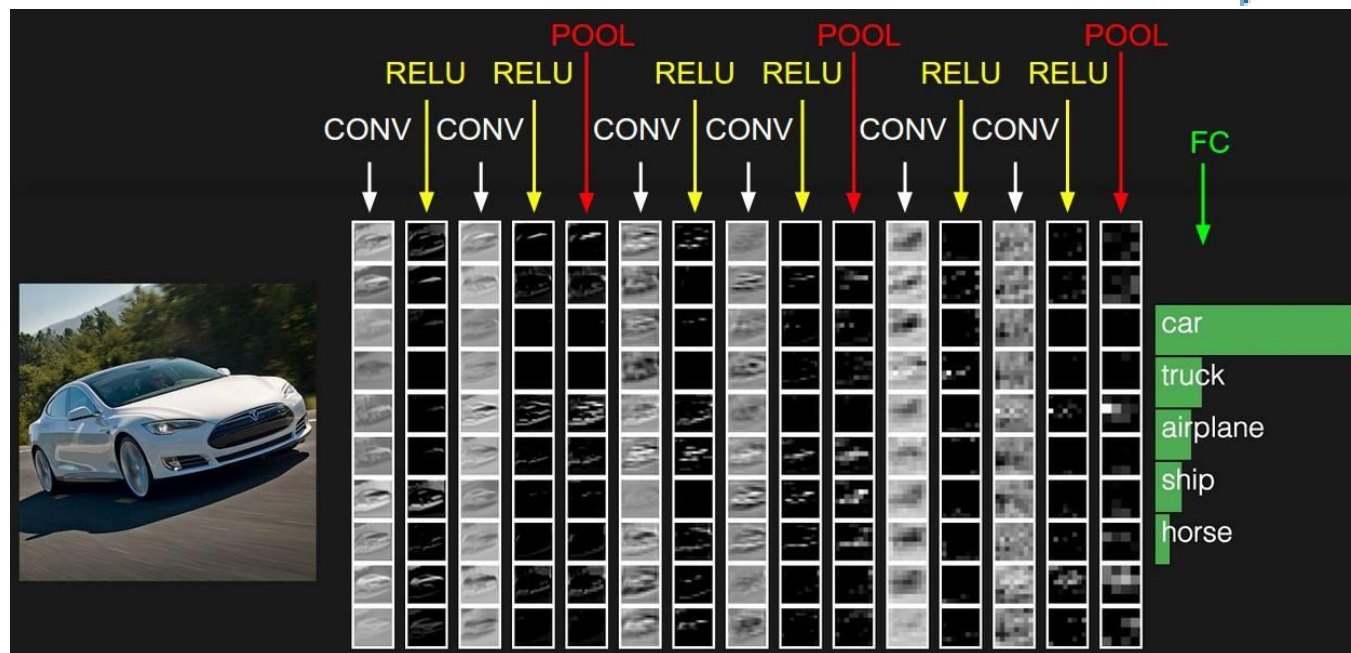
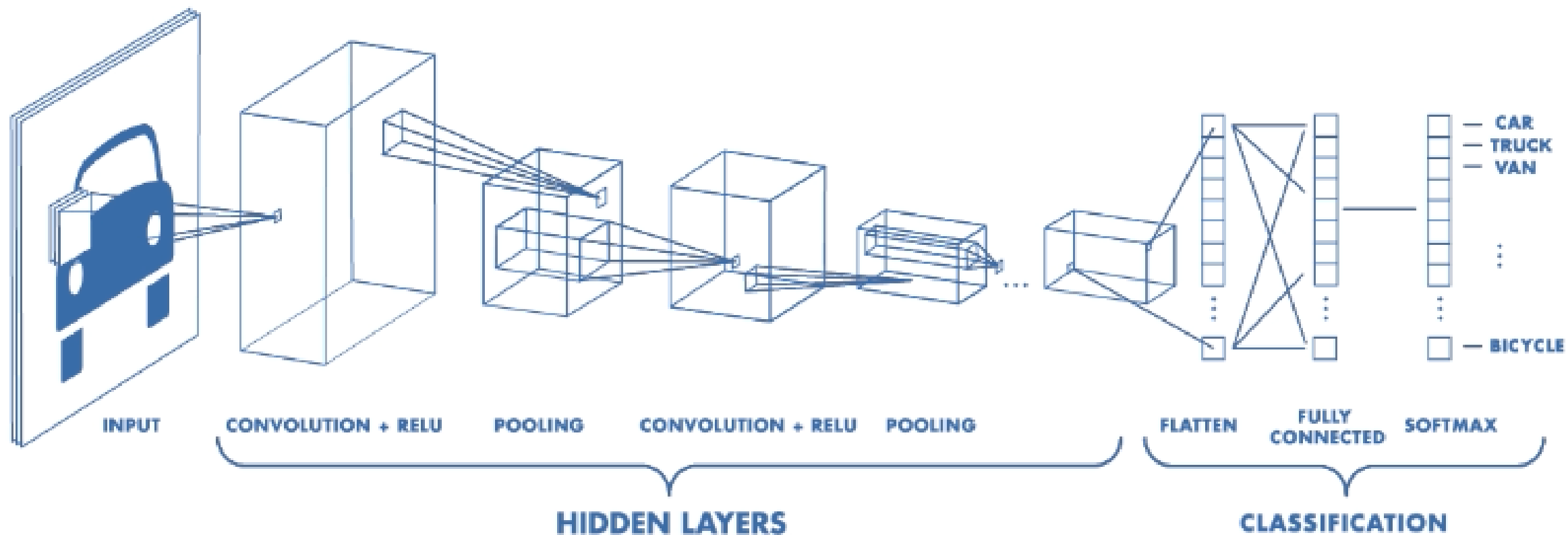


卷积神经网络

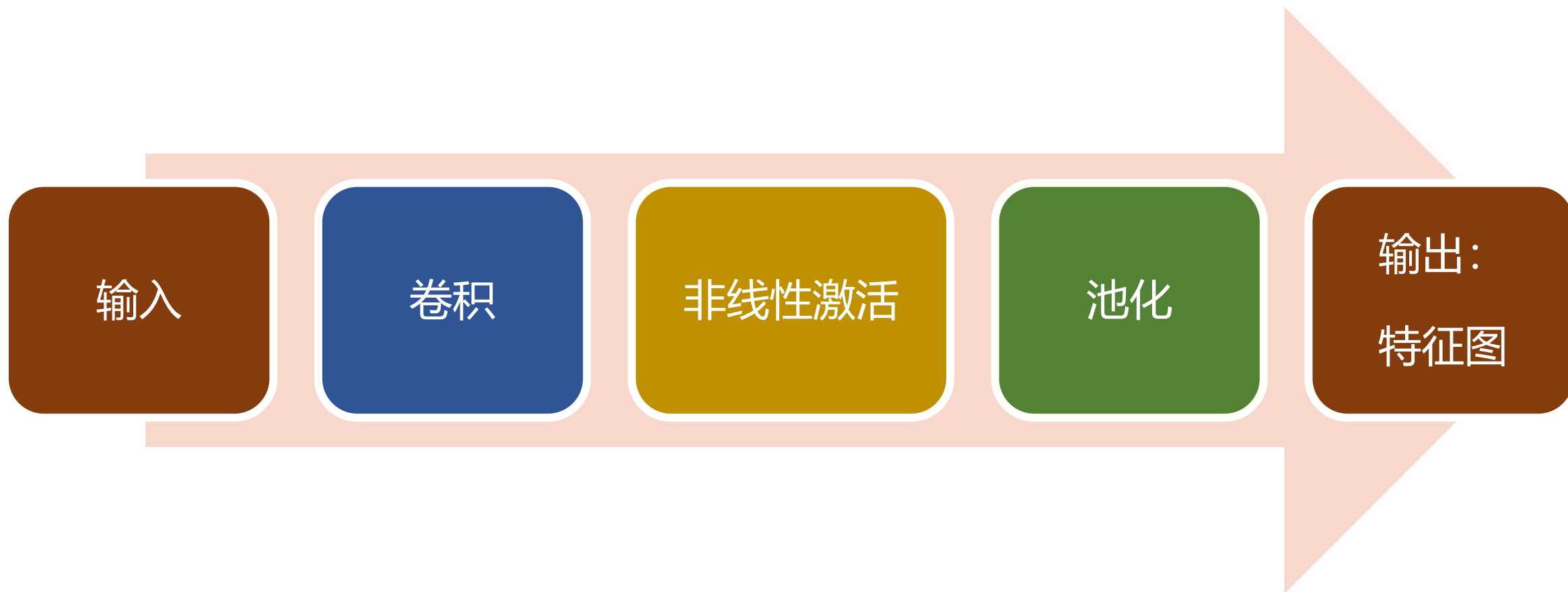
CNN (Convolutional neural network)



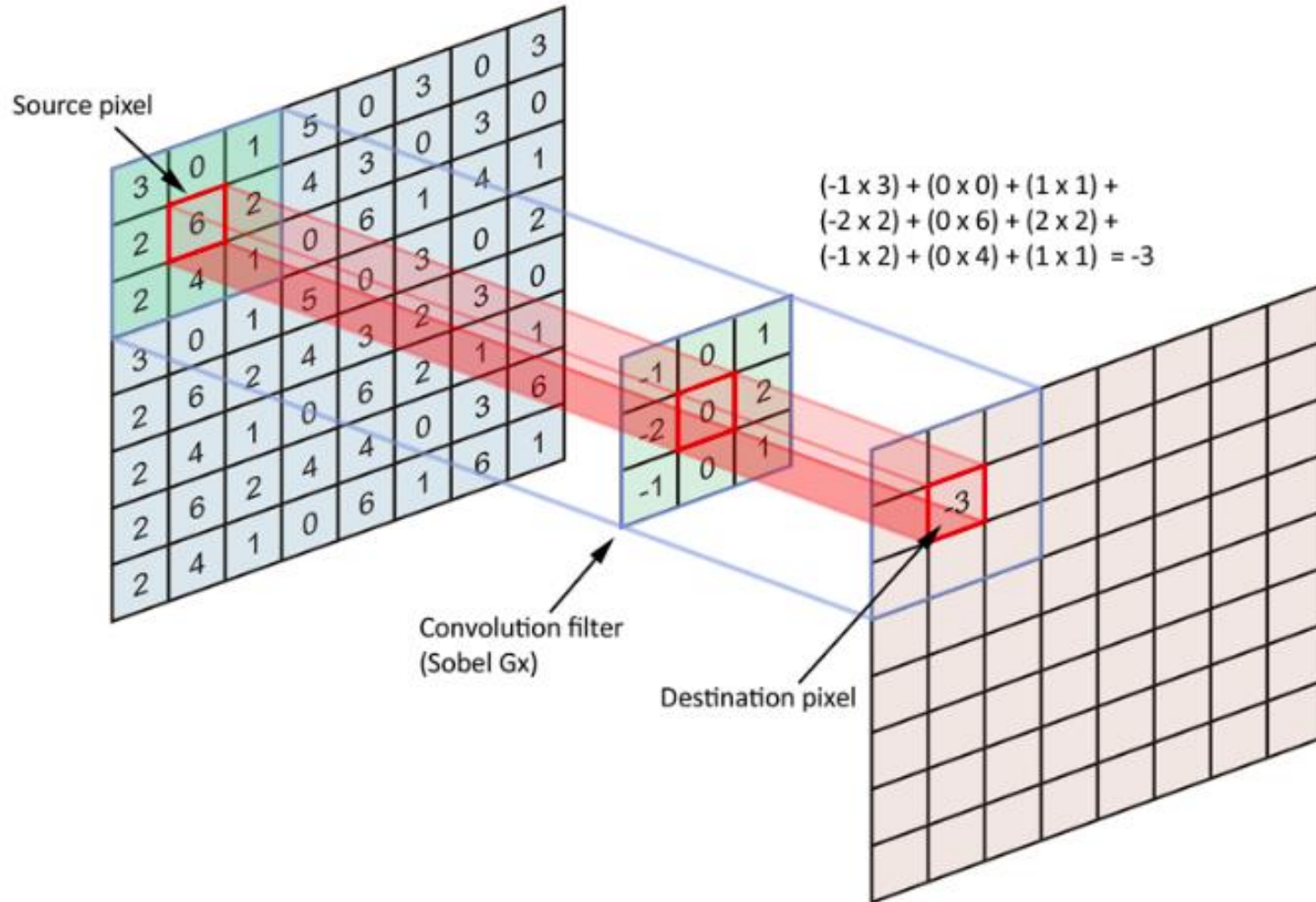
卷积神经网络架构



典型卷积神经网络的层结构



卷积(Convolution)运算



实际上是相关(Cross-Correlation)运算

卷积运算

| | | | | |
|-----------------|-----------------|-----------------|---|---|
| 1 _{x1} | 1 _{x0} | 1 _{x1} | 0 | 0 |
| 0 _{x0} | 1 _{x1} | 1 _{x0} | 1 | 0 |
| 0 _{x1} | 0 _{x0} | 1 _{x1} | 1 | 1 |
| 0 | 0 | 1 | 1 | 0 |
| 0 | 1 | 1 | 0 | 0 |

Image

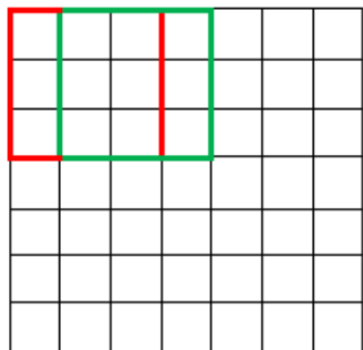
| | | |
|---|--|--|
| 4 | | |
| | | |
| | | |

Convolved
Feature

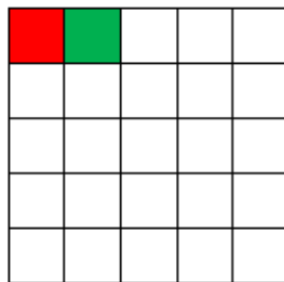
Stride (步幅)和Padding (填充)

7 x 7 Input Volume

5 x 5 Output Volume



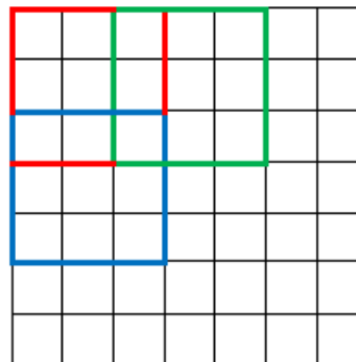
3 x 3 filter



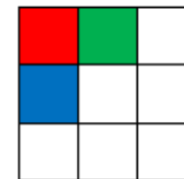
stride = 1

7 x 7 Input Volume

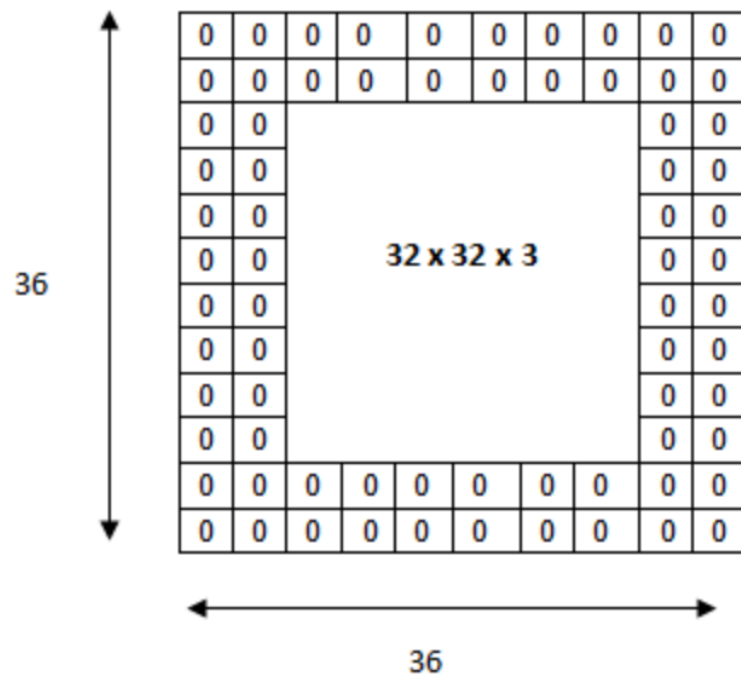
3 x 3 Output Volume



3 x 3 filter



stride = 2



No Zero Padding

$$\text{Zero Padding} = \frac{K - 1}{2}$$

$$O = \frac{W - K + 2P}{S} + 1$$

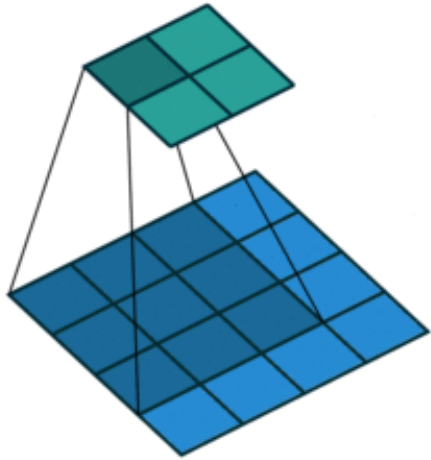
O is the output height/length, W is the input height/length, K is the filter size, P is the padding, and S is the stride



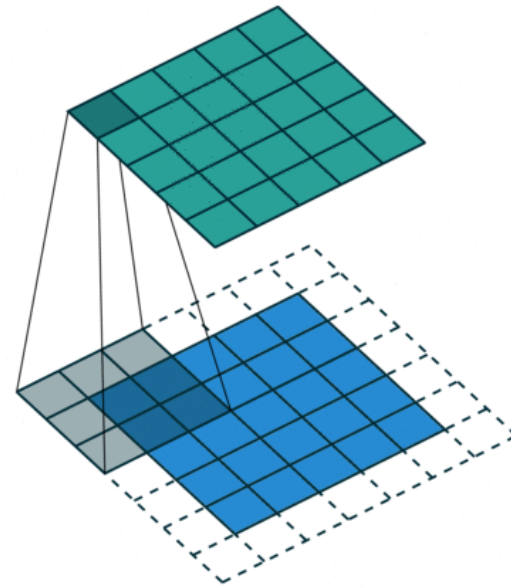
Valid: 输入和输出尺寸不同



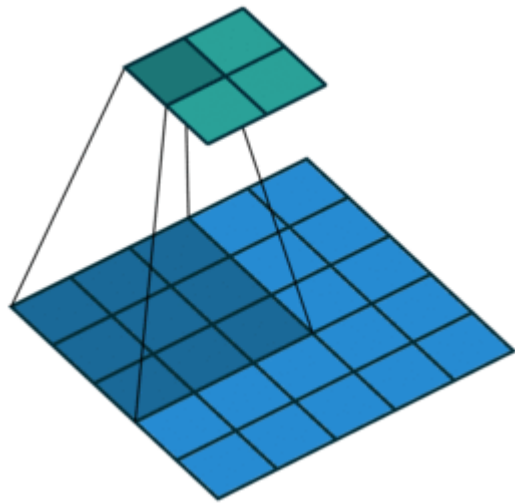
Same: 输入和输出尺寸相同



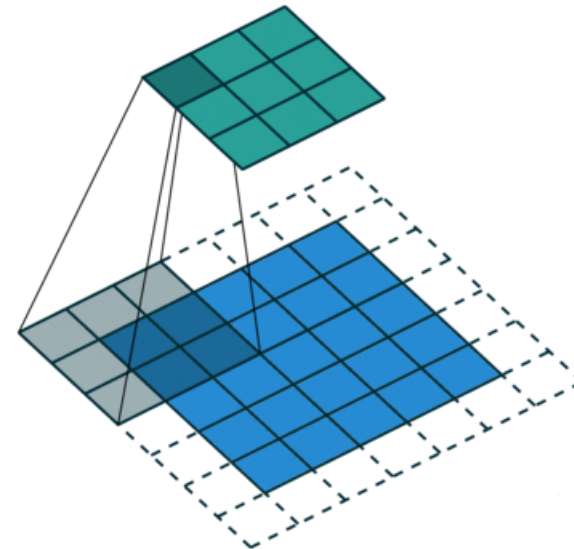
No padding, no strides



Half padding, no strides

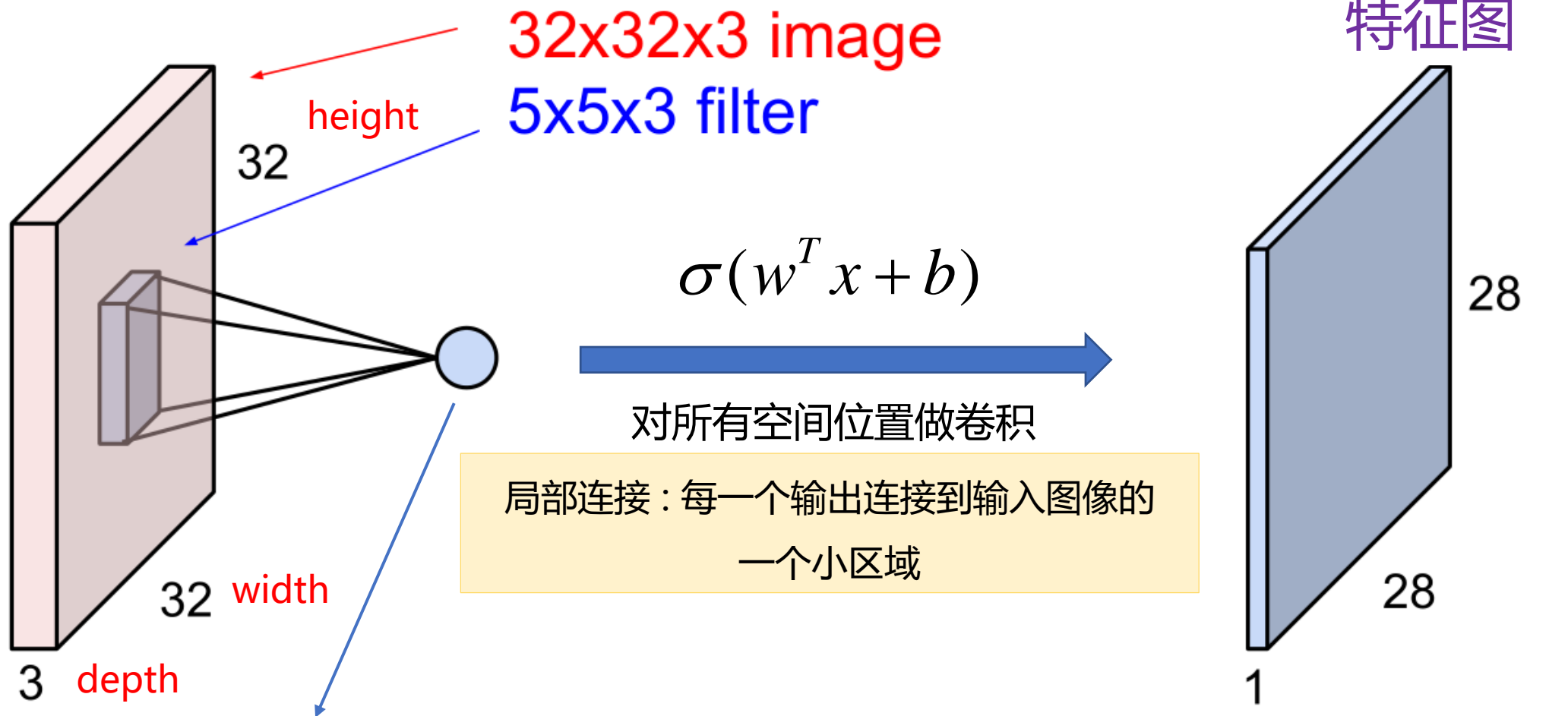


No padding, strides



Padding, strides

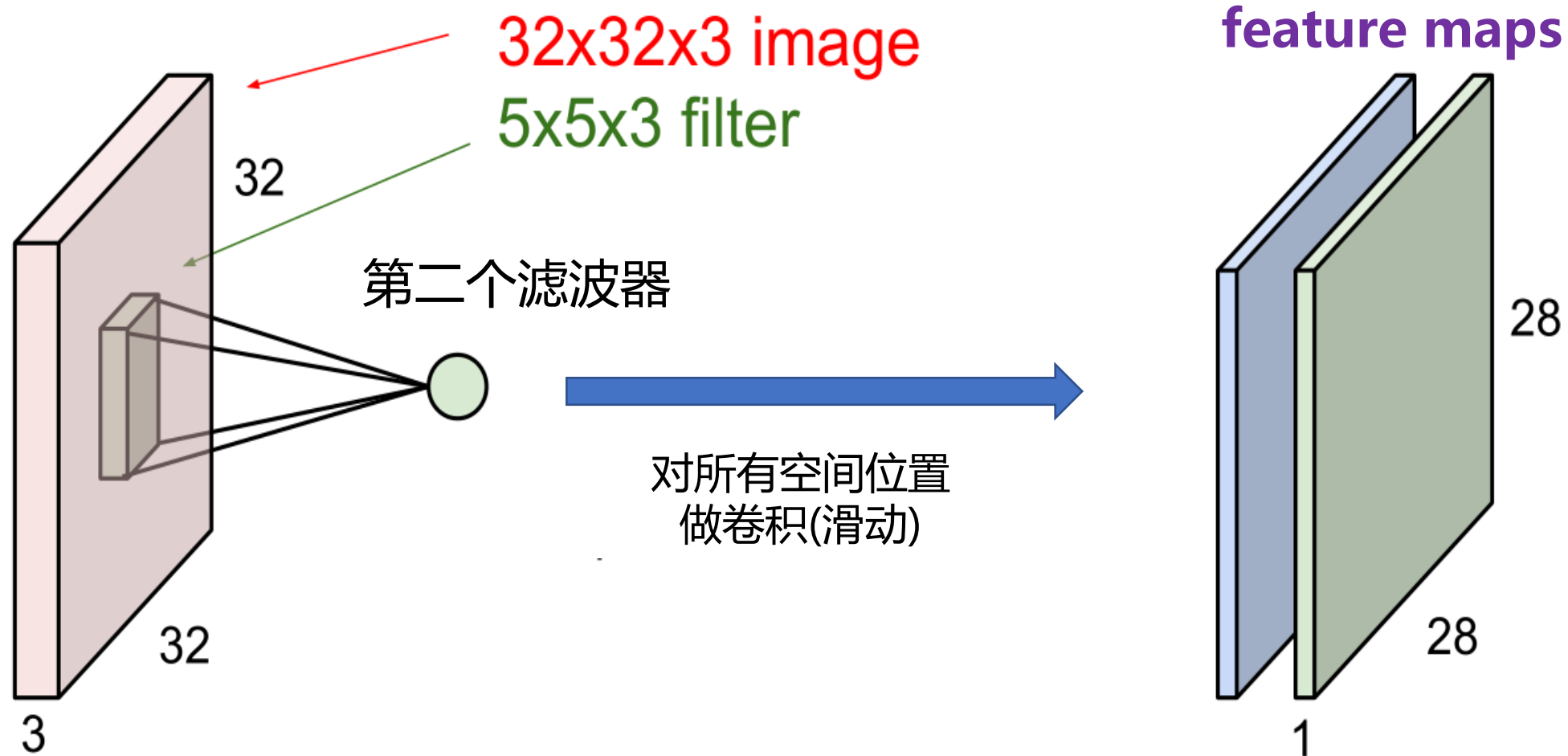
卷积层特点一：局部连接



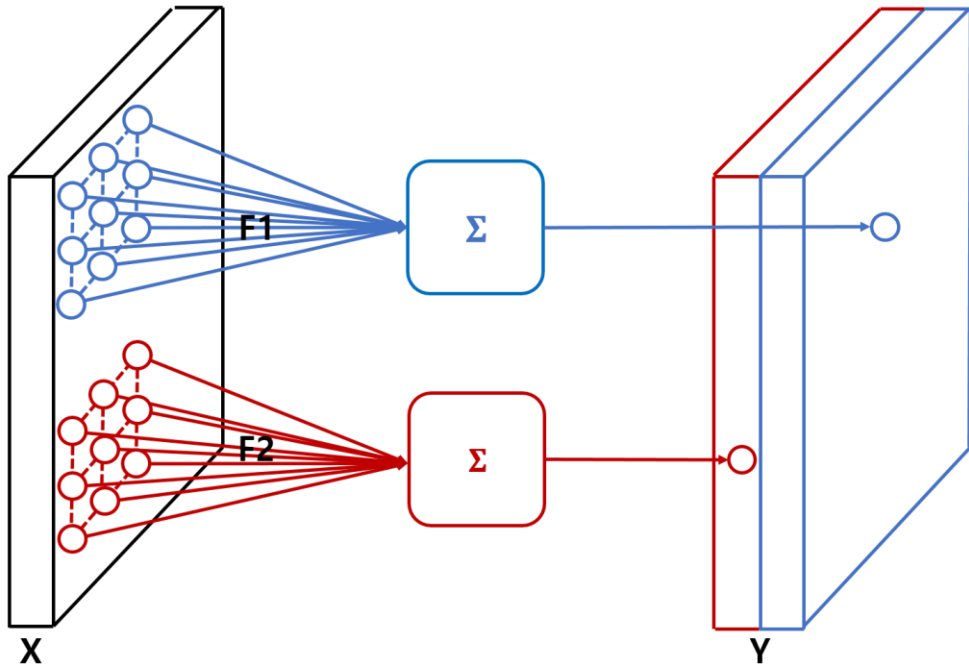
一个数值：滤波器和部分图像像素的点积
($5 \times 5 \times 3 = 75$ -维点积+bias)

5x5 filter → 每个神经元的感受野是5x5

特征图：通过使用线性滤波器对图像进行卷积，添加偏置项并应用非线性函数来获得

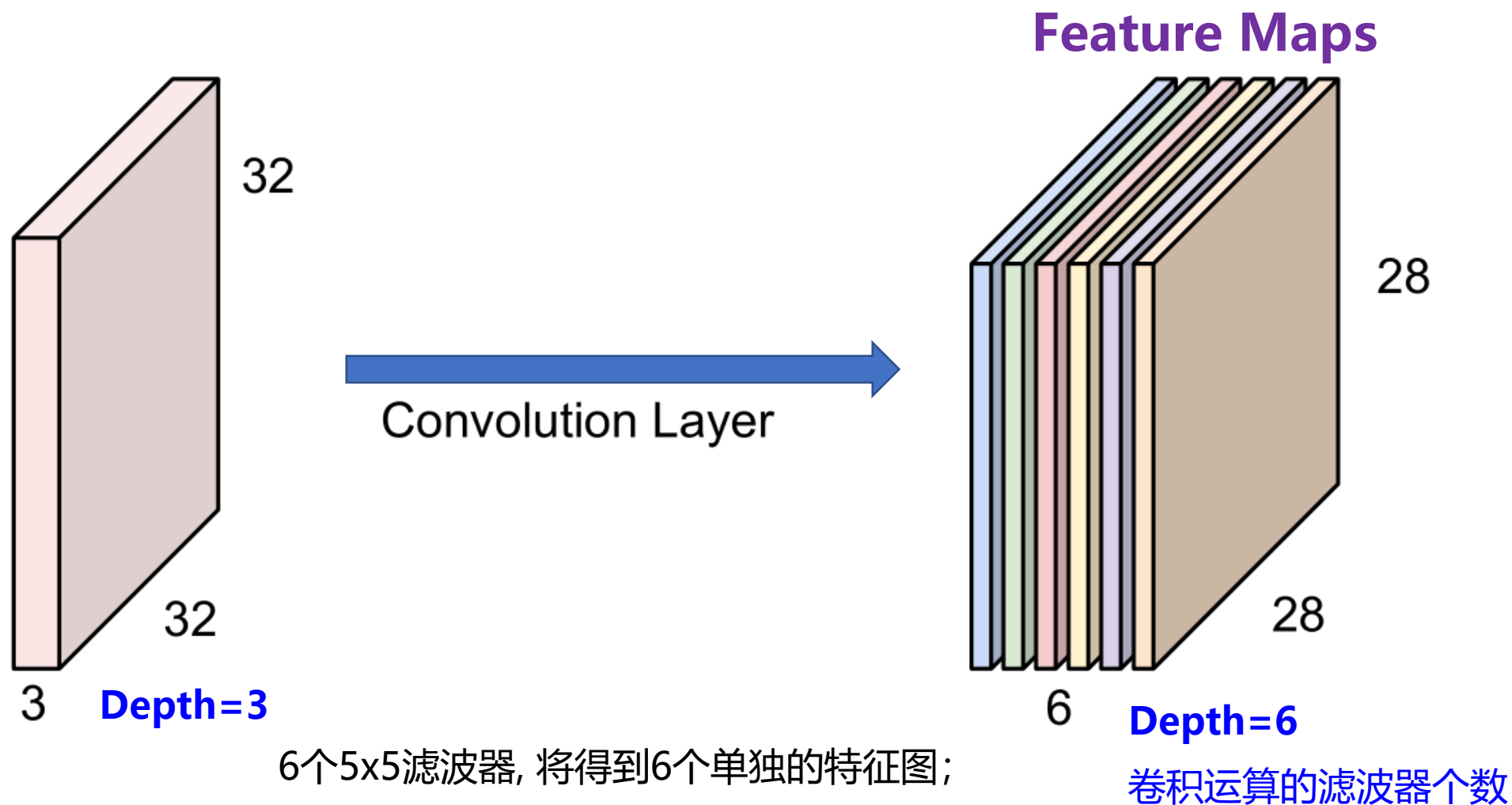


卷积层特点二：参数共享



- 卷积层在空间上**共享权重**；对不同位置的所有输入权重是相同的
- 导致**平移不变性 (translation-invariant)**：平移将在目标相应平移的位置产生相同的响应。

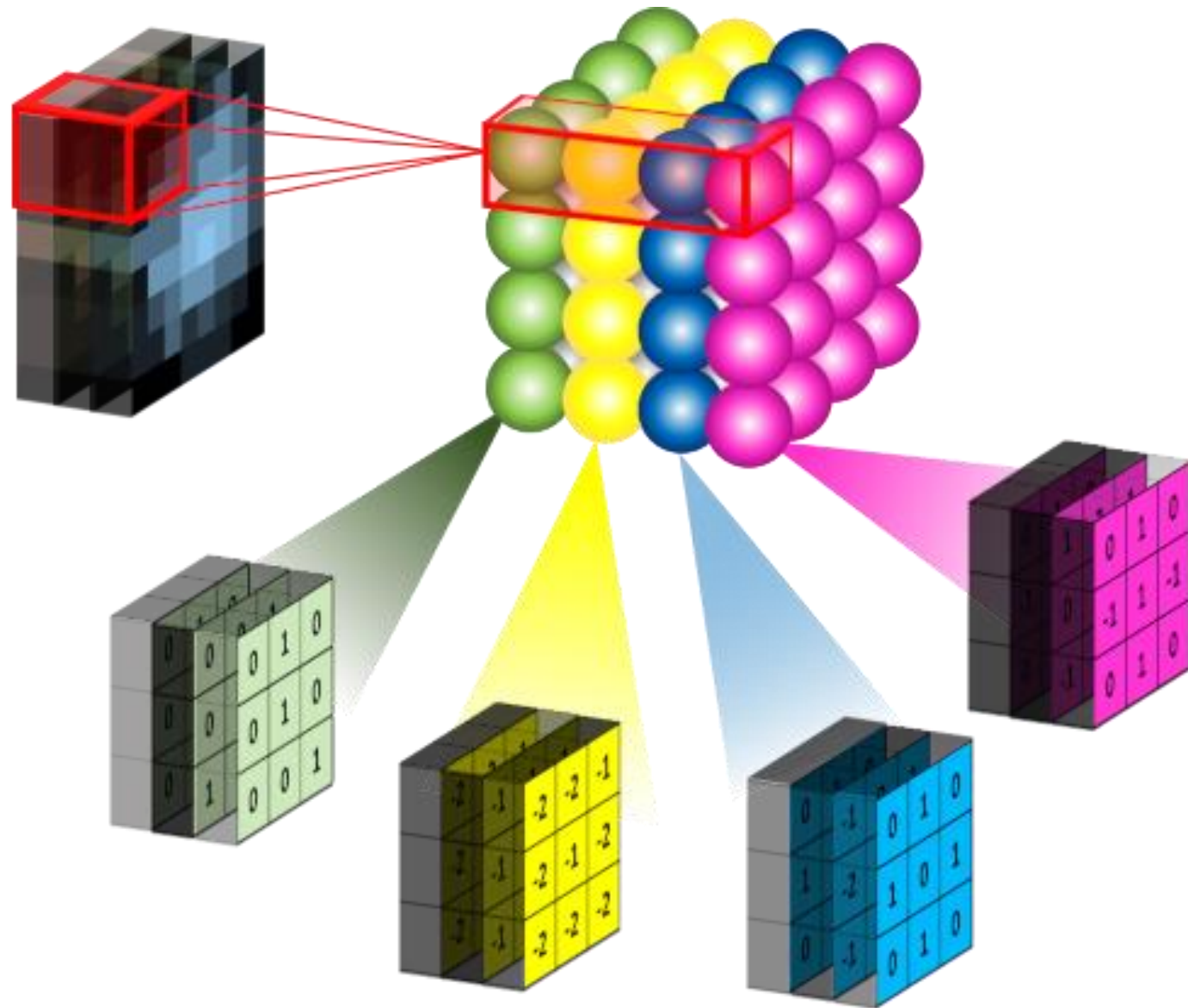




6个5x5滤波器, 将得到6个单独的特征图;
堆叠后得到一个28x28x6的“新图像”

每个隐藏层就是由多个feature maps组成

多通道图像+多卷积核的卷积



Input Volume (+pad 1) (7x7x3)

 $x[:, :, 0]$

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 1 | 0 | 2 | 0 |
| 0 | 1 | 0 | 2 | 0 | 1 | 0 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 1 | 0 | 2 | 2 | 0 | 0 |
| 0 | 2 | 0 | 0 | 2 | 0 | 0 |
| 0 | 2 | 1 | 2 | 2 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |

 $x[:, :, 1]$

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 2 | 1 | 2 | 1 | 1 | 0 |
| 0 | 2 | 1 | 2 | 0 | 1 | 0 |
| 0 | 0 | 2 | 1 | 0 | 1 | 0 |
| 0 | 1 | 2 | 2 | 2 | 2 | 0 |
| 0 | 0 | 1 | 2 | 0 | 1 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 2 | 1 | 0 | 1 | 0 |
| 0 | 1 | 2 | 2 | 2 | 2 | 0 |
| 0 | 0 | 1 | 2 | 0 | 1 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |

 $x[:, :, 2]$

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 2 | 1 | 1 | 2 | 0 | 0 |
| 0 | 1 | 0 | 0 | 1 | 0 | 0 |
| 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 0 | 1 | 0 | 2 | 1 | 0 | 0 |
| 0 | 2 | 2 | 1 | 1 | 1 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Filter W0 (3x3x3)

 $w0[:, :, 0]$

| | | |
|----|----|---|
| -1 | 0 | 1 |
| 0 | 0 | 1 |
| 1 | -1 | 1 |

 $w0[:, :, 1]$

| | | |
|----|----|---|
| -1 | 0 | 1 |
| 1 | -1 | 1 |
| 0 | 1 | 0 |

 $w0[:, :, 2]$

| | | |
|----|----|---|
| -1 | 1 | 1 |
| 1 | 1 | 0 |
| 0 | -1 | 0 |

Bias b0 (1x1x1)

 $b0[:, :, 0]$

| |
|---|
| 1 |
|---|

Filter W1 (3x3x3)

 $w1[:, :, 0]$

| | | |
|---|----|----|
| 0 | 1 | -1 |
| 0 | -1 | 0 |
| 0 | -1 | 1 |

 $w1[:, :, 1]$

| | | |
|----|----|---|
| -1 | 0 | 0 |
| 1 | -1 | 0 |
| 1 | -1 | 0 |

 $w1[:, :, 2]$

| | | |
|----|----|----|
| -1 | 1 | -1 |
| 0 | -1 | -1 |
| 1 | 0 | 0 |

Bias b1 (1x1x1)

 $b1[:, :, 0]$

| |
|---|
| 0 |
|---|

Output Volume (3x3x2)

 $o[:, :, 0]$

| | | |
|---|----|----|
| 2 | 3 | 3 |
| 3 | 7 | 3 |
| 8 | 10 | -3 |

 $o[:, :, 1]$

| | | |
|----|----|----|
| -8 | -8 | -3 |
| -3 | 1 | 0 |
| -3 | -8 | -5 |

多通道图像+多卷积核的卷积

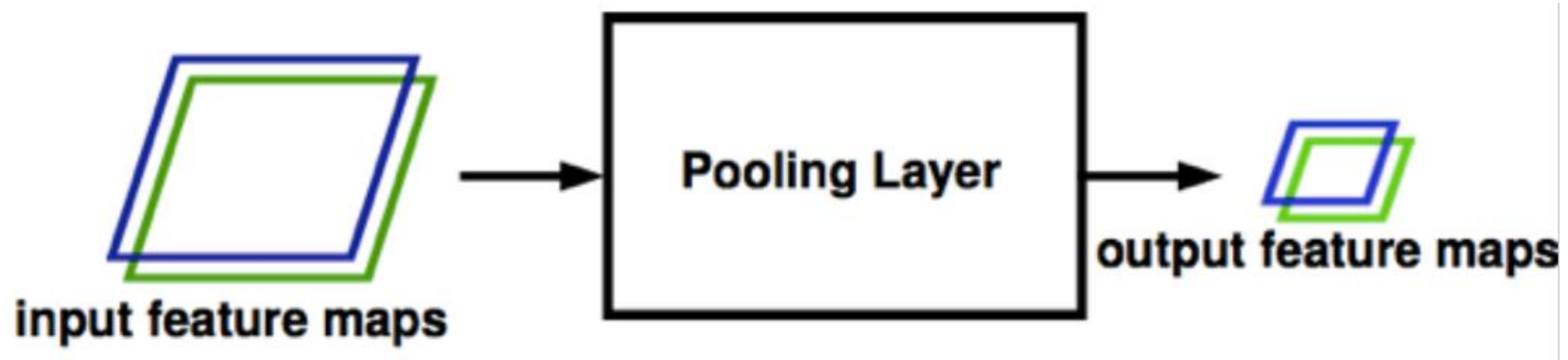
输入有3个通道，同时有2个卷积核。对于每个卷积核，先在输入3个通道分别作卷积，再将3个通道结果加起来得到卷积输出。

所以对于某个卷积层，无论输入图像有多少个通道，输出图像通道数总是等于卷积核数量！

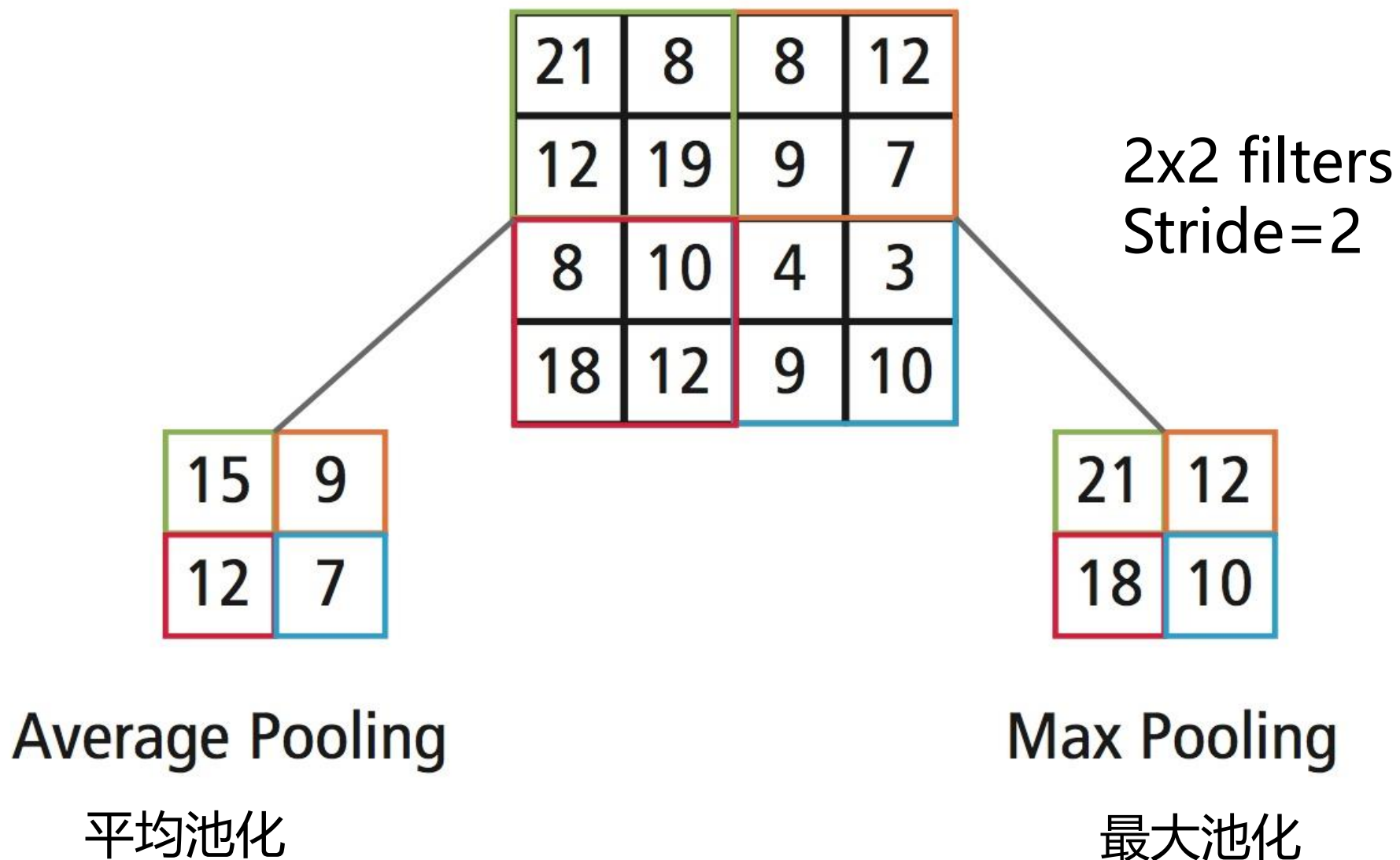
toggle movement

池化 (Pooling)

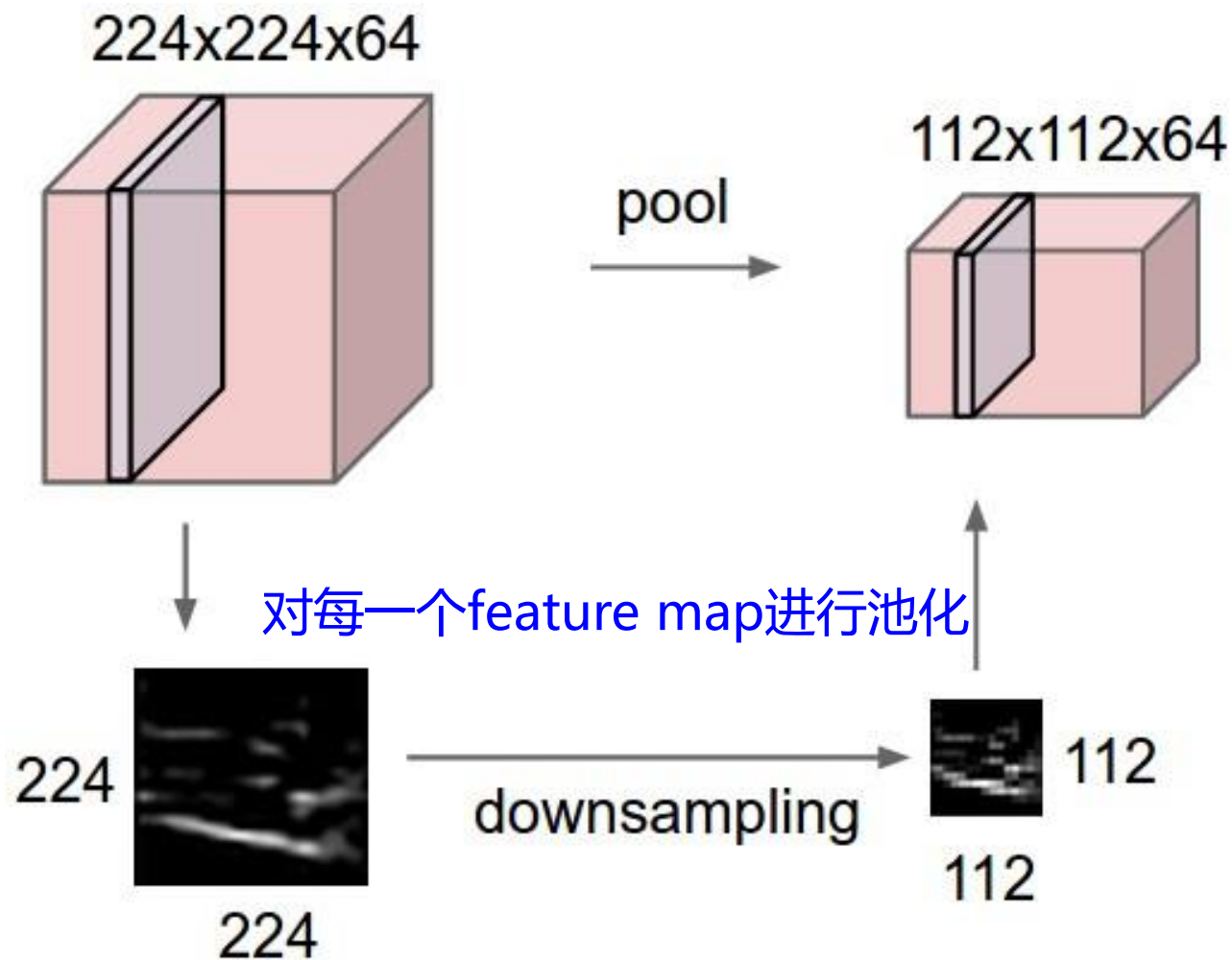
- 非线性下采样(down-sampling)来减小特征图尺寸



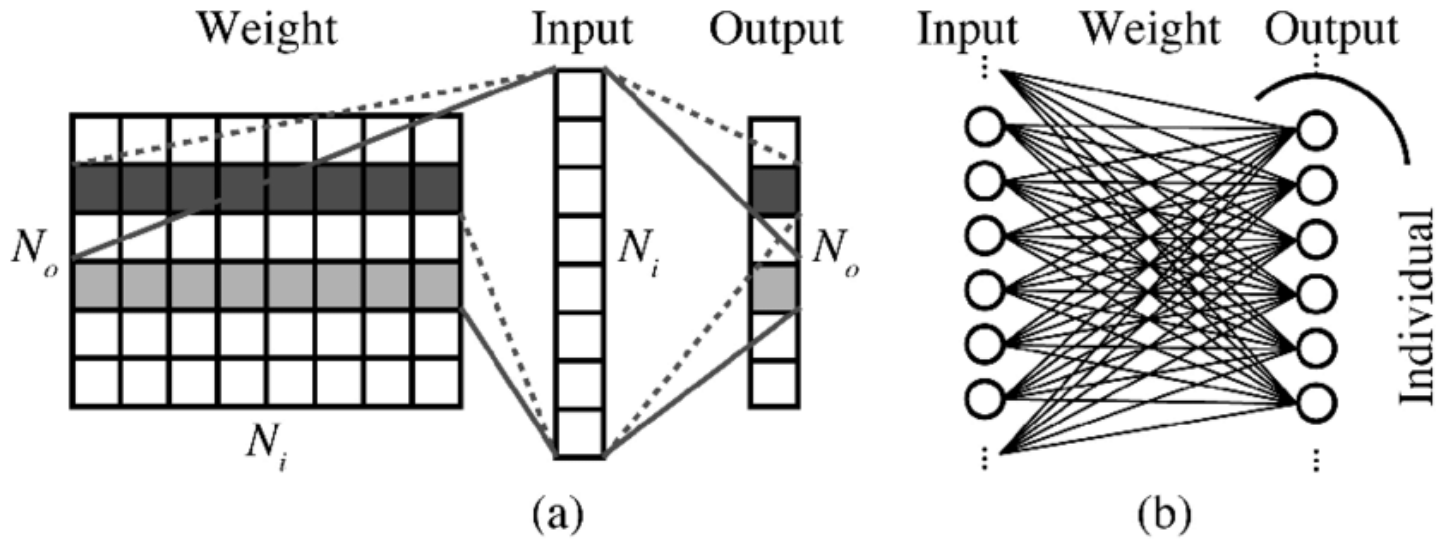
池化 (Pooling)



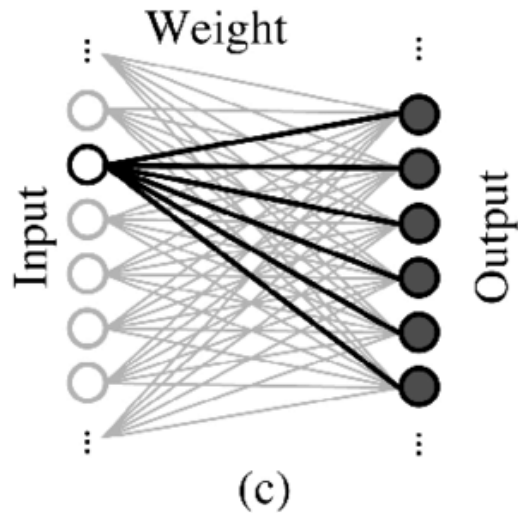
池化层



全连接层(Fully Connected Layer)



将学习到的特征表示映射到
样本的标记空间



全连接层(Fully Connected Layer)

32x32x3 image → 展平成 3072 x 1

