AI VIETNAM
AI Insight Course

Convolutional Neural Network

(Session 2)

Quang-Vinh Dinh
Ph.D. in Computer Science

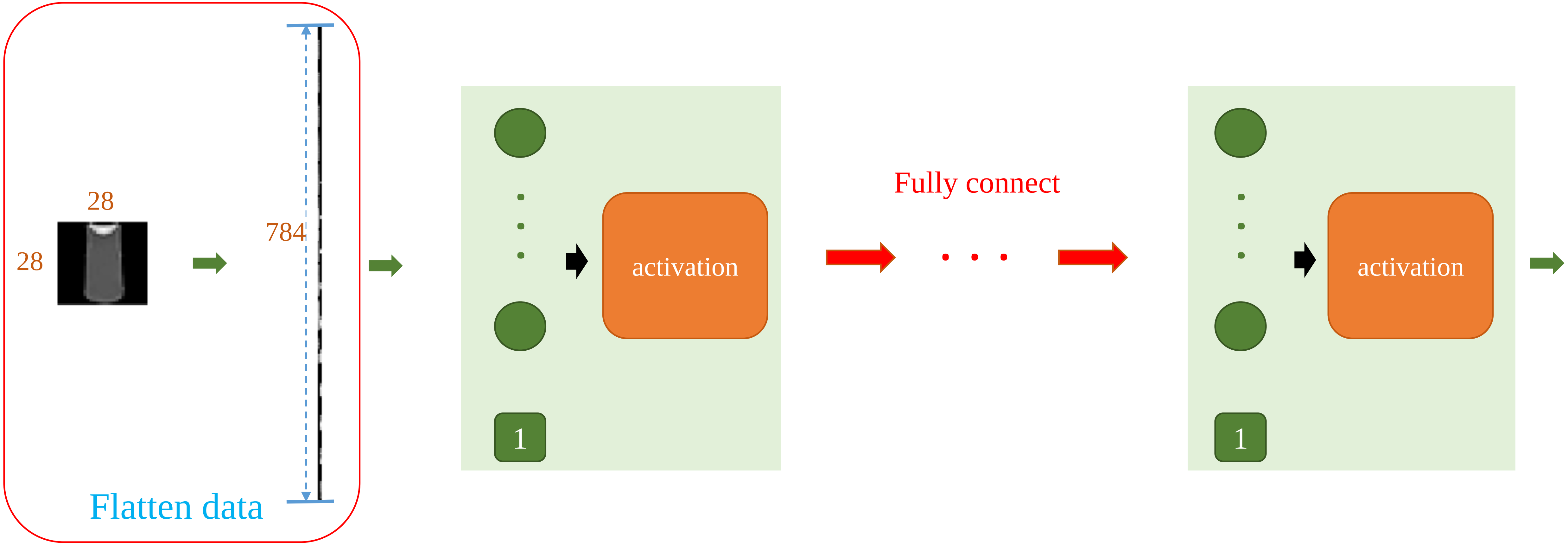
Year 2020

Outline

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

From MLP to CNN

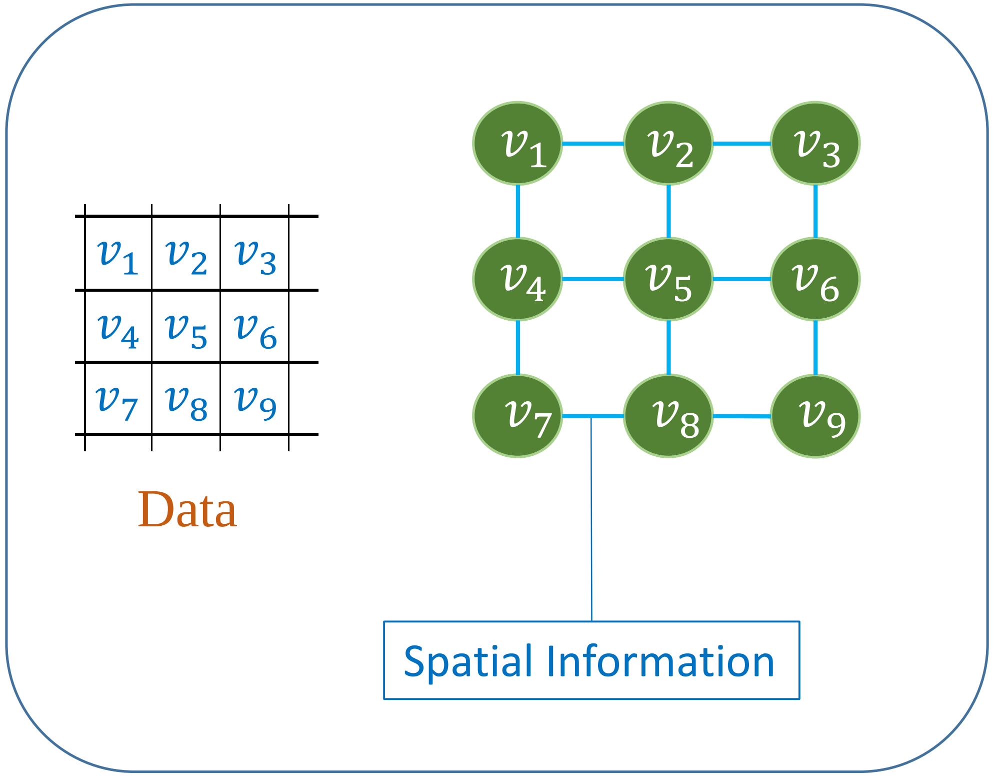
❖ Multi-layer Perceptron

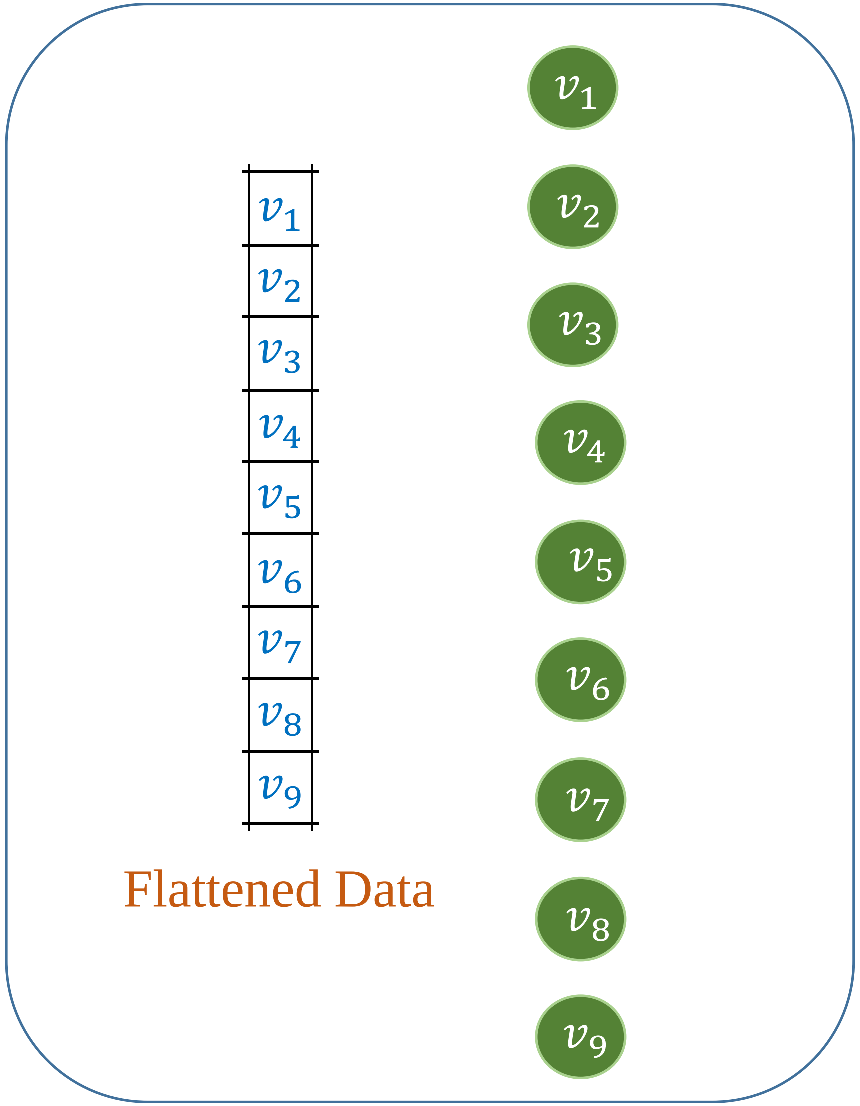


Problem: Remove spatial information of the data
Inefficiently have a large amount of parameters

From MLP to CNN

❖ Problem of flattening data



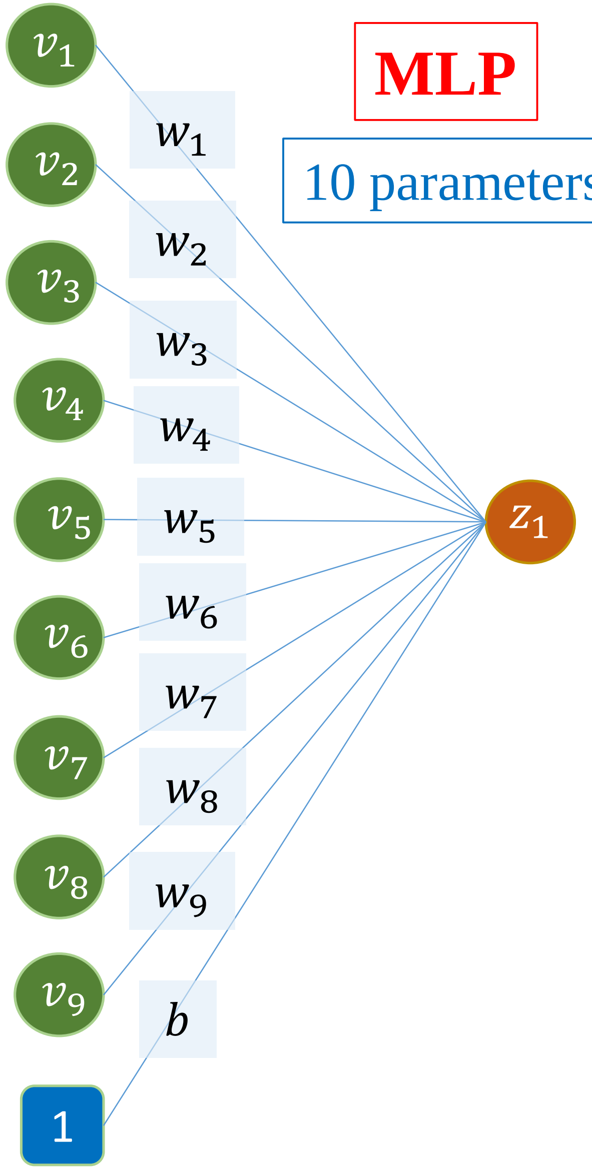


Remove spatial information of the data

From MLP to CNN

MLP

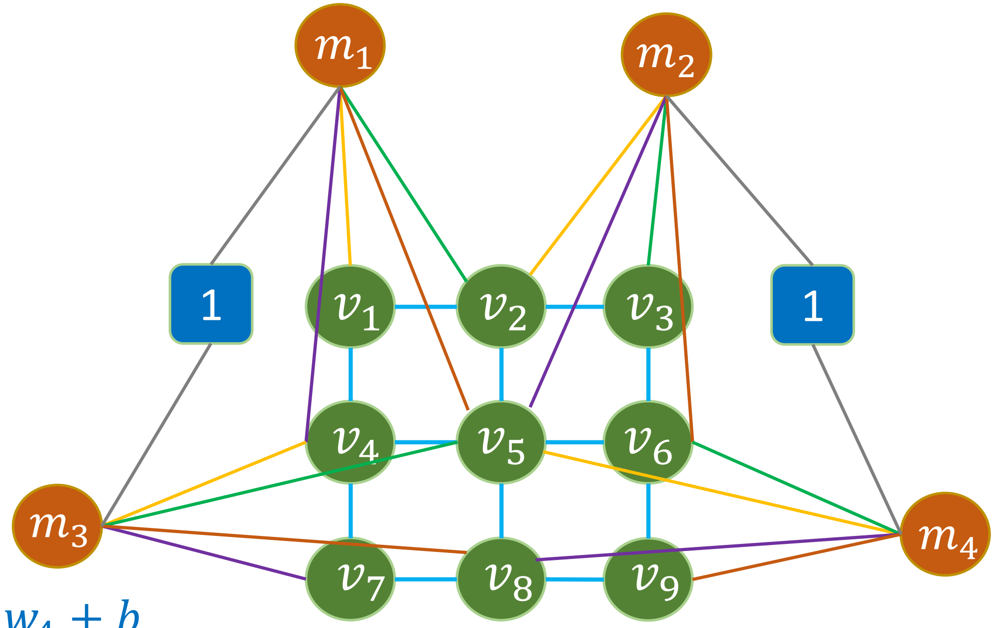
10 parameters



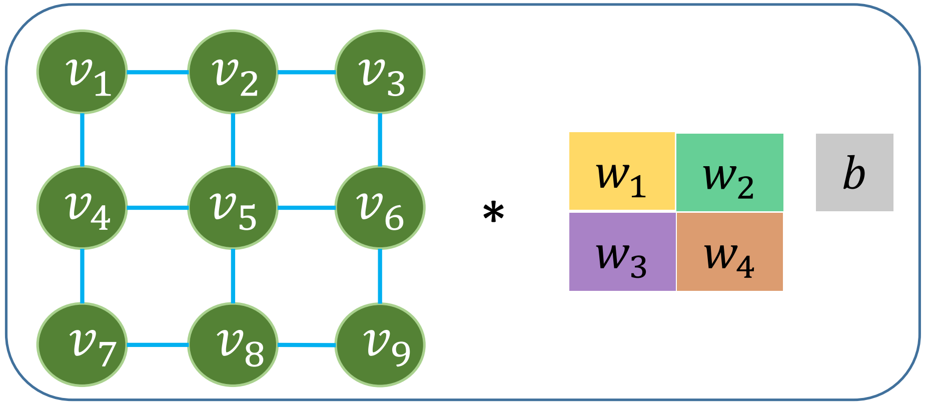
CNN

5 parameters

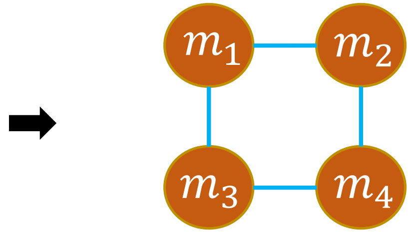
Kernel of parameters



$$m_1 = v_1w_1 + v_2w_2 + v_4w_3 + v_5w_4 + b$$



Convolution(~Correlation)

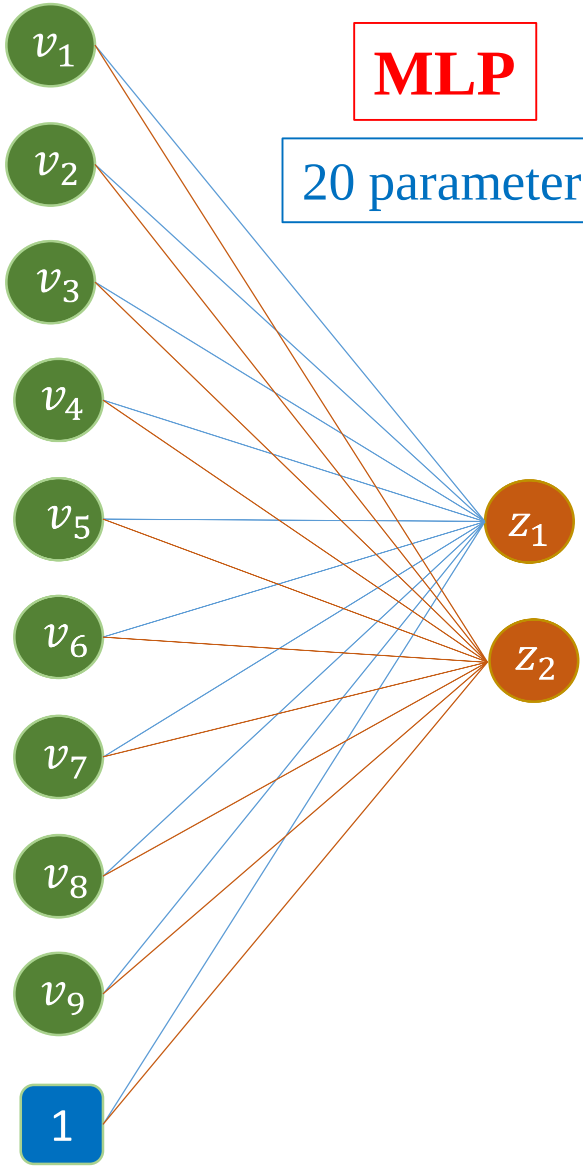


Feature Map

From MLP to CNN

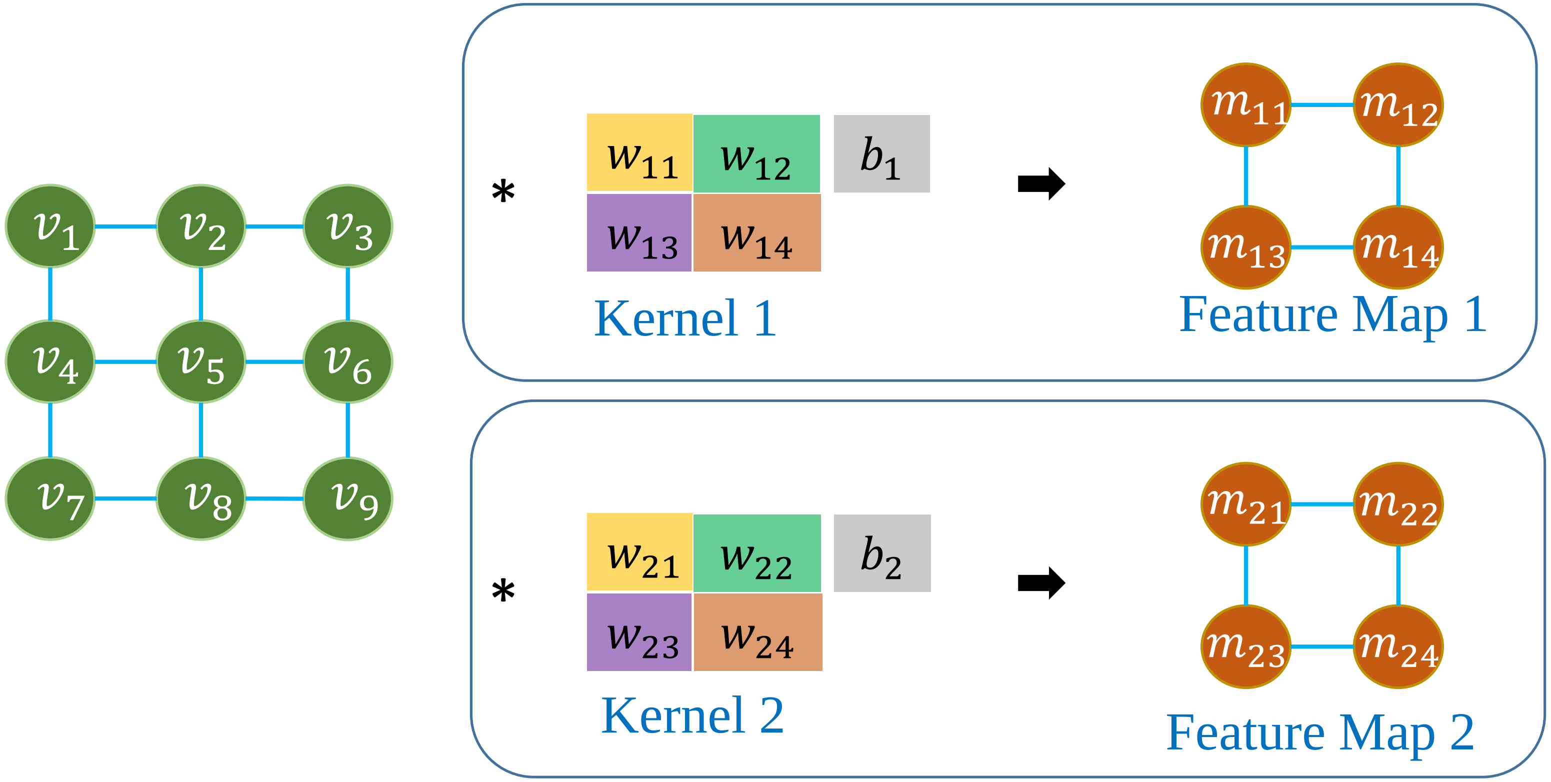
MLP

20 parameters



CNN

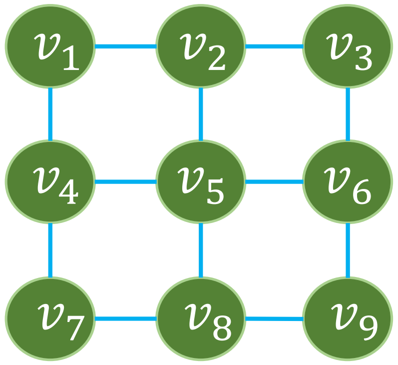
10 parameters



Kernel 1 $\neq$ Kernel 2

From MLP to CNN

❖ Understand convolution



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

Shape=(3,3,1)

$*$

w_1	w_2
w_3	w_4

b

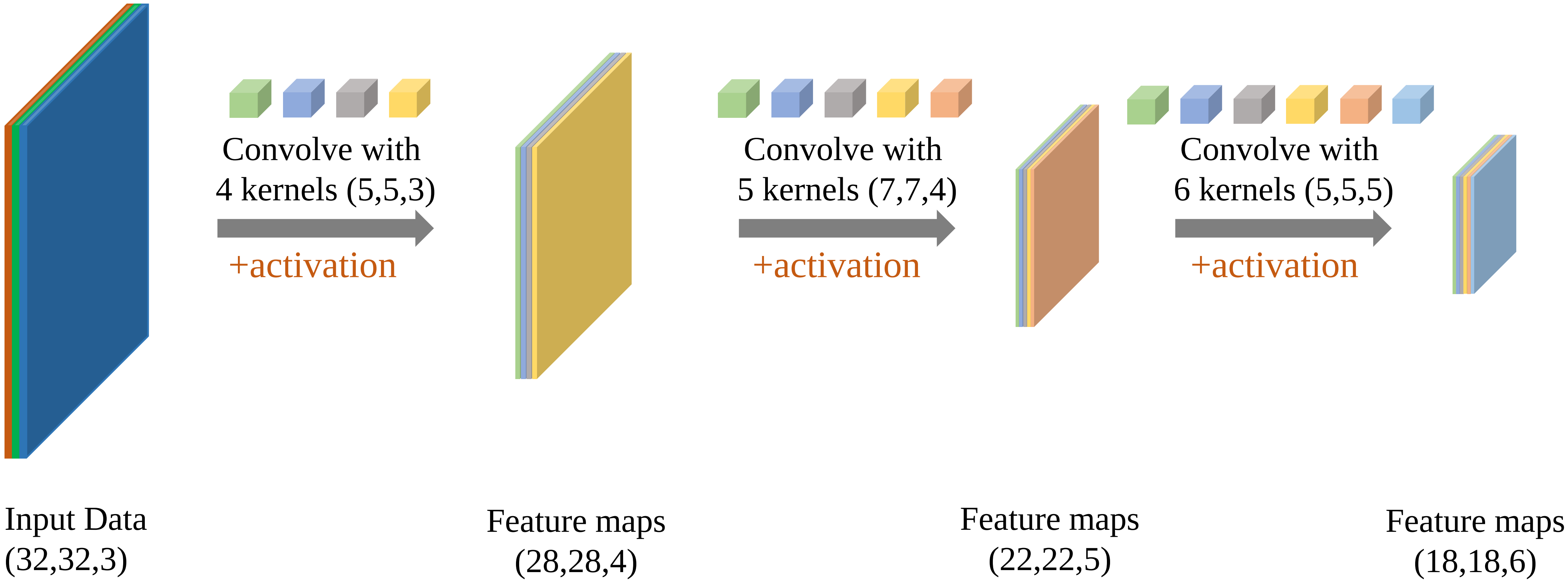
Shape=(2,2,1)

#parameters (including bias) = 5

#channels of data $\overset{\text{must}}{=}$ #channels of kernel

From MLP to CNN

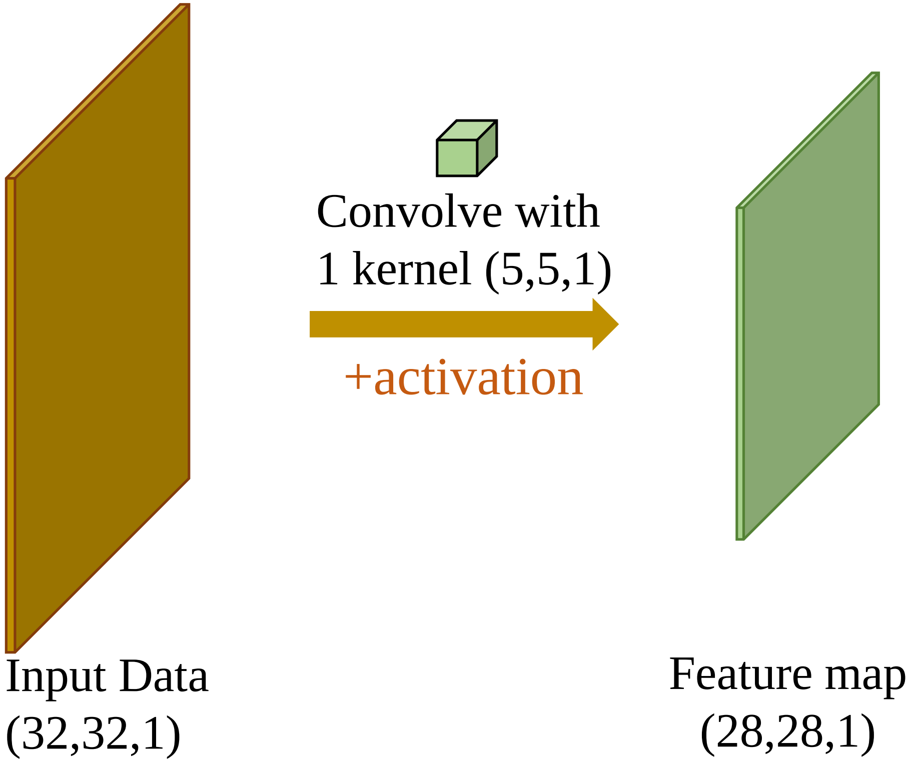
❖ **A stack of pairs of convolution+activation**

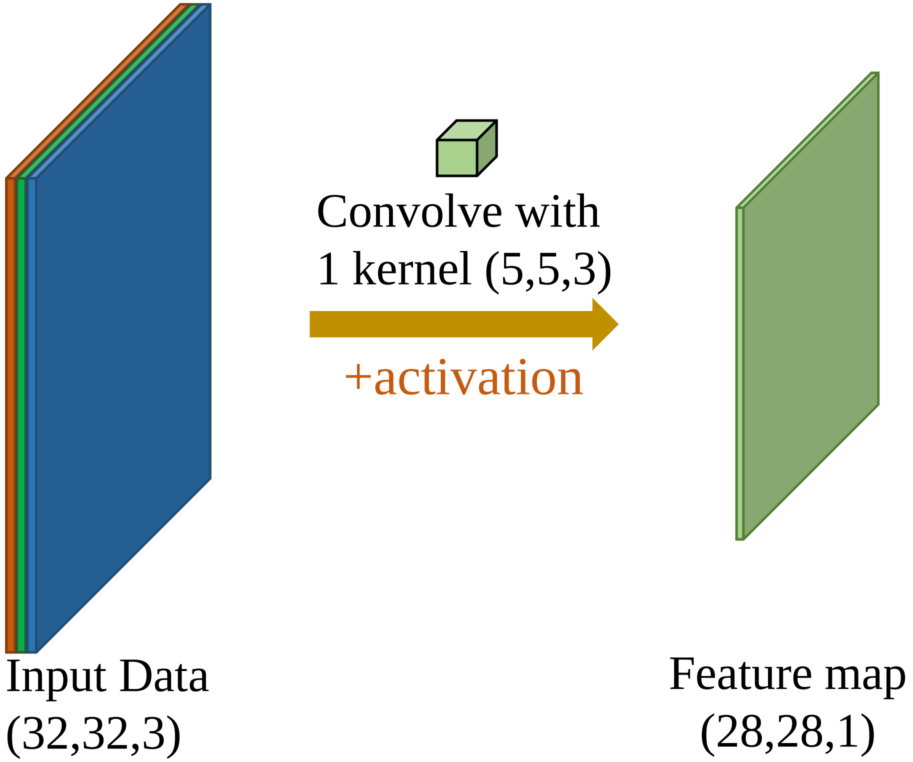


From MLP to CNN

❖ Convolution layer in Keras

```
keras.layers.Conv2D(filters=1, kernel_size=5, activation='relu')
```

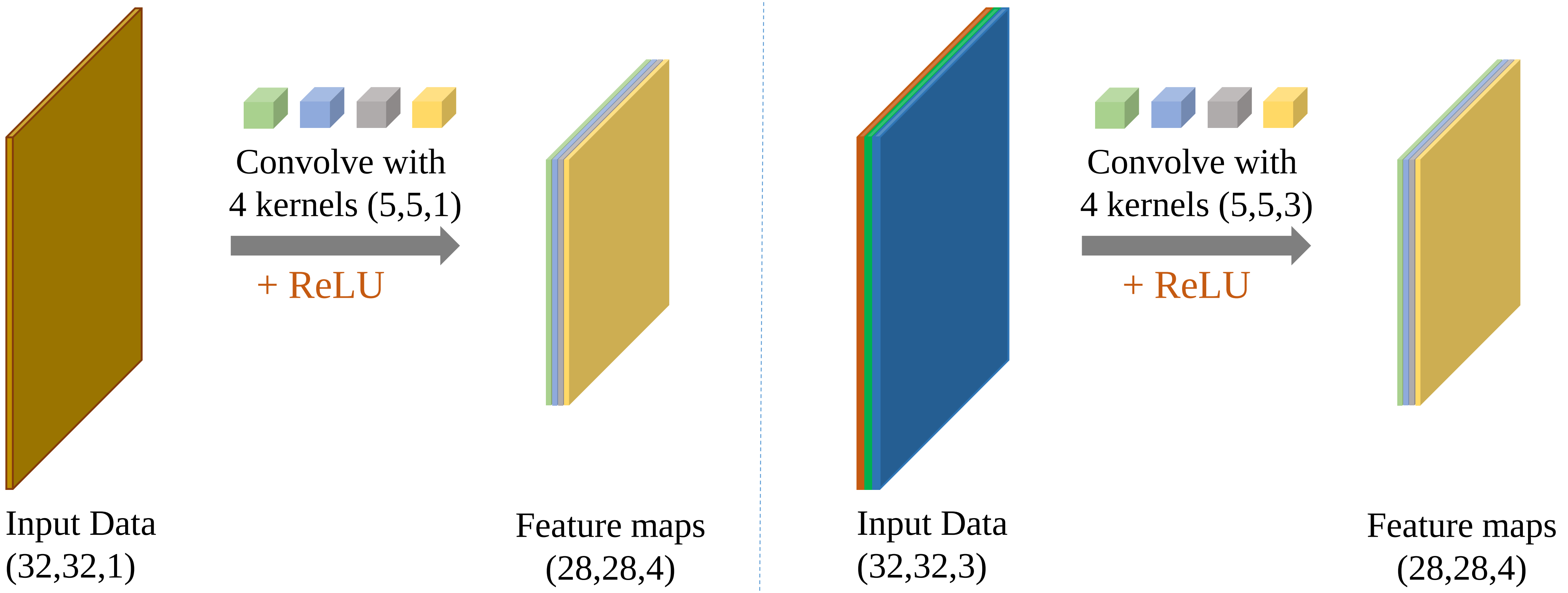




From MLP to CNN

❖ Convolution layer in Keras

```
keras.layers.Conv2D(filters=4, kernel_size=5, activation='relu')
```



From MLP to CNN

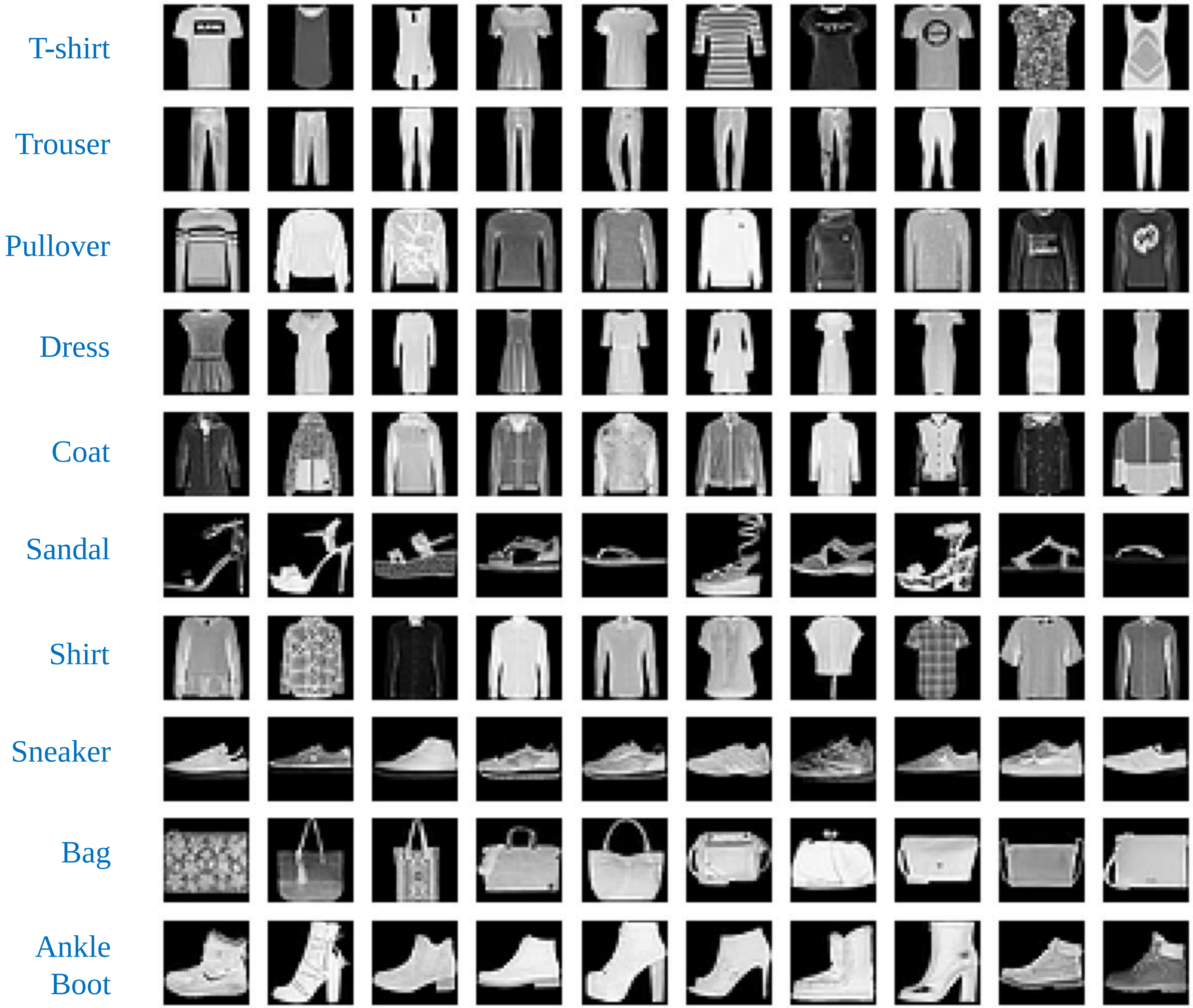
Fashion-MNIST dataset

Grayscale images

Resolution=28x28

Training set: 60000 samples

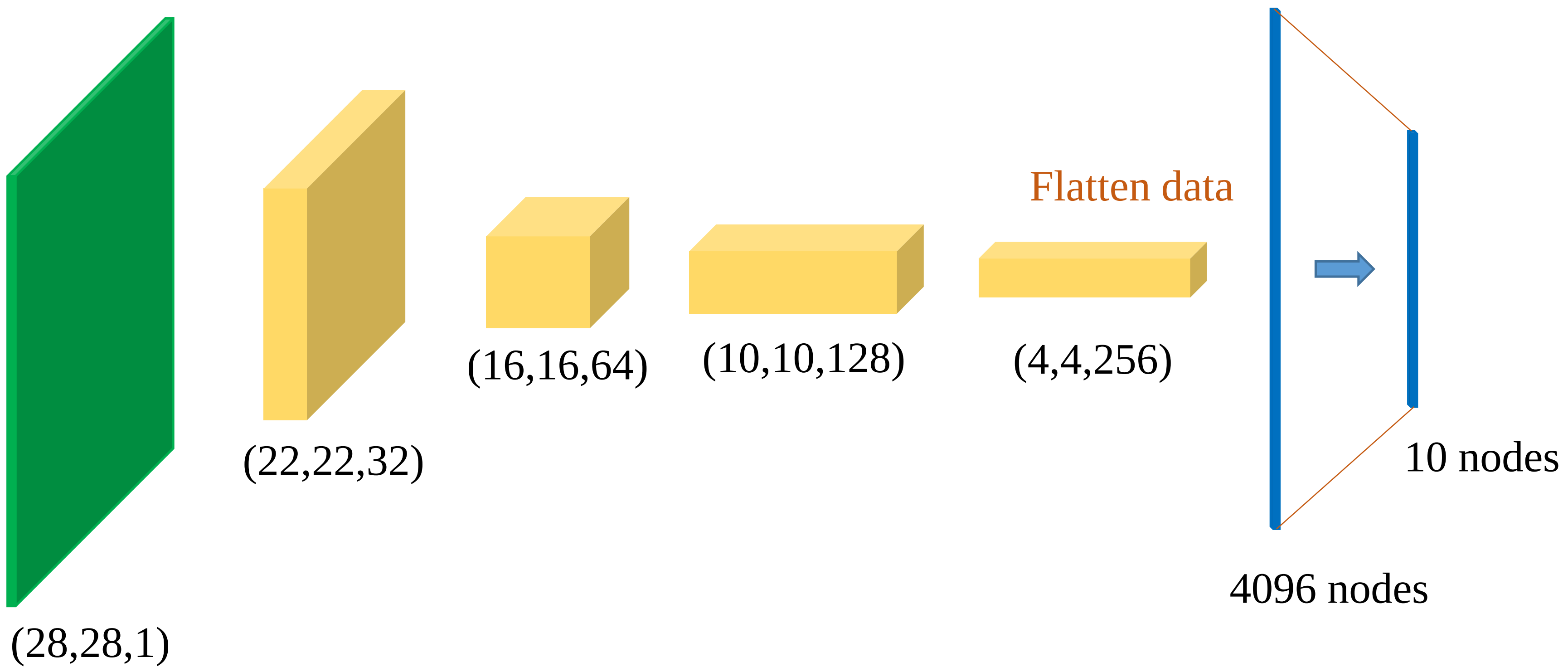
Testing set: 10000 samples



Year 2020

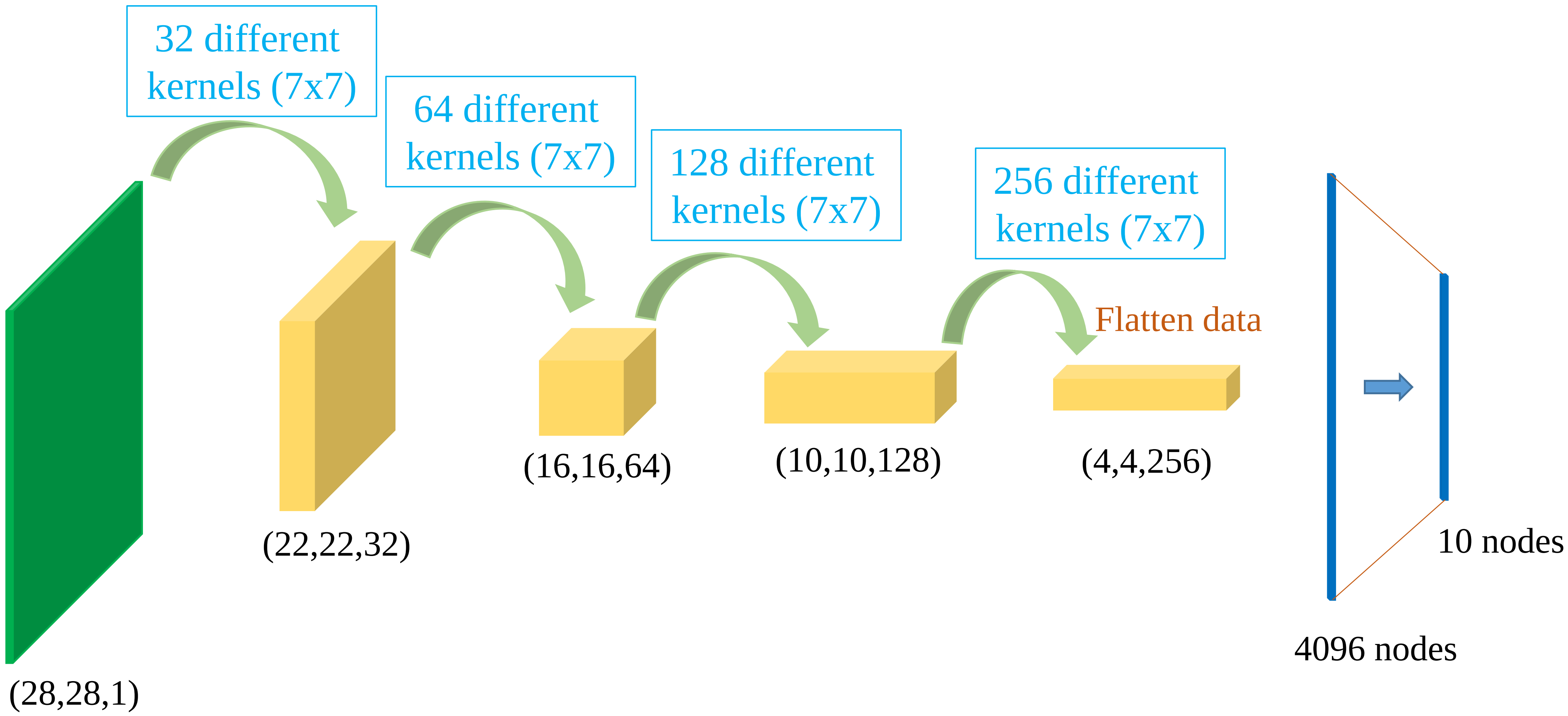
From MLP to CNN

❖ Apply for Fashion-MNIST dataset



From MLP to CNN

❖ Apply for Fashion-MNIST dataset



From MLP to CNN

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

# input is with the shape of (28, 28, 1)
model.add(tf.keras.Input(shape=(28, 28, 1)))

# Convolve with 32 (7x7) kernel; Output: (22x22x32)
model.add(keras.layers.Conv2D(32, (7, 7), activation='relu'))
# Convolve with 64 (7x7) kernel; Output: (16x16x64)
model.add(keras.layers.Conv2D(64, (7, 7), activation='relu'))
# Convolve with 128 (7x7) kernel; Output: (10x10x128)
model.add(keras.layers.Conv2D(128, (7, 7), activation='relu'))
# Convolve with 256 (7x7) kernel; Output: (4x4x256)
model.add(keras.layers.Conv2D(256, (7, 7), activation='relu'))

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

# compile and train
model.compile(optimizer='adam', metrics=['accuracy'],
              loss='sparse_categorical_crossentropy')
model.fit(train_images, train_labels, epochs=10)

# testing
test_loss, test_acc = model.evaluate(test_images,
                                     test_labels, verbose=2)
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
```

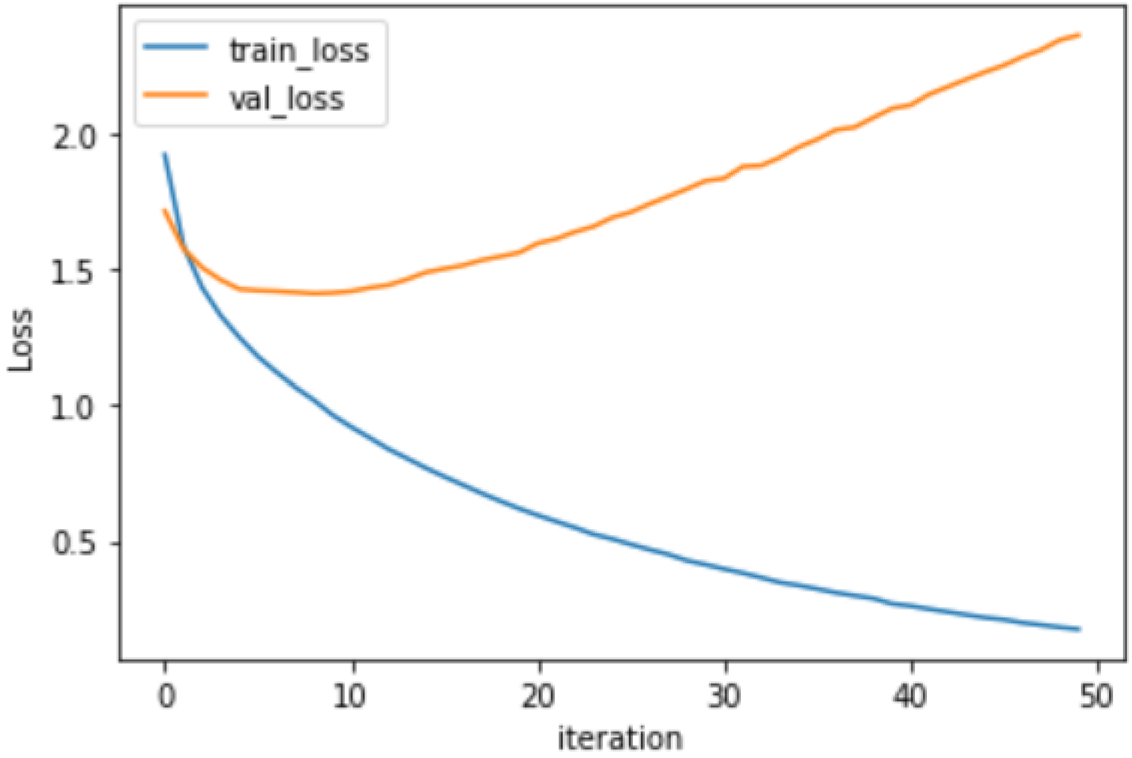
Case Study

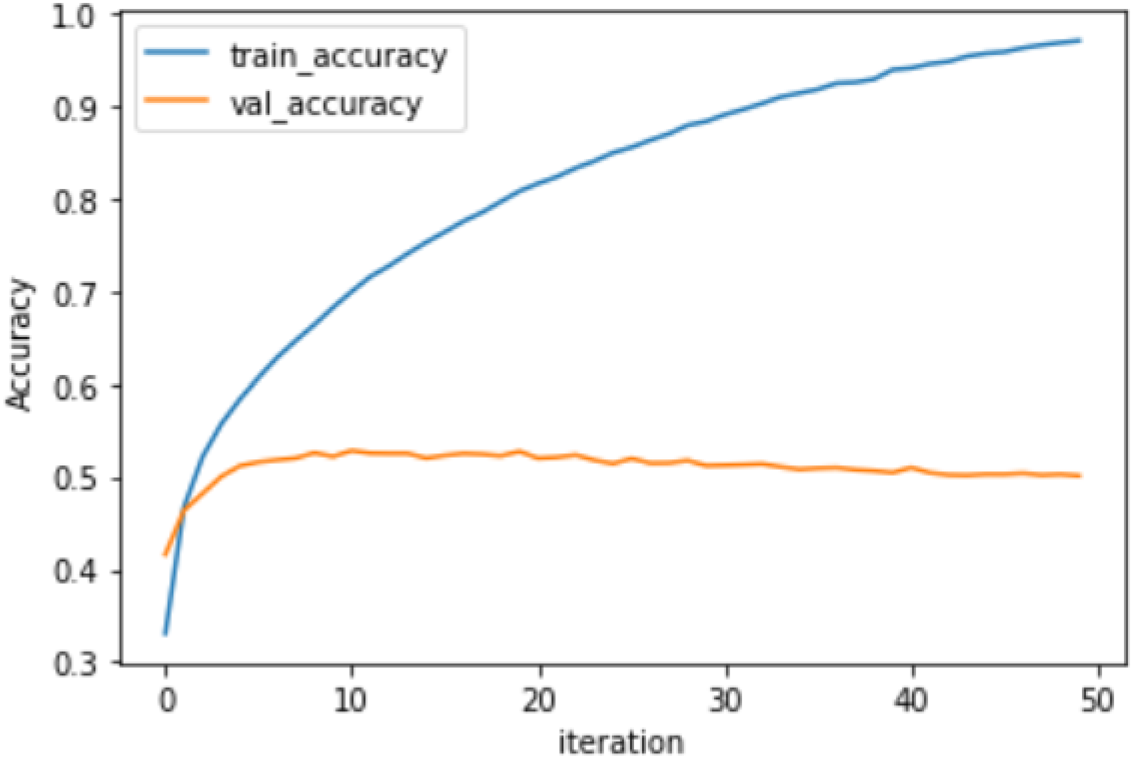
❖ **Classic feature extractors vs. CNN filters**

```python
import tensorflow as tf
from tensorflow import keras

def construct_model():
    inp = keras.layers.Input(shape=[32,32,3])

    # get edges
    edges = tf.image.sobel_edges(inp)
    edges = tf.keras.layers.Reshape((32,32,6))(edges)

    dx, dy = tf.image.image_gradients(inp)
    x = tf.keras.layers.Concatenate(axis=3)([dx, dy, edges])

    x = keras.layers.MaxPooling2D(2)(x)
    x = keras.layers.Flatten()(x)
    x = keras.layers.Dense(128, activation='relu')(x)
    x = keras.layers.Dense(10, activation='softmax')(x)

    return tf.keras.Model(inputs=[inp], outputs=x)

cifar10 = keras.datasets.cifar10
(train_images, train_labels), (test_images, test_labels) = cifar10.load_data()

train_images = train_images / 255.0
test_images  = test_images / 255.0

train_images = tf.reshape(train_images, (50000, 32, 32, 3))
test_images  = tf.reshape(test_images, (10000, 32, 32, 3))

# model
model = construct_model()
model.summary()

model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(),
              metrics=['accuracy'])
history_data = model.fit(train_images, train_labels, batch_size=1024,
                         validation_data=(test_images, test_labels), epochs=50)
```

Case Study

❖ **Classic feature extractors vs. CNN filters**





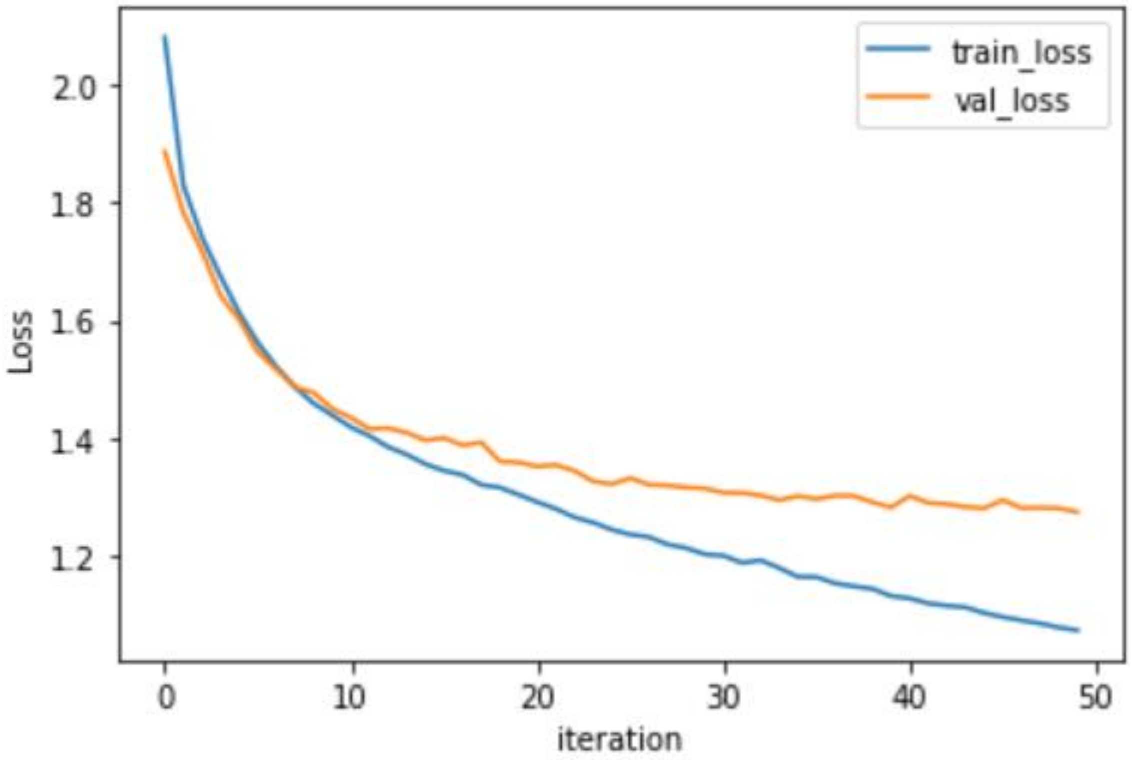
Case Study

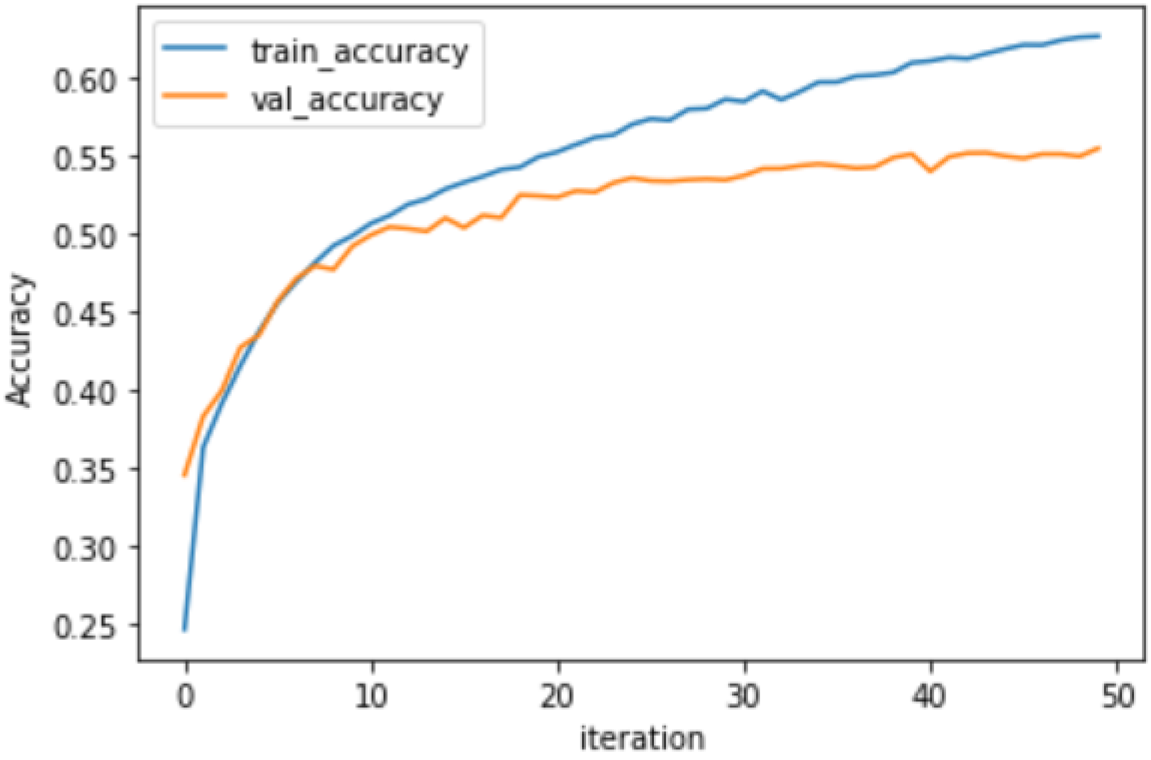
❖ **Classic feature extractors vs. CNN filters**

```python
import tensorflow as tf
from tensorflow import keras

cifar10 = keras.datasets.cifar10
(train_images, train_labels), (test_images, test_labels) = cifar10.load_data()

train_images = train_images / 255.0
test_images  = test_images / 255.0

train_images = tf.reshape(train_images, (50000, 32, 32, 3))
test_images  = tf.reshape(test_images, (10000, 32, 32, 3))

# model
model = keras.models.Sequential()
model.add(tf.keras.Input(shape=(32, 32, 3)))
model.add(keras.layers.Conv2D(4, (3, 3), activation='relu'))
model.add(keras.layers.MaxPooling2D(2))

# flatten
model.add(keras.layers.Flatten())
model.add(keras.layers.Dense(128, activation='relu'))
model.add(keras.layers.Dense(10, activation='softmax'))

model.summary()

model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(),
              metrics=['accuracy'])
history_data = model.fit(train_images, train_labels, batch_size=1024,
                         validation_data=(test_images, test_labels), epochs=50)
```

Case Study

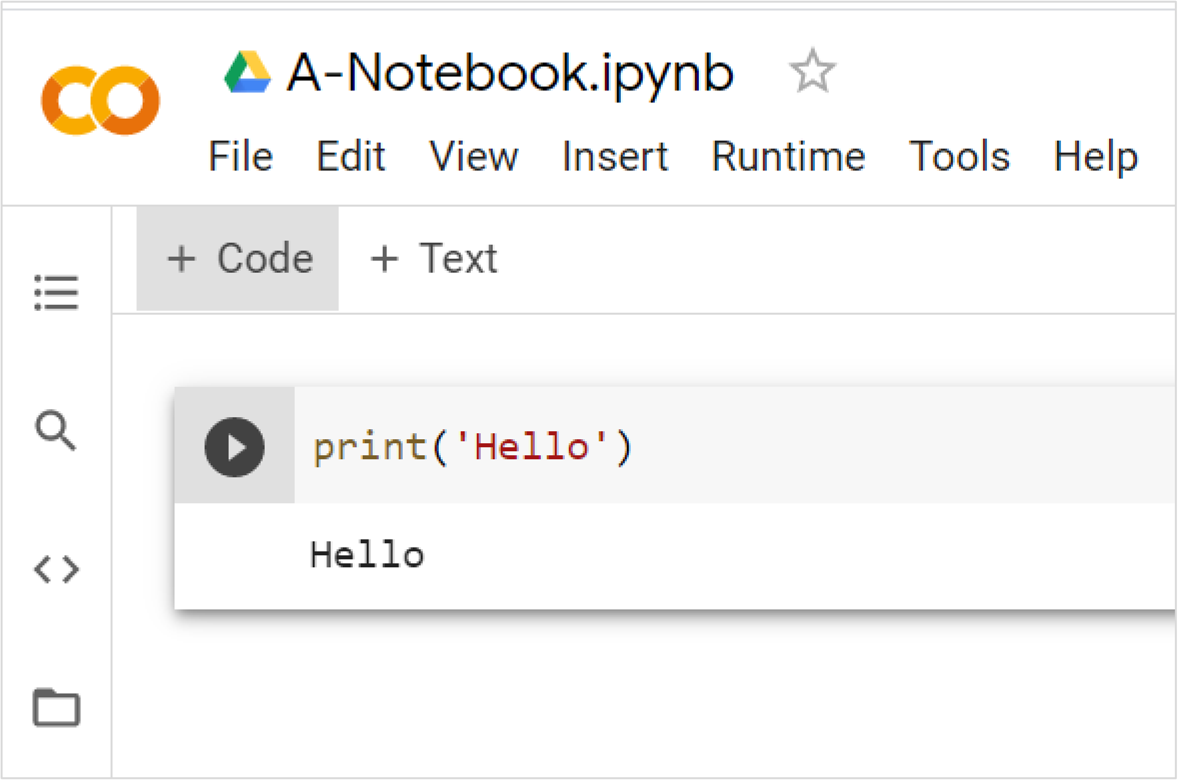
❖ Classic feature extractors vs. CNN filters





Google Colab

❖ Introduction



https://colab.research.google.com/

Google Colab

❖ Introduction

```
[2] import tensorflow as tf
    if tf.test.gpu_device_name():
        print('Default GPU Device: {}'.format(tf.test.gpu_device_name()))
    else:
        print("Please install GPU version of TF")

    Default GPU Device: /device:GPU:0
```

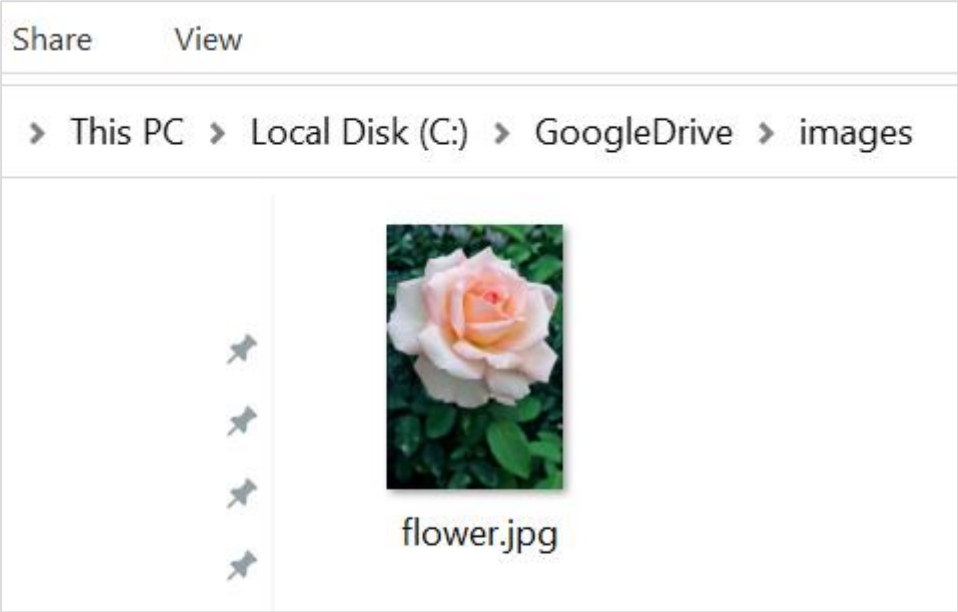
```
import tensorflow as tf

print("Num GPUs Available: ",
      len(tf.config.experimental.list_physical_devices('GPU')))

Num GPUs Available:  1
```

Google Colab

❖ Introduction

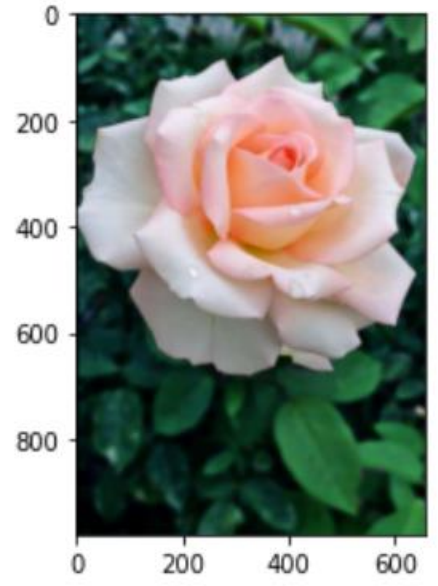
```python
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```




```python
import matplotlib.pyplot as plt
import matplotlib.image as mpimg

img = mpimg.imread('drive/My Drive/images/flower.jpg')
imgplot = plt.imshow(img)
```

```
Populating the interactive namespace from numpy and matplotlib
```



Google Colab

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

Year 2020

Google Colab

Cifar-10 dataset

Color images

Resolution=32x32

Training set: 50000 samples

Testing set: 10000 samples

Outline

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

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

$$\text{2x2 max pooling}\left(\begin{array}{|c|c|c|c|} \hline v_1 & v_2 & v_3 & v_4 \\ \hline v_5 & v_6 & v_7 & v_8 \\ \hline v_9 & v_{10} & v_{11} & v_{12} \\ \hline v_{13} & v_{14} & v_{15} & v_{16} \\ \hline \end{array}\right) = \begin{array}{|c|c|} \hline m_1 & m_2 \\ \hline m_3 & m_4 \\ \hline \end{array}$$

$$m_1 = \max(v_1, v_2, v_5, v_6)$$
$$m_2 = \max(v_3, v_4, v_7, v_8)$$
$$m_3 = \max(v_9, v_{10}, v_{13}, v_{14})$$
$$m_4 = \max(v_{11}, v_{12}, v_{15}, v_{16})$$

Feature map (220x220)

max pooling (2x2)

Feature map (110x110)

max pooling (2x2)

Feature map (55x55)

Down-sample Feature Map

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

$$m_1 = \max(v_1, v_2, v_5, v_6)$$
$$m_2 = \max(v_3, v_4, v_7, v_8)$$
$$m_3 = \max(v_9, v_{10}, v_{13}, v_{14})$$
$$m_4 = \max(v_{11}, v_{12}, v_{15}, v_{16})$$

```
keras.layers.MaxPooling2D(pool_size=2)
```

Feature map (220x220)

max pooling (2x2) →

Feature map (110x110)

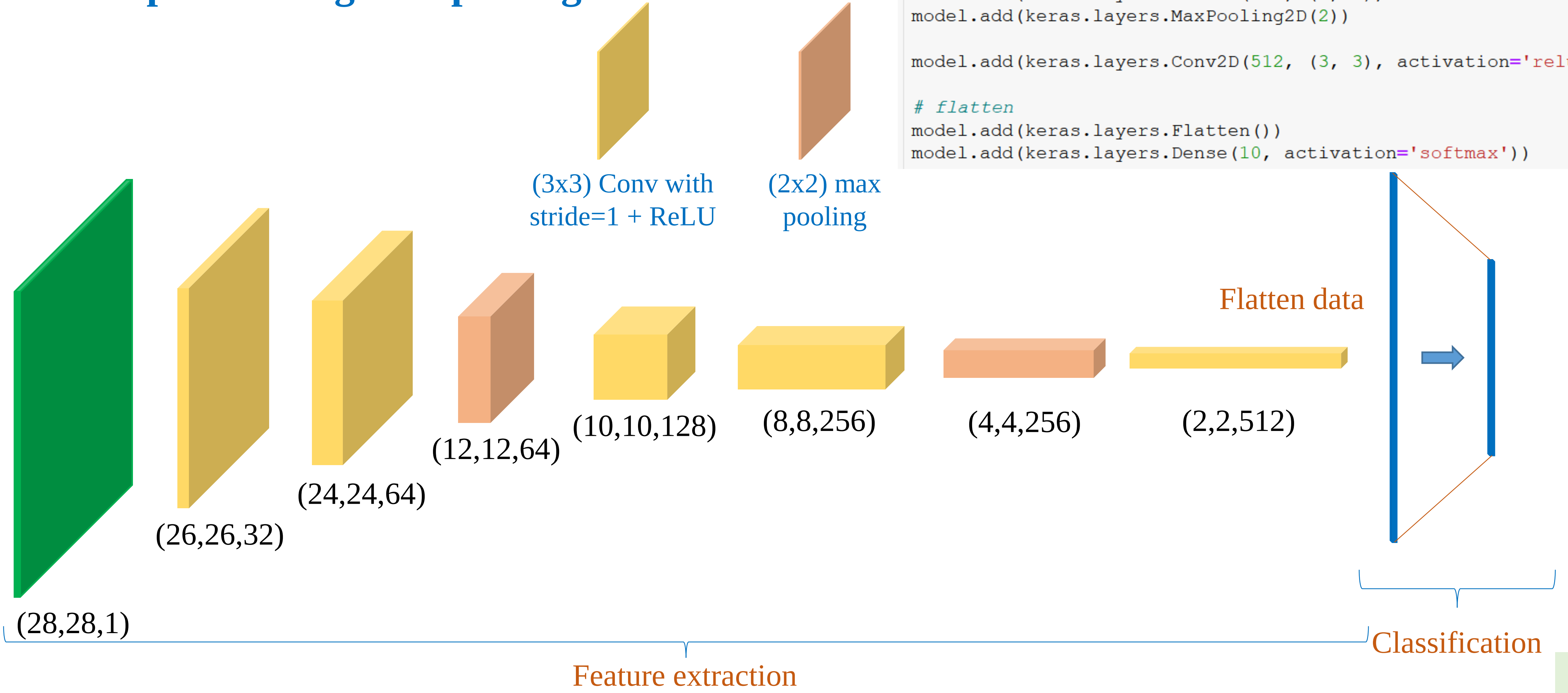
max pooling (2x2) →

Feature map (55x55)

Down-sample Feature Map

```
# 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'))
```

Example 1: Using max pooling



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

Average 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

average 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

$$m_1 = \text{mean}(v_1, v_2, v_5, v_6)$$

$$m_2 = \text{mean}(v_3, v_4, v_7, v_8)$$

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

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

Feature map (220x220)

Average Pooling (2x2)

Feature map (110x110)

Average Pooling (2x2)

Feature map (55x55)

Down-sample Feature Map

Average 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

$$\text{average pooling}\left(\begin{array}{|c|c|c|c|}\hline v_1 & v_2 & v_3 & v_4 \\ \hline v_5 & v_6 & v_7 & v_8 \\ \hline v_9 & v_{10} & v_{11} & v_{12} \\ \hline v_{13} & v_{14} & v_{15} & v_{16} \\ \hline \end{array}\right) = \begin{array}{|c|c|}\hline m_1 & m_2 \\ \hline m_3 & m_4 \\ \hline \end{array}$$

$$m_1 = \text{mean}(v_1, v_2, v_5, v_6)$$
$$m_2 = \text{mean}(v_3, v_4, v_7, v_8)$$
$$m_3 = \text{mean}(v_9, v_{10}, v_{13}, v_{14})$$
$$m_4 = \text{mean}(v_{11}, v_{12}, v_{15}, v_{16})$$

keras.layers. AveragePooling2D (pool_size=2)

Feature map (220x220)

Average Pooling (2x2)

Feature map (110x110)

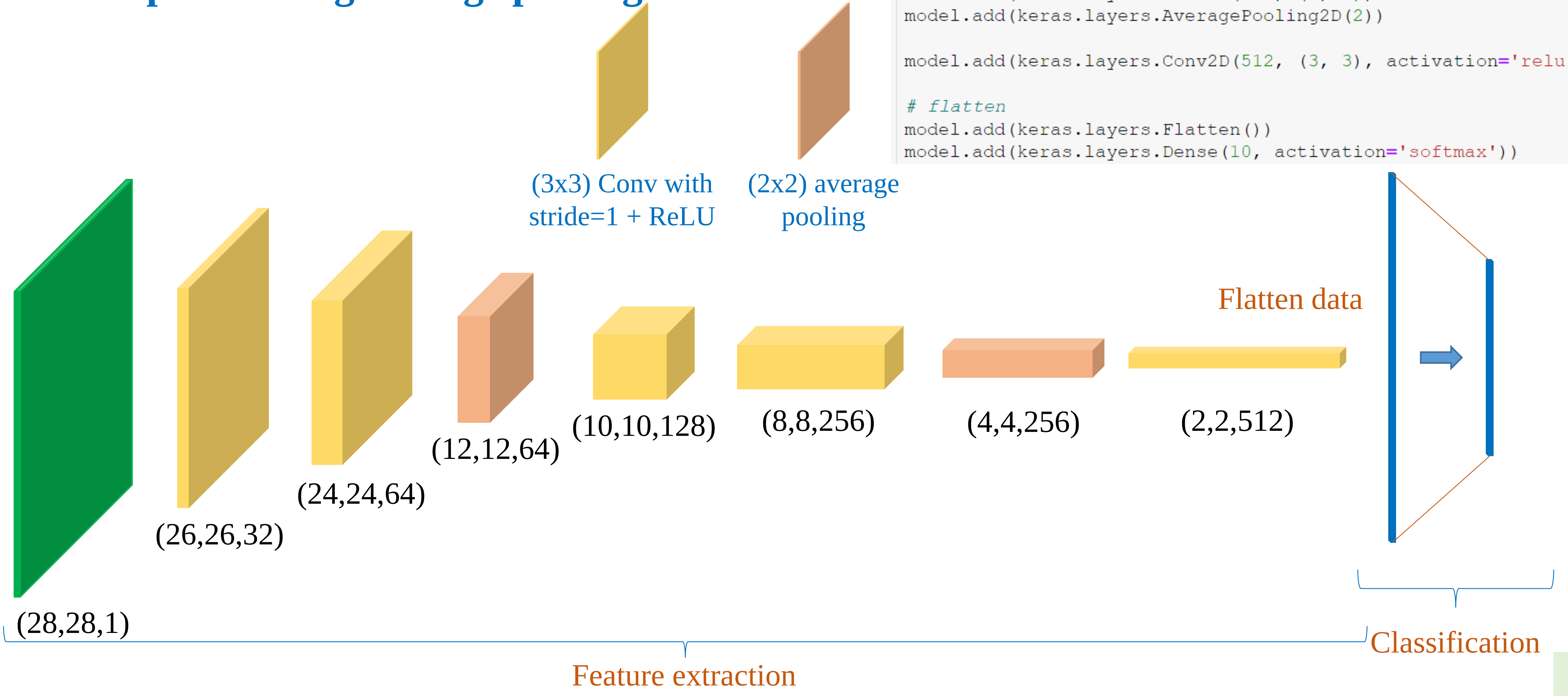
Average Pooling (2x2)

Feature map (55x55)

Down-sample Feature Map

Example 2: Using average 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.AveragePooling2D(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.AveragePooling2D(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

Max pooling vs. Average pooling

Feature map (220x220)

max pooling (2x2)

max pooling (2x2)

Feature map (55x55)

Feature map (220x220)

Average Pooling (2x2)

Feature map (110x110)

Average Pooling (2x2)

Feature map (55x55)

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**

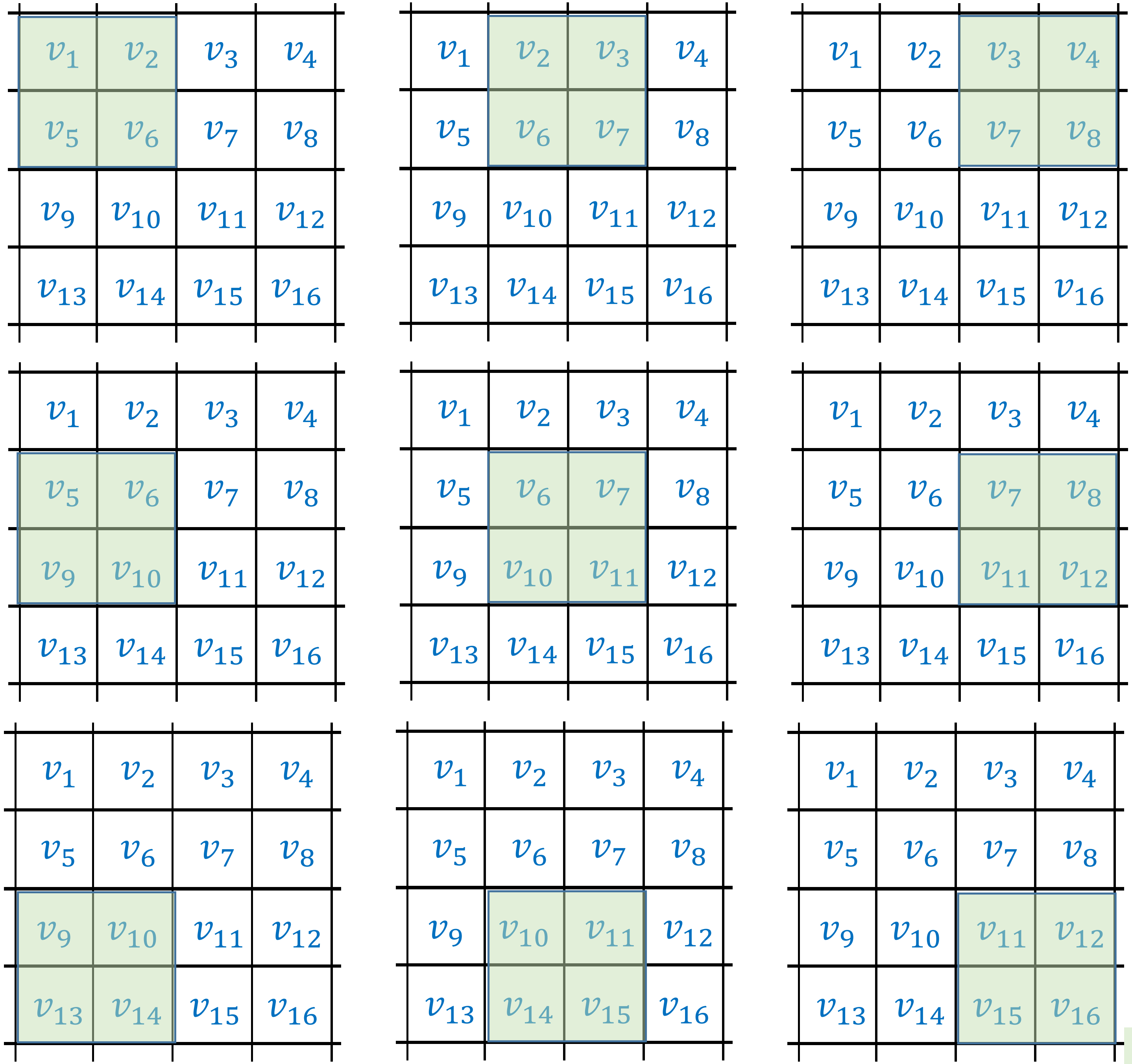
w_1	w_2	b
w_3	w_4	

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



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}

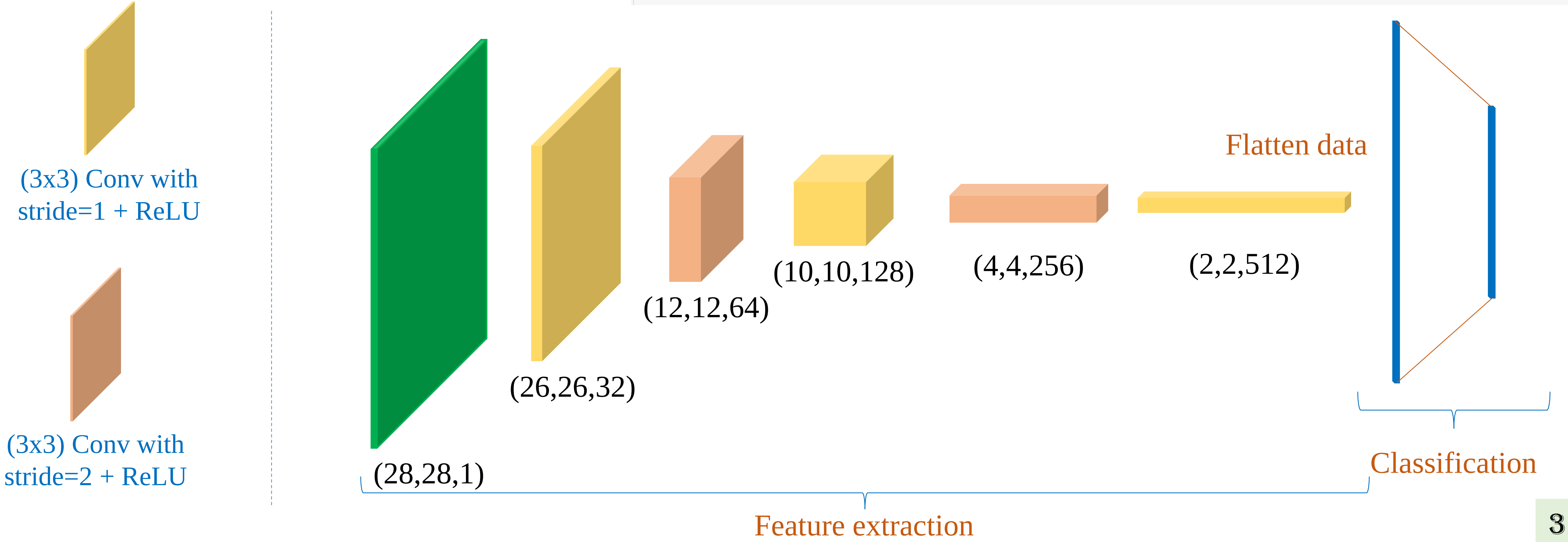
```
keras.layers.Conv2D(32, (3, 3), strides=1, activation='relu')
```

```
keras.layers.Conv2D(32, (3, 3), strides=2, activation='relu')
```

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
- Backpropagation

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 $\boldsymbol{D}$
(4x4)

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

b

Kernel of parameters

Without using padding
or padding=0

Convolve with stride=1 $(\boldsymbol{D}) =$

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 $\boldsymbol{D}_p$

Convolve with stride=1 $(\boldsymbol{D}_p) =$

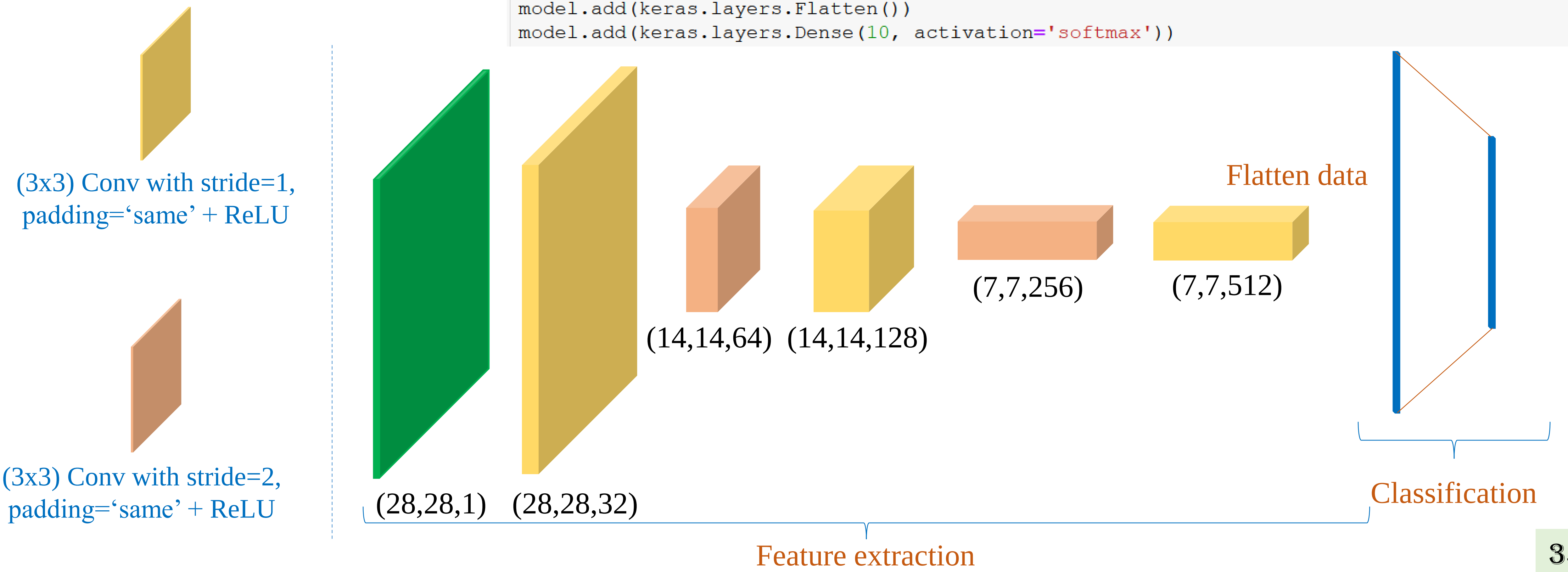
m_1	m_2	m_3	m_4
m_5	m_6	m_7	m_8
m_9	m_{10}	m_{11}	m_{12}
m_{13}	m_{14}	m_{15}	m_{16}

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'))
```

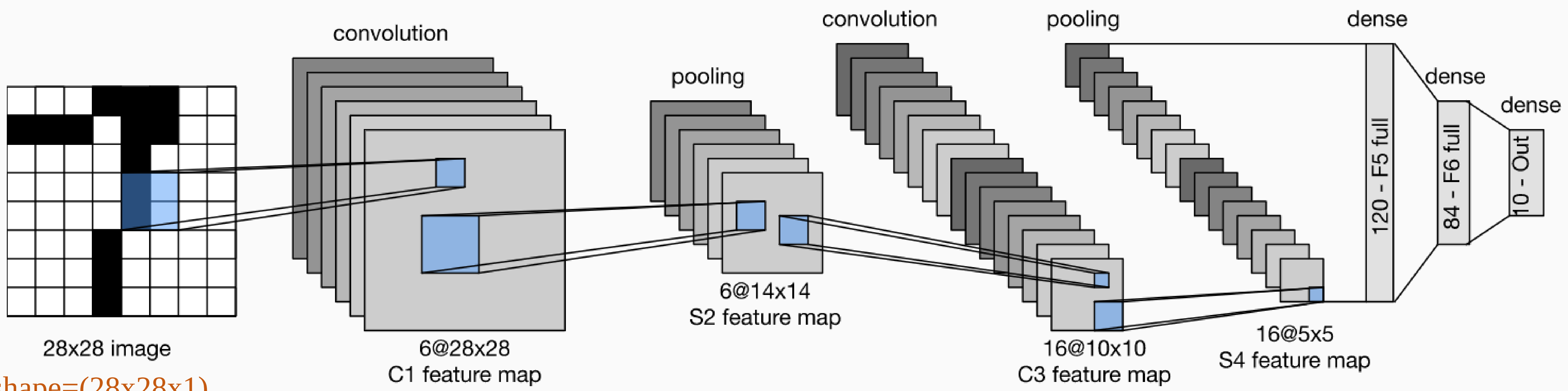


Padding

❖ **LeNet (1990s)**

2x2 max pooling

2x2 max pooling



shape=(28x28x1)

6 Convolutions
kernel=(3x3x1), pad='same'

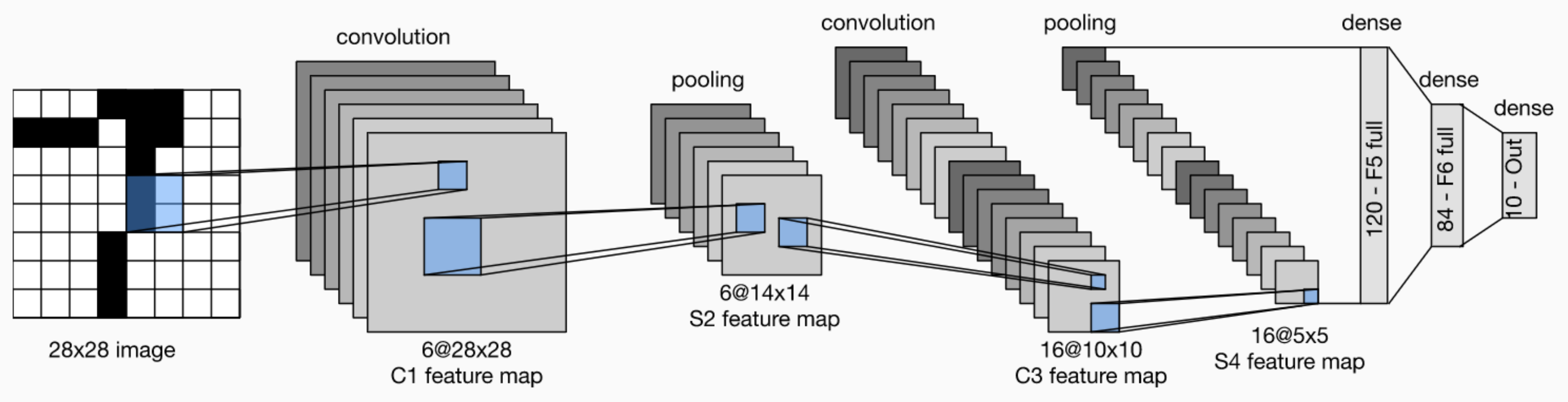
16 Convolutions
kernel=(5x5x6)

6 Convolutions
kernel=(5x5x1), pad='same'

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
- Backpropagation

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

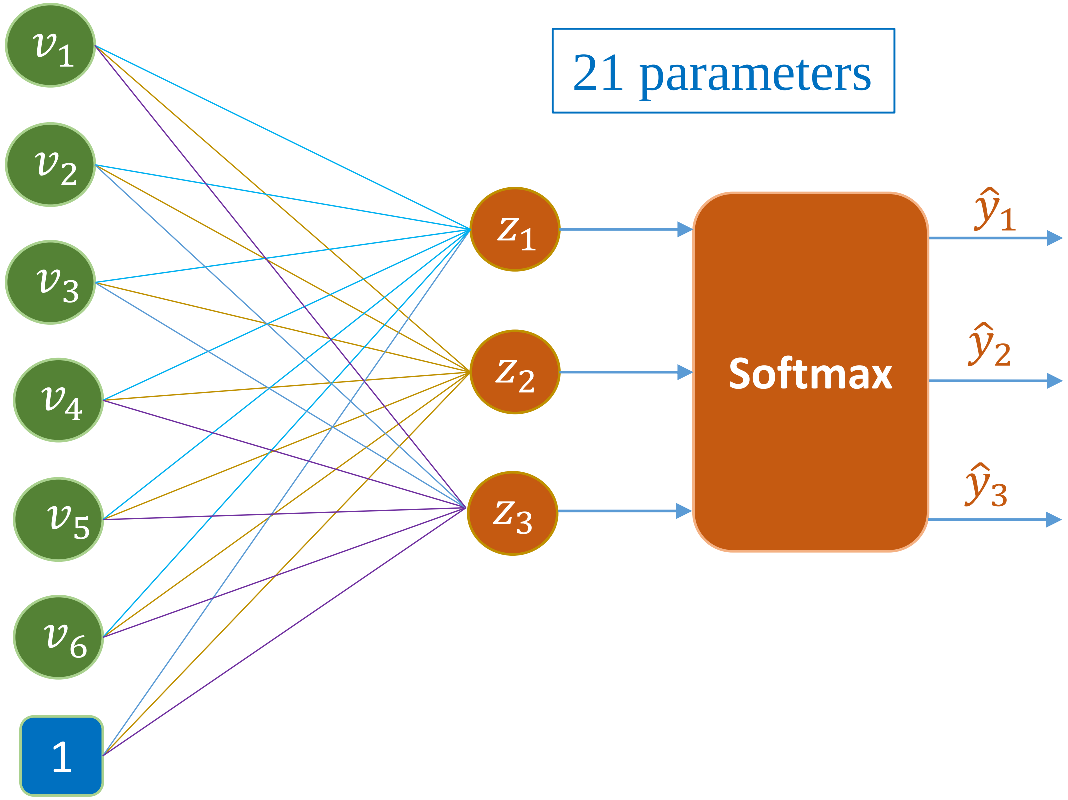
Born	July 8, 1960 (age 60) Soisy-sous-Montmorency, France
Alma mater	ESIEE Paris (MSc) Pierre and Marie Curie University (PhD)
Known for	Deep learning
Awards	Turing Award (2018) AAAI Fellow (2019) Legion of Honour (2020)
Scientific career	
Institutions	Bell Labs (1988-1996) New York University Facebook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

1x1 Convolution

❖ Comparison

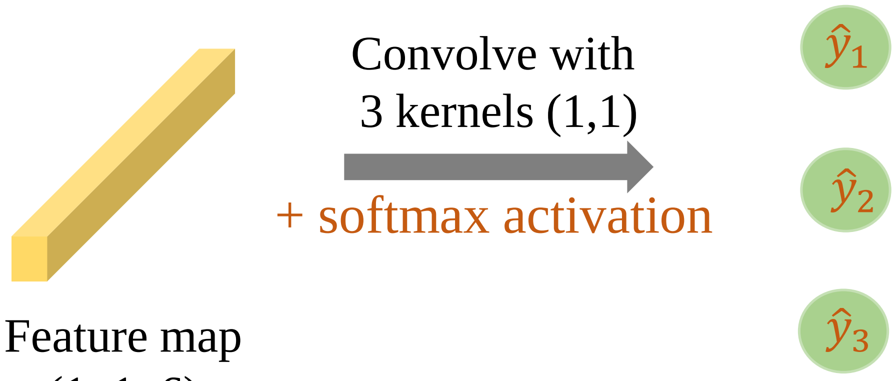
Fully connected layer

21 parameters



CNN

21 parameters

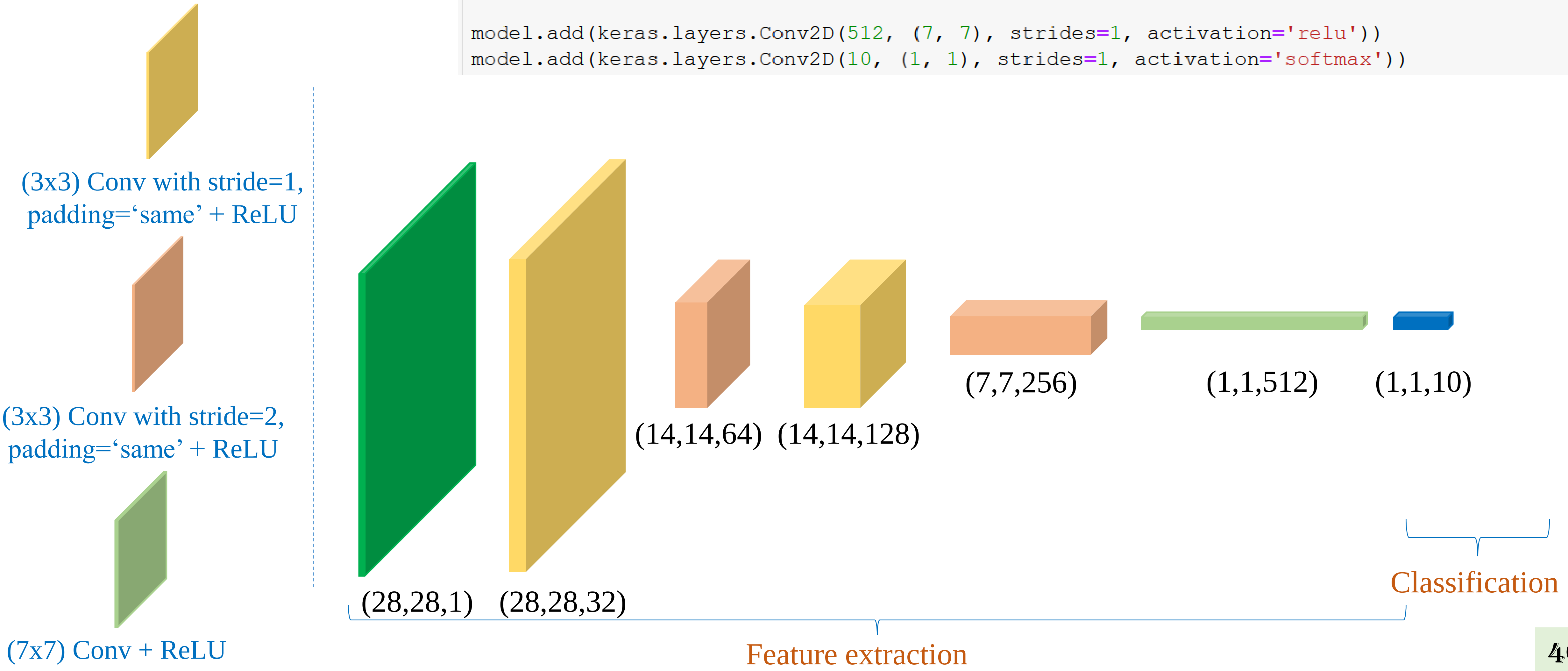


Feature map
(1x1x6)

1x1 Convolution

```python
# 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'))
```

Replace FC by 1x1 Conv



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'))
```

```
shape = (32,28,28,1)
data = tf.random.normal(shape)
print(data.shape)

output = model.predict(data)
print(output.shape)
```

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

```
shape = (32,64,64,1)
data = tf.random.normal(shape)
print(data.shape)

output = model.predict(data)
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
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Size of Feature Maps

Summary. To summarize, the Conv Layer:

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F + 2P)/S + 1$
  - $H_2 = (H_1 - F + 2P)/S + 1$ (i.e. width and height are computed equally by symmetry)
  - $D_2 = K$
- With parameter sharing, it introduces $F \cdot F \cdot D_1$ weights per filter, for a total of $(F \cdot F \cdot D_1) \cdot K$ weights and K biases.
- In the output volume, the d-th depth slice (of size $W_2 \times H_2$) is the result of performing a valid convolution of the d-th filter over the input volume with a stride of S, and then offset by d-th bias.

Image Classification

Cifar-10 dataset

Color images

Resolution=32x32

Training set: 50000 samples

Testing set: 10000 samples

Cifar-10 Image Classification

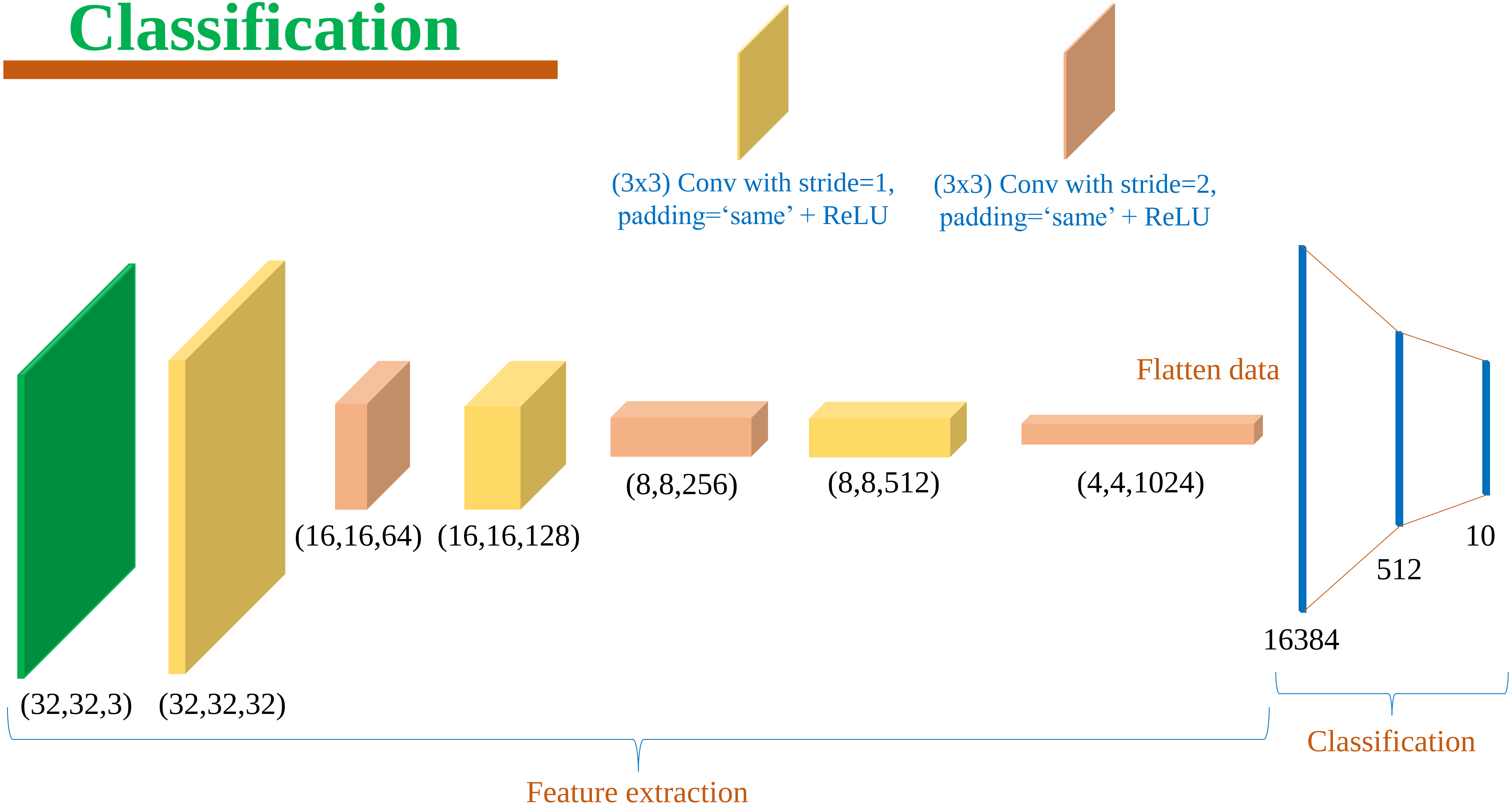


Image Classification

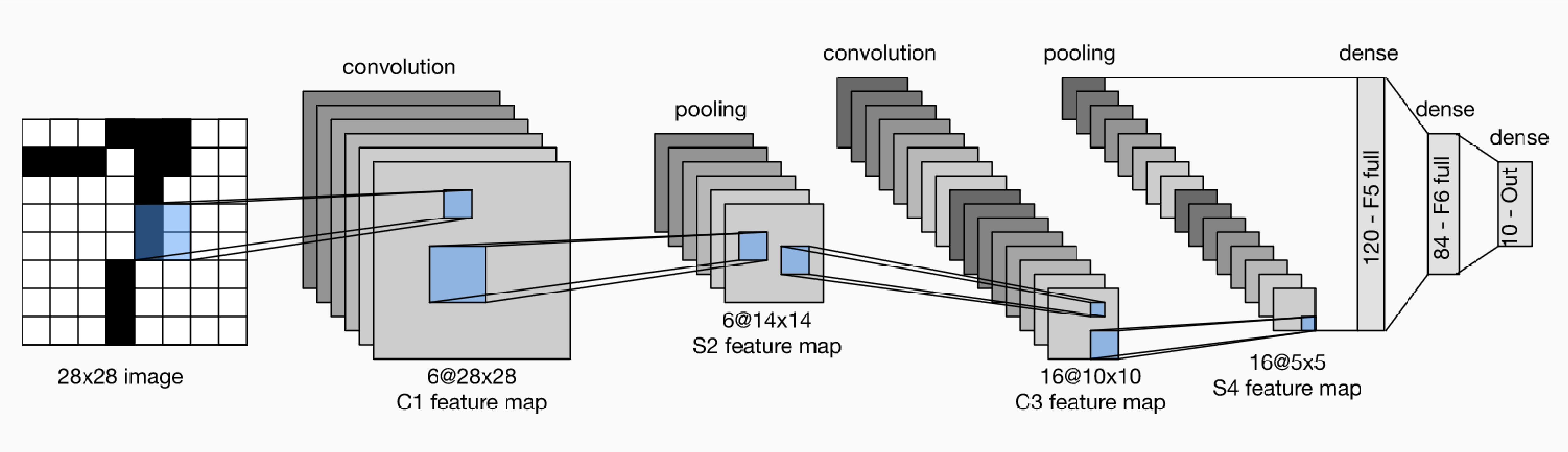
Cifar-10

```python
import tensorflow as tf

# data preparation
cifar10 = tf.keras.datasets.cifar10
(x_train, y_train),(x_test, y_test) = cifar10.load_data()

# normalize
x_train, x_test = x_train / 255.0, x_test / 255.0
```

```python
# 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()
```

LeNet Architecture

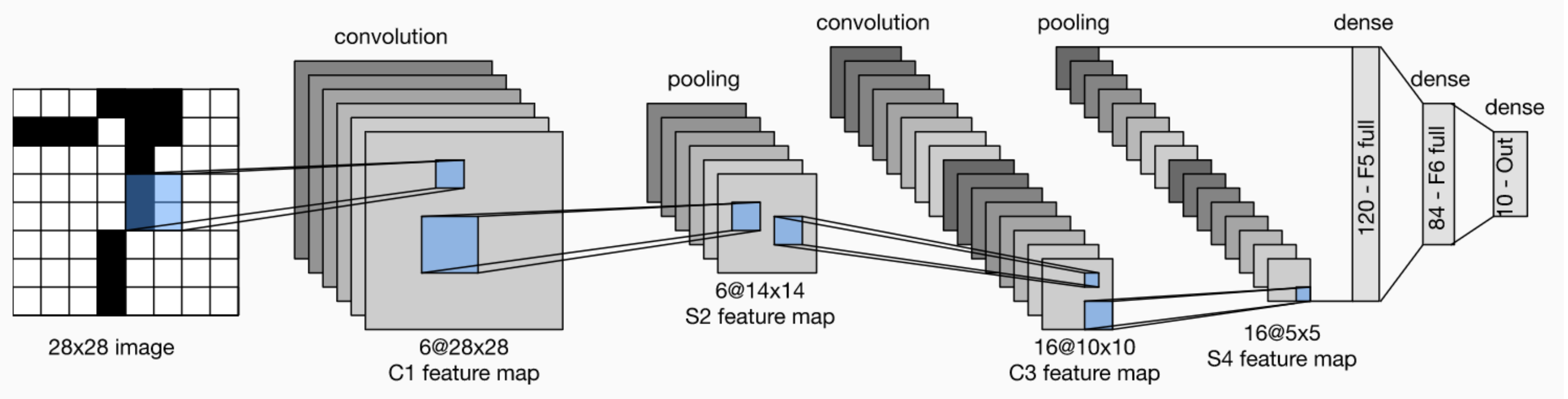
❖ Model Construction



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

LeNet Architecture

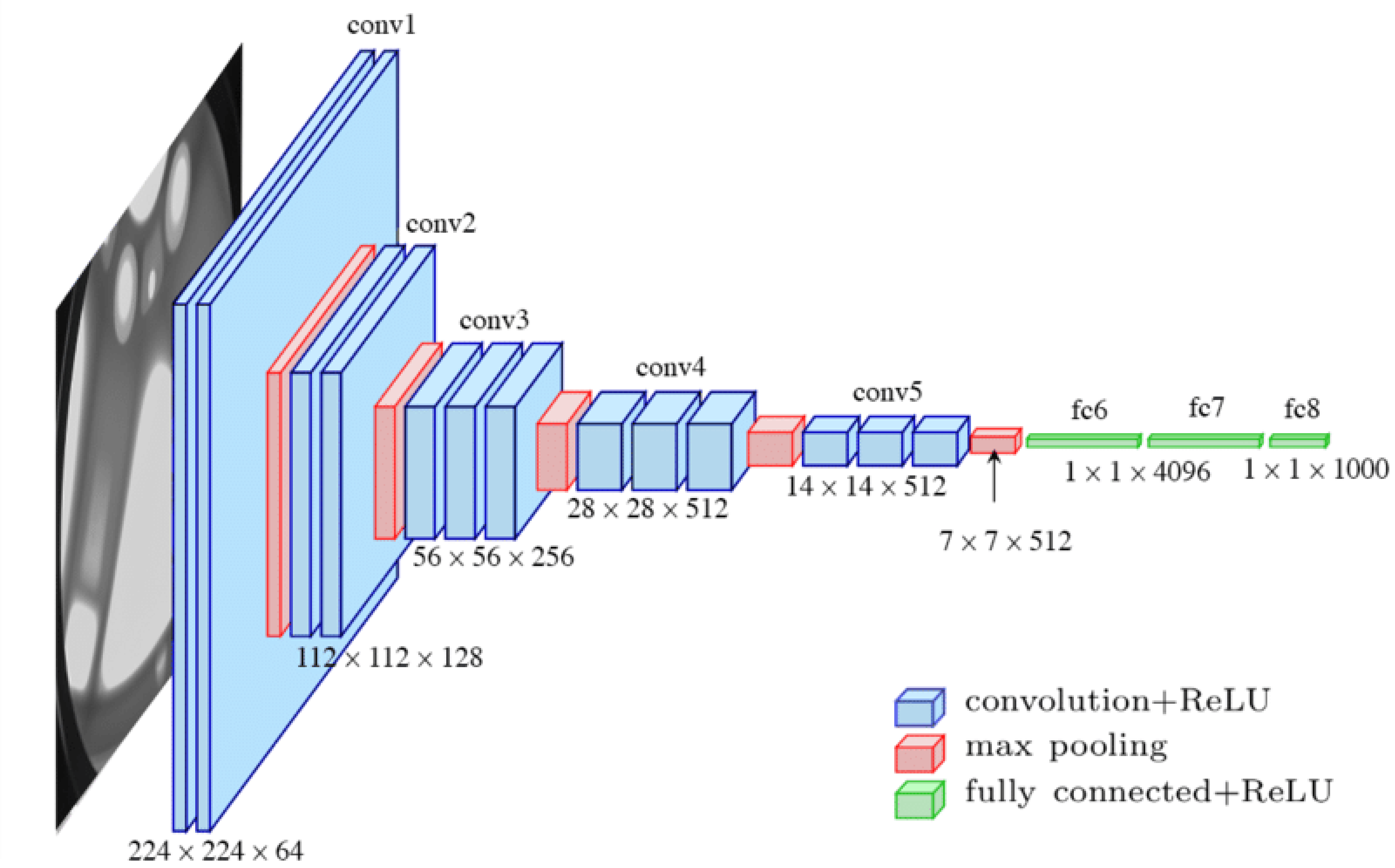
❖ **Model Construction**




```python
# 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'))
```

VGG16 Architecture

❖ Model Construction



VGG16 Architecture

- ❖ **Model Construction**

```
def VGG_16():
    model = Sequential()
    model.add(Convolution2D(64, 3, padding='same', activation='relu',
                            input_shape=(224,224, 1)))
    model.add(Convolution2D(64, 3, padding='same', activation='relu'))
    model.add(MaxPooling2D((2,2), strides=(2,2)))

    model.add(Convolution2D(128, 3, padding='same', activation='relu'))
    model.add(Convolution2D(128, 3, padding='same', activation='relu'))
    model.add(MaxPooling2D((2,2), strides=(2,2)))


    model.add(Convolution2D(256, 3, padding='same', activation='relu'))
    model.add(Convolution2D(256, 3, padding='same', activation='relu'))
    model.add(Convolution2D(256, 3, padding='same', activation='relu'))
    model.add(MaxPooling2D((2,2), strides=(2,2)))

    model.add(Convolution2D(512, 3, padding='same', activation='relu'))
    model.add(Convolution2D(512, 3, padding='same', activation='relu'))
    model.add(Convolution2D(512, 3, padding='same', activation='relu'))
    model.add(MaxPooling2D((2,2), strides=(2,2)))

    model.add(Convolution2D(512, 3, padding='same', activation='relu'))
    model.add(Convolution2D(512, 3, padding='same', activation='relu'))
    model.add(Convolution2D(512, 3, padding='same', activation='relu'))
    model.add(MaxPooling2D((2,2), strides=(2,2)))

    model.add(Flatten())
    model.add(Dense(4096, activation='relu'))
    model.add(Dense(4096, activation='relu'))
    model.add(Dense(1000, activation='softmax'))

    return model
```

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]
```

Outline

- From MLP to CNN
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Sigmoid Function

❖ Sigmoid function

$$\text{sigmoid}(x) = \frac{1}{1+e^{-x}}$$

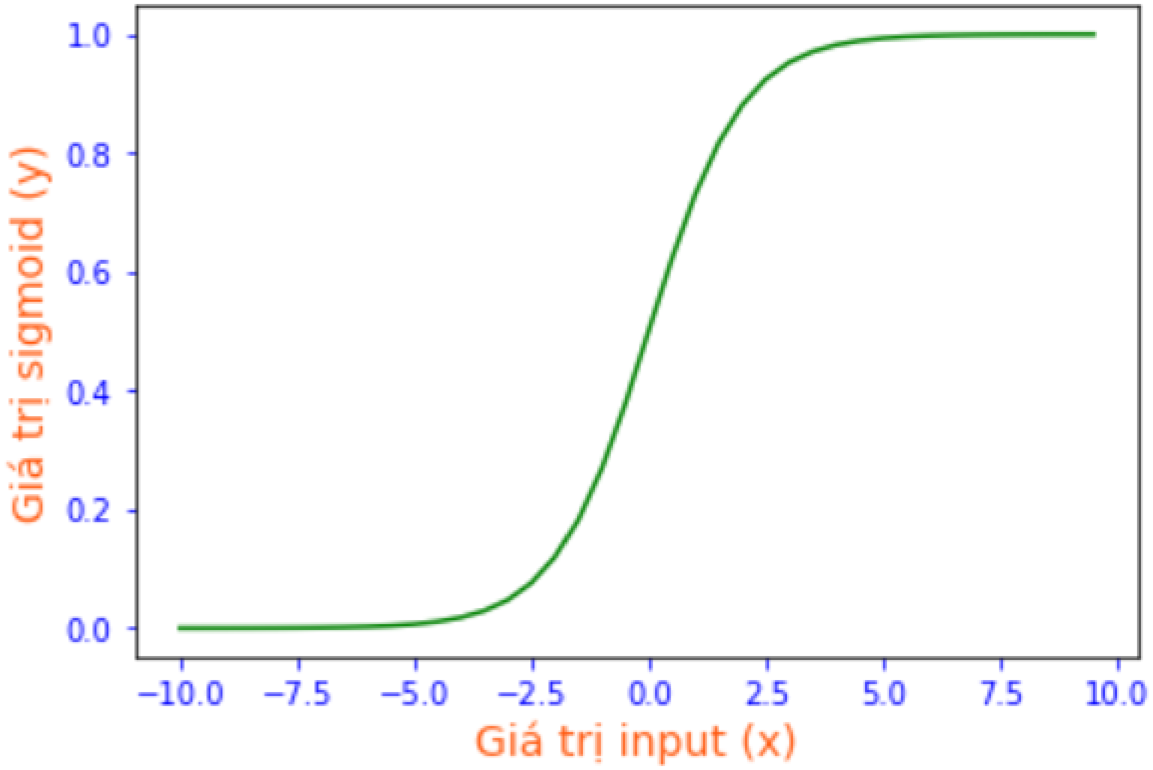
data =

1	5	-4	3	-2

data_a = sigmoid(data)

data_a =

0.731	0.993	0.017	0.95	0.119



Sigmoid Function

Sigmoid function

$$y = \sigma(u) = \frac{1}{1 + e^{-u}}$$

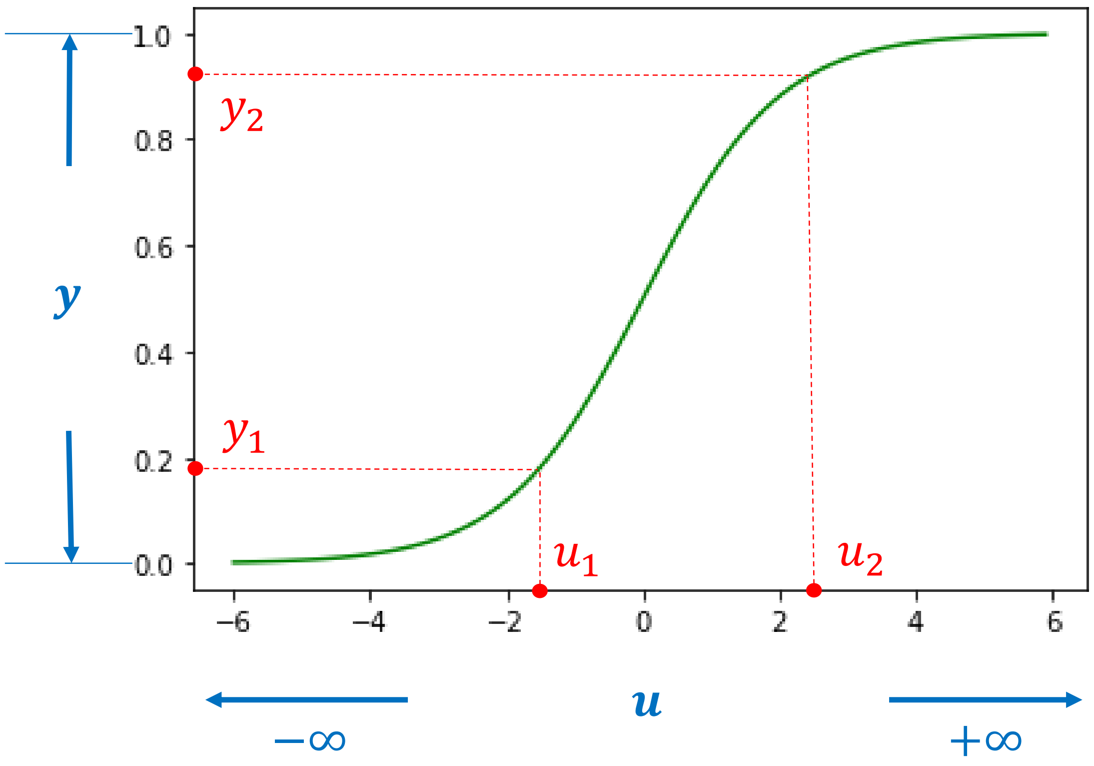
$$u \in (-\infty \quad +\infty)$$

$$y \in (0 \quad 1)$$

Property

$$\forall u_1 u_2 \in [a \;\; b] \text{ và } u_1 \leq u_2$$

$$\rightarrow \sigma(u_1) \leq \sigma(u_1)$$



Sigmoid Function

❖ Construct loss

Model and Loss

$$z = \boldsymbol{\theta}^T \boldsymbol{x}$$

$$\hat{y} = \sigma(z) = \frac{1}{1 + e^{-z}}$$

$$\mathrm{L} = \frac{1}{N}[-y^T \log(\hat{y}) - (1 - y^T)\log(1 - \hat{y})]$$

Derivative

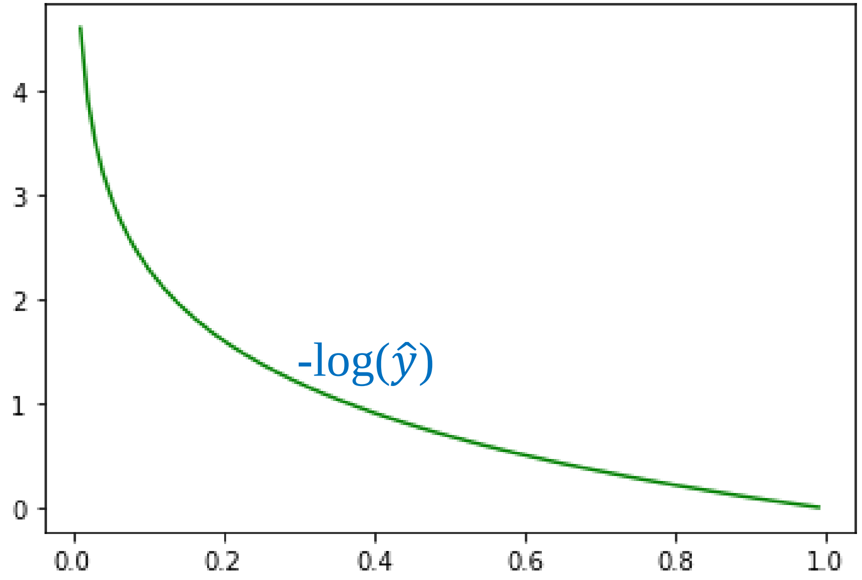
$$\frac{\partial L}{\partial \theta} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial z} \frac{\partial z}{\partial \theta}$$

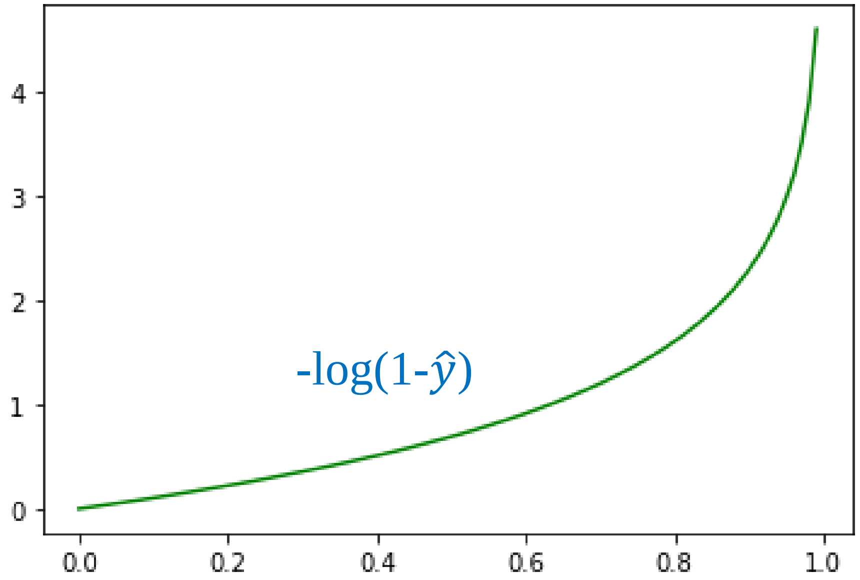
$$\frac{\partial L}{\partial \hat{y}} = \frac{1}{N}\left(-\frac{y}{\hat{y}} + \frac{1-y}{1-\hat{y}}\right) = \frac{1}{N}\frac{\hat{y} - y}{\hat{y}(1-\hat{y})}$$

$$\frac{\partial \hat{y}}{\partial z} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial z}{\partial \theta} = x$$

$$\frac{\partial L}{\partial \theta} = \frac{1}{N} x^T (\hat{y} - y)$$





Tanh Function

❖ Tanh function

$$\tanh(x) = \frac{2}{1 + e^{-2x}} - 1$$

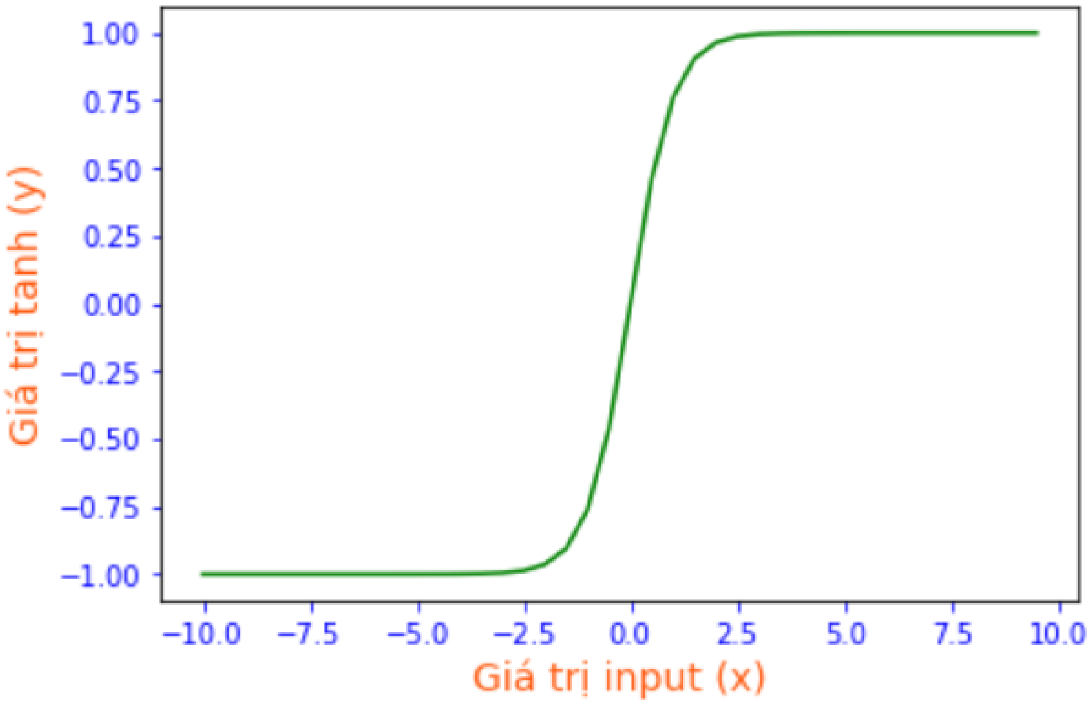
data =

1	5	-4	3	-2

data_a = tanh(data)

data_a =

0.761	0.999	-0.999	0.995	-0.964



Tanh Function

❖ Construct loss

Model and Loss

$$z = \boldsymbol{\theta}^T \boldsymbol{x}$$

$$\hat{y} = tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

$$\mathrm{L} = \frac{1}{N}[-y^T \log(\hat{y}) - (1 - y^T)\log(1 - \hat{y})]$$

Derivative

$$\frac{\partial L}{\partial \theta} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial z} \frac{\partial z}{\partial \theta}$$

$$\frac{\partial L}{\partial \hat{y}} = \frac{1}{N}\left(-\frac{y}{\hat{y}} + \frac{1-y}{1-\hat{y}}\right) = \frac{1}{N}\frac{\hat{y} - y}{\hat{y}(1-\hat{y})}$$

$$\frac{\partial \hat{y}}{\partial z} = 1 - \hat{y}^2$$

$$\frac{\partial z}{\partial \theta} = x$$

$$\frac{\partial L}{\partial \theta} = \frac{1}{N} x^T \frac{(\hat{y} - y)(1 + \hat{y})}{\hat{y}}$$

To-do List for Training

❖ ReLU function

$$\text{ReLU}(x) = \begin{cases} 0 & \text{if } x < 0 \\ x & \text{if } x \geq 0 \end{cases}$$

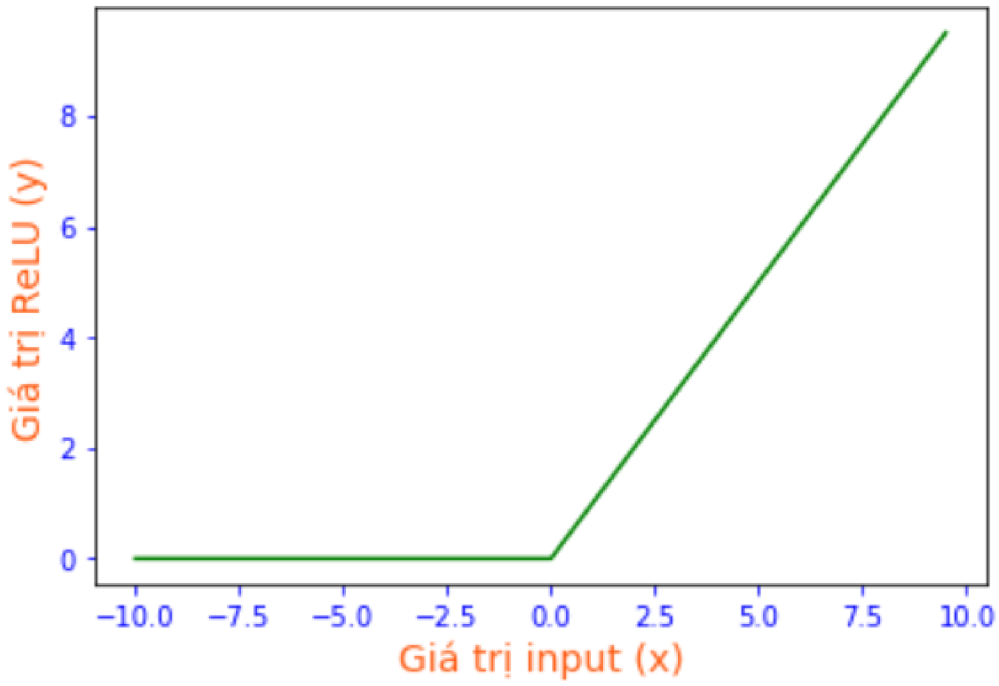
data =

1	5	-4	3	-2

data_a = ReLU(data)

data_a =

1	5	0	3	0



Implementation (straightforward)

Softmax function

Chuyển các giá trị của một vector thành các giá trị xác suất

Formula

$$f(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}}$$

$$0 \leq f(x_i) \leq 1$$

$$\sum_i f(x_i) = 1$$

Input		Probability
$x_1 = 1.0$		$f(x_1) = 0.09$
$x_2 = 2.0$	→ **Softmax** →	$f(x_2) = 0.24$
$x_3 = 3.0$		$f(x_3) = 0.67$

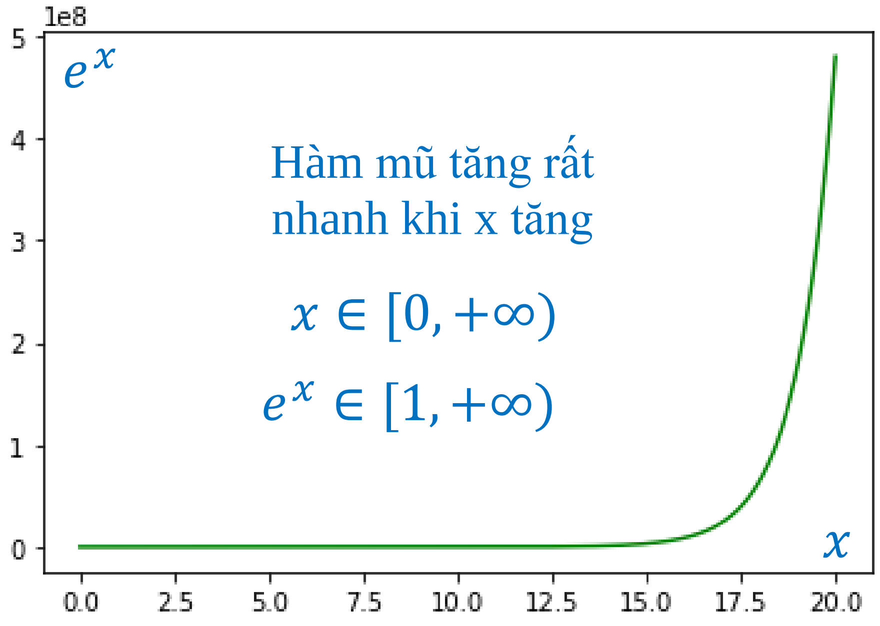
```python
import numpy as np

def softmax(X):
    exps = np.exp(X)
    return exps / np.sum(exps)
```

```python
X = np.array([1.0, 2.0, 3.0])
f = softmax(X)
print(f)
```

```
[0.09003057 0.24472847 0.66524096]
```

```python
X = np.array([1000.0, 1001.0, 1002.0])
f = softmax(X)
print(f)
```

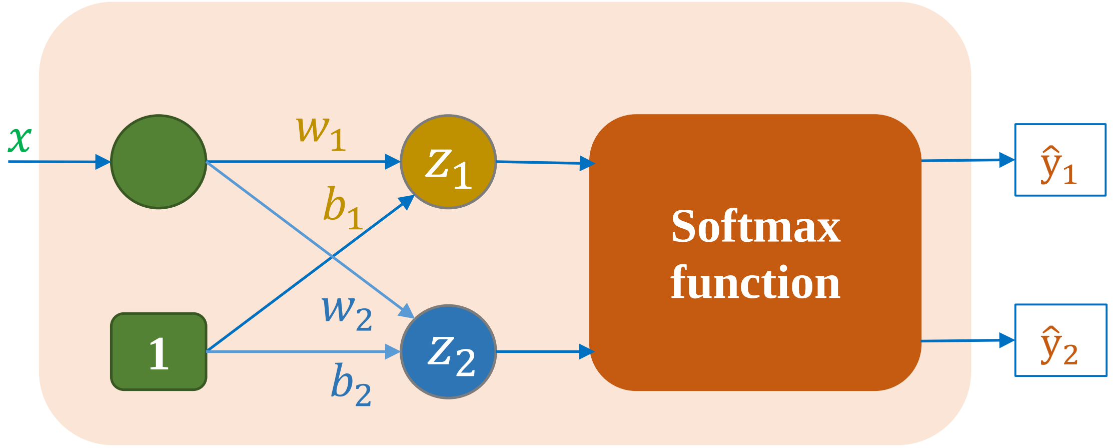
```
[nan nan nan]
```



Giá trị nan vì e^x vượt giới hạn lưu trữ của biến

Loss function

Model



$$L(\boldsymbol{\theta}) = -\sum_{i=1}^{2} \delta(i, y)\log\hat{y}_i$$

$$\hat{y}_1 = \frac{e^{z_1}}{\sum_{j=1}^{2} e^{z_j}}$$

$$\hat{y}_2 = \frac{e^{z_2}}{\sum_{j=1}^{2} e^{z_j}}$$

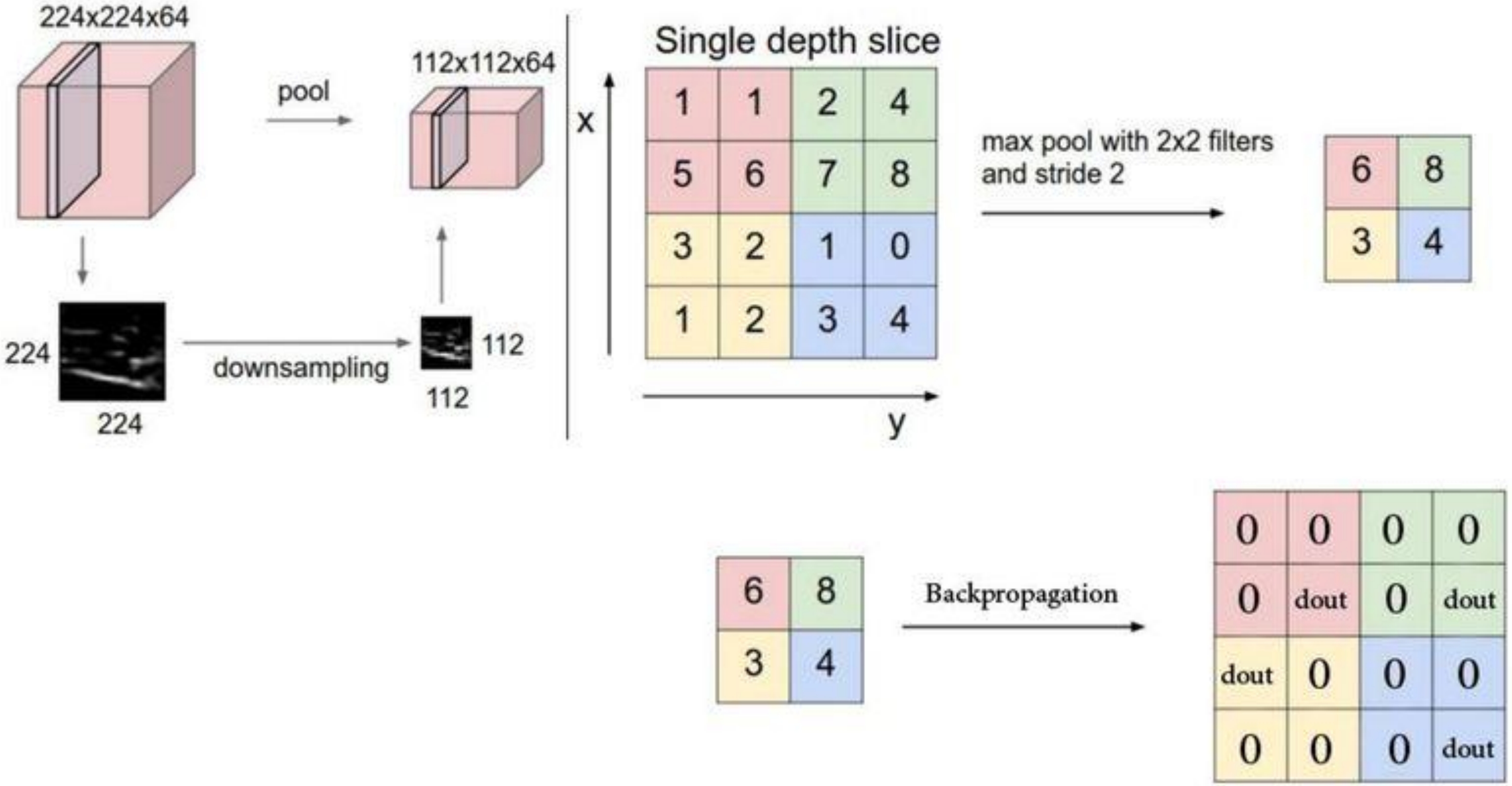
Derivative

$$\frac{\partial \hat{y}_i}{\partial z_j} = \hat{y}_i\big(\delta(i,j) - \hat{y}_j\big)$$

$$\frac{\partial L}{\partial z_i} = \hat{y}_i - \delta(i, y)$$

Max Pooling

Forward and Backward Max Pooling



https://slideplayer.com/slide/15983712/

Max Pooling

```
import tensorflow as tf
import tensorflow.keras as keras
import numpy as np

max_pooling = keras.layers.MaxPooling2D(pool_size=2, strides=2)

data_X = np.array([[1, 5, 3, 7],
                   [7, 3, 9, 2],
                   [3, 5, 8, 4],
                   [8, 7, 3, 5]])*1.0
data_X = data_X.reshape(1, 4, 4, 1)
data_X = tf.Variable(data_X)

data_y = np.ones((1, 2, 2, 1))*1.0
data_y = tf.Variable(data_y)

print('\n\n data_X: \n', data_X[0,:,:,0])
print('\n\n data_y: \n', data_y[0,:,:,0])

with tf.GradientTape(persistent=True) as tape:
    data_after_mp = max_pooling(data_X)
    print('\n\n data_after_mp: \n', data_after_mp[0,:,:,0])

    loss = tf.reduce_mean((data_after_mp-data_y)**2)
    print('\n\n loss: \n', loss)

    dloss = tape.gradient(loss, data_after_mp)
    print('\n\n dloss: \n', dloss[0,:,:,0])

    ddata_X = tape.gradient(loss, data_X)
    print('\n\n ddata_X: \n', ddata_X[0,:,:,0])
```

```
data_X:
tf.Tensor(
[[1. 5. 3. 7.]
 [7. 3. 9. 2.]
 [3. 5. 8. 4.]
 [8. 7. 3. 5.]], shape=(4, 4), dtype=float64)


data_y:
tf.Tensor(
[[1. 1.]
 [1. 1.]], shape=(2, 2), dtype=float64)


data_after_mp:
tf.Tensor(
[[7. 9.]
 [8. 8.]], shape=(2, 2), dtype=float64)


loss:
tf.Tensor(49.5, shape=(), dtype=float64)


dloss:
tf.Tensor(
[[3.  4. ]
 [3.5 3.5]], shape=(2, 2), dtype=float64)


ddata_X:
tf.Tensor(
[[0.  0.  0.  0. ]
 [3.  0.  4.  0. ]
 [0.  0.  3.5 0. ]
 [3.5 0.  0.  0. ]], shape=(4, 4), dtype=float64)
```

Average Pooling

Formula

4	3	1	5
1	3	4	8
4	5	4	3
6	5	9	4

2.8	4.5
5.3	5.0

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Average Pooling

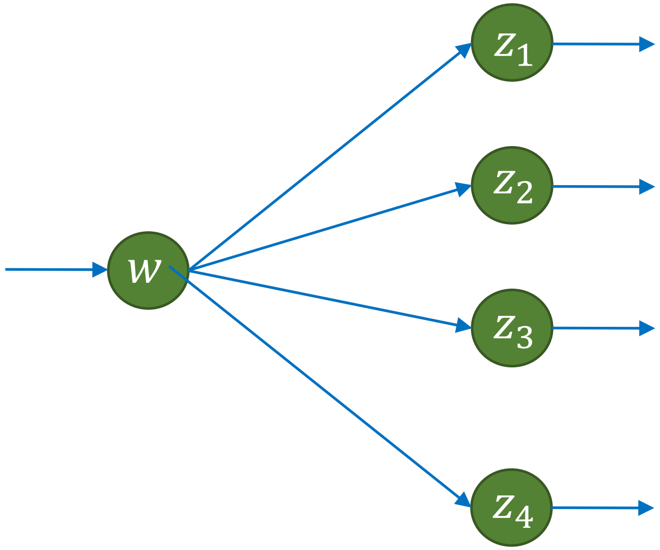
```python
import tensorflow as tf
import tensorflow.keras as keras
import numpy as np

avg_pooling = keras.layers.AveragePooling2D(pool_size=2, strides=2)

data_X = np.array([[1, 5, 3, 7],
                   [7, 3, 9, 2],
                   [3, 5, 8, 4],
                   [8, 7, 3, 5]])*1.0
data_X = data_X.reshape(1, 4, 4, 1)
data_X = tf.Variable(data_X)

data_y = np.ones((1, 2, 2, 1))*1.0
data_y = tf.Variable(data_y)

print('\n\n data_X: \n', data_X[0,:,:,0])
print('\n\n data_y: \n', data_y[0,:,:,0])

with tf.GradientTape(persistent=True) as tape:
    data_after_ap = avg_pooling(data_X)
    print('\n\n data_after_ap: \n', data_after_ap[0,:,:,0])

    loss = tf.reduce_mean((data_after_ap-data_y)**2)
    print('\n\n loss: \n', loss)

    dloss = tape.gradient(loss, data_after_ap)
    print('\n\n dloss: \n', dloss[0,:,:,0])

    ddata_X = tape.gradient(loss, data_X)
    print('\n\n ddata_X: \n', ddata_X[0,:,:,0])
```

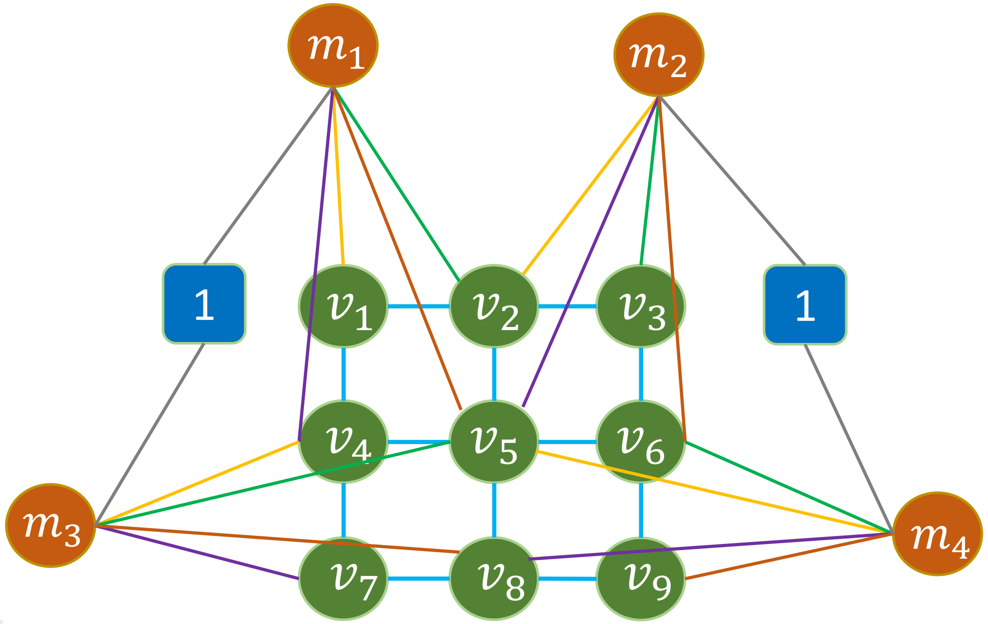
```
data_X:
tf.Tensor(
[[1. 5. 3. 7.]
 [7. 3. 9. 2.]
 [3. 5. 8. 4.]
 [8. 7. 3. 5.]], shape=(4, 4), dtype=float64)


data_y:
tf.Tensor(
[[1. 1.]
 [1. 1.]], shape=(2, 2), dtype=float64)


data_after_ap:
tf.Tensor(
[[4.   5.25]
 [5.75 5.  ]], shape=(2, 2), dtype=float64)


loss:
tf.Tensor(16.40625, shape=(), dtype=float64)


dloss:
tf.Tensor(
[[1.5   2.125]
 [2.375 2.   ]], shape=(2, 2), dtype=float64)


ddata_X:
tf.Tensor(
[[0.375   0.375   0.53125 0.53125]
 [0.375   0.375   0.53125 0.53125]
 [0.59375 0.59375 0.5     0.5    ]
 [0.59375 0.59375 0.5     0.5    ]], shape=(4, 4)
```

Convolution

w_1	w_2	b
w_3	w_4	

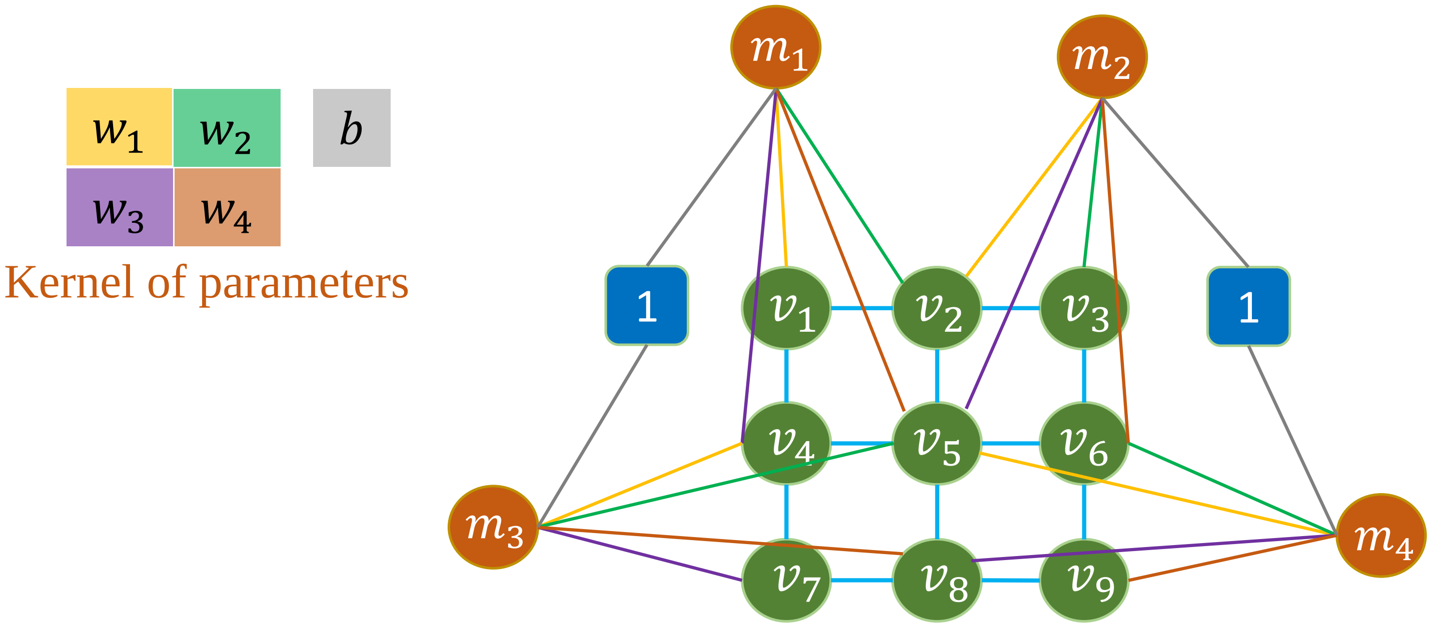
Kernel of parameters

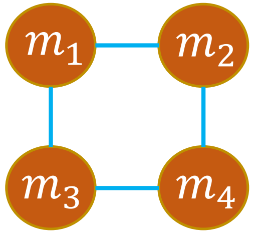




$$\frac{\partial L}{\partial w} = \sum_{i=1}^{4} \frac{\partial L}{\partial z_i} \frac{\partial z_i}{\partial w}$$

Convolution





Feature Map

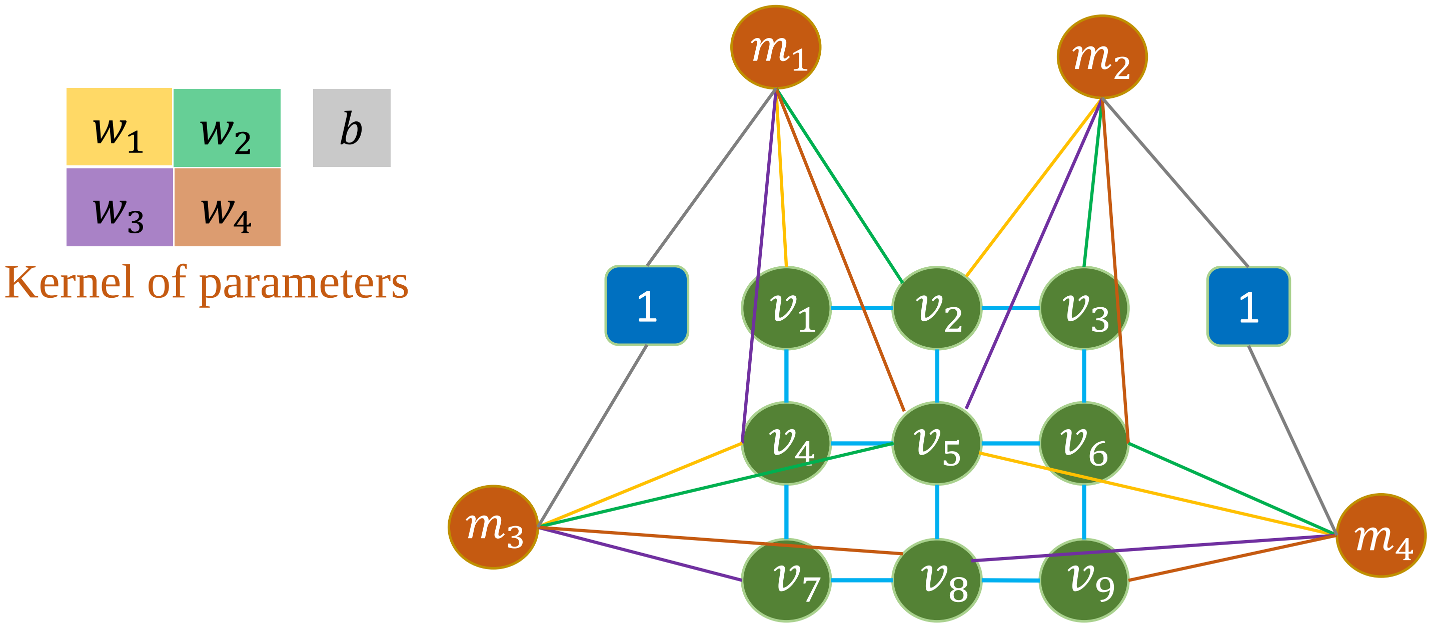
$$m_1 = v_1w_1 + v_2w_2 + v_4w_3 + v_5w_4 + b$$

$$m_2 = v_2w_1 + v_3w_2 + v_5w_3 + v_6w_4 + b$$

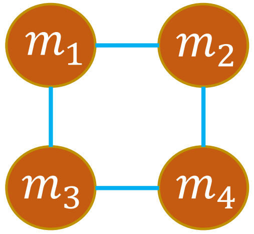
$$m_3 = v_4w_1 + v_5w_2 + v_7w_3 + v_8w_4 + b$$

$$m_4 = v_5w_1 + v_6w_2 + v_8w_3 + v_9w_4 + b$$

Convolution



$$\frac{\partial L}{\partial w_1} = \sum_i \frac{\partial L}{\partial m_i}\frac{\partial m_i}{\partial w_1}$$



Feature Map

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

$$m_2 = v_2 w_1 + v_3 w_2 + v_5 w_3 + v_6 w_4 + b$$

$$m_3 = v_4 w_1 + v_5 w_2 + v_7 w_3 + v_8 w_4 + b$$

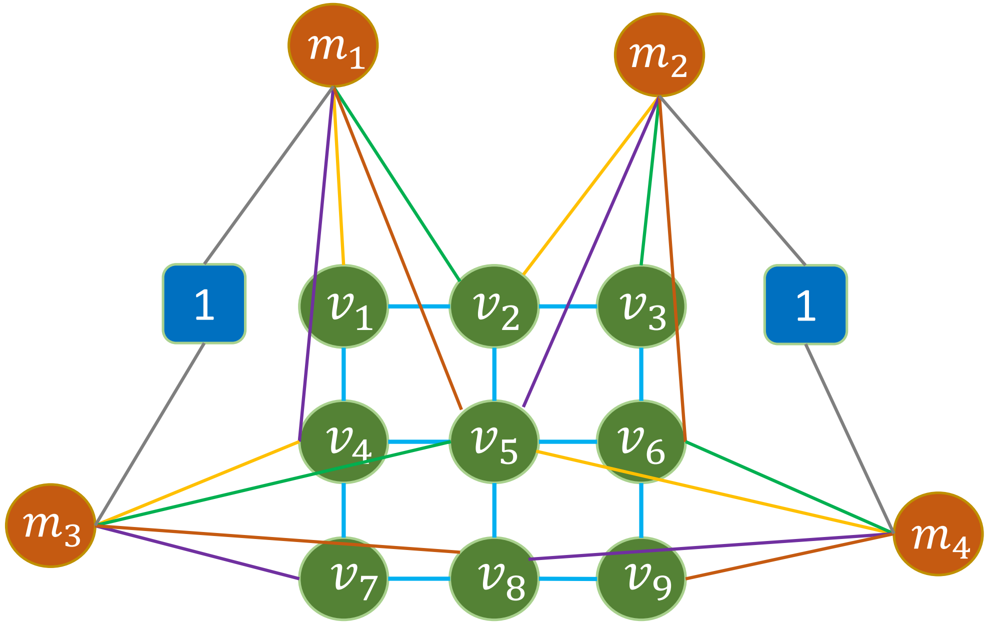
$$m_4 = v_5 w_1 + v_6 w_2 + v_8 w_3 + v_9 w_4 + b$$

Convolution

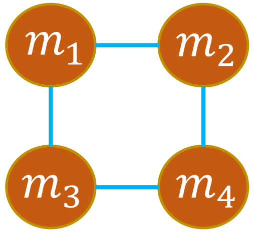
w_1	w_2
w_3	w_4

b

Kernel of parameters



$$\frac{\partial L}{\partial w_1} = \sum_i v_i \frac{\partial L}{\partial m_i}$$



Feature Map

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

$$m_2 = v_2 w_1 + v_3 w_2 + v_5 w_3 + v_6 w_4 + b$$

$$m_3 = v_4 w_1 + v_5 w_2 + v_7 w_3 + v_8 w_4 + b$$

$$m_4 = v_5 w_1 + v_6 w_2 + v_8 w_3 + v_9 w_4 + b$$

Convolution

```
import tensorflow as tf
import tensorflow.keras as keras
import numpy as np

conv2D = keras.layers.Conv2D(1, (2, 2), activation='relu')

data_X = np.array([[1, 1, 2],
                   [1, 2, 1],
                   [2, 1, 1]])
data_X = data_X.reshape(1, 3, 3, 1)
data_X = tf.Variable(data_X, dtype=tf.float32)

data_y = np.ones((1, 2, 2, 1))
data_y = tf.Variable(data_y, dtype=tf.float32)

print('\n\n data_X: \n', data_X[0,:,:,0])
print('\n\n data_y: \n', data_y[0,:,:,0])

with tf.GradientTape(persistent=True) as tape:
    data_after_conv = conv2D(data_X)
    print('\n\n data_after_conv: \n', data_after_conv[0,:,:,0])

    # Check the values of the current conv weight
    print('\n\n conv_weight: \n', conv2D.trainable_weights[0][:,:,0,0])
    print('\n conv_bias: \n', conv2D.trainable_weights[1][0])

    loss = tf.reduce_mean((data_after_conv-data_y)**2)
    print('\n\n loss: \n', loss)

    dloss = tape.gradient(loss, data_after_conv)
    print('\n\n dloss: \n', dloss[0,:,:,0])

    dconv_weight = tape.gradient(loss, conv2D.trainable_weights)
    print('\n\n dconv_weight: \n', dconv_weight[0][:,:,0,0])
    print('\n dconv_bias: \n', dconv_weight[1][0])
```

```
data_X:
tf.Tensor(
[[1. 1. 2.]
 [1. 2. 1.]
 [2. 1. 1.]], shape=(3, 3), dtype=float32)

data_y:
tf.Tensor(
[[1. 1.]
 [1. 1.]], shape=(2, 2), dtype=float32)

data_after_conv:
tf.Tensor(
[[0.9292677 1.2405912]
 [1.2405912 1.6272811]], shape=(2, 2), dtype=float32)

conv_weight:
tf.Tensor(
[[ 0.6779961  -0.3282364 ]
 [ 0.61954254 -0.02001727]], shape=(2, 2), dtype=float32)

conv_bias:
tf.Tensor(0.0, shape=(), dtype=float32)

loss:
tf.Tensor(0.12856321, shape=(), dtype=float32)

dloss:
tf.Tensor(
[[-0.03536615  0.12029558]
 [ 0.12029558  0.31364053]], shape=(2, 2), dtype=float32)

dconv_weight:
tf.Tensor(
[[0.83250606 0.75945675]
 [0.75945675 0.4834994 ]], shape=(2, 2), dtype=float32)

dconv_bias:
tf.Tensor(0.5188656, shape=(), dtype=float32)
```

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

https://stanford.edu/~shervine/teaching/cs-230/cheatsheet-convolutional-neural-networks

Thank you!