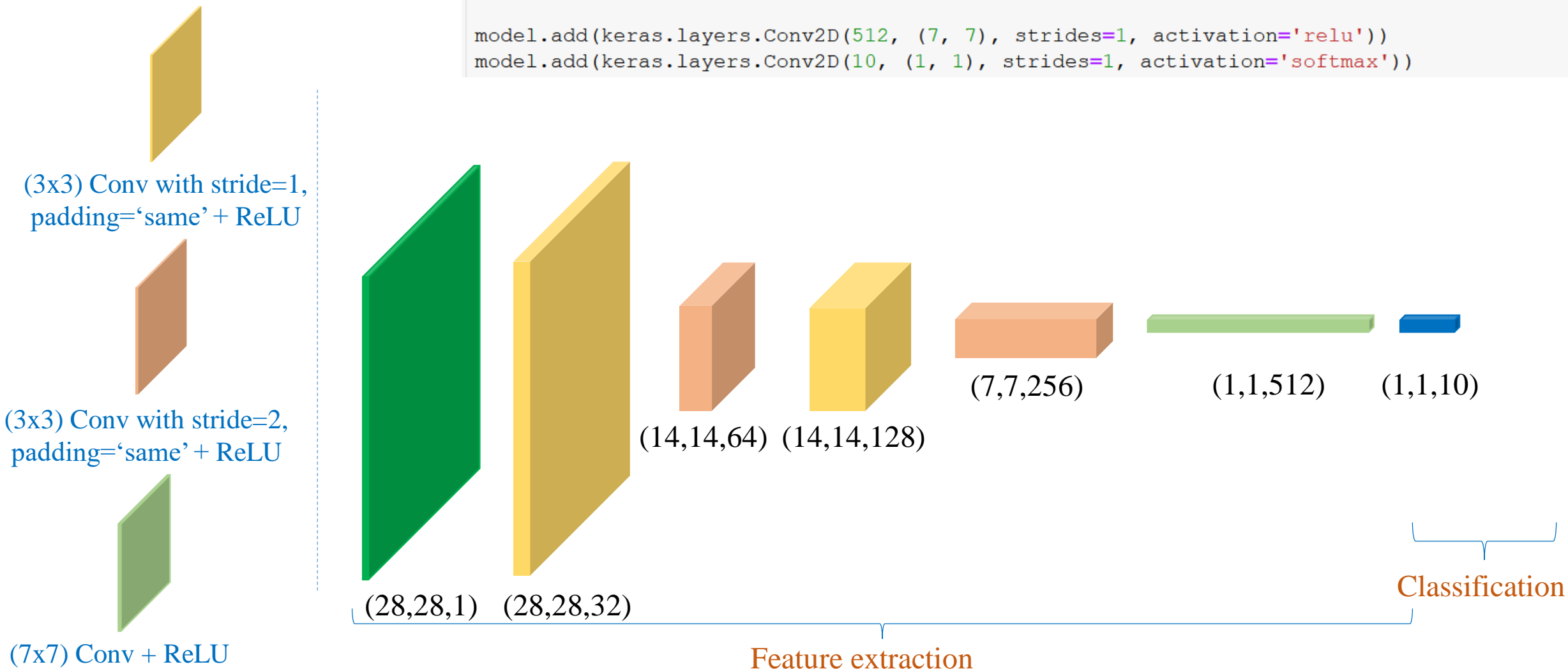
```
model.add(keras.layers.Conv2D(64, (3, 3), strides=2, padding='same', activation='relu'))
```

```
model.add(keras.layers.Conv2D(128, (3, 3), strides=1, padding='same', activation='relu'))
```

```
model.add(keras.layers.Conv2D(256, (3, 3), strides=2, padding='same', activation='relu'))
```

```
model.add(keras.layers.Conv2D(512, (7, 7), strides=1, activation='relu'))
```

```
model.add(keras.layers.Conv2D(10, (1, 1), strides=1, activation='softmax'))
```



1x1 Convolution

Dynamic input sizes

```
# model
model = keras.models.Sequential()
model.add(tf.keras.Input(shape=(None, None, 1)))

model.add(keras.layers.Conv2D(32, (3, 3), strides=1, padding='same', activation='relu'))
model.add(keras.layers.Conv2D(64, (3, 3), strides=2, padding='same', activation='relu'))

model.add(keras.layers.Conv2D(128, (3, 3), strides=1, padding='same', activation='relu'))
model.add(keras.layers.Conv2D(256, (3, 3), strides=2, padding='same', activation='relu'))

model.add(keras.layers.Conv2D(512, (7, 7), strides=1, activation='relu'))
model.add(keras.layers.Conv2D(10, (1, 1), strides=1, activation='softmax'))
```

```
1 shape = (32, 28, 28, 1)
2 data = tf.random.normal(shape)
3 print(data.shape)
4
5 output = model.predict(data)
6 print(output.shape)
```

```
(32, 28, 28, 1)
(32, 1, 1, 10)
```

```
1 shape = (32, 64, 64, 1)
2 data = tf.random.normal(shape)
3 print(data.shape)
4
5 output = model.predict(data)
6 print(output.shape)
```

```
(32, 64, 64, 1)
(32, 10, 10, 10)
```

Shape=(batch size, height, width, channel)

1x1 Convolution

Dynamic
input
sizes

```
# model
model = keras.models.Sequential()
model.add(tf.keras.Input(shape=(None, None, 1)))

model.add(keras.layers.Conv2D(32, (3, 3), activation='relu'))
model.add(keras.layers.Conv2D(64, (3, 3), activation='relu'))
model.add(keras.layers.MaxPooling2D(2))

model.add(keras.layers.Conv2D(128, (3, 3), activation='relu'))
model.add(keras.layers.Conv2D(256, (3, 3), activation='relu'))
model.add(keras.layers.MaxPooling2D(2))

model.add(keras.layers.Conv2D(512, (3, 3), activation='relu'))

# flatten
model.add(keras.layers.Flatten())
model.add(keras.layers.Dense(10, activation='softmax'))
```

```
C:\installed\lib\site-packages\tensorflow_core\python\keras\layers\core.py in build(self, input_shape)
    1013     input_shape = tensor_shape.TensorShape(input_shape)
    1014     if tensor_shape.dimension_value(input_shape[-1]) is None:
-> 1015         raise ValueError('The last dimension of the inputs to `Dense` '
    1016                           'should be defined. Found `None`.')
    1017     last_dim = tensor_shape.dimension_value(input_shape[-1])
```

ValueError: The last dimension of the inputs to `Dense` should be defined. Found `None`.

Outline

- **From MLP to CNN**
- **Feature Map Down-sampling**
- **Padding**
- **1x1 Convolution**
- **Image classification: Cifar-10 data**

Image Classification

Cifar-10 dataset

Color images
Resolution=32x32
Training set: 50000 samples
Testing set: 10000 samples

airplane



automobile



bird



cat



deer



dog



frog



horse



ship



truck



Cifar-10 Image Classification

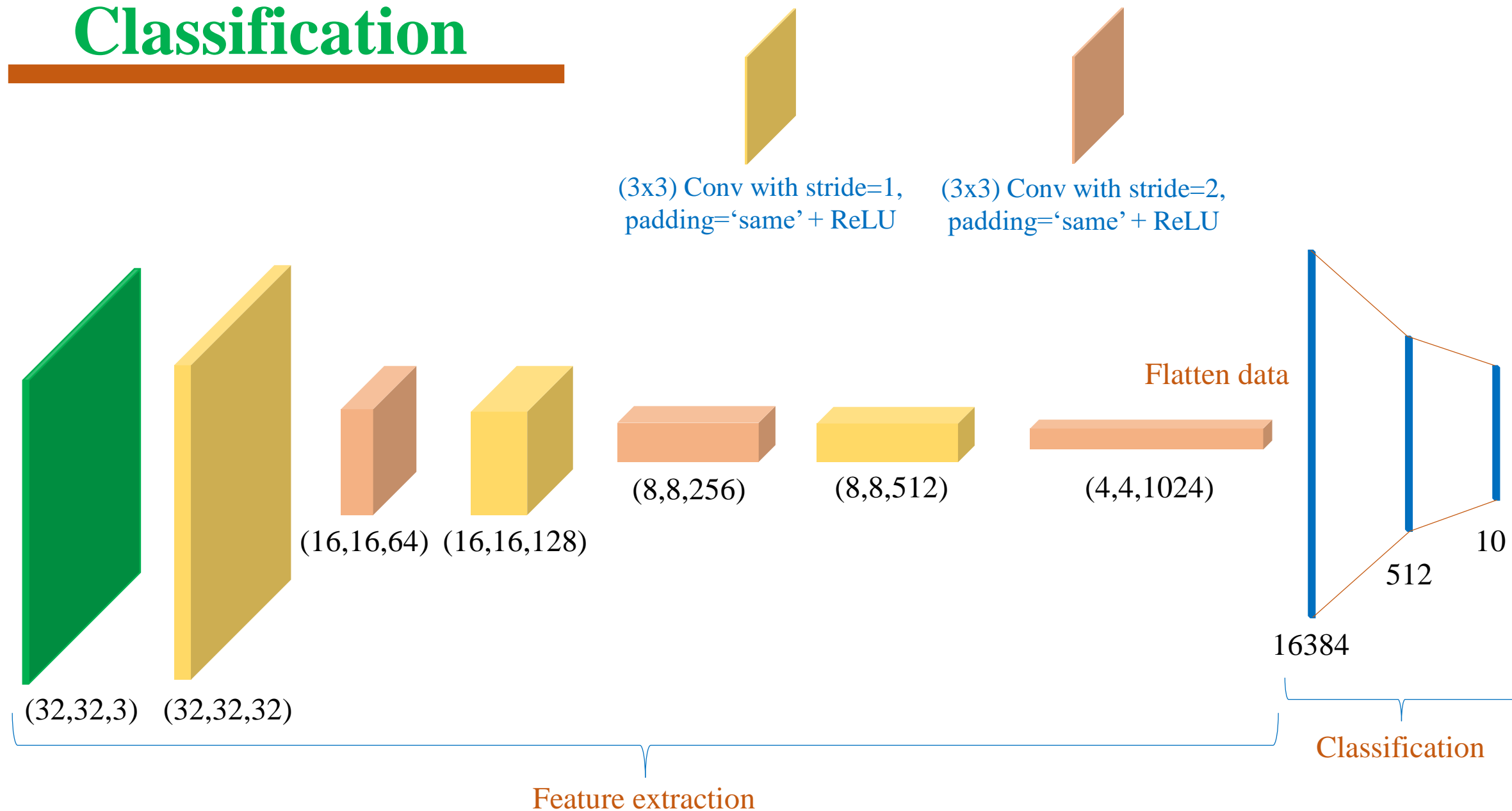


Image Classification

Cifar-10

```
1 import tensorflow as tf
2
3 # data preparation
4 cifar10 = tf.keras.datasets.cifar10
5 (x_train, y_train), (x_test, y_test) = cifar10.load_data()
6
7 # normalize
8 x_train, x_test = x_train / 255.0, x_test / 255.0
```

```
# model
model = keras.models.Sequential()
model.add(tf.keras.Input(shape=(height, width, 3)))

model.add(keras.layers.Conv2D(32, (3, 3), strides=1, padding='same', activation='relu'))
model.add(keras.layers.Conv2D(64, (3, 3), strides=2, padding='same', activation='relu'))

model.add(keras.layers.Conv2D(128, (3, 3), strides=1, padding='same', activation='relu'))
model.add(keras.layers.Conv2D(256, (3, 3), strides=2, padding='same', activation='relu'))

model.add(keras.layers.Conv2D(512, (3, 3), strides=1, padding='same', activation='relu'))
model.add(keras.layers.Conv2D(1024, (3, 3), strides=2, padding='same', activation='relu'))

# flatten
model.add(keras.layers.Flatten())
model.add(keras.layers.Dense(512, activation='relu'))
model.add(keras.layers.Dense(10, activation='softmax'))
model.summary()
```

Image Classification

❖ Demo

```
Python 3.7.3 (default, Apr 24 2019, 15:29:51) [MSC v.1915 64 bit (AMD64)] ::  
Type "help", "copyright", "credits" or "license" for more information.  
>>>  
>>>  
>>>  
>>>  
>>>  
>>>  
>>>  
>>>  
>>> for epoch in range(n_epochs):  
...     sum_of_losses = 0  
...     gradients = np.zeros((2,1))  
...  
...     for index in range(4):  
...         xi = X_b[index:index+1]  
...         yi = y[index:index+1]
```

Reading and Exercises

❖ Exercises

- 1) Use LeNet for the fashion-MNIST and Cifar-10 data sets
- 2) What are the advantages of using 1x1 Conv instead of FC

❖ Reading

<https://cs231n.github.io/convolutional-networks/>

<https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53>

