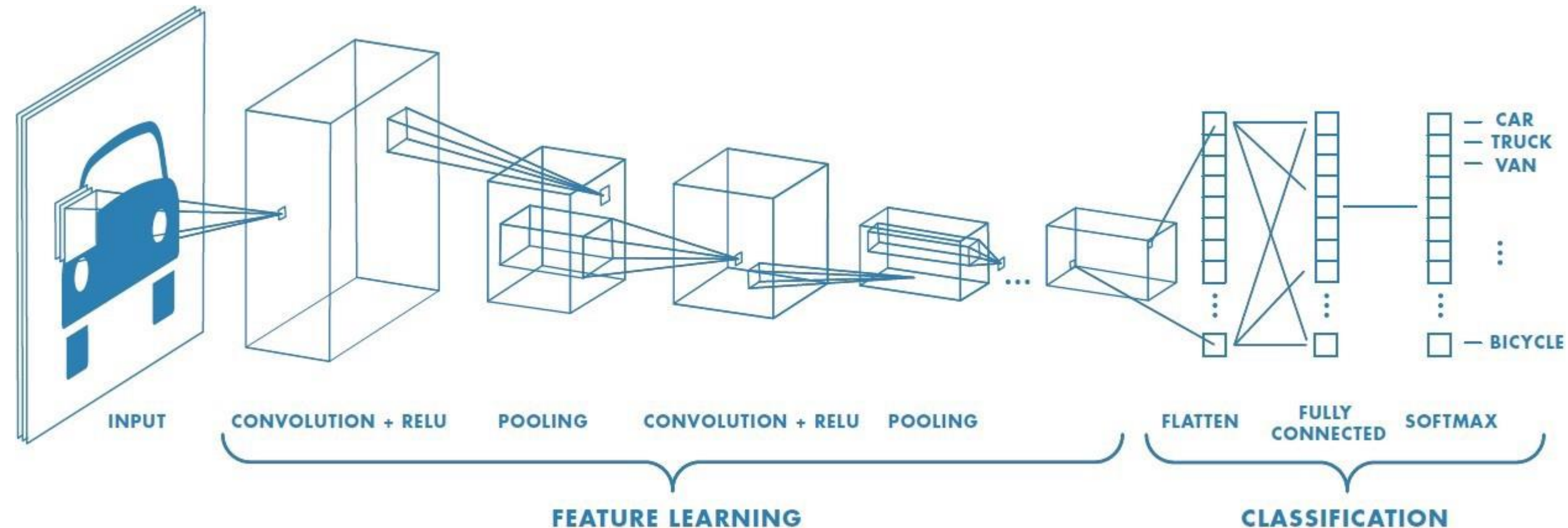


# Classification Model

# Convolutional Neural network

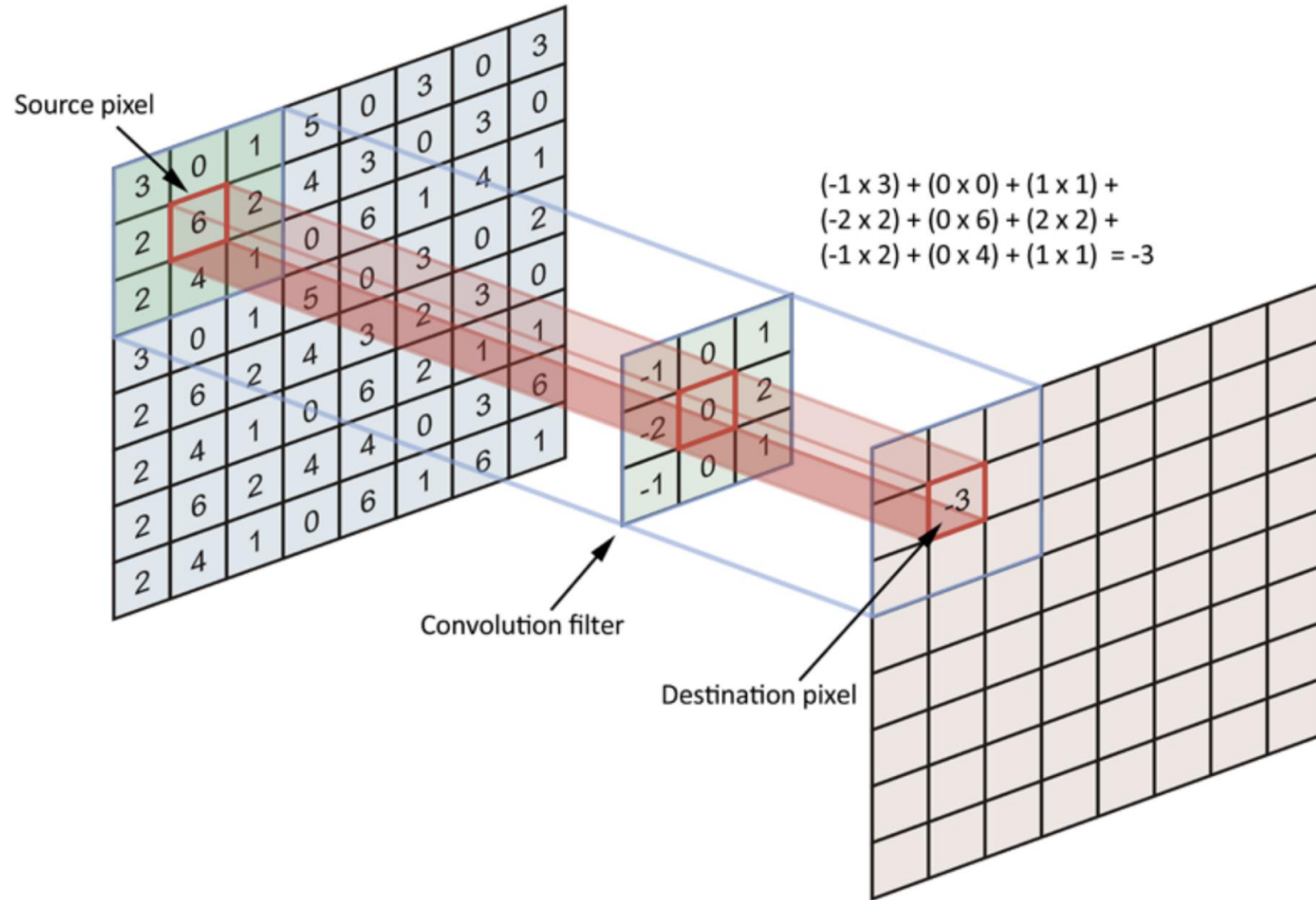
# Convolutional Neural network(CNN) terminology



# Convolutional Neural network(CNN) terminology

- **Convolution**
- **Convolutional mask (kernel)**
- **Edge detection mask**
- **Padding**
- **Convolution Stride**
- **Convolutions over volume**
- **Pooling**

# CNN terminology: convolution



- **Convolution**

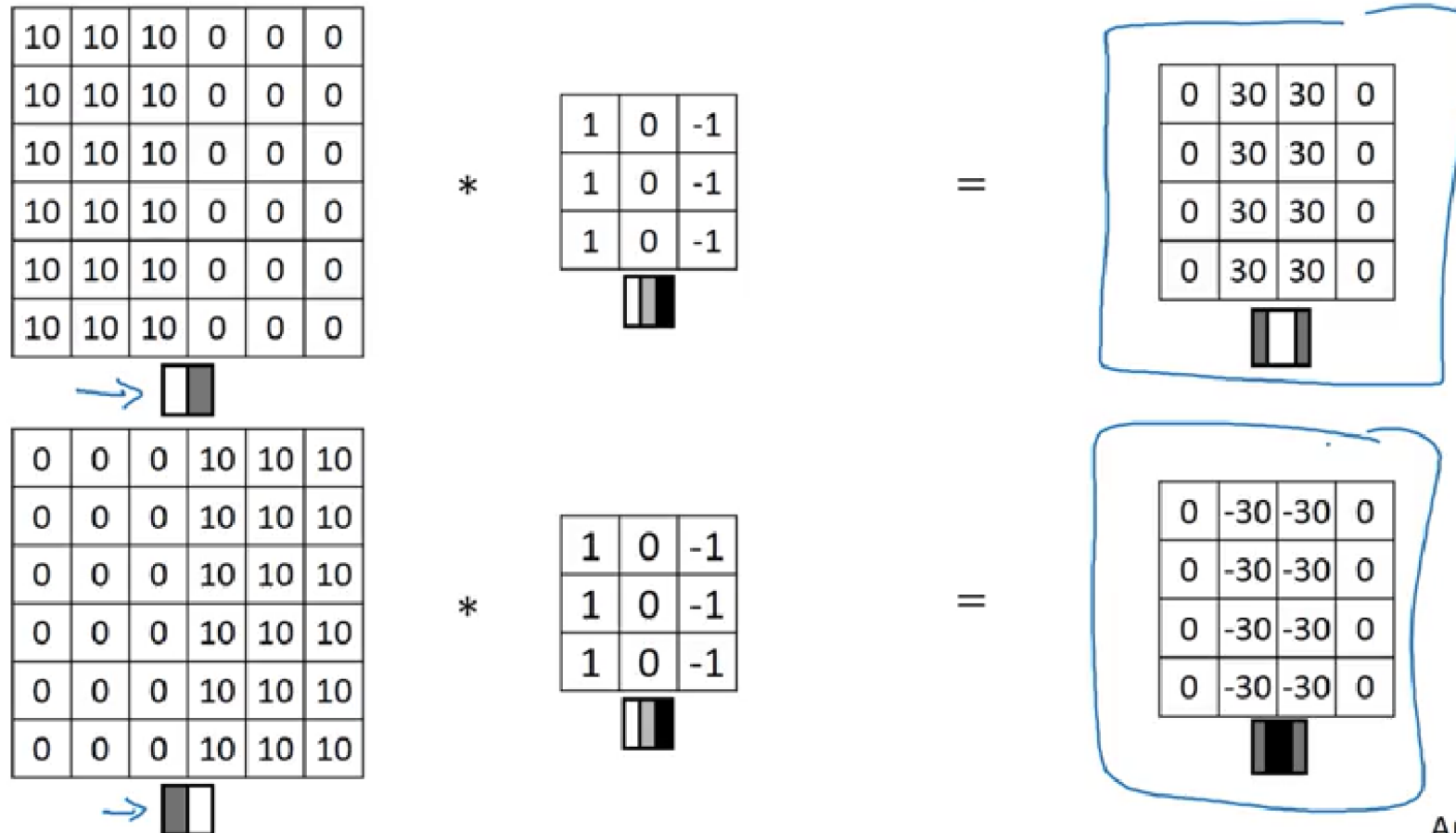
- **Operation:**

- Dot Product or
    - Weighted sum

- **Task**

- **Local pattern detection**
    - Search for a particular local pattern in input

# CNN terminology: convolution



- **Ex.**

- **Vertical Local pattern detection**
- **Sign of convolution results**
  - According to convolutional mask
- **Adaptive mask**
  - Learning from data or domain problem

# Convolution padding

## Zero Padding the border

0	0	0	0	0	0			
0								
0								
0								
0								

e.g. input 7x7

3x3 filter, applied with **stride 1**

**pad with 1 pixel border** => what is the output?

**7x7 output!**

in general, common to see CONV layers with stride 1, filters of size  $F \times F$ , and zero-padding with  $(F-1)/2$ . (will preserve size spatially)

e.g.  $F = 3 \Rightarrow$  zero pad with 1

$F = 5 \Rightarrow$  zero pad with 2

$F = 7 \Rightarrow$  zero pad with 3

- **Padding**

- **Boundary extending**
  - In order to maintain convolution results the same dimension as input

- **Padding size**

- Depend on mask size

- **Padding value**

- Zero (mostly used)
- Reflected border
- Circular index

# Convolution Stride

Output resolution = Input resolution / 2

2	3	7 <sup>3</sup>	4 <sup>4</sup>	6 <sup>4</sup>	2	9
6	6	9 <sup>1</sup>	8 <sup>0</sup>	7 <sup>2</sup>	4	3
3	4	8 <sup>-1</sup>	3 <sup>0</sup>	8 <sup>3</sup>	9	7
7	8	3	6	6	3	4
4	2	1	8	3	4	6
3	2	4	1	9	8	3
0	1	3	9	2	1	4

7x7

3	4	4
1	0	2
-1	0	3

3x3  
stride = 2

91	100	

2	3	7	4	6	2	9
6	6	9	8	7	4	3
3 <sup>3</sup>	4 <sup>4</sup>	8 <sup>4</sup>	3	8	9	7
7 <sup>1</sup>	8 <sup>0</sup>	3 <sup>2</sup>	6	6	3	4
4 <sup>-1</sup>	2 <sup>0</sup>	1 <sup>3</sup>	8	3	4	6
3	2	4	1	9	8	3
0	1	3	9	2	1	4

7x7

3	4	4
1	0	2
-1	0	3

3x3  
stride = 2

91	100	83
69		

- **Stride**

- **Convolution resolution selection**

- **Stride = 1**

- Convolution on every input position

- Reserve output resolution = input resolution

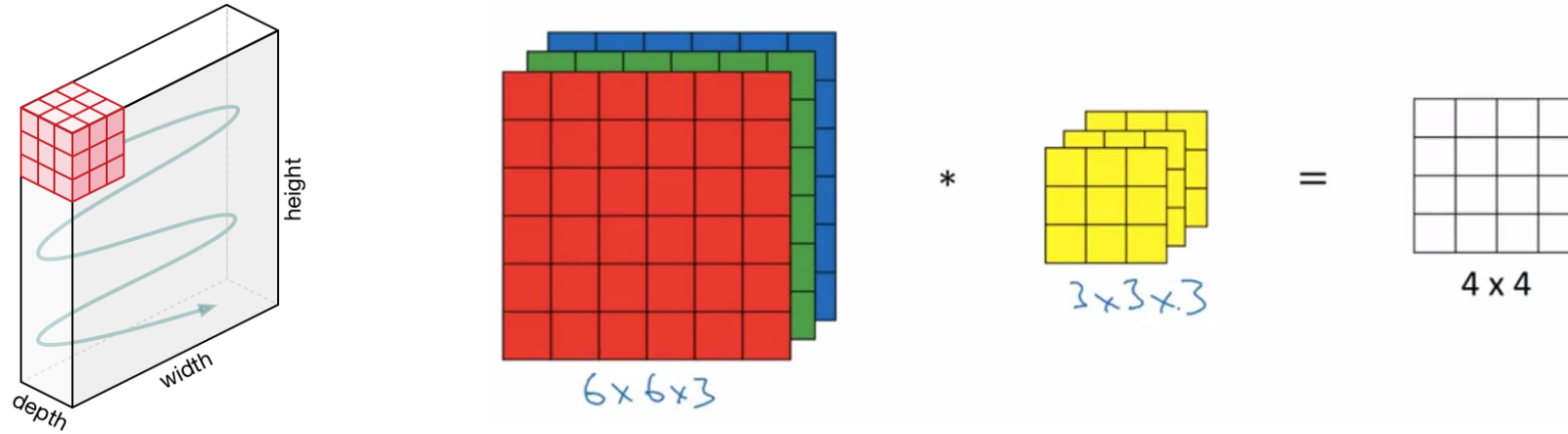
- **Stride > 1**

- Convolution skipping

- Output resolution < Input resolution

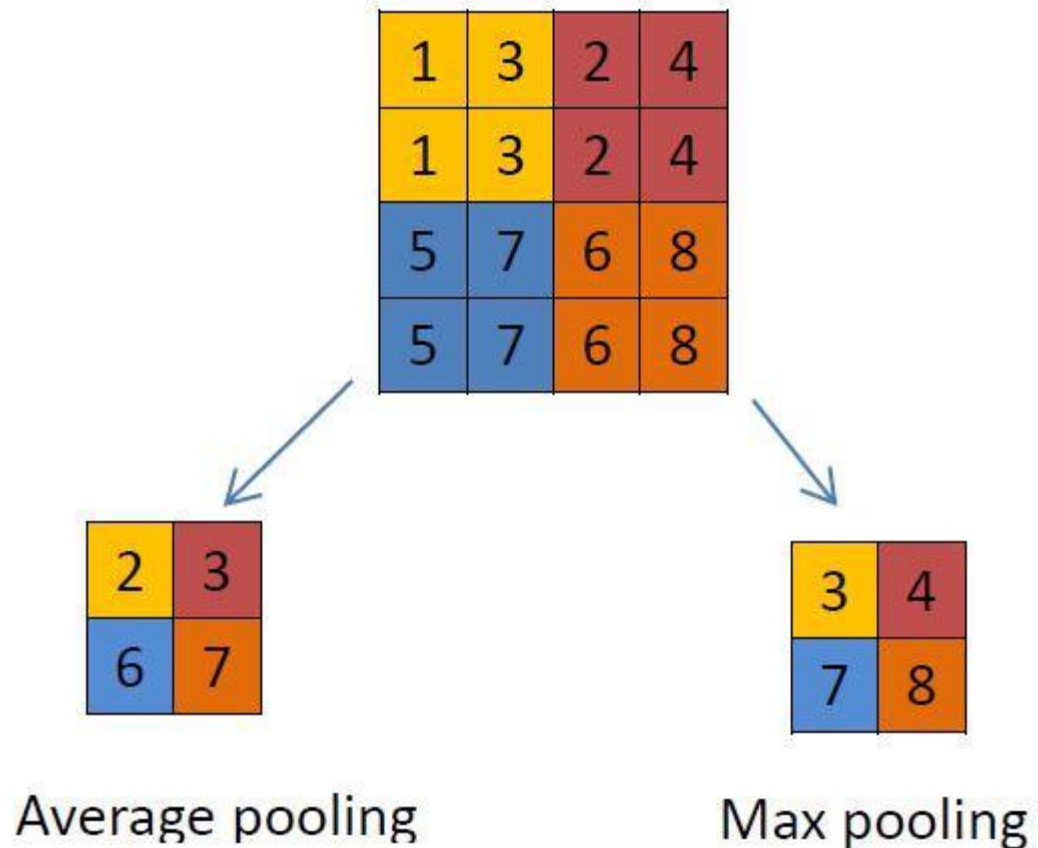


# Convolution **over volume**



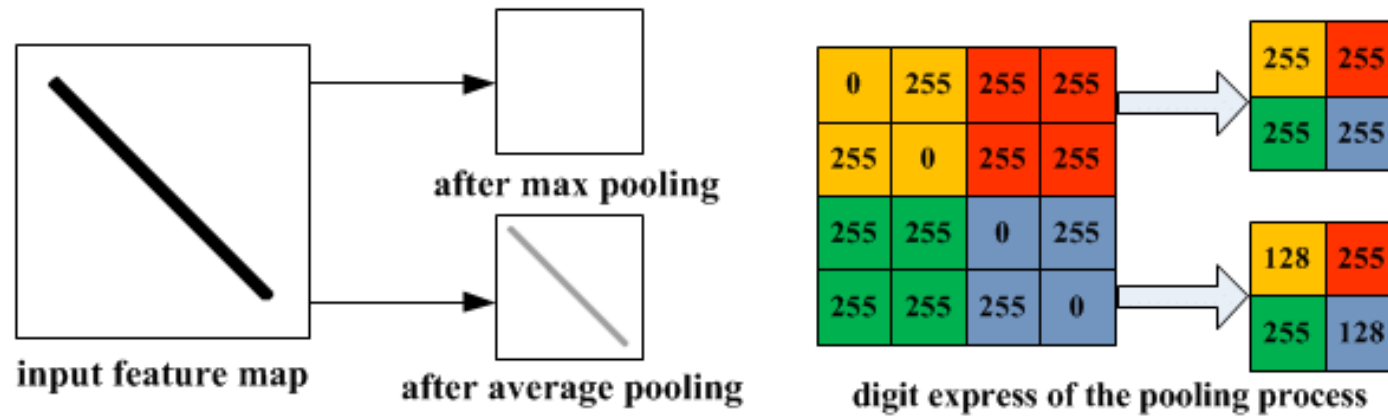
- 3 input planes / 3 convolutional masks / 1 output
- **Output Results (with no zero padding example) = 4x4**
  - = Red plane (1) \* mask (1) + Green plane (2) \* mask (2) + Blue plane (3) \* mask (3)
- **Sum all detected local pattern from all Red / Green / Blue planes**
  - Return a single output of all detected patterns in input planes

# Convolution Pooling

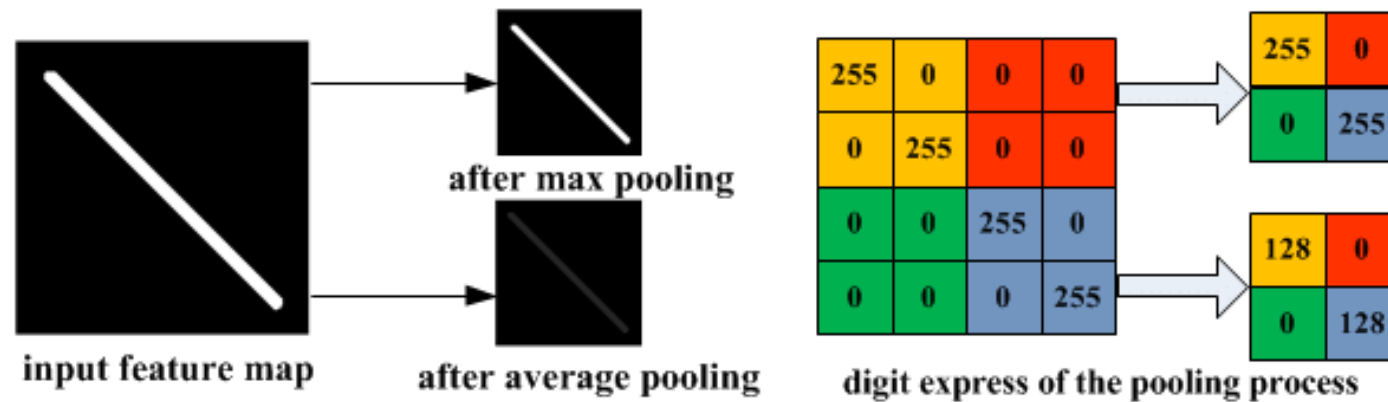


- Reduce the dimensionality and the number of parameters and computation in the network.
  - This shortens the training time and controls overfitting.
- Pooling functions
  - Max pooling
  - Average pooling

# Convolution Pooling

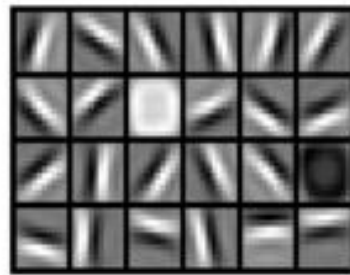
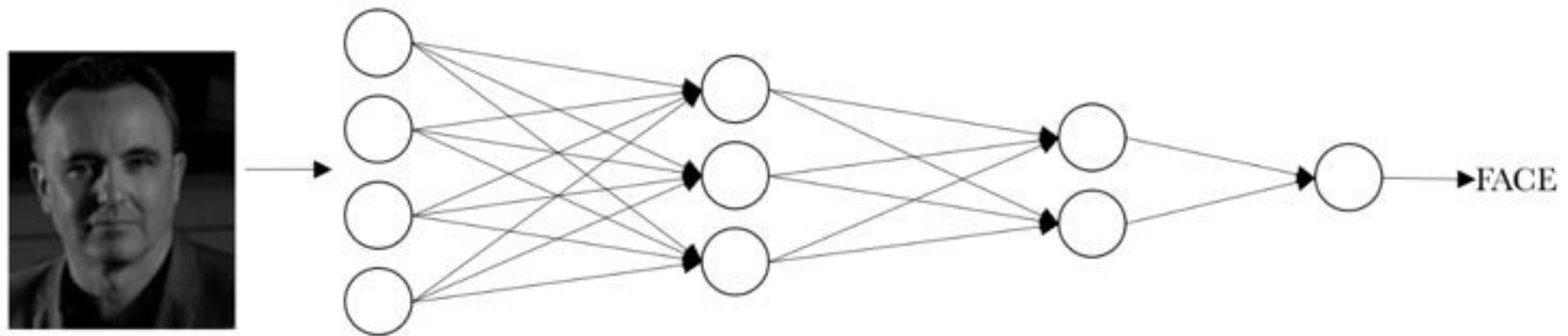


(a) Illustration of max pooling drawback



(b) Illustration of average pooling drawback

# Multi-level feature extraction



Low-level features

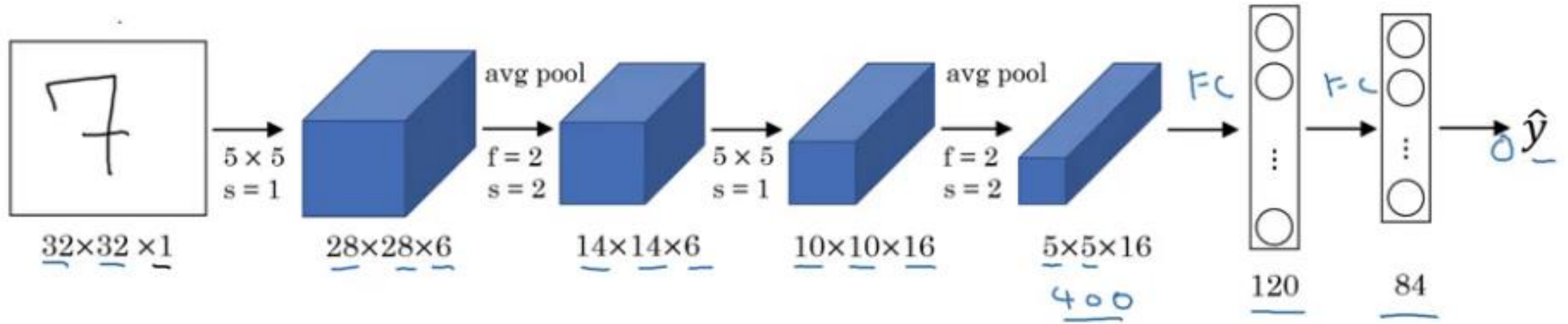


Mid-level features

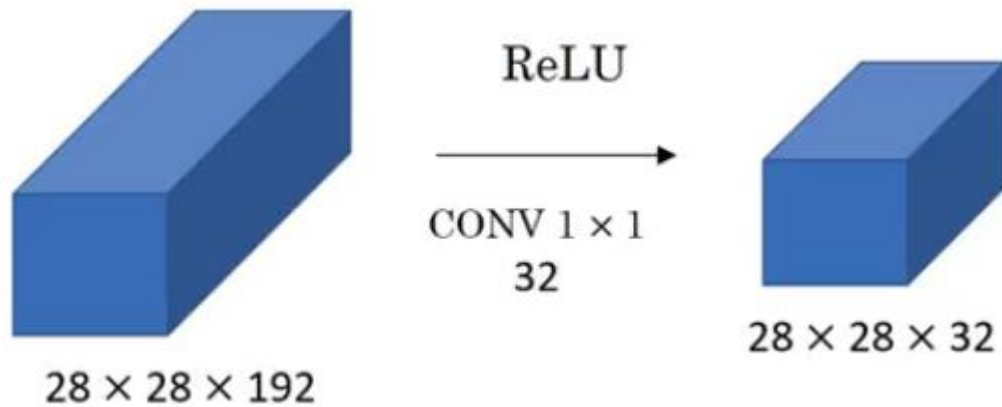


High-level features

# Example of CNN structure (Lenet)



# CNN structure (resnet)



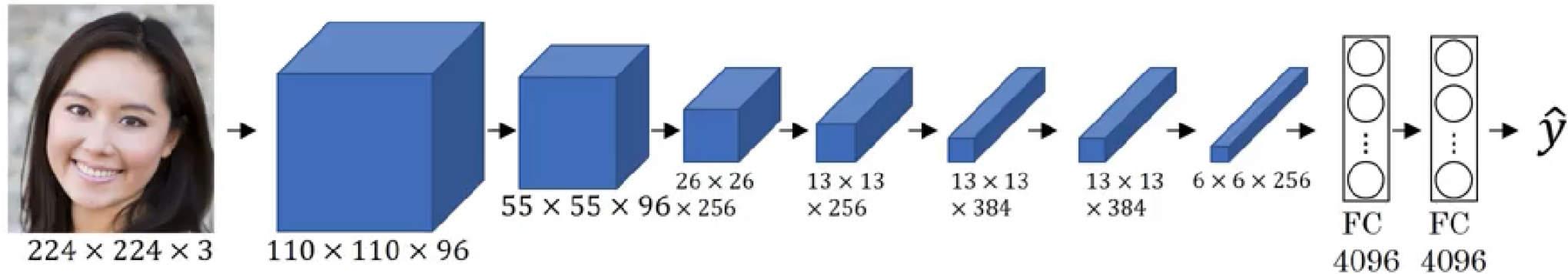
The basic idea of using  $1 \times 1$  convolution is to reduce the number of channels from the image. A couple of points to keep in mind:

We generally use a pooling layer to shrink the height and width of the image

To reduce the number of channels from an image, we convolve it using a  $1 \times 1$  filter (hence reducing the computation cost as well)

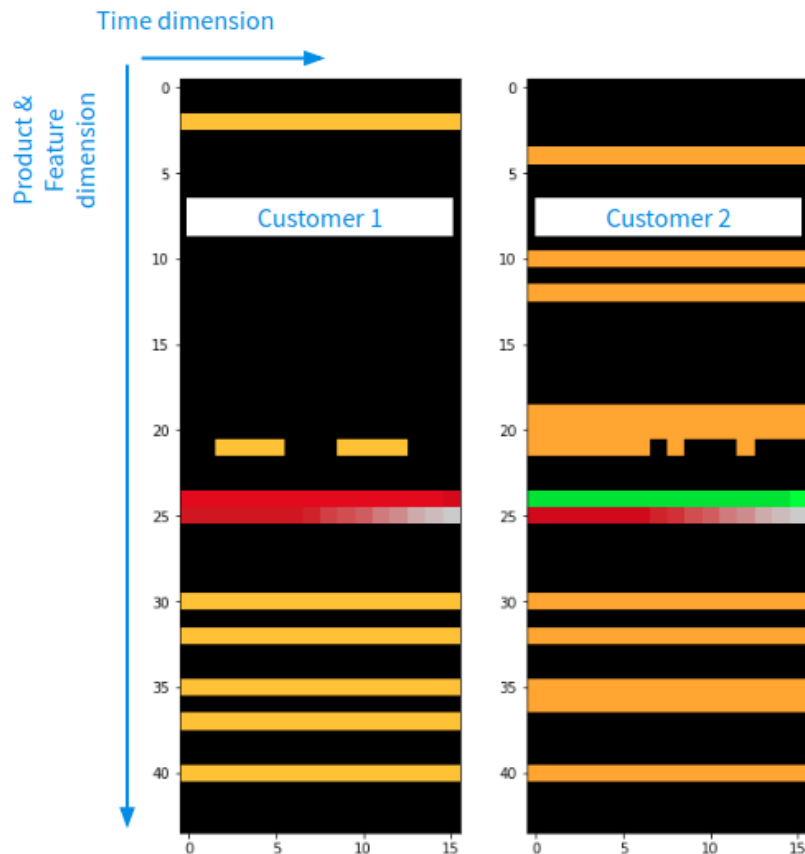
# Activity: CNN for images

## Visualizing what a deep network is learning



1. ระบุ Convolutional layer Structure (Filter size, padding, stride, maxpooling)
2. คำนวณจำนวนพารามิเตอร์ทั้งหมดในโครงสร้าง (convolutional + fully connected layers)

# CNN for time series data for bank product prediction



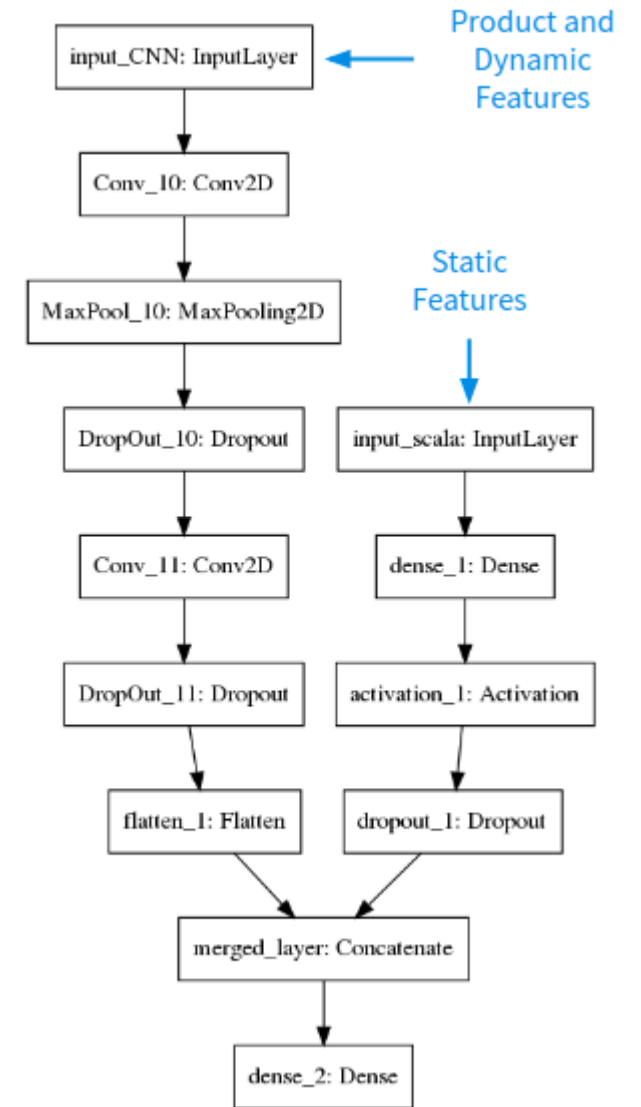
Some features like income and relationship with the bank changed overtime

ended up with some 45 by 17 pixels

$n\_features = 45$   
 $timesteps = 17$

Training shape: [samples, timesteps,  $n\_features$ ]

$input\_shape = (timesteps, n\_features)$





# Dropout layer

[https://d2l.ai/chapter\\_multilayer-perceptrons/dropout.html](https://d2l.ai/chapter_multilayer-perceptrons/dropout.html)

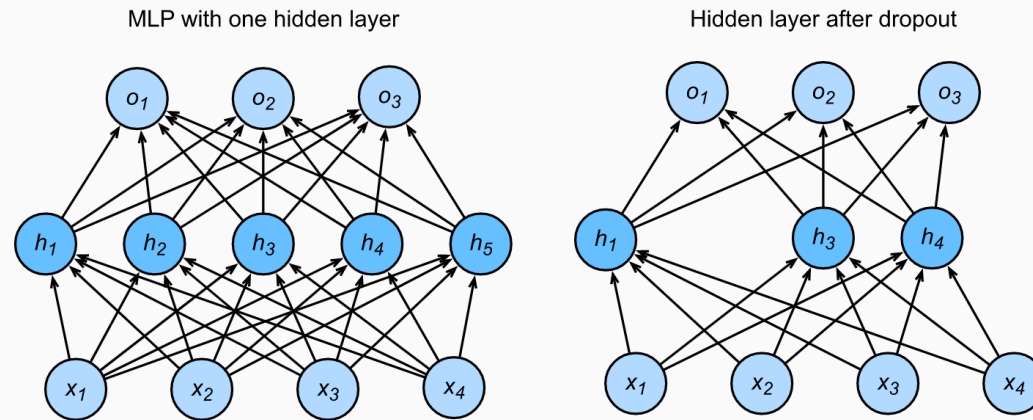
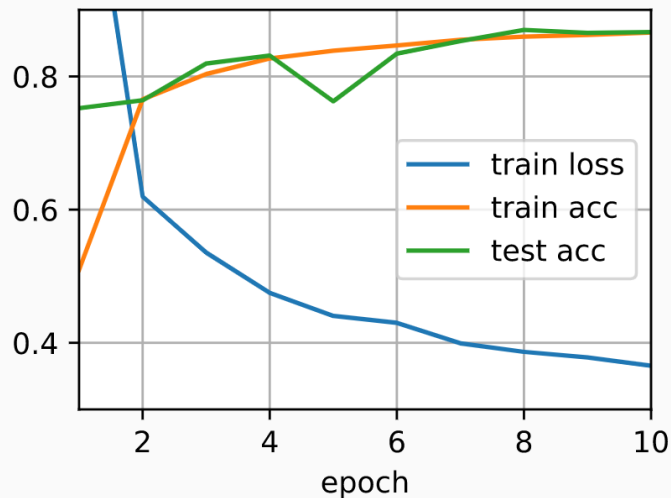
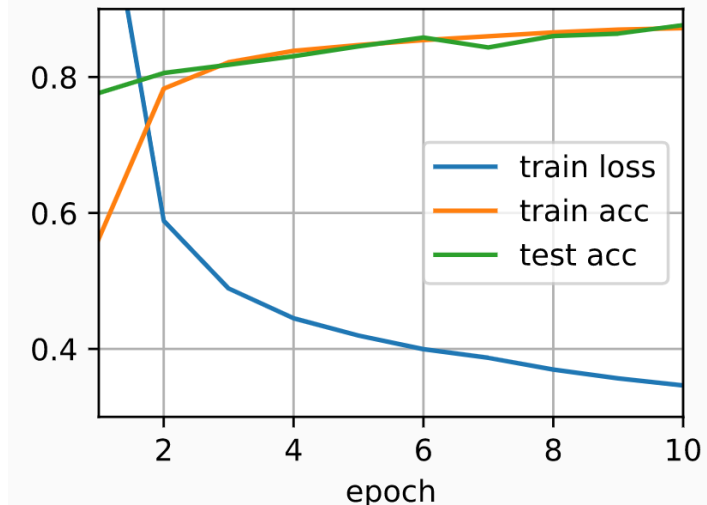


Fig. 4.6.1 MLP before and after dropout



Dropout drops out some nodes of the network to reduce overfitting and learn a fraction of the weights in the network in each training iteration.

**dropout rate,  $p = 0.5$ , yields the maximum**

network without Dropout may perform better at the training phase while Dropout network may perform worse. However, at the test time, Dropout network is not just performed better, but *consistently better*.

<https://wiseodd.github.io/techblog/2016/06/25/dropout/>

conv2d_7 (Conv2D)	(None, 32, 6, 32)	40992
batch_normalization_8 (Batch Normalization)	(None, 32, 6, 32)	128
activation_8 (Activation)	(None, 32, 6, 32)	0
conv2d_8 (Conv2D)	(None, 32, 6, 32)	40992
batch_normalization_9 (Batch Normalization)	(None, 32, 6, 32)	128
activation_9 (Activation)	(None, 32, 6, 32)	0
max_pooling2d_2 (MaxPooling2D)	(None, 32, 3, 16)	0
flatten_2 (Flatten)	(None, 1536)	0
dense_2 (Dense)	(None, 128)	196736
batch_normalization_10 (Batch Normalization)	(None, 128)	512
activation_10 (Activation)	(None, 128)	0
dropout_2 (Dropout)	(None, 128)	0
feature_dense (Dense)	(None, 100)	12900
batch_normalization_11 (Batch Normalization)	(None, 100)	400
activation_11 (Activation)	(None, 100)	0
dense_3 (Dense)	(None, 2)	202
activation_12 (Activation)	(None, 2)	0
=====		

## Feature extraction @Intermediate layer

```
intermediate_layer_model = Model(inputs=model.input,
outputs=model.get_layer('feature_dense').output)
```