# IT5005 Artificial Intelligence

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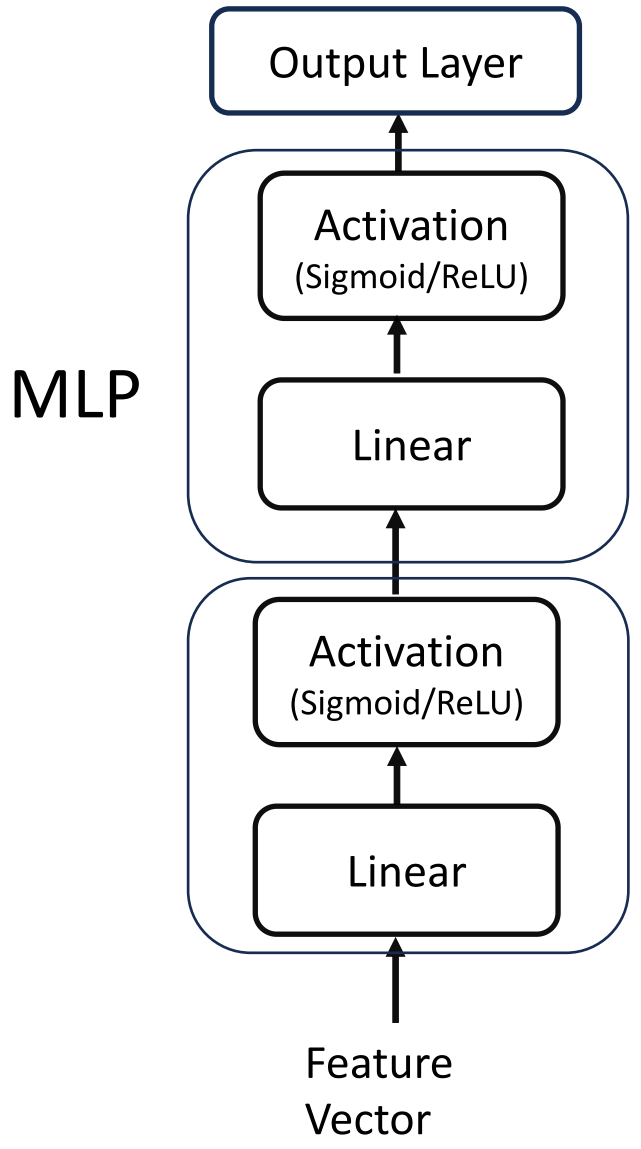
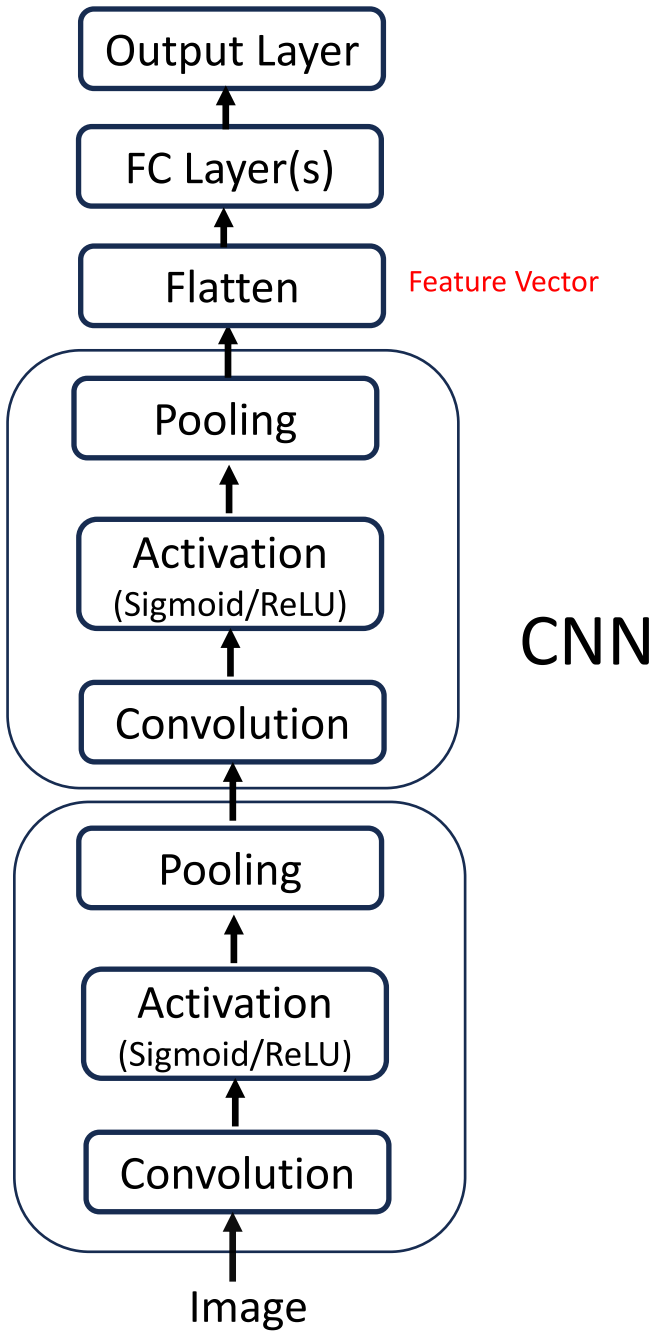
AY2025/2026: Semester 1

## CNN Contd.

# MLP Vs CNN


Output Layer
Activation
(Sigmoid/ReLU)
Linear
MLP
Activation
(Sigmoid/ReLU)
Linear
Feature
Vector

Vs


Output Layer
FC Layer(s)
Flatten
Feature Vector
Pooling
Activation
(Sigmoid/ReLU)
Convolution
CNN
Pooling
Activation
(Sigmoid/ReLU)
Convolution
Image

# A Closer Look at CNN Architecture

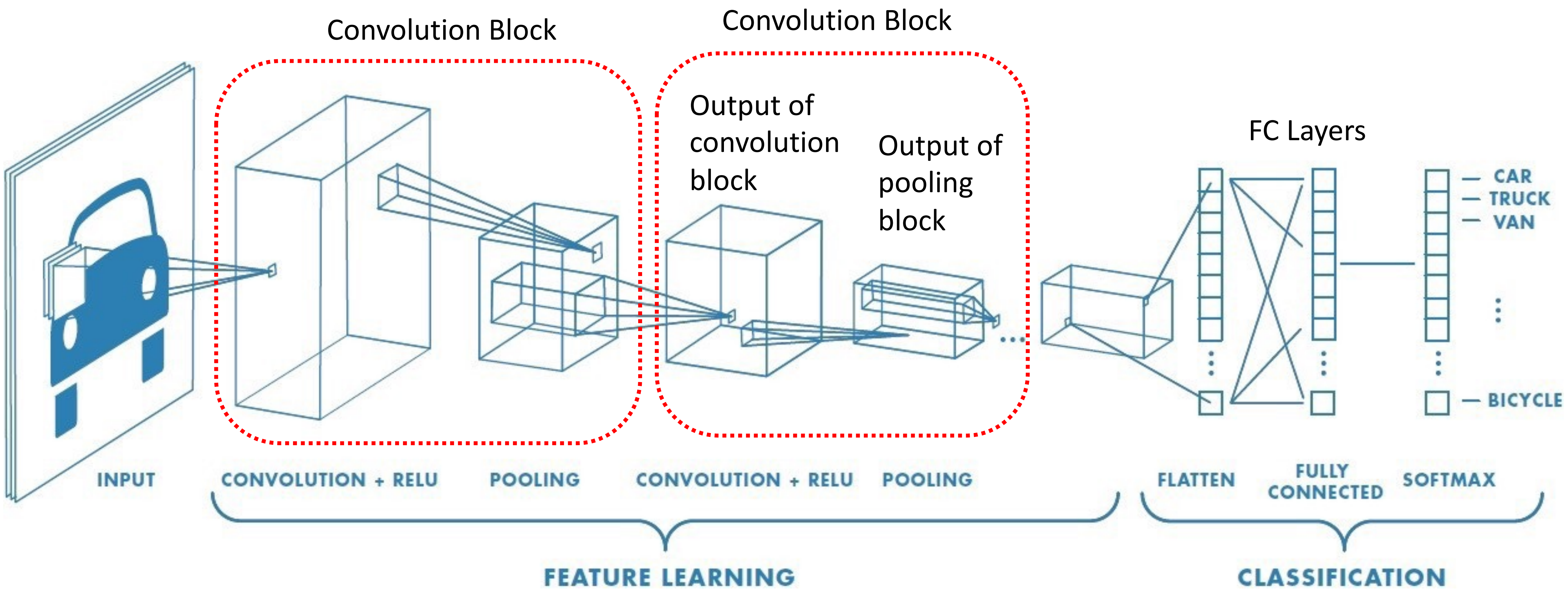
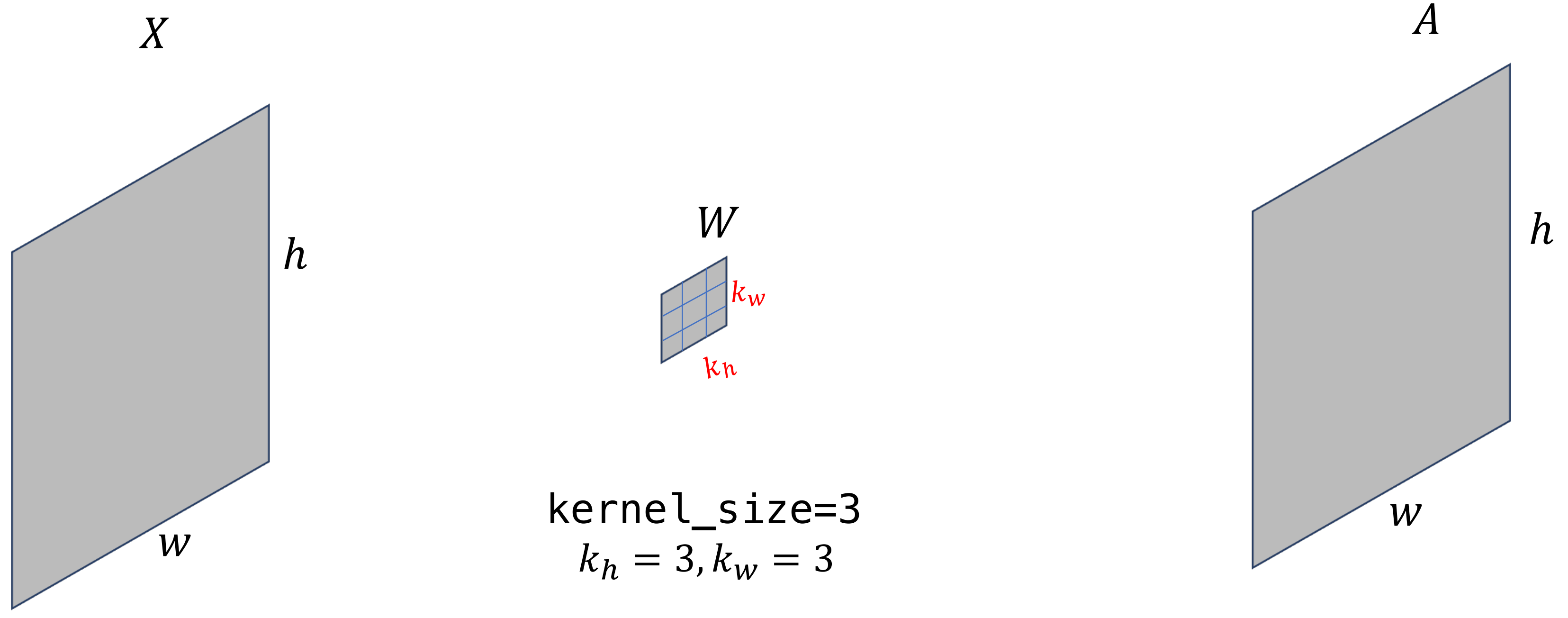


Image credit: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

# Convolution Layer

```
nn.Conv2d(in_channels= , out_channels= , kernel_size=3, stride=1, padding=1)
```



`kernel_size=3`

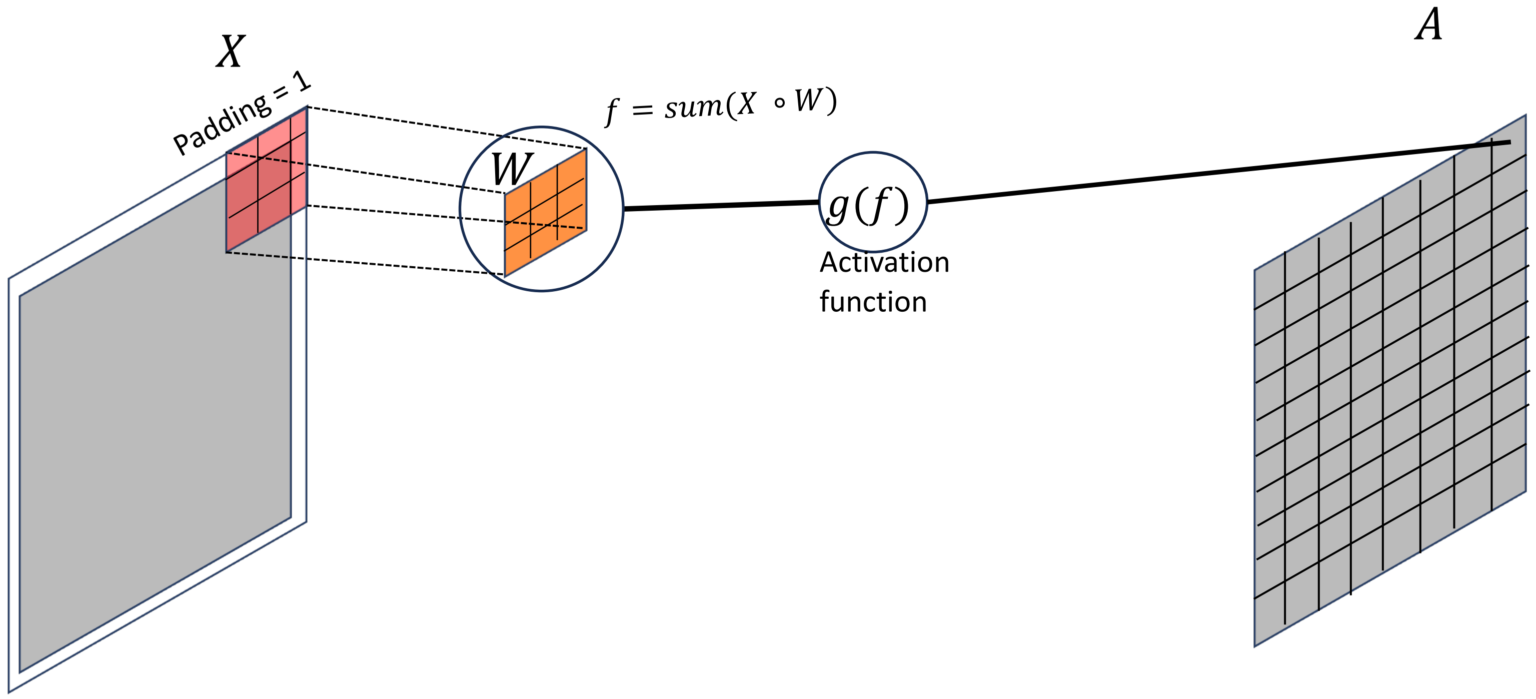
$k_h = 3, k_w = 3$

# Convolution Layer

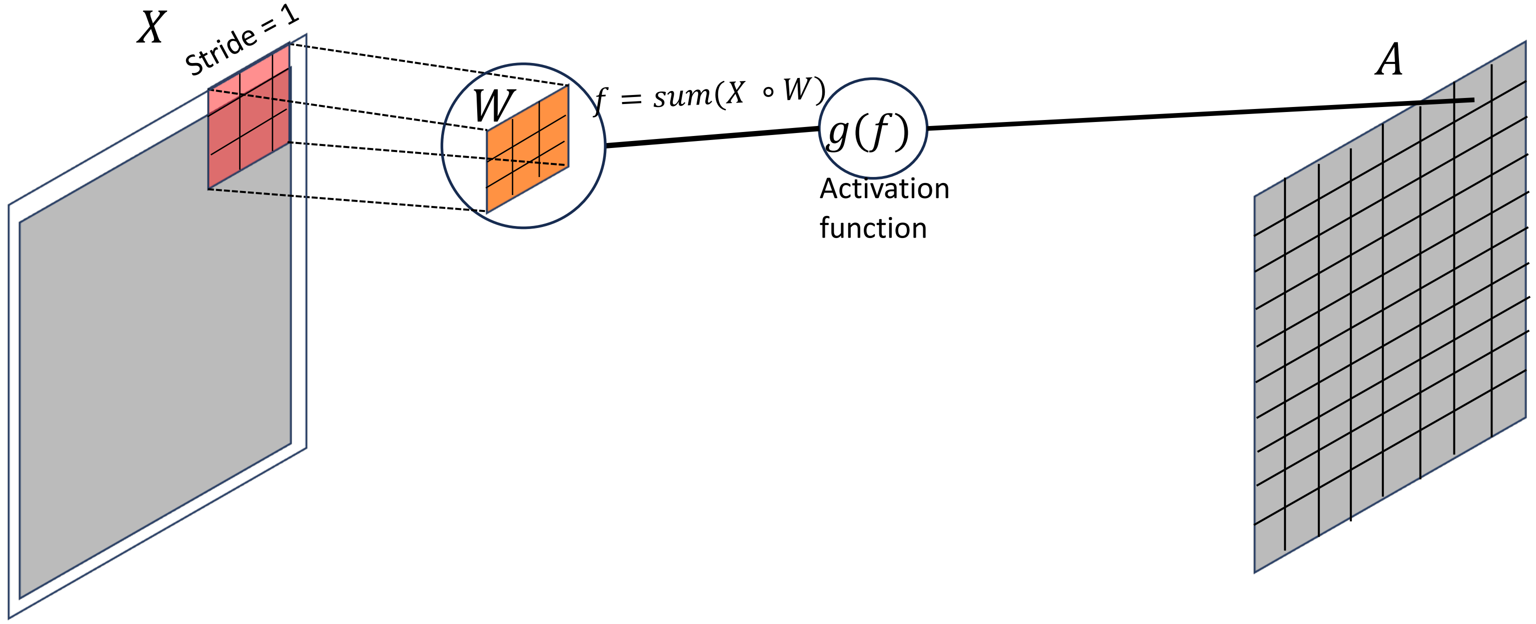
$$f = sum(X \circ W)$$

1. $X \circ W$ : Elementwise multiplication of $W$ and $X$
2. $sum(X \circ W)$ sum of the elements of $X \circ W$

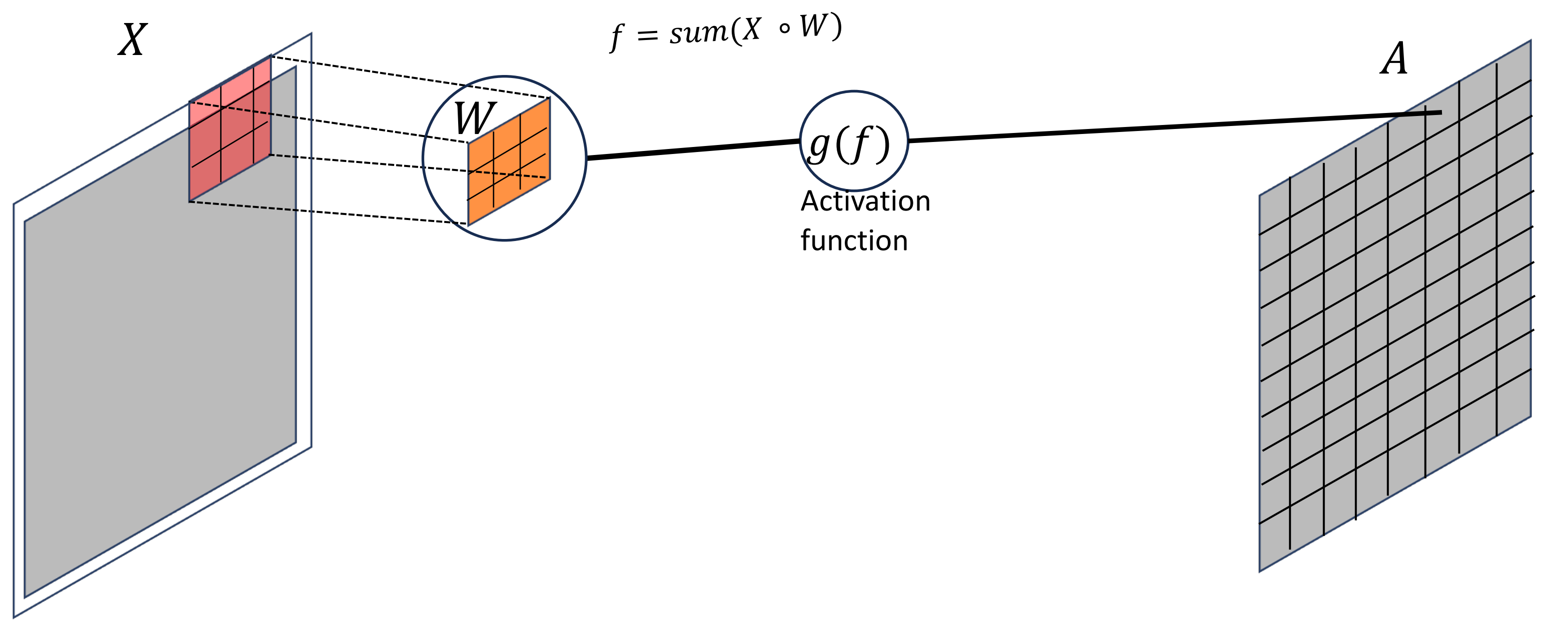
$\left.\right\}$ MAC: Multiply-Accumulate



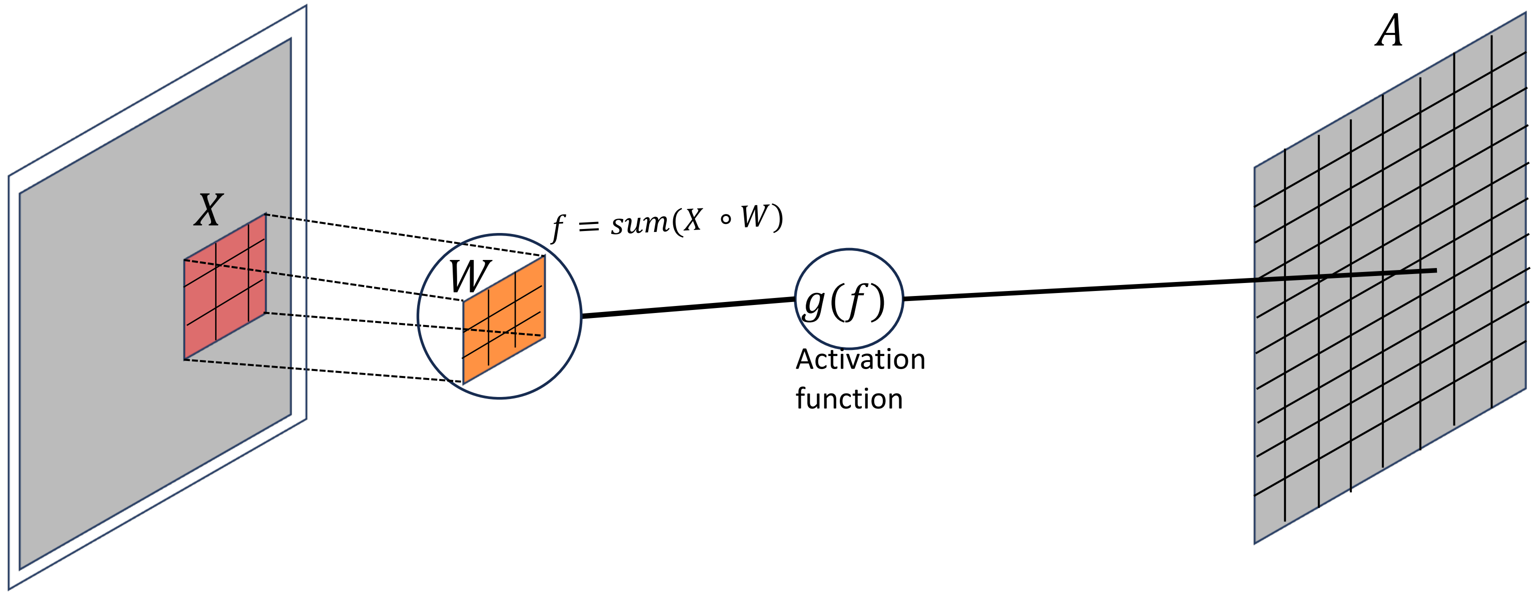
# Convolution + Pooling Layer: Gray Scale Image



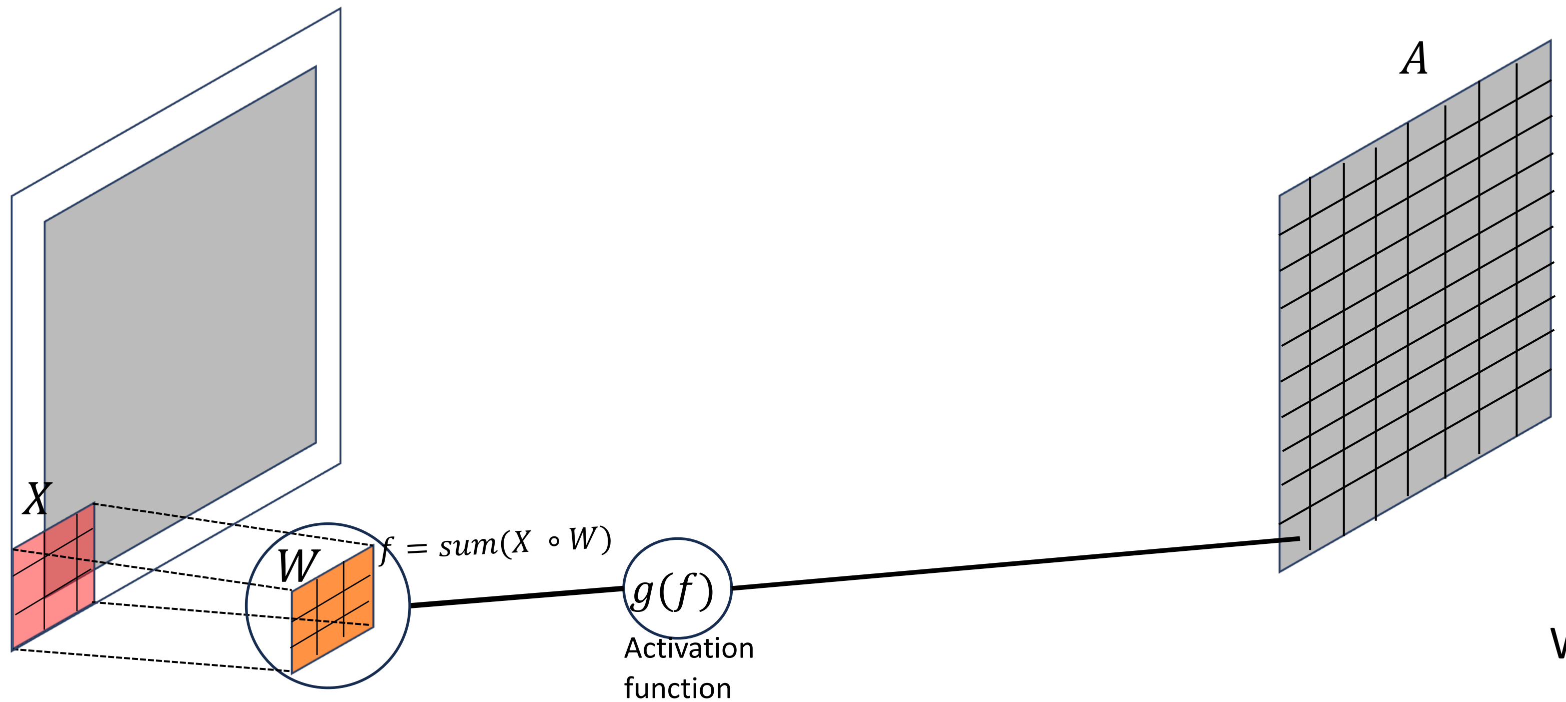
# Convolution + Pooling Layer: Gray Scale Image



# Convolution + Pooling Layer: Gray Scale Image



# Convolution + Pooling Layer: Gray Scale Image



What is the shape of $A$?

How many parameters (weights)?

# Size of Each Kernel's Output

$$O = \left\lfloor \frac{I + 2P - K}{S} \right\rfloor + 1$$

where

$O$ is the output dimension (either height or width).

$I$ is the output dimension (either height or width).

$P = padding$

$K = kernel\_size$

$S = stride$

Usually, the convolution layer is designed to retain the height and width of input, i.e., $O = I$

Height and width of convolution layer's output are independent of $in\_channels$ and $out\_channels$

```
nn.Conv2d(in_channels= 1,out_channels= 1, kernel_size=3, stride=1, padding=1)
```

## Parameter Count for Convolution Layers

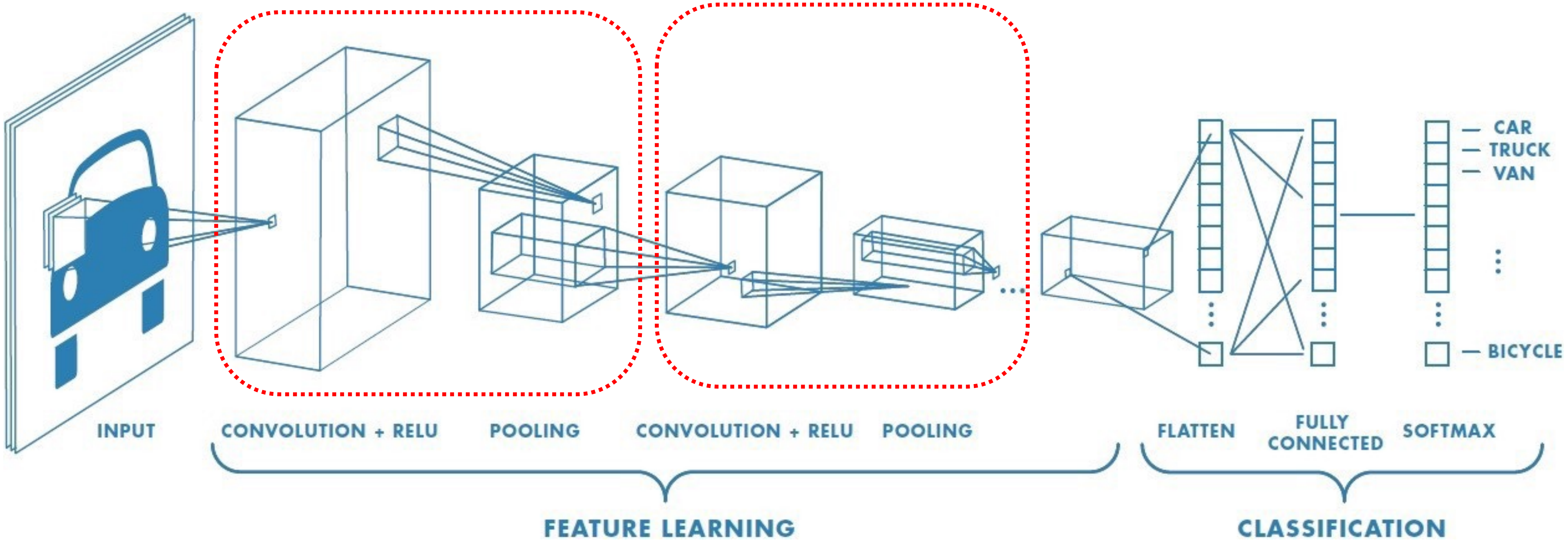
- # of Parameters = ($kernel\_size * kernel\_size * in\_channels * out\_channels$) + # of bias terms

- Each kernel (neuron) has one bias term
  - # of kernels = $out\_channels$
  - # of bias terms = $out\_channels$

- Parameter count is independent of $stride$ and $padding$

```
nn.Conv2d(in_channels= , out_channels= , kernel_size=3, stride=1, padding=1)
```

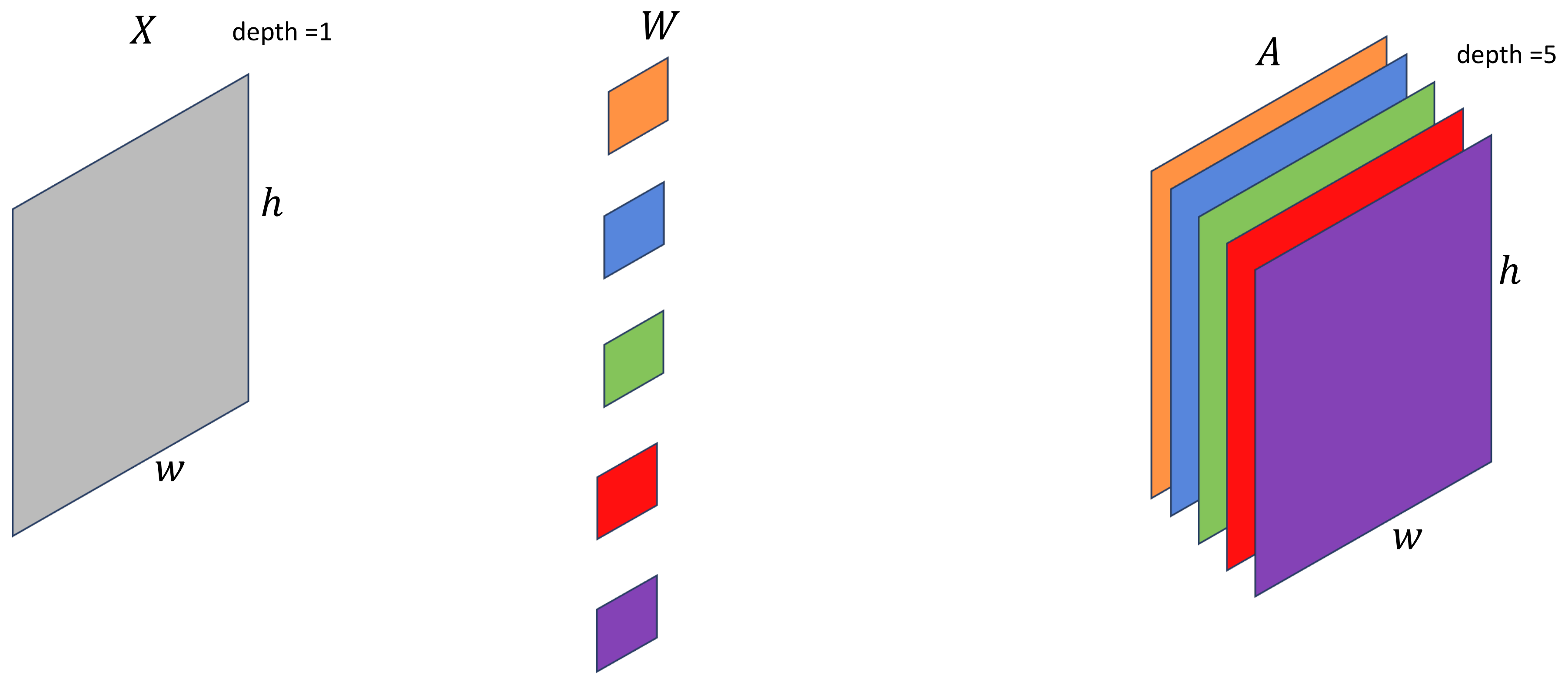
## How to increase depth?



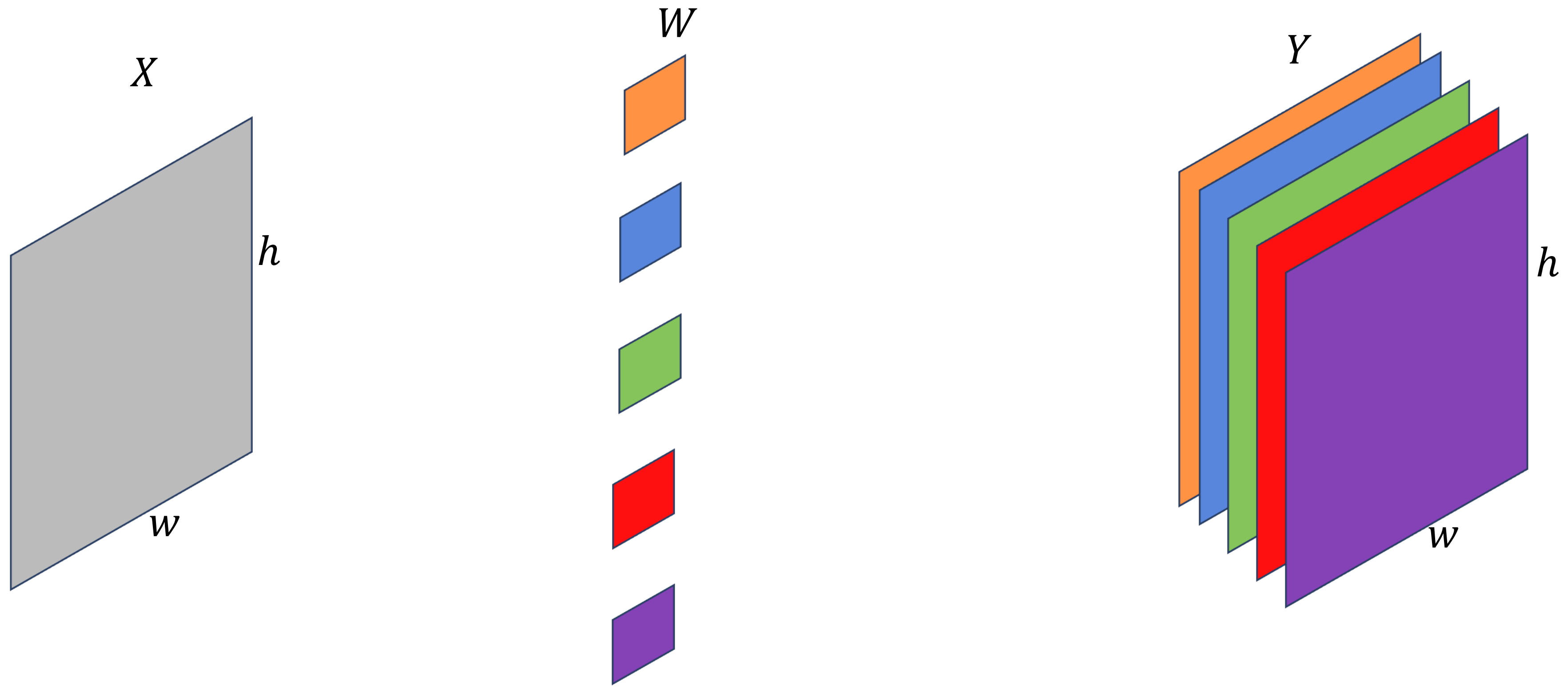
# Convolution Layer: Gray Scale Image

How to increase the depth?

Multiple Kernels!!!



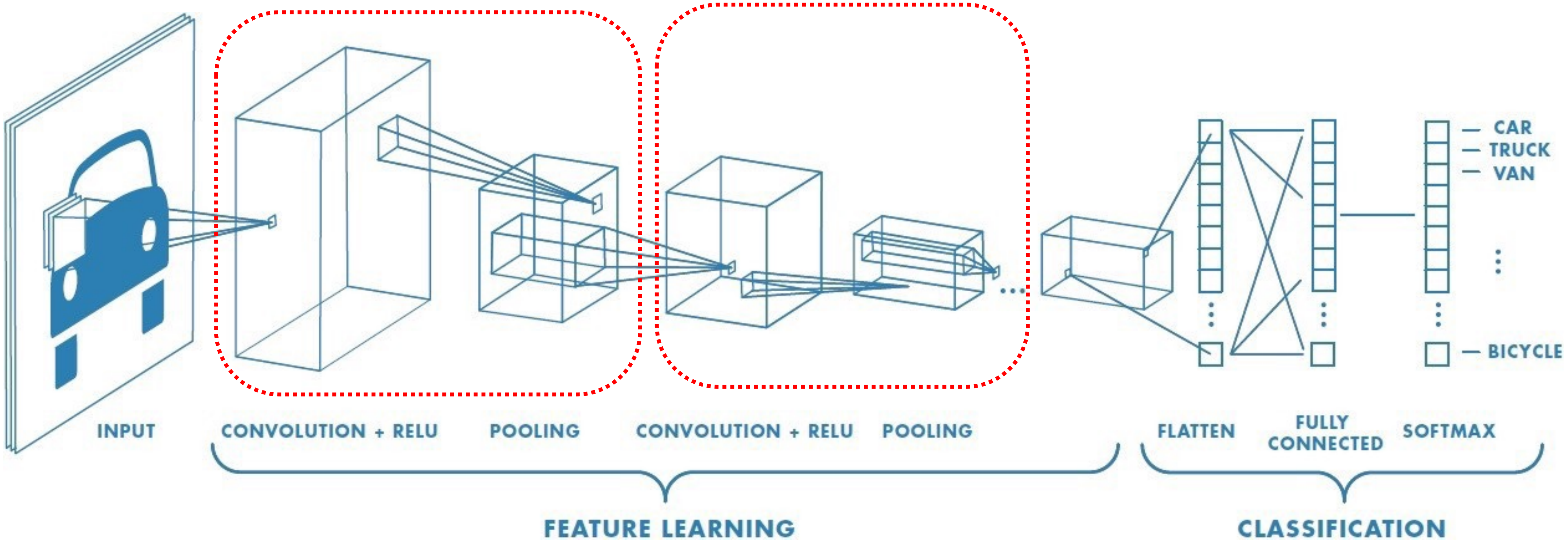
# Convolution Layer



```
nn.Conv2d(in_channels=__, out_channels= __, kernel_size= 3 , stride=1, padding=1)
```

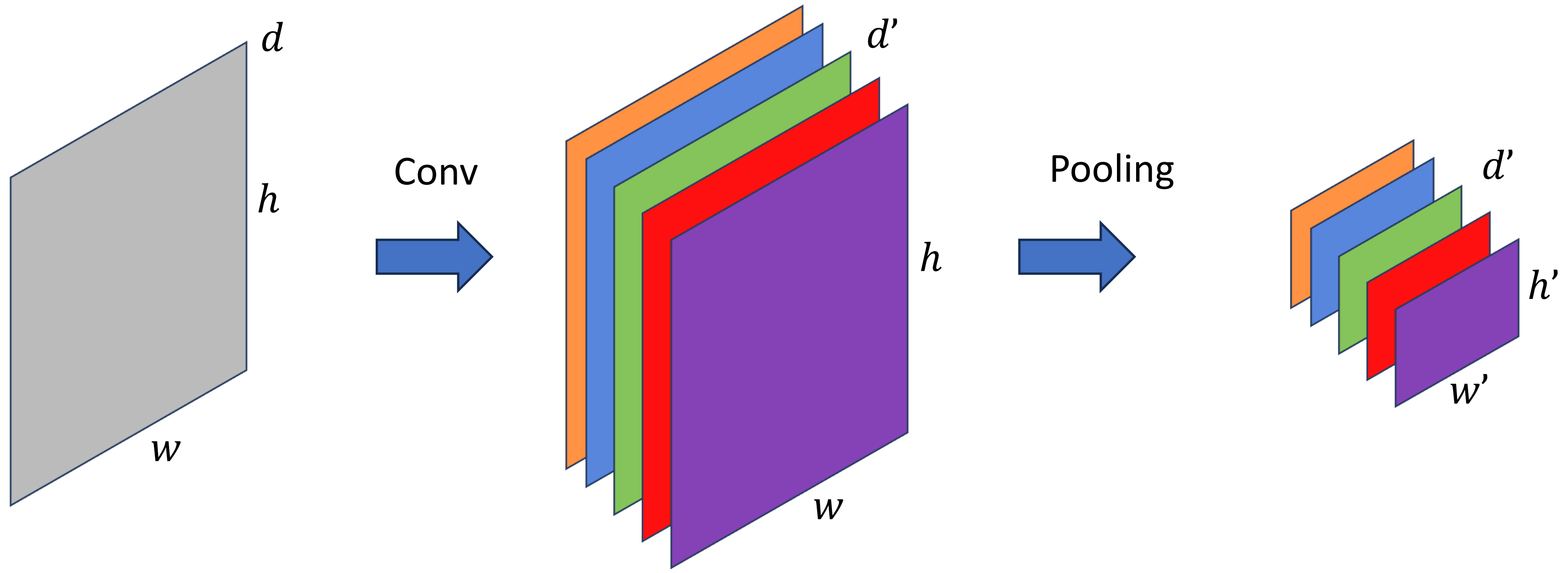
**What is the dimension of each kernel**?

How to reduce height and width?
Why should we reduce height and width?



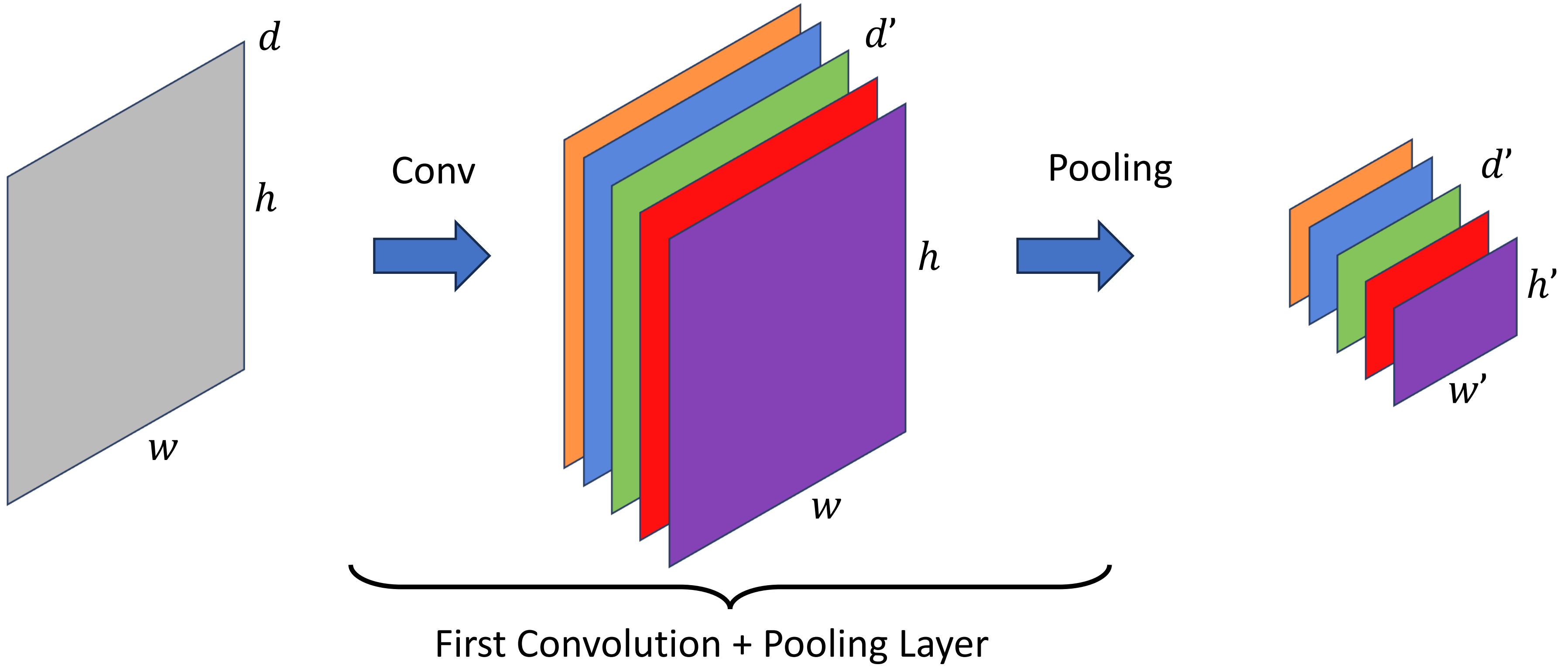
# How to reduce height and width?

$h' = \frac{h}{2}$ $w' = \frac{w}{2}$



# How to reduce height and width?

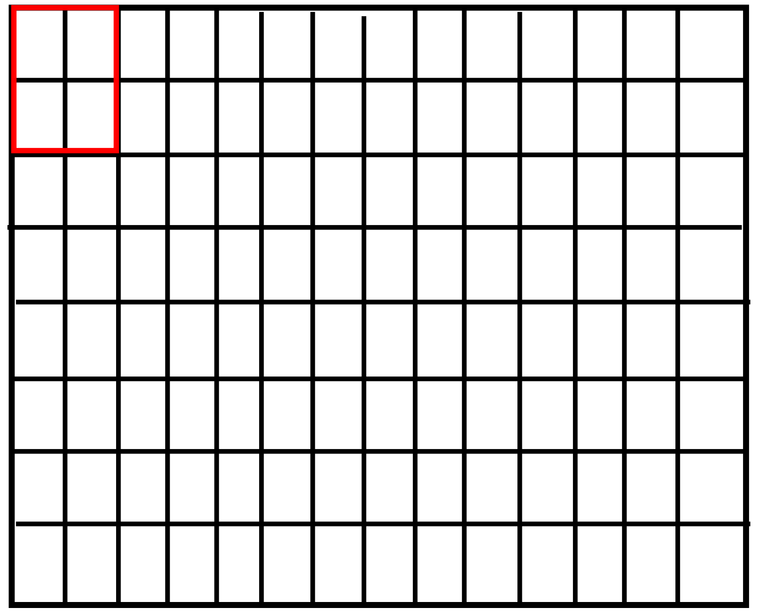
$$h' = \frac{h}{2} \qquad w' = \frac{w}{2}$$

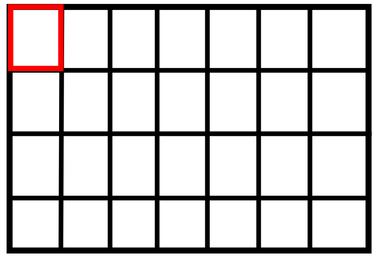


```
nn.Conv2d(in_channels=1, out_channels= 5, kernel_size= 3 , stride=1, padding=1)
max_pool_2D = nn.MaxPool2d(kernel_size = 2,stride = 2)
```

# Max Pooling

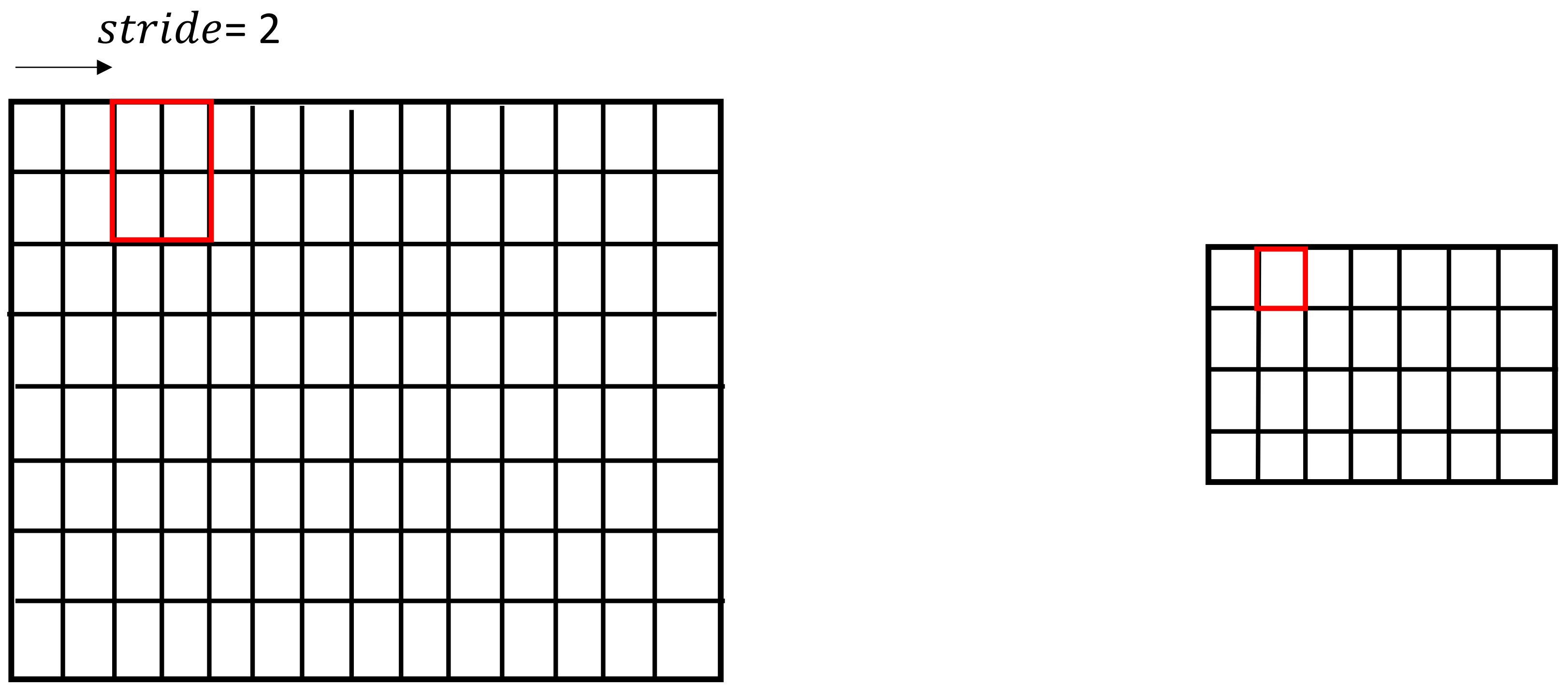
$kernel\_size = 2$





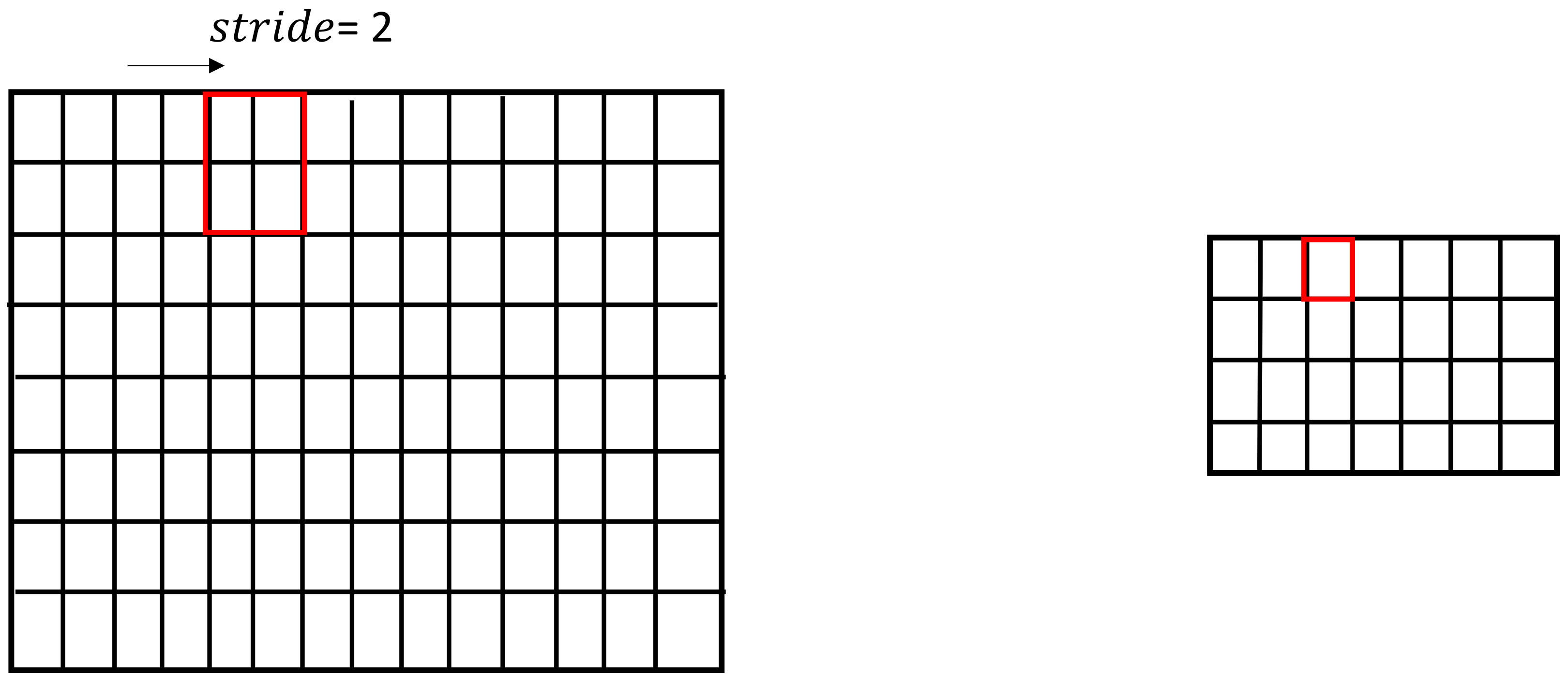
```
max_pool_2D = nn.MaxPool2d(kernel_size = 2,stride = 2)
```

# Max Pooling



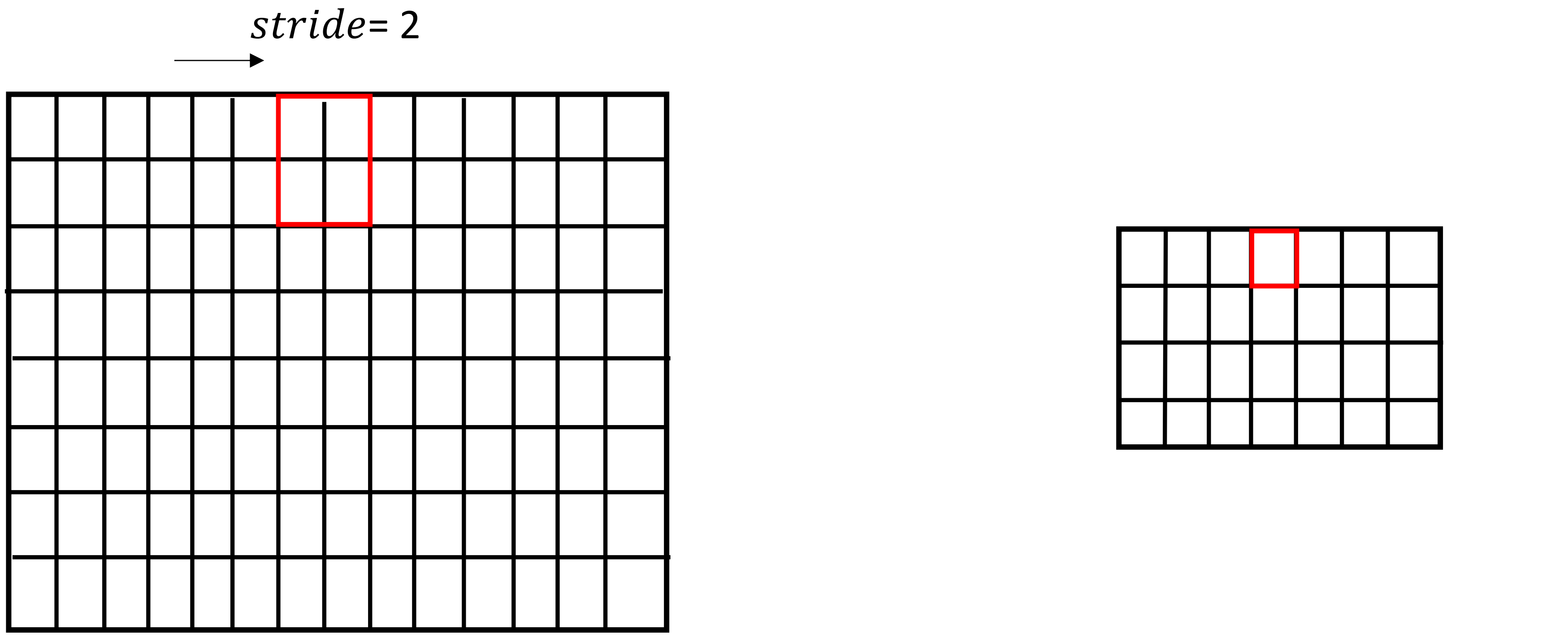
```
max_pool_2D = nn.MaxPool2d(kernel_size = 2,stride = 2)
```

# Max Pooling



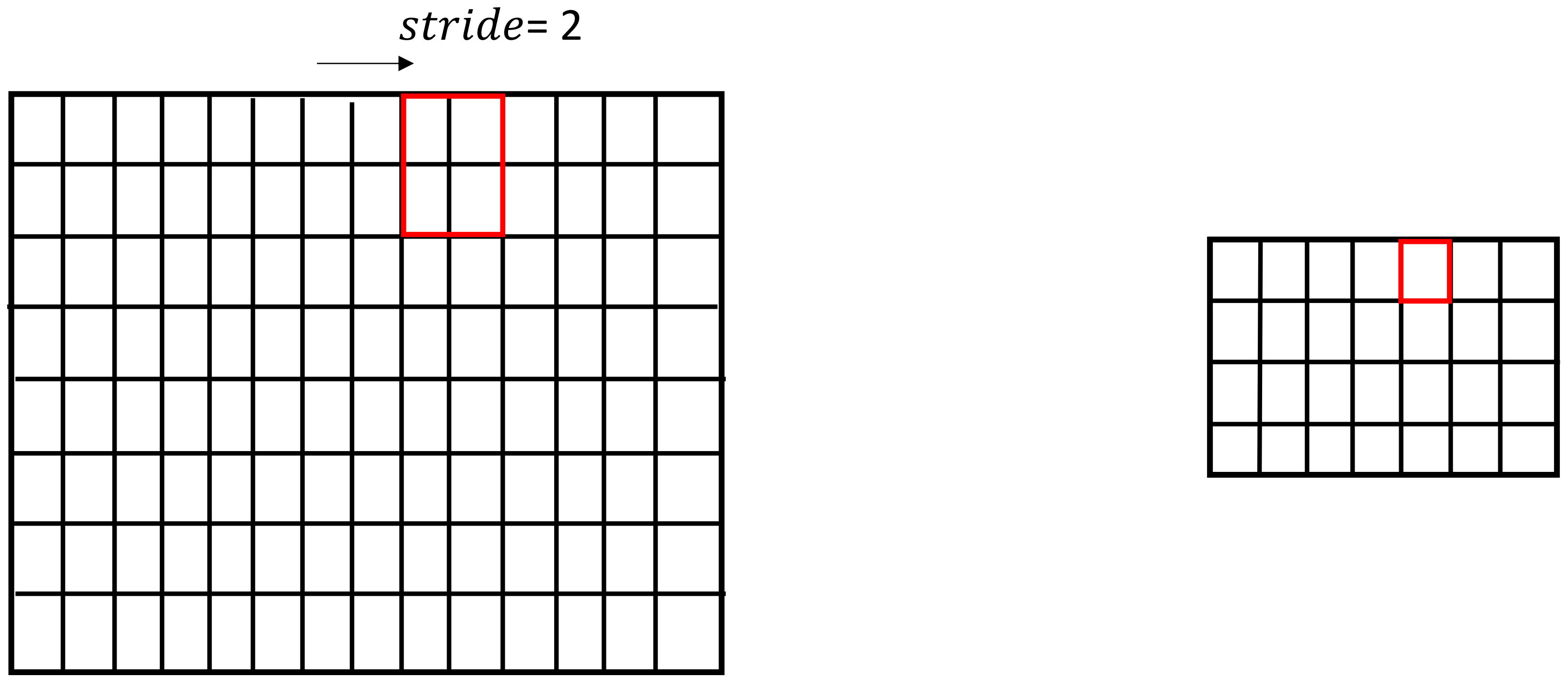
```
max_pool_2D = nn.MaxPool2d(kernel_size = 2,stride = 2)
```

# Max Pooling



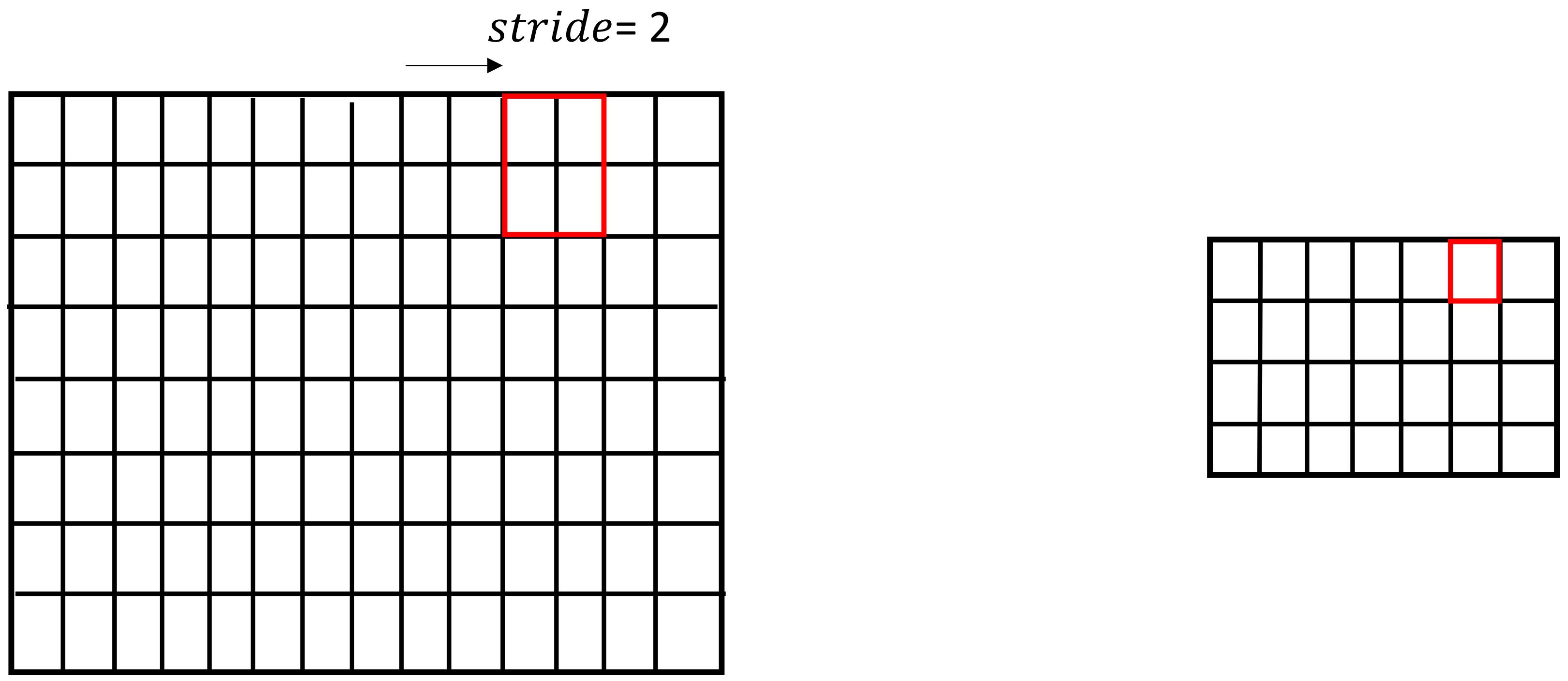
```
max_pool_2D = nn.MaxPool2d(kernel_size = 2,stride = 2)
```

# Max Pooling



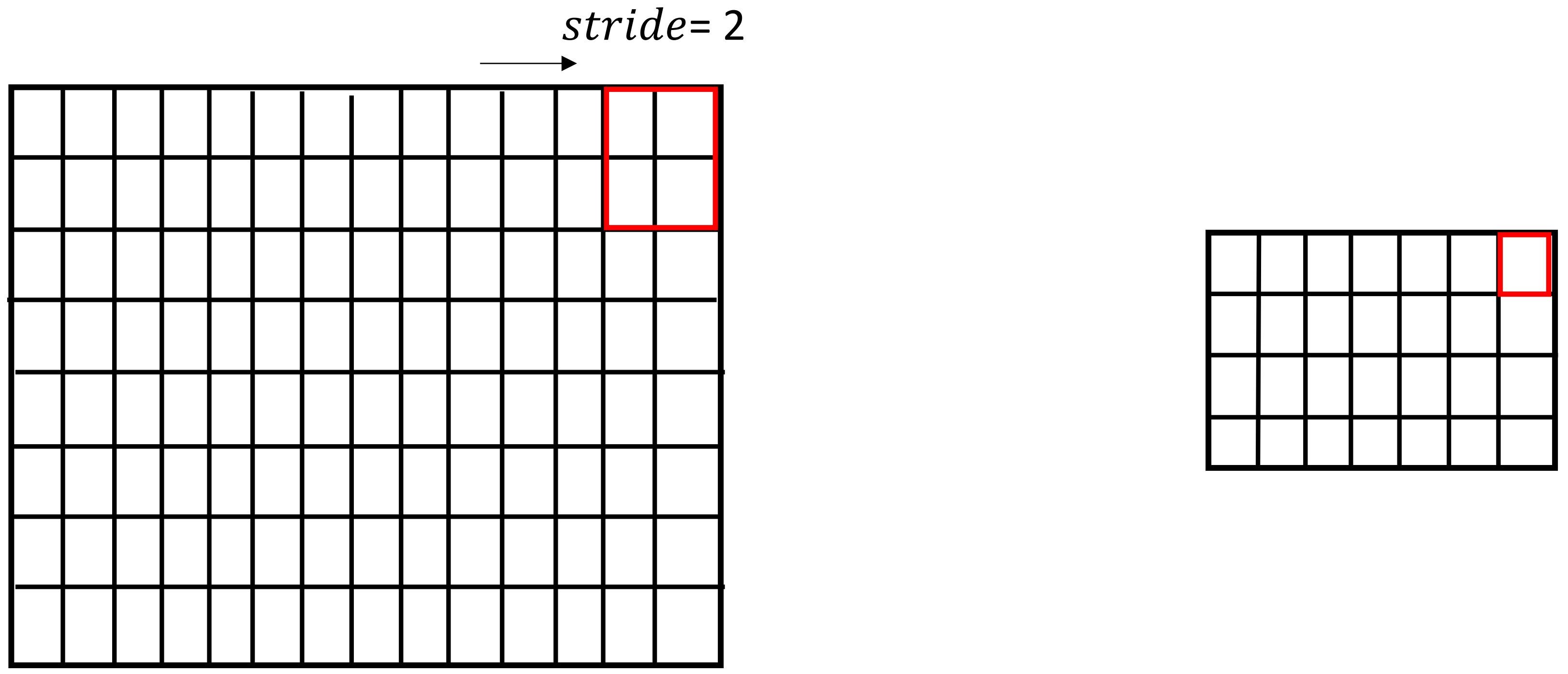
```
max_pool_2D = nn.MaxPool2d(kernel_size = 2,stride = 2)
```

# Max Pooling



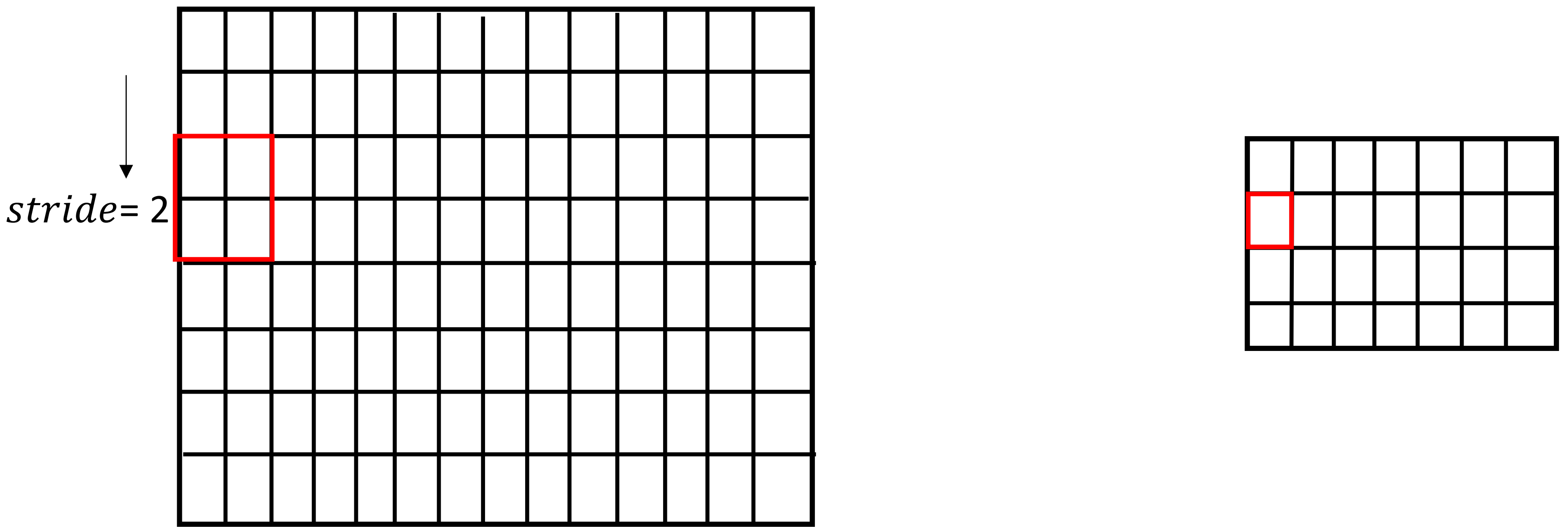
```
max_pool_2D = nn.MaxPool2d(kernel_size = 2,stride = 2)
```

# Max Pooling



```
max_pool_2D = nn.MaxPool2d(kernel_size = 2,stride = 2)
```

# Max Pooling



```
max_pool_2D = nn.MaxPool2d(kernel_size = 2,stride = 2)
```

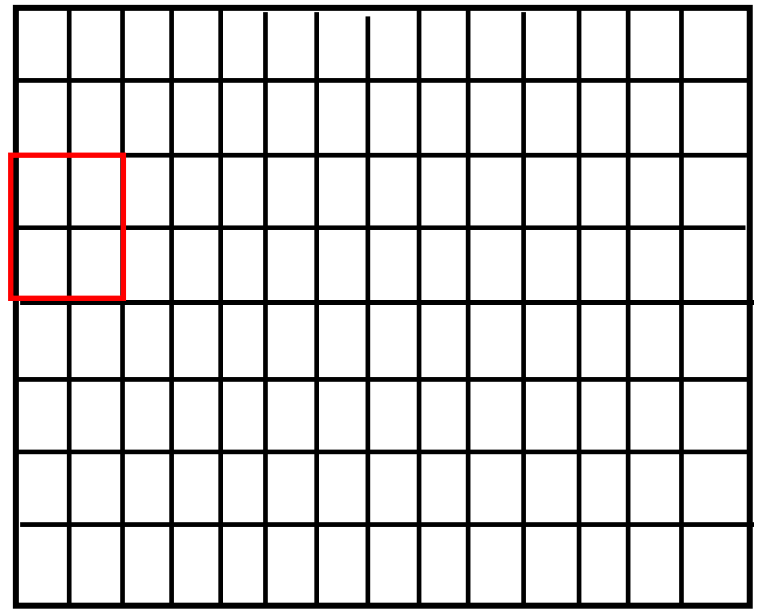
# FLOPS for MaxPool Layer

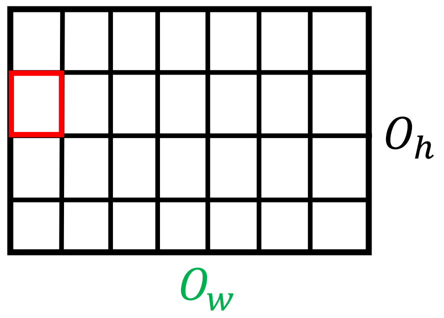
Output width

- FLOPS = $in\_channels * O_h * O_w * (k^2 - 1)$

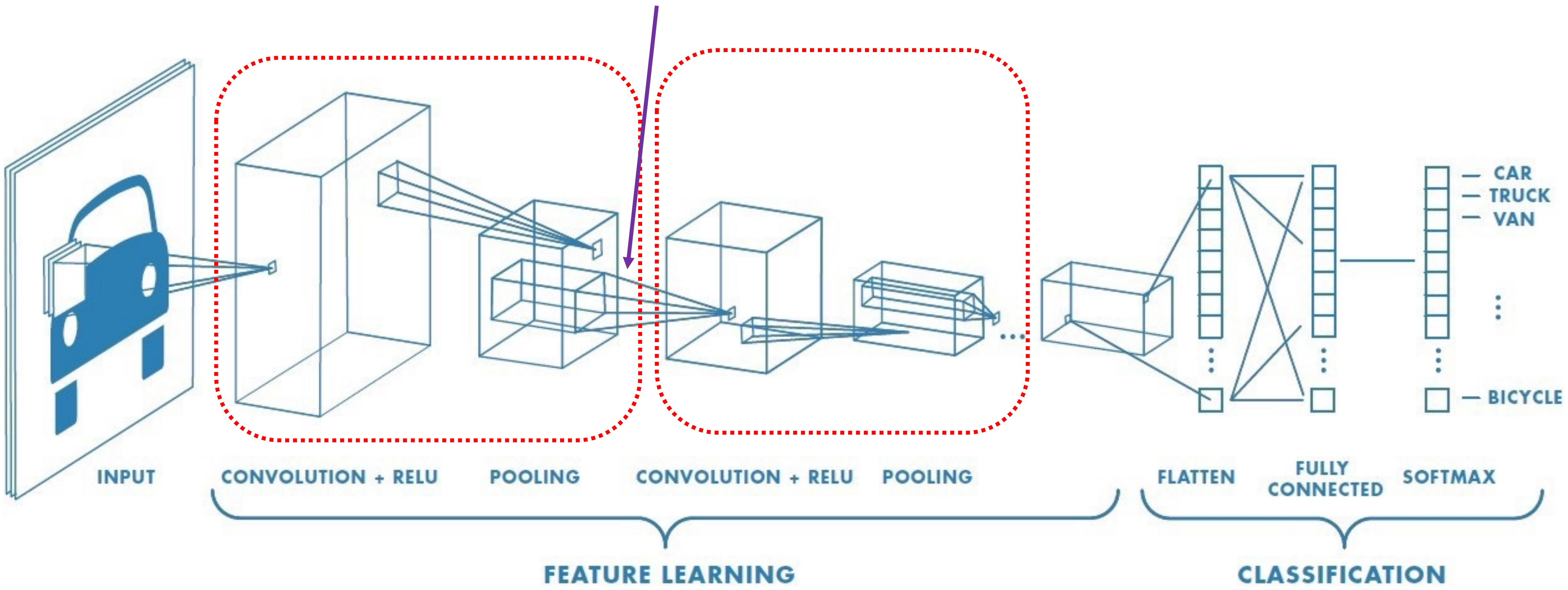
# of channels Output height # of comparisons

- $k$ is the kernel size





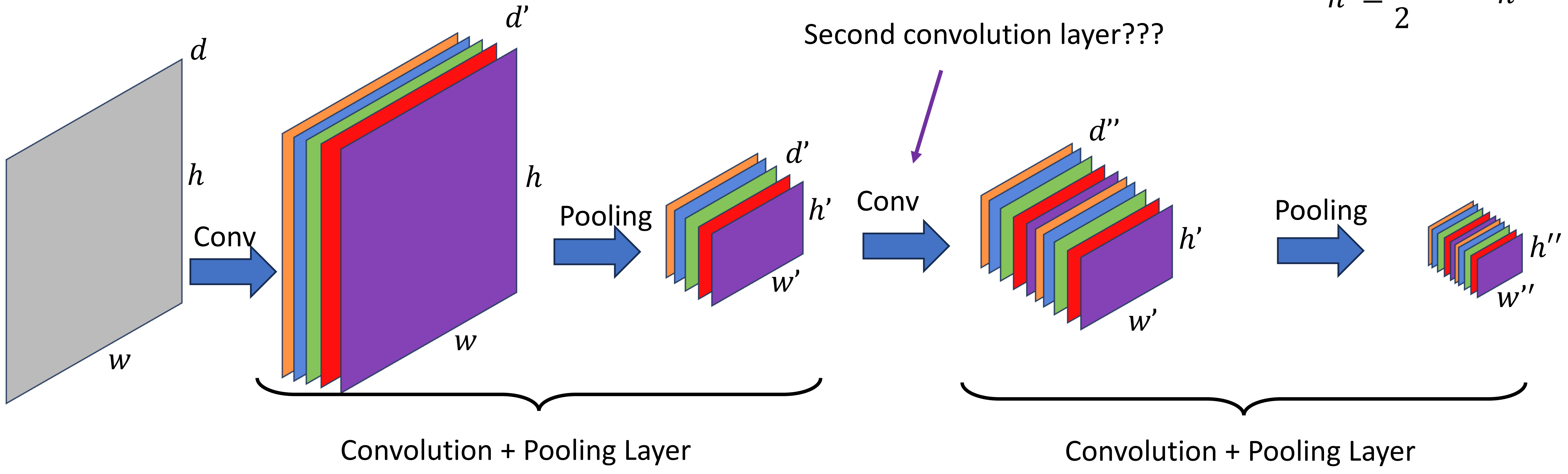
Second convolution layer???



# Adding another Conv+Pooling Layer

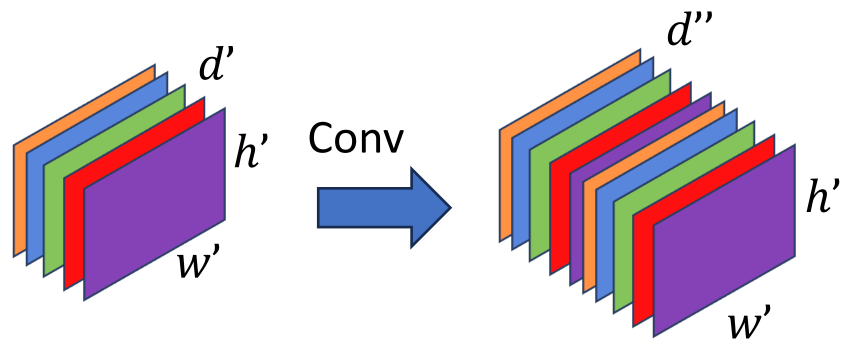
$w' = \frac{w}{2}$ $\quad w'' = \frac{w'}{2}$

$h' = \frac{h}{2}$ $\quad h'' = \frac{w'}{2}$



d
h
w
Conv
d'
h
w
Pooling
d'
h'
w'
Second convolution layer???
Conv
d''
h'
w'
Pooling
h''
w''
Convolution + Pooling Layer
Convolution + Pooling Layer

# Adding another Conv + Pooling Layer



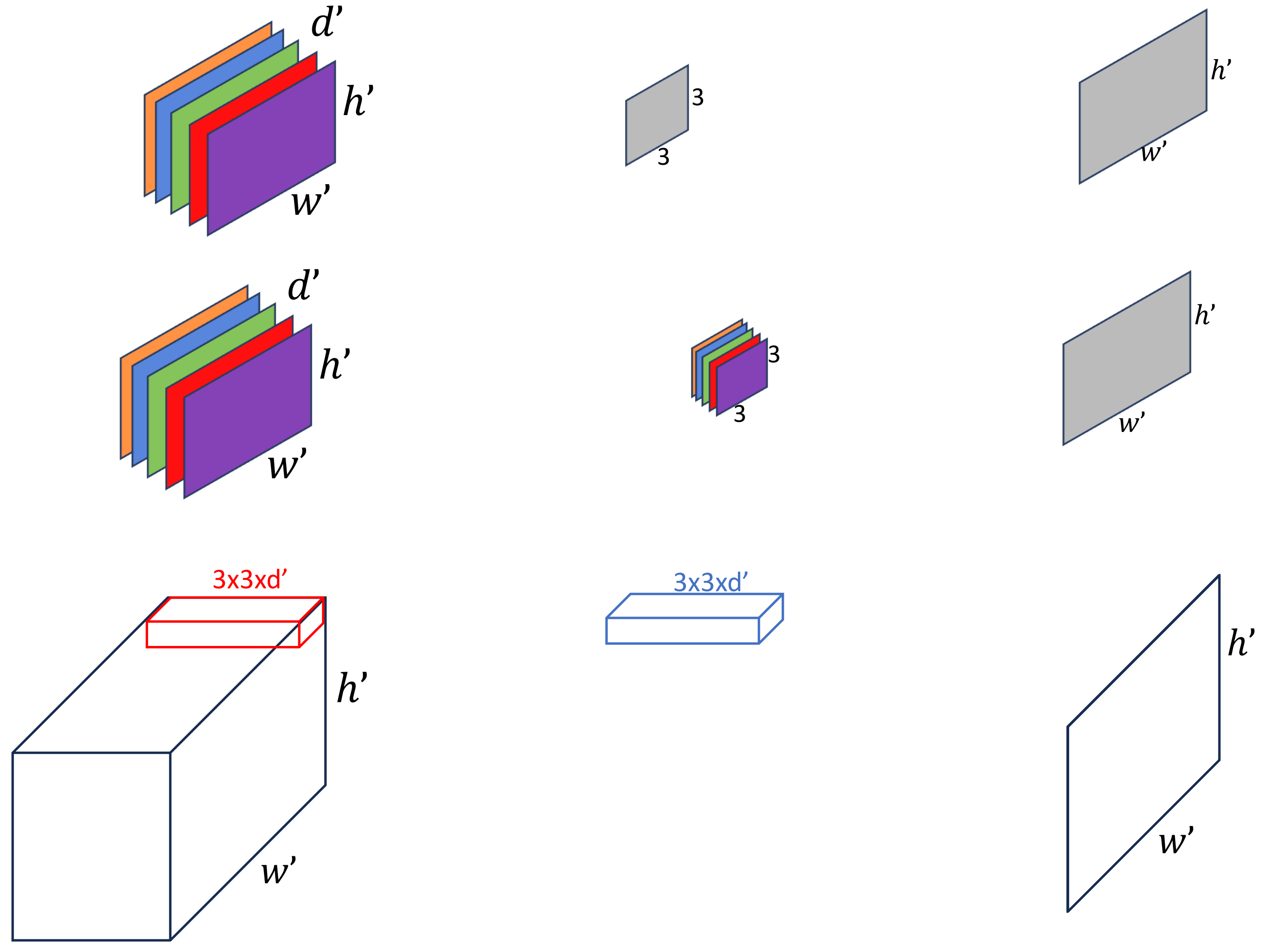
$$w' = \frac{w}{2}$$

$$h' = \frac{h}{2}$$

**Questions**:
How many kernels?
What is the shape of each kernel?

# Adding another Conv+Pooling Layer

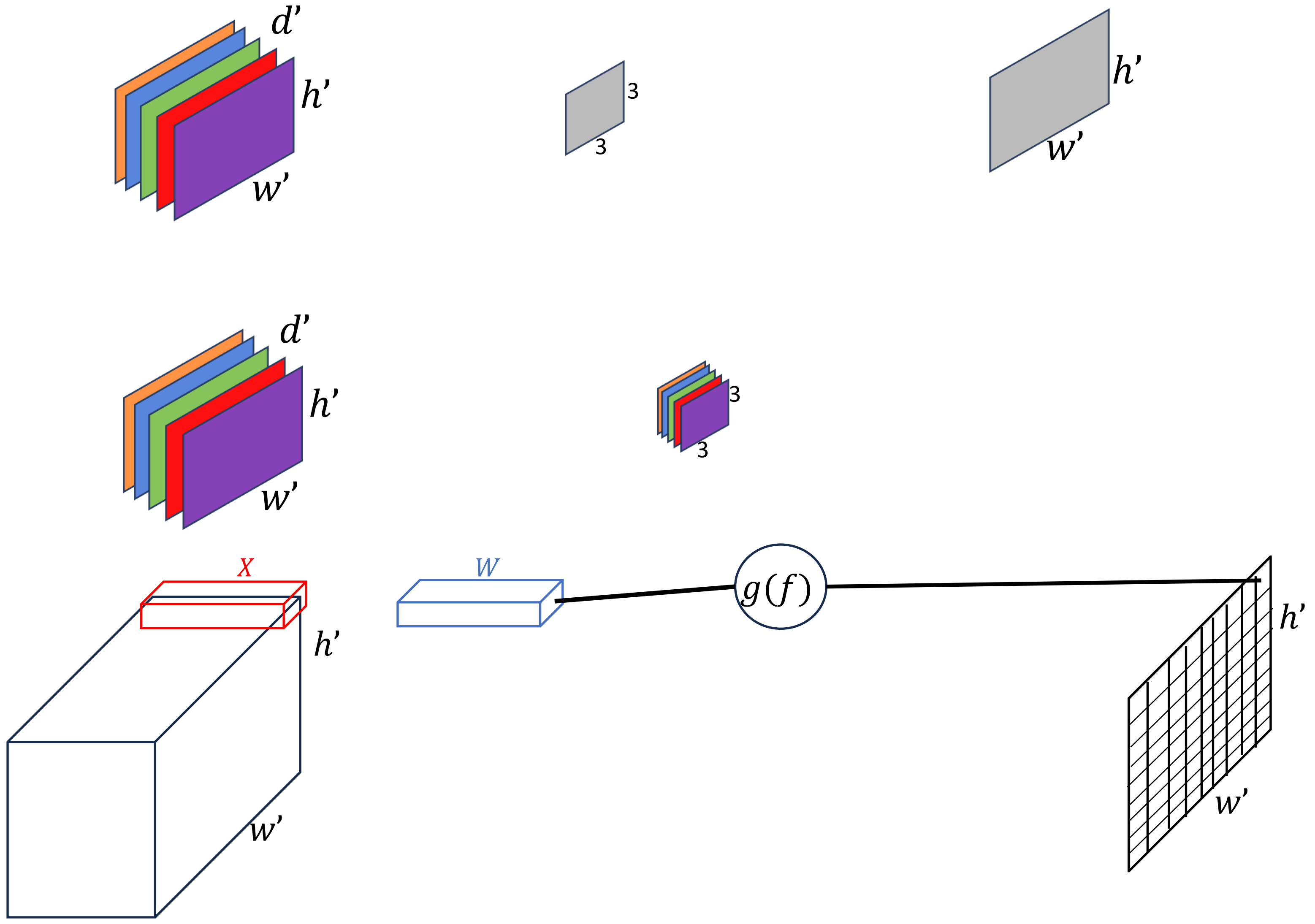
```
nn.Conv2d(in_channels=__, out_channels= __, kernel_size= 3 , stride=1, padding=1)
```



Shape of the kernel:______

# Adding another Conv+Pooling Layer

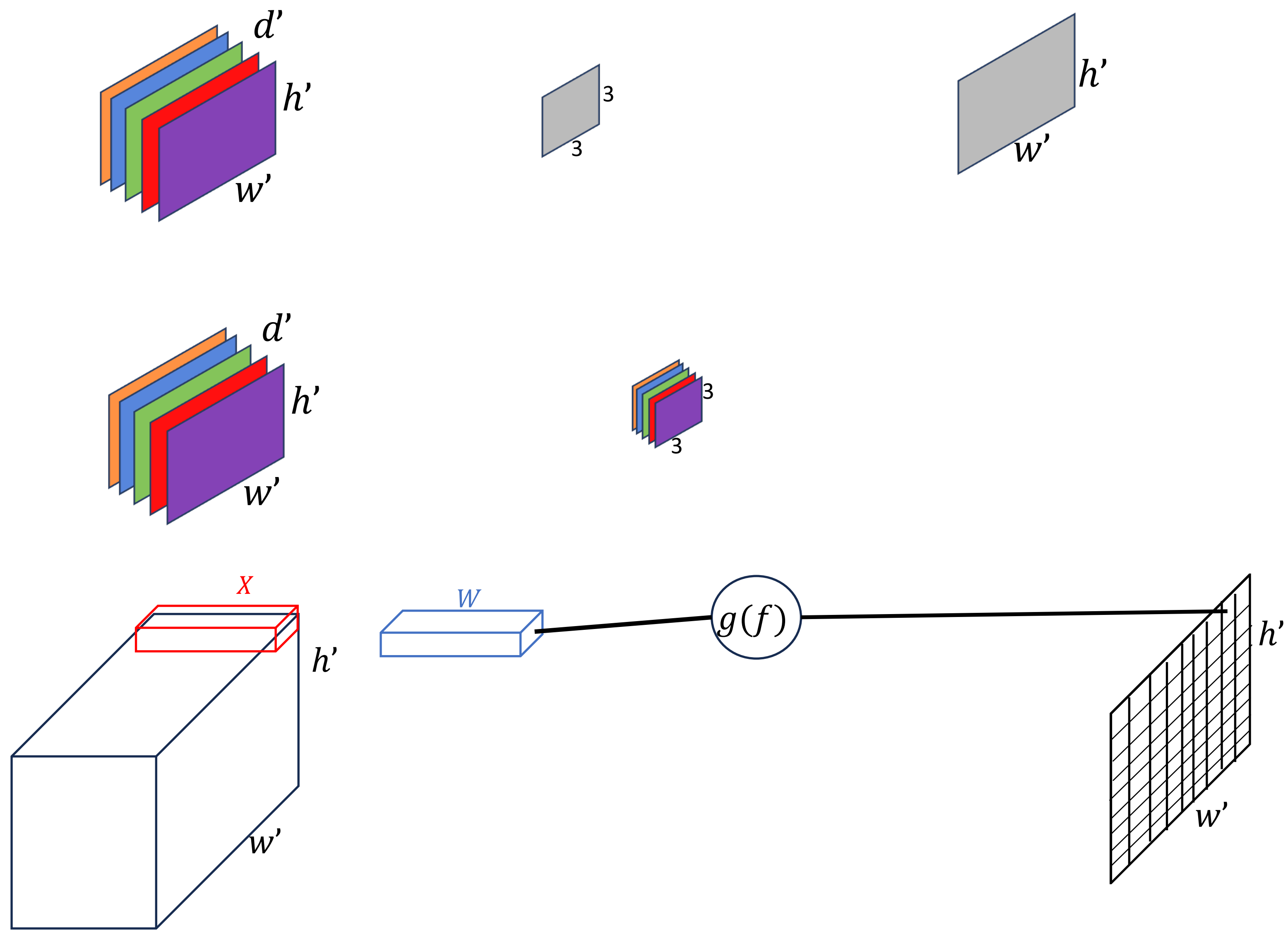
```
nn.Conv2d(in_channels=__, out_channels= __, kernel_size= 3 , stride=1, padding=1)
```



$f = sum(X \circ W)$

# Adding another Conv+Pooling Layer

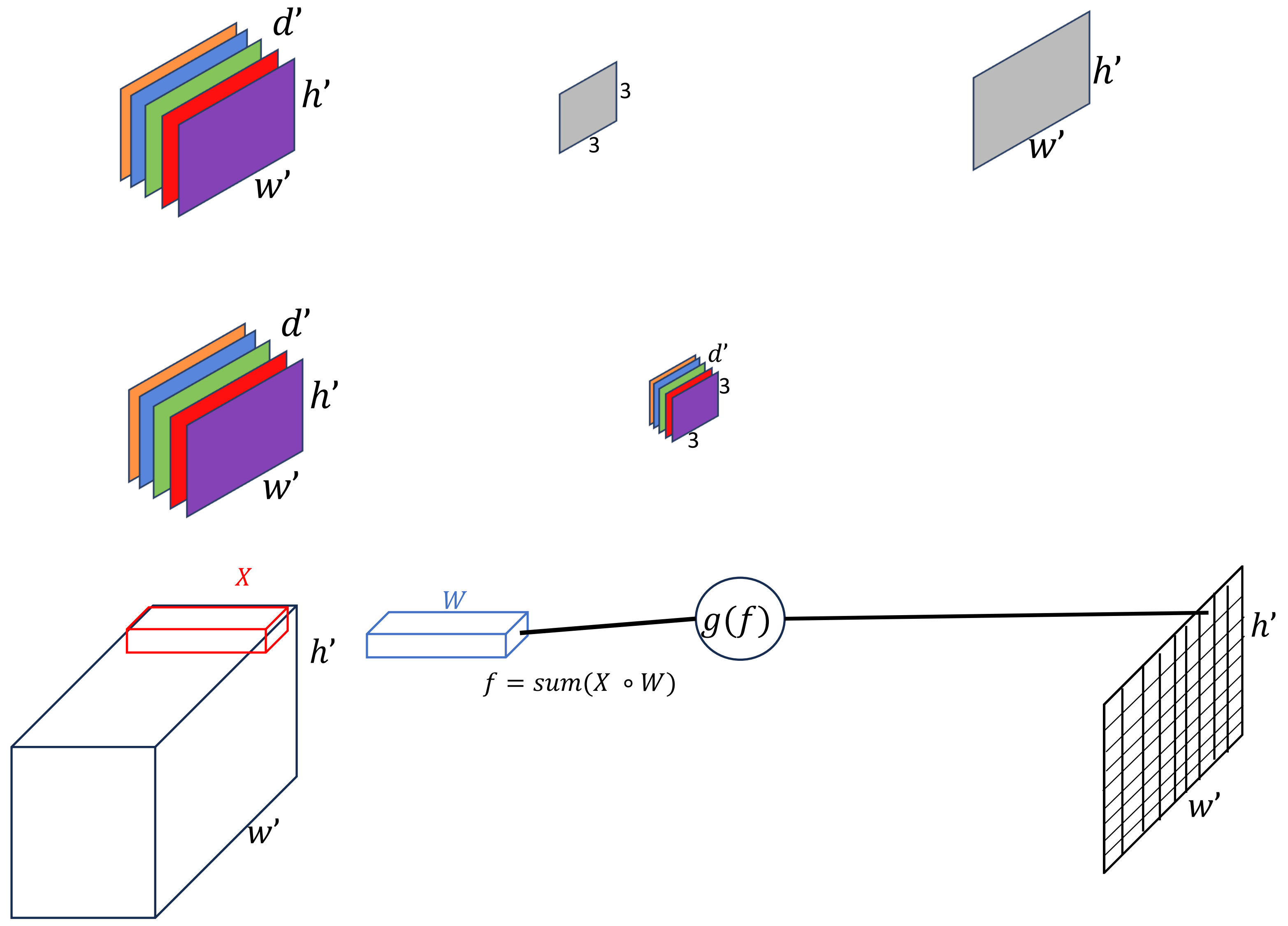
```
nn.Conv2d(in_channels=__, out_channels= __, kernel_size= 3 , stride=1, padding=1)
```



$f = sum(X \circ W)$

# Adding another Conv+Pooling Layer

```
nn.Conv2d(in_channels=__, out_channels= __, kernel_size= 3 , stride=1, padding=1)
```



# Adding another Conv+Pooling Layer

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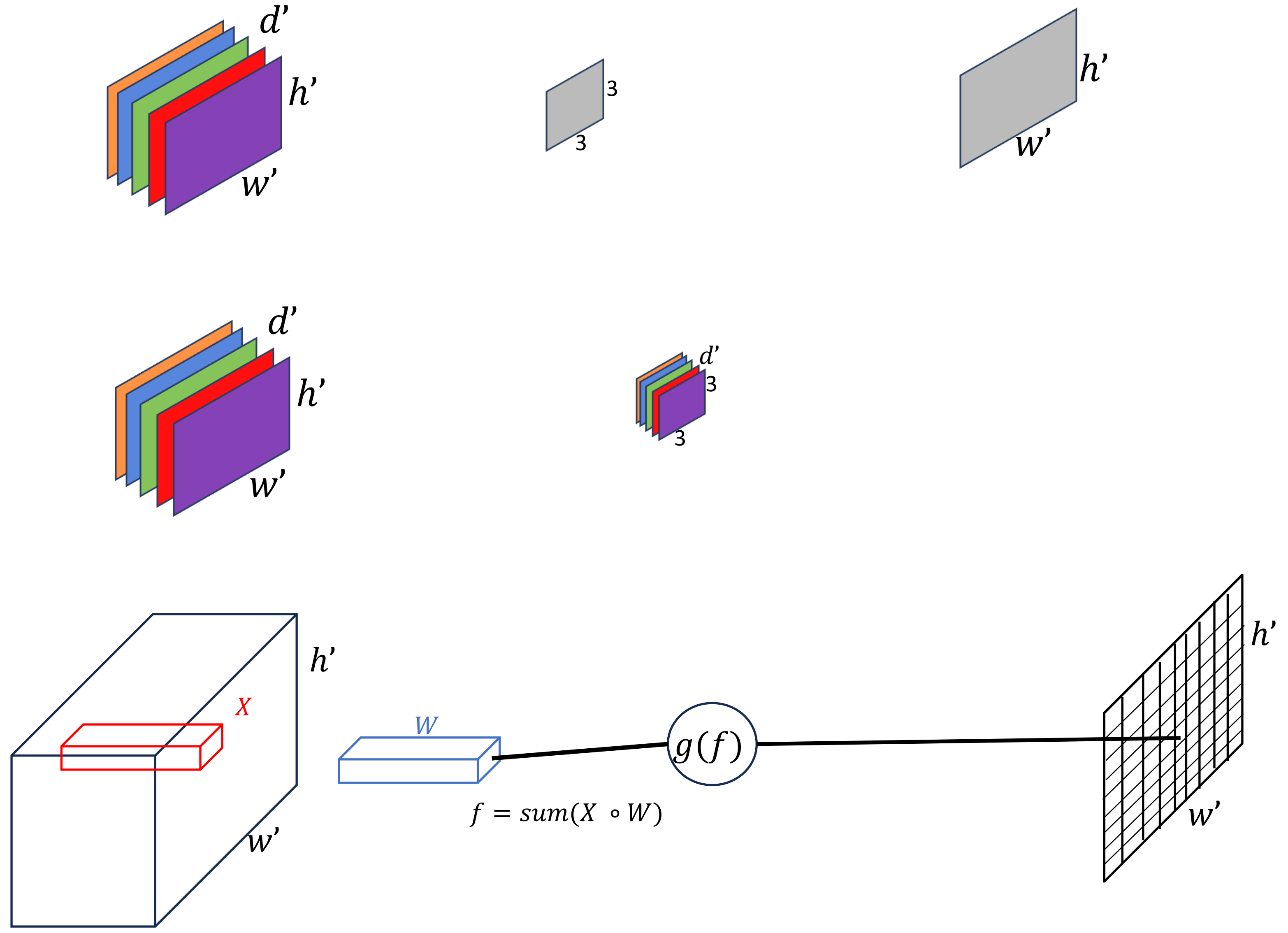
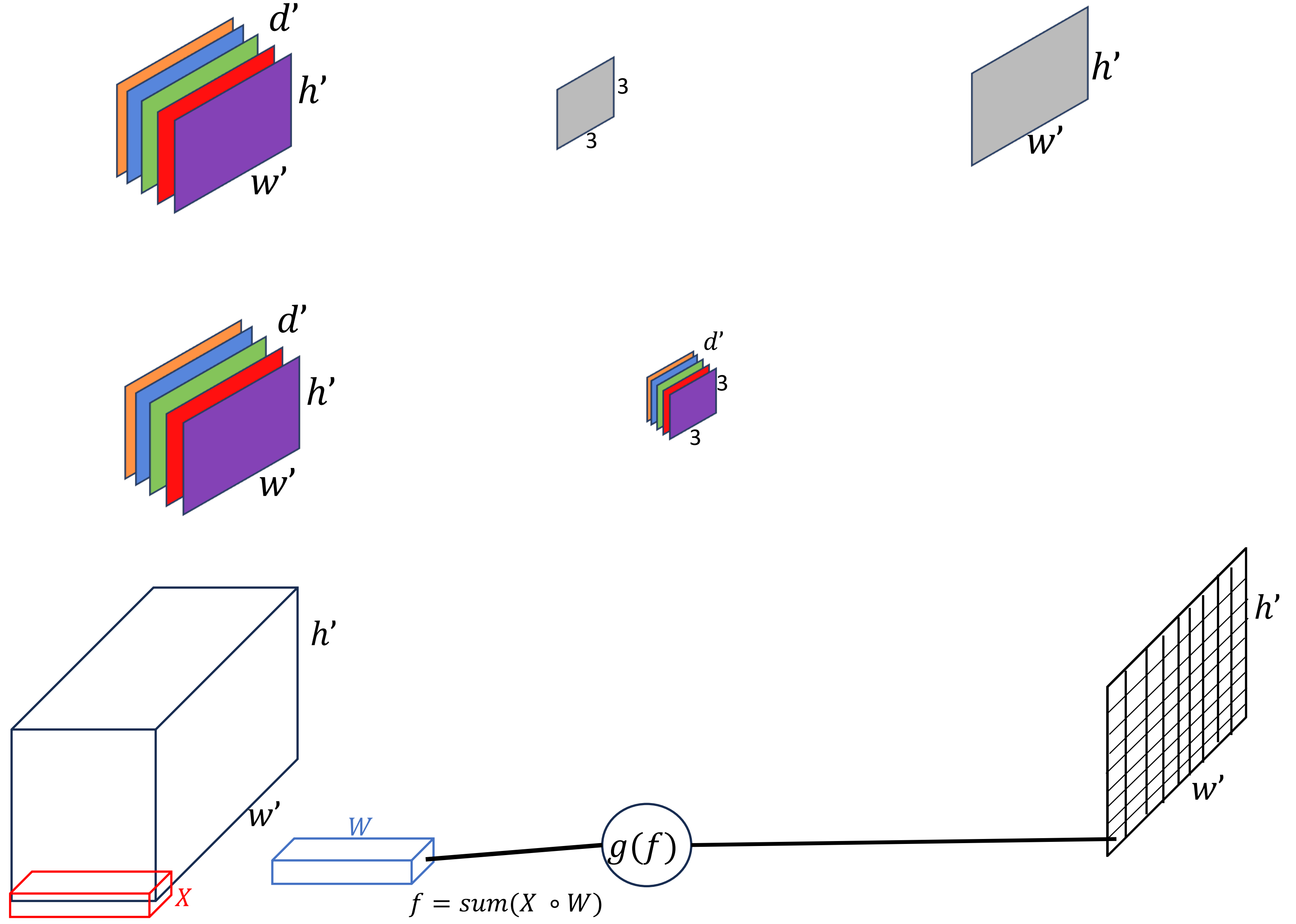
nn.Conv2d(in_channels=__, out_channels= __, kernel_size= 3 , stride=1, padding=1)
```



# Adding another Conv+Pooling Layer

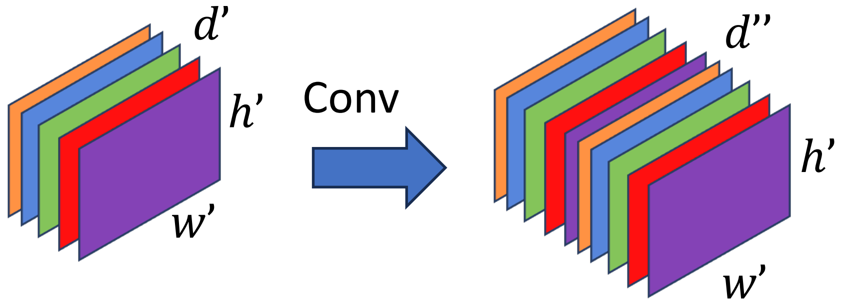
```
nn.Conv2d(in_channels=__, out_channels= __, kernel_size= 3 , stride=1, padding=1)
```



# Adding another Conv+Pooling Layer

$$w' = \frac{w}{2}$$

$$h' = \frac{h}{2}$$

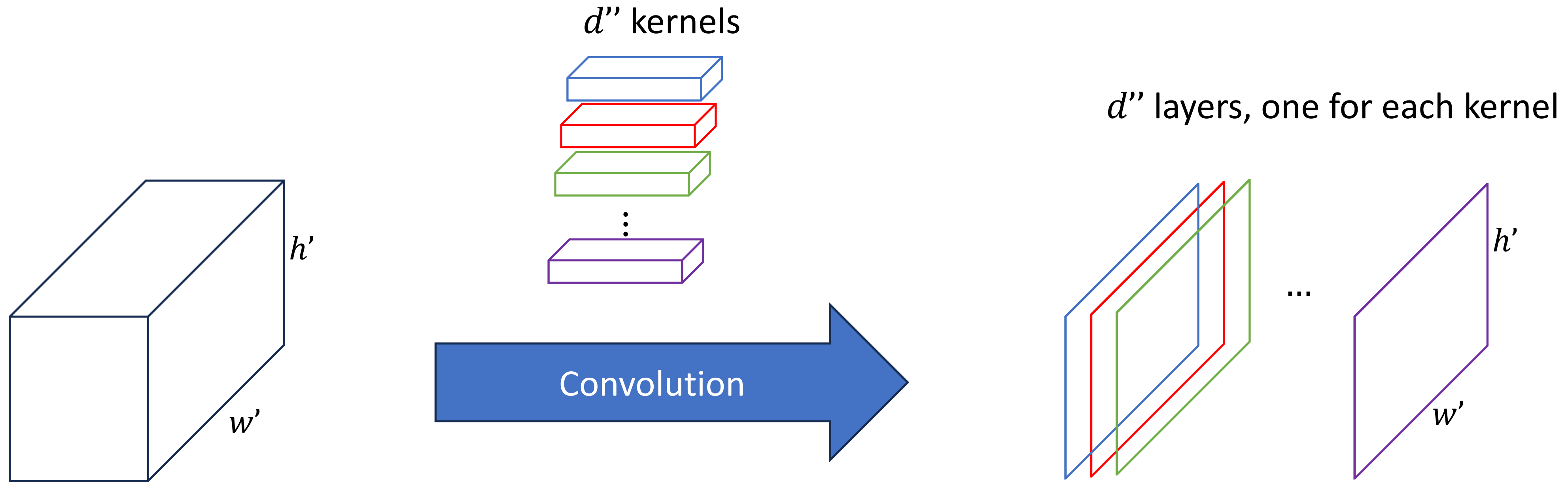


```
nn.Conv2d(in_channels=__, out_channels= __, kernel_size= 3 , stride=1, padding=1)
```

**Questions**:
How many kernels?
What is the shape of each kernel?

# Adding another Conv+Pooling Layer

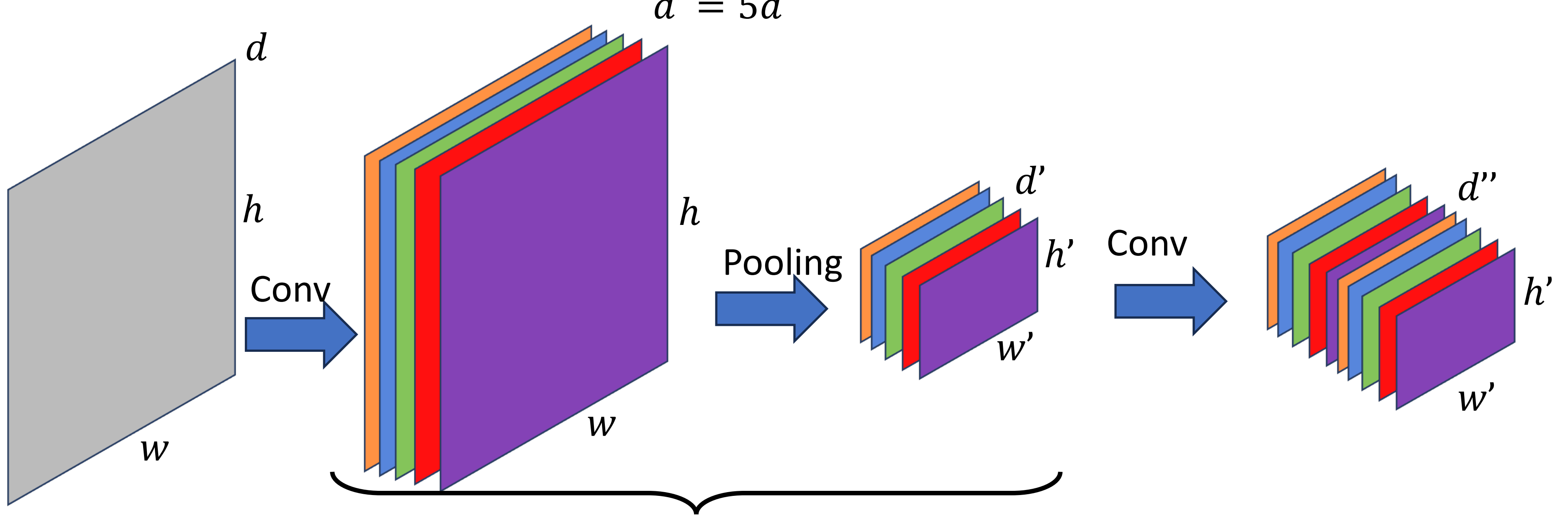
```
nn.Conv2d(in_channels=__, out_channels= __, kernel_size= 3 , stride=1, padding=1)
```



# Adding another Conv+Pooling Layers

$$w' = \frac{w}{2}$$

$$h' = \frac{h}{2}$$



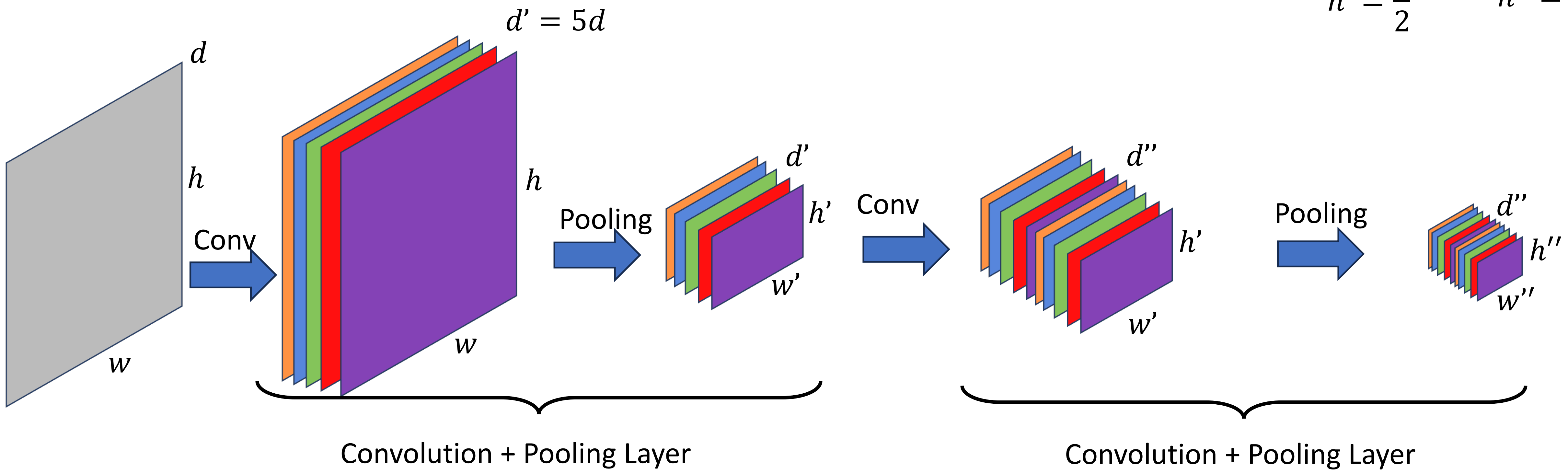
Convolution + Pooling Layer

**Questions**:
How many FLOPS?

# Adding another Conv+Pooling Layer

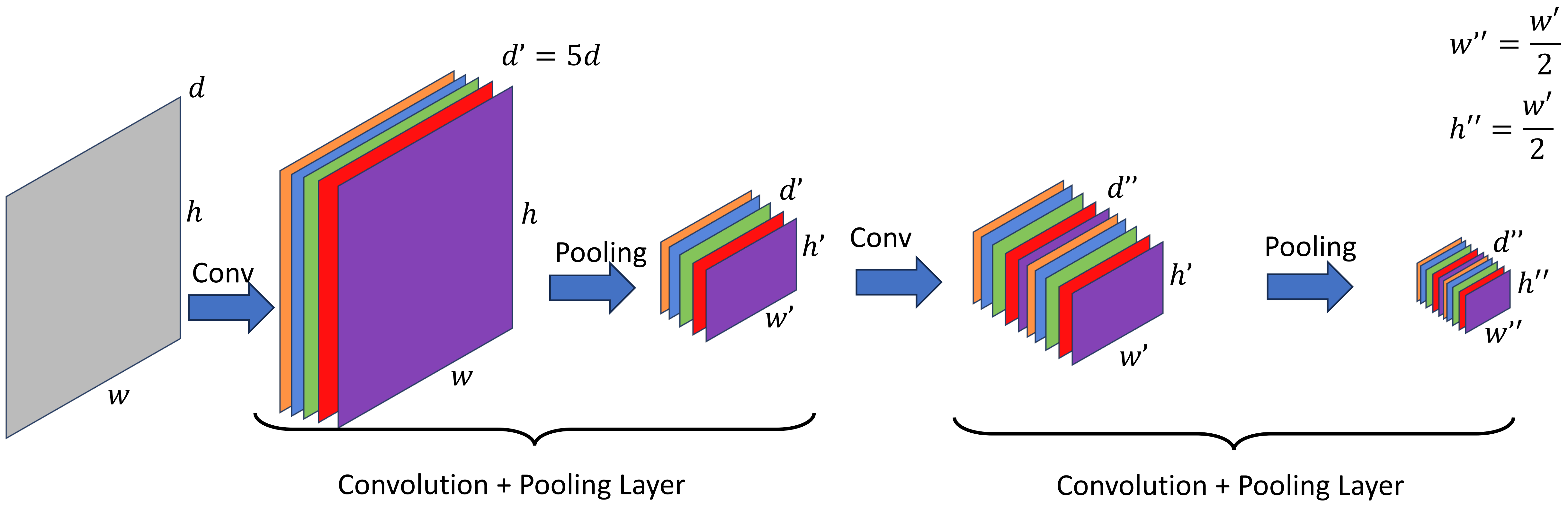
$w' = \frac{w}{2}$ $\quad w'' = \frac{w'}{2}$

$h' = \frac{h}{2}$ $\quad h'' = \frac{w'}{2}$



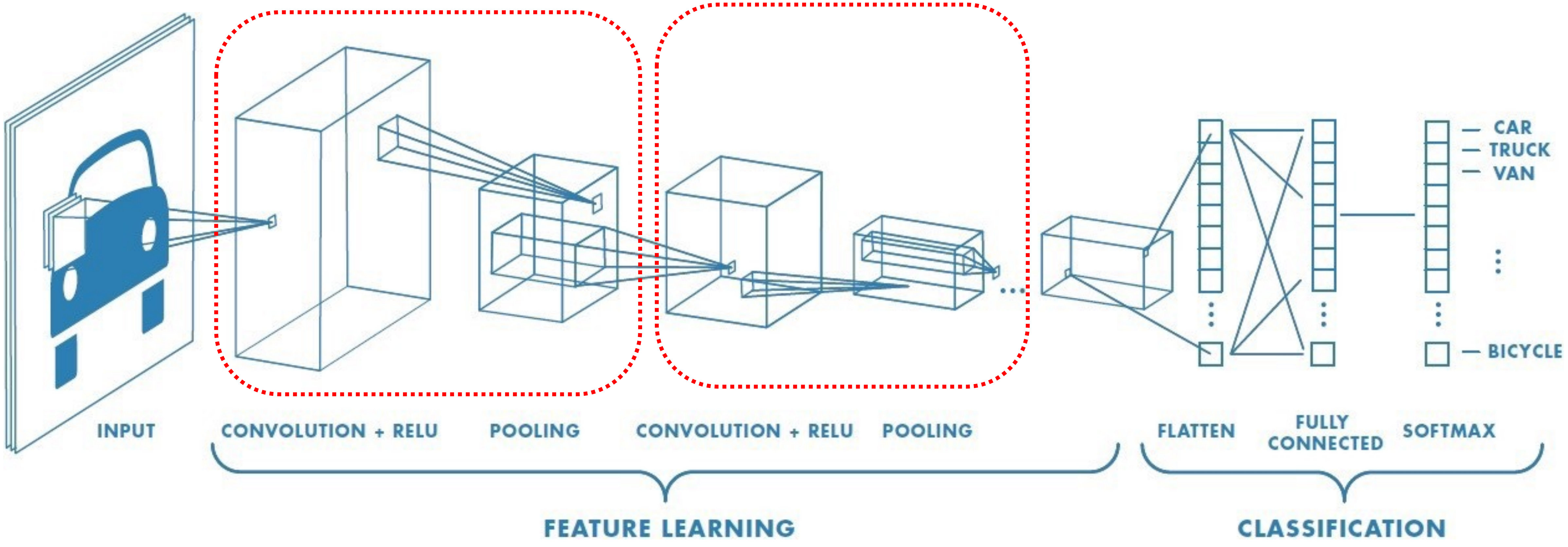
```
nn.MaxPool2d(kernel_size=__, stride=__)
```

# Adding another Conv+Pooling Layer

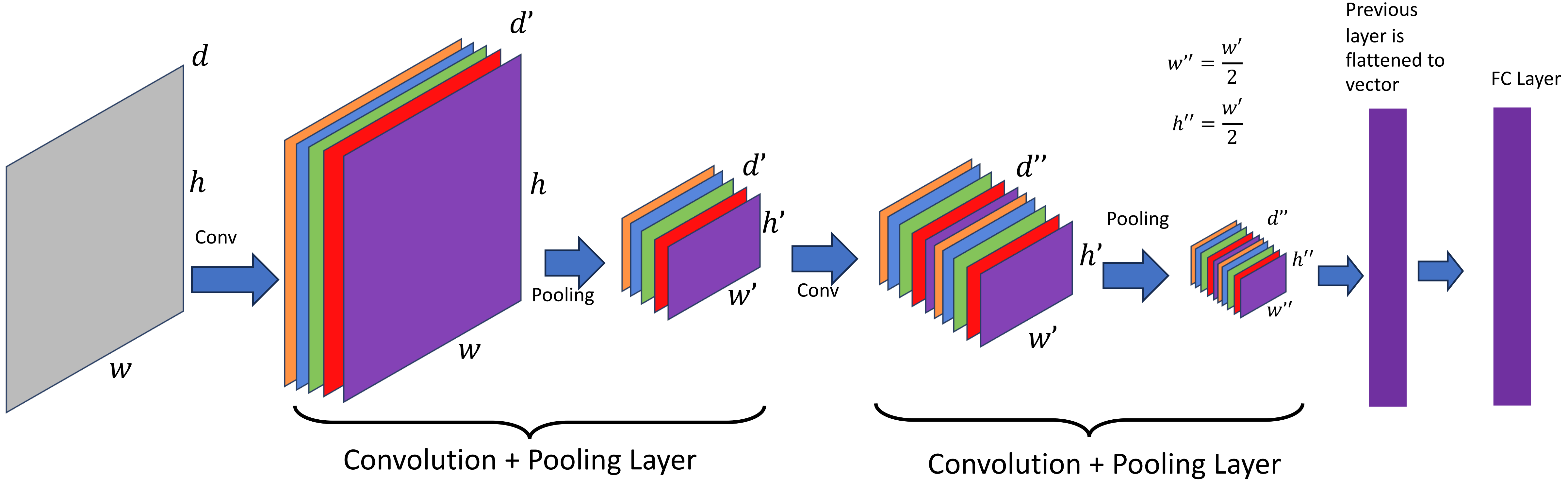


```
nn.Conv2d(in_channels=__, out_channels= __, kernel_size= 3 , stride=1, padding=1)

nn.MaxPool2d(kernel_size=__, stride=__)
```


INPUT
CONVOLUTION + RELU
POOLING
CONVOLUTION + RELU
POOLING
FLATTEN
FULLY CONNECTED
SOFTMAX
CAR
TRUCK
VAN
BICYCLE
FEATURE LEARNING
CLASSIFICATION

# Flatten + FC Layers

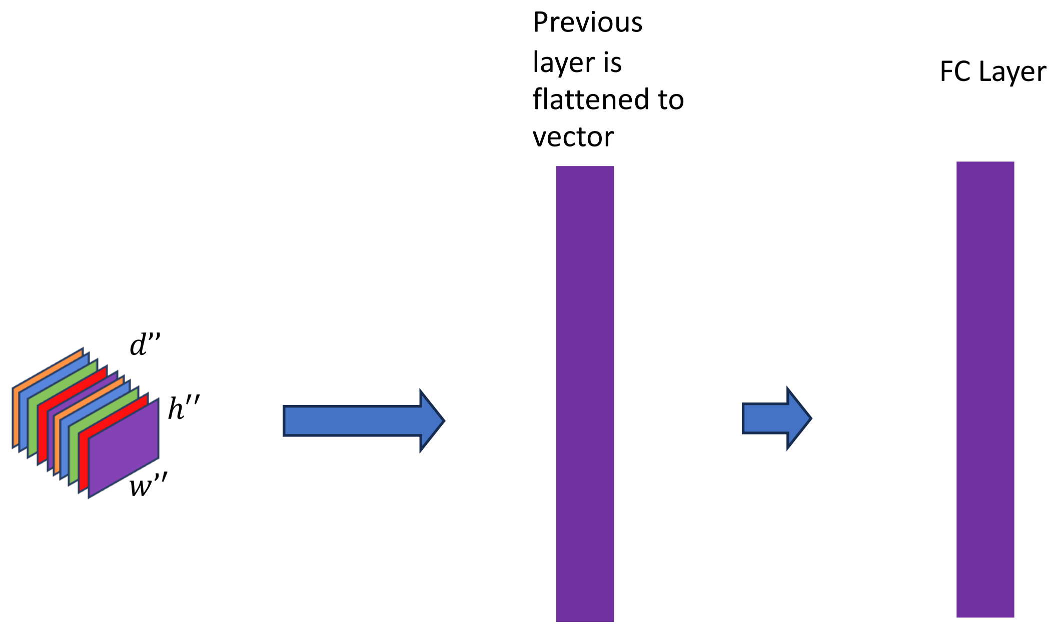


What is the size of flattened vector?

Think of flatten vector as feature vector

Fully Connected (FC) layer is traditional neural network layer with predefined number of neurons

# Flattened Layer + FC Layer

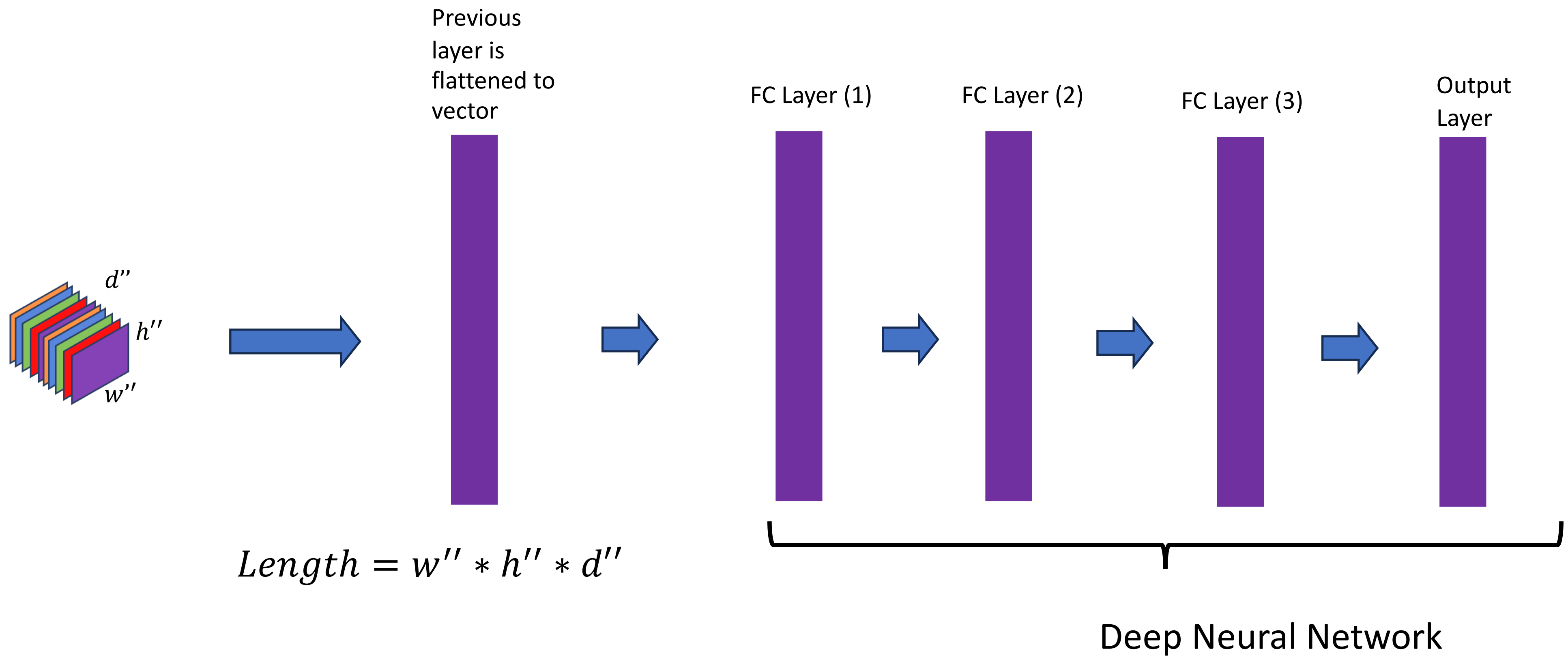


$$Length = w'' * h'' * d''$$

Length of the flattened layer is equal to the size of the input for FC layer

Design of FC layers require the knowledge of size of final Conv+Pooling layer

# Flattened Layer + FC Layer(s)



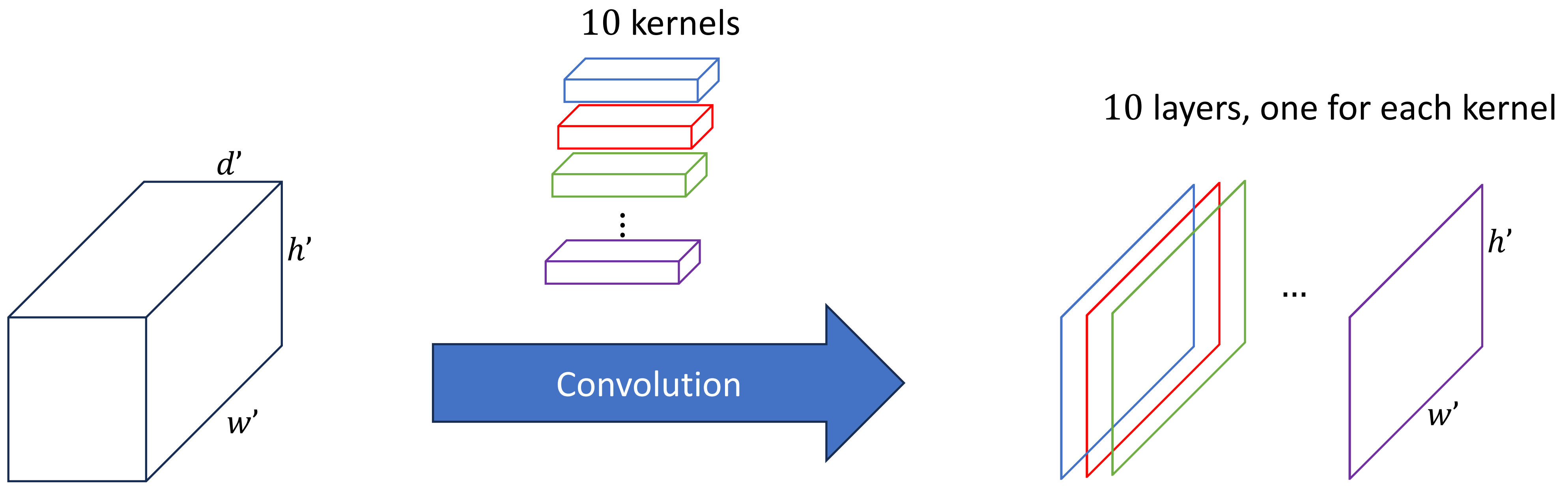
Length of the flattened layer is equal to the size of the input for FC layer

Design of FC layers require the knowledge of size of final Conv+Pooling layer

# How many FLOPS per layer?

- FLOPS: Floating Point Operations

```
nn.Conv2d(in_channels=5, out_channels= 10, kernel_size= 3 , stride=1, padding=1)
```

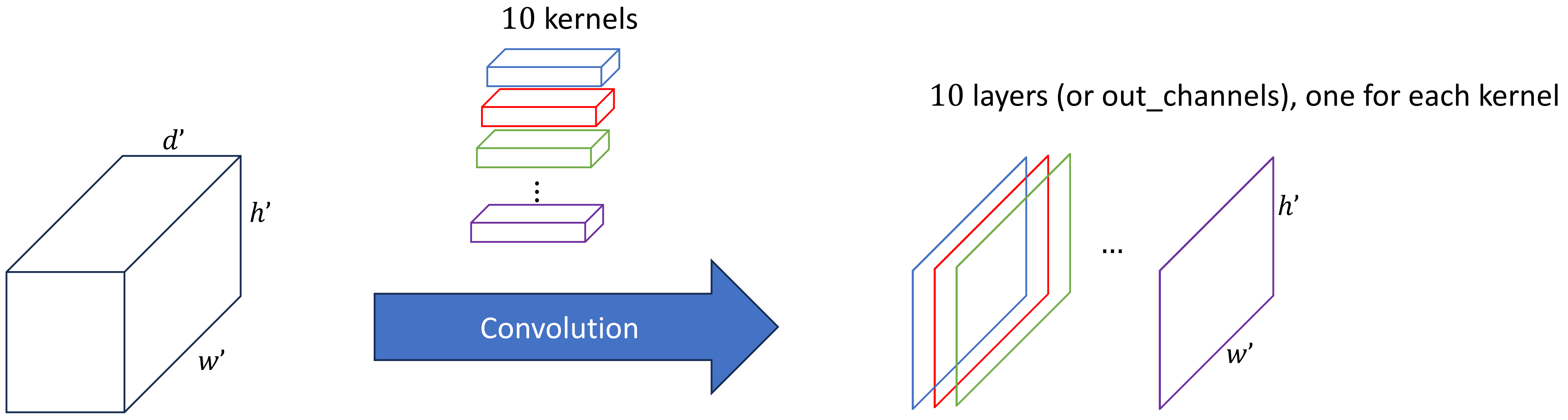


$h' = w' = 16$

$d' = 5$

# How many FLOPS per layer?

```
nn.Conv2d(in_channels=5, out_channels= 10, kernel_size= 3 , stride=1, padding=1)
```



$h' = w' = 16$ $\quad d' = 5$

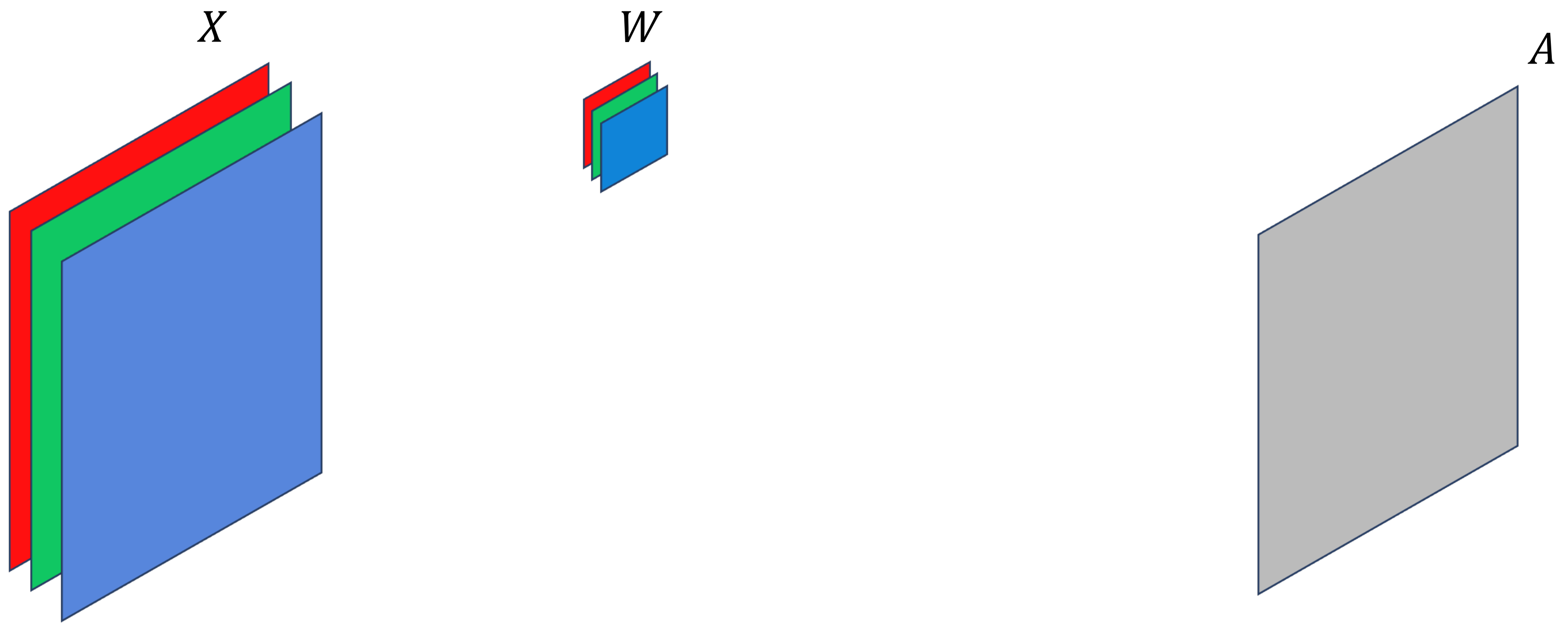
$(out\_channels * out\_height * out\_width) * 2 * (in\_channels * kernel\_height * kernel\_width)$

# of pixels in output

(# of multiplications + # of additions ) per pixel

# Convolution Layer: RGB Input

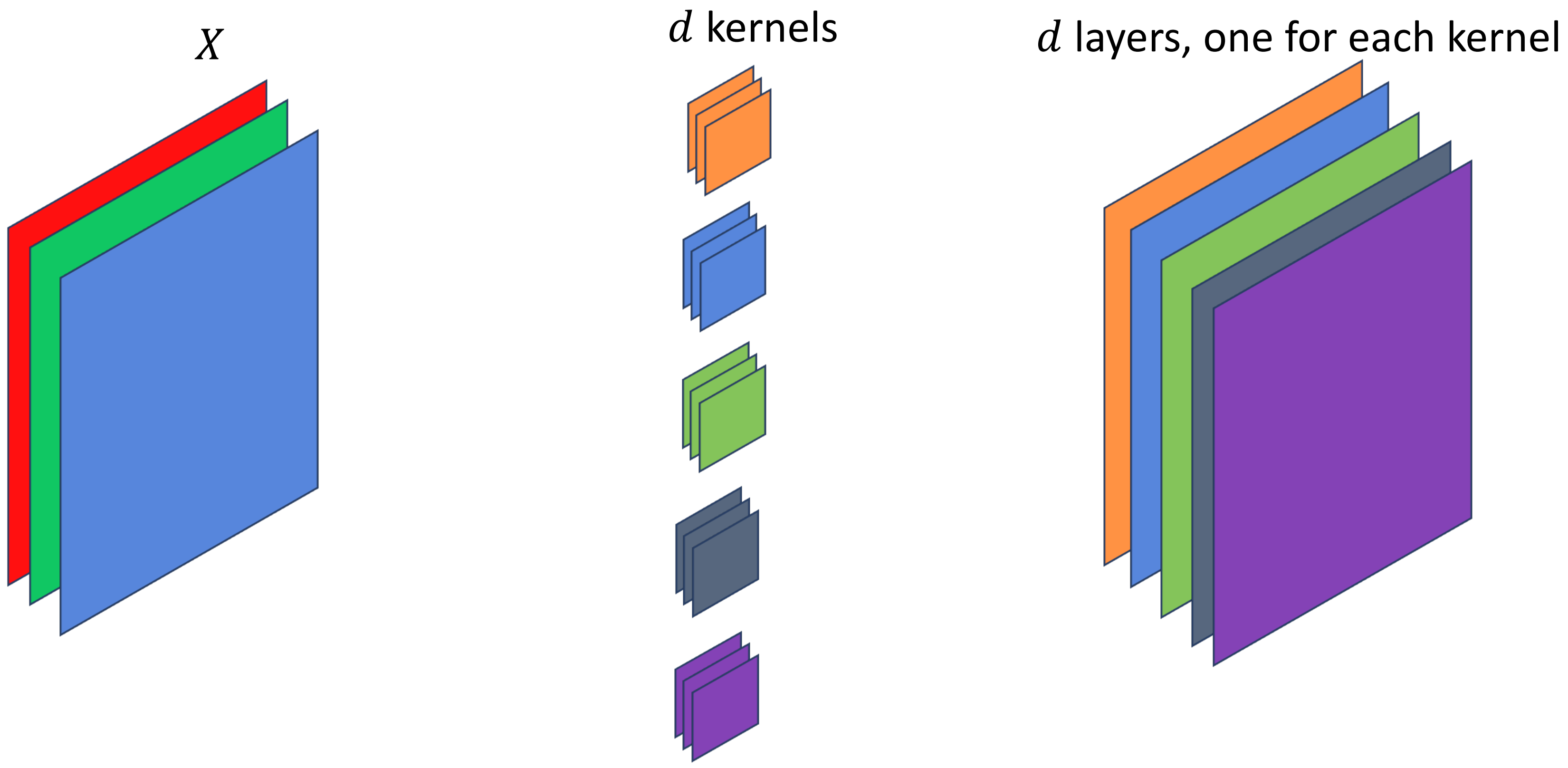
```
nn.Conv2d(in_channels=___, out_channels=__, kernel_size= 3 , stride=1, padding=1)
```



```
Shape of kernel:________
```

# Convolution Layer: RGB Input

```
nn.Conv2d(in_channels=__, out_channels=__, kernel_size= 3 , stride=1, padding=1)
```

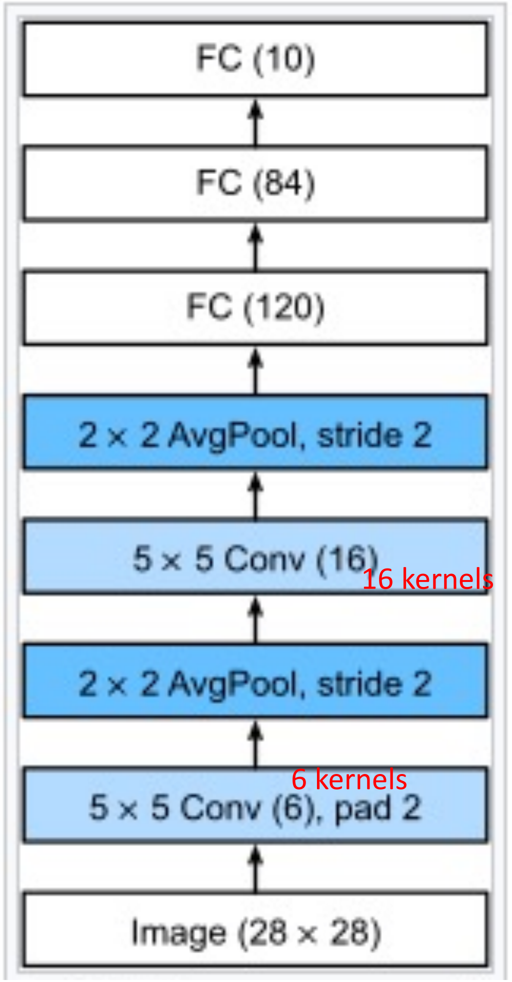


Assuming kernel size of 3 for each kernel, how many parameters in the convolution layer?

# CNN Architectures

- AlexNet
- VGG-16
- ResNet-50
  - Residual connections
  - Bottleneck layer to reduce parameter count
- MobileNetV2
  - Depthwise Convolution

# LetNet5 Architecture: Tutorial!!



```
nn.Linear(in_features =__, out_features=__)

nn.Linear(in_features=__, out_features=__)

nn.Linear(in_features=__, out_features=__)

nn.AvgPool2d(kernel_size=__, stride=__)

nn.Conv2d(in_channels=__, out_channels=__, kernel_size=__, stride=2, padding=2)

nn.AvgPool2d(kernel_size=__, stride=__)

nn.Conv2d(in_channels=__, out_channels=__, kernel_size=__, stride=1, padding=2)
```

Image taken from: https://en.wikipedia.org/wiki/LeNet

# VGGNet: Homework

- Visual Geometry Group (VGG) at the University of Oxford

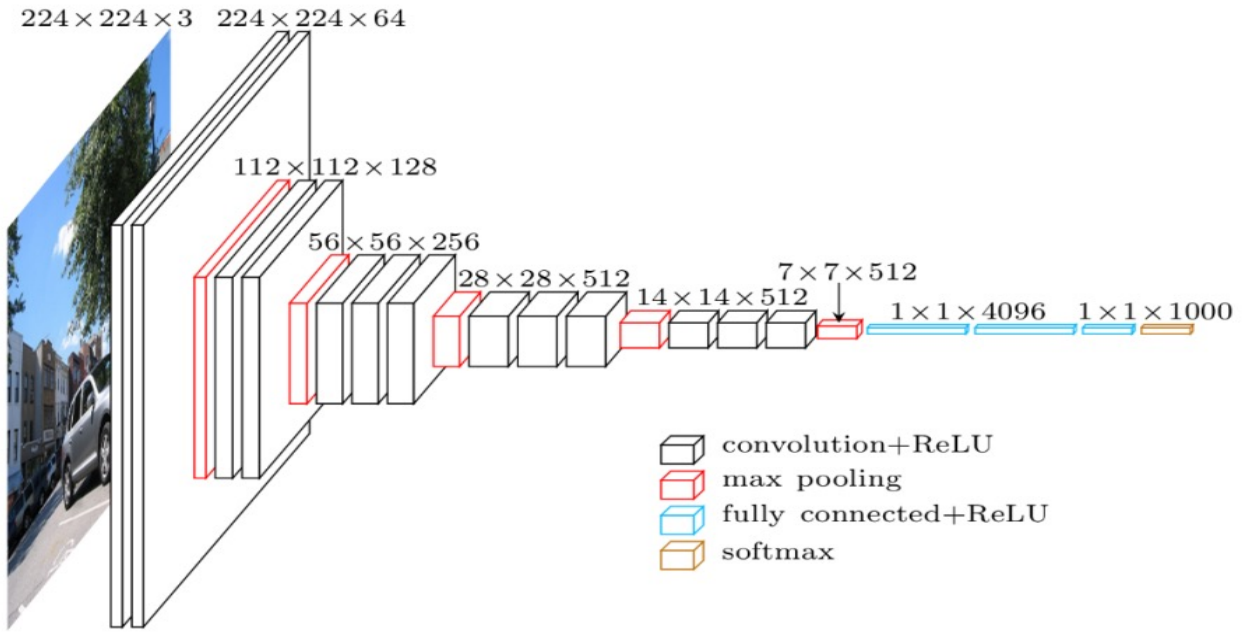
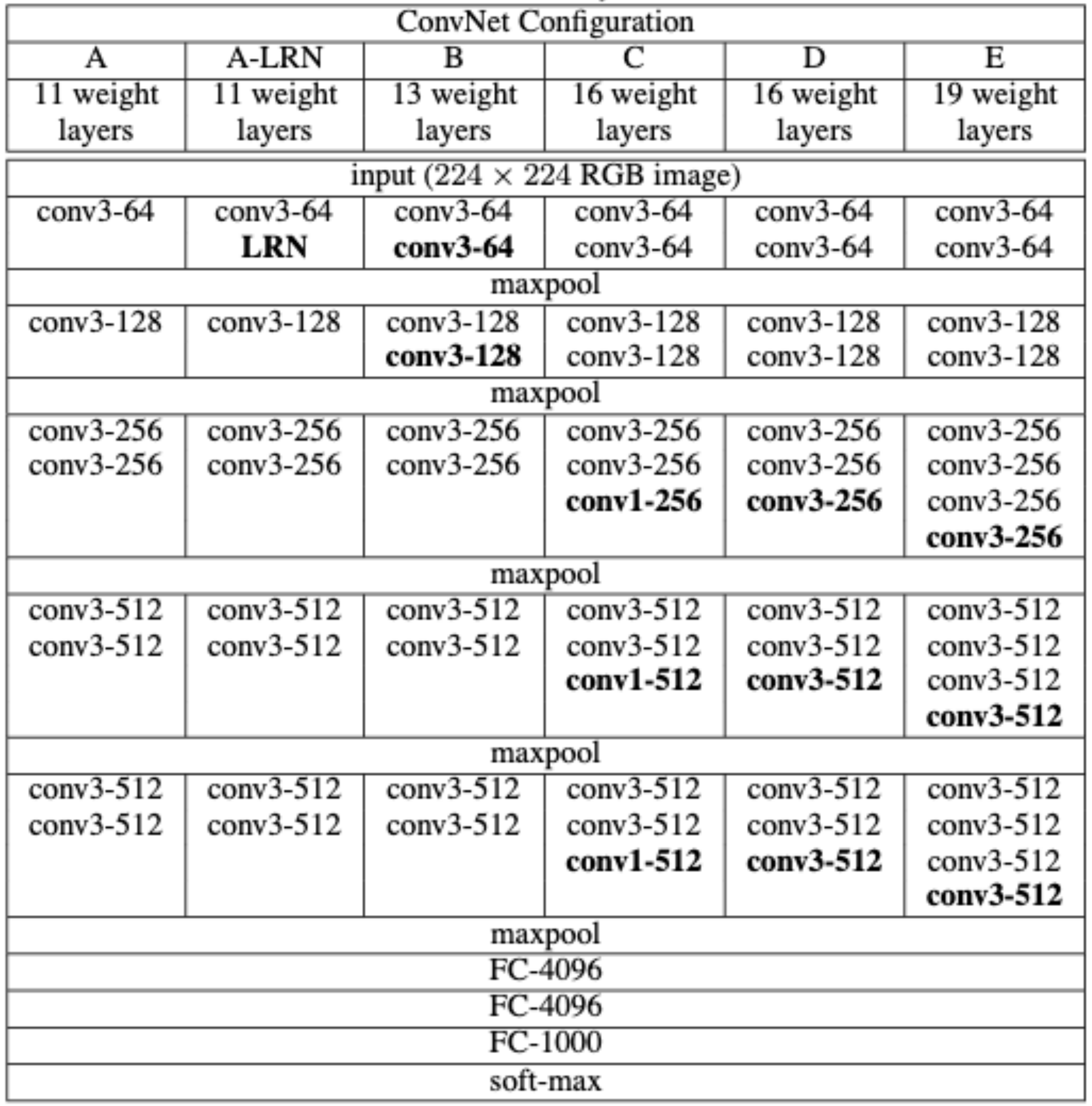


Table 1: **ConvNet configurations** (shown in columns). The depth of the configurations increases from the left (A) to the right (E), as more layers are added (the added layers are shown in bold). The convolutional layer parameters are denoted as "conv⟨receptive field size⟩-⟨number of channels⟩". The ReLU activation function is not shown for brevity.

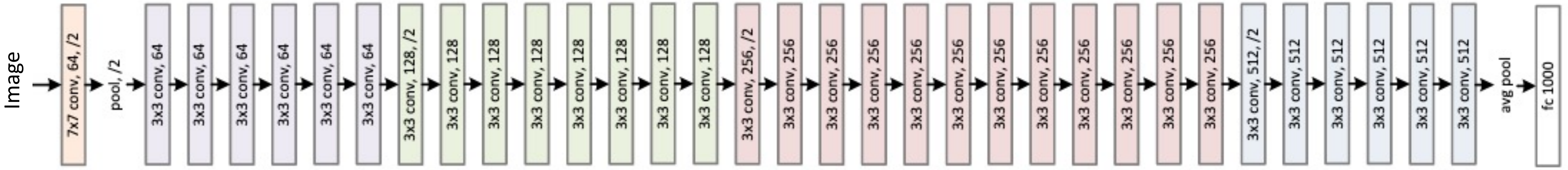


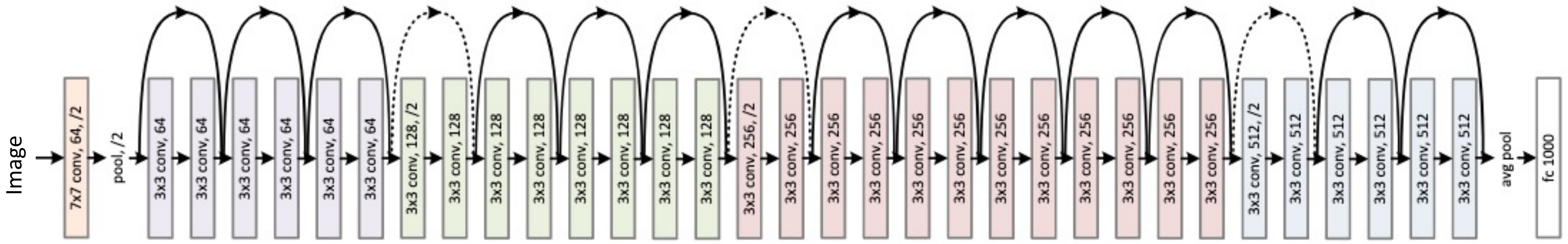
| ConvNet Configuration | | | | | |
|---|---|---|---|---|---|
| A | A-LRN | B | C | D | E |
| 11 weight layers | 11 weight layers | 13 weight layers | 16 weight layers | 16 weight layers | 19 weight layers |
| input (224 × 224 RGB image) | | | | | |
| conv3-64 | conv3-64<br>**LRN** | conv3-64<br>**conv3-64** | conv3-64<br>conv3-64 | conv3-64<br>conv3-64 | conv3-64<br>conv3-64 |
| maxpool | | | | | |
| conv3-128 | conv3-128 | conv3-128<br>**conv3-128** | conv3-128<br>conv3-128 | conv3-128<br>conv3-128 | conv3-128<br>conv3-128 |
| maxpool | | | | | |
| conv3-256<br>conv3-256 | conv3-256<br>conv3-256 | conv3-256<br>conv3-256 | conv3-256<br>conv3-256<br>**conv1-256** | conv3-256<br>conv3-256<br>**conv3-256** | conv3-256<br>conv3-256<br>conv3-256<br>**conv3-256** |
| maxpool | | | | | |
| conv3-512<br>conv3-512 | conv3-512<br>conv3-512 | conv3-512<br>conv3-512 | conv3-512<br>conv3-512<br>**conv1-512** | conv3-512<br>conv3-512<br>**conv3-512** | conv3-512<br>conv3-512<br>conv3-512<br>**conv3-512** |
| maxpool | | | | | |
| conv3-512<br>conv3-512 | conv3-512<br>conv3-512 | conv3-512<br>conv3-512 | conv3-512<br>conv3-512<br>**conv1-512** | conv3-512<br>conv3-512<br>**conv3-512** | conv3-512<br>conv3-512<br>conv3-512<br>**conv3-512** |
| maxpool | | | | | |
| FC-4096 | | | | | |
| FC-4096 | | | | | |
| FC-1000 | | | | | |
| soft-max | | | | | |

https://arxiv.org/pdf/1409.1556v6

# ResNet: Homework

Deeeeper Network: How many layers?
Potential Issues with this network!!!

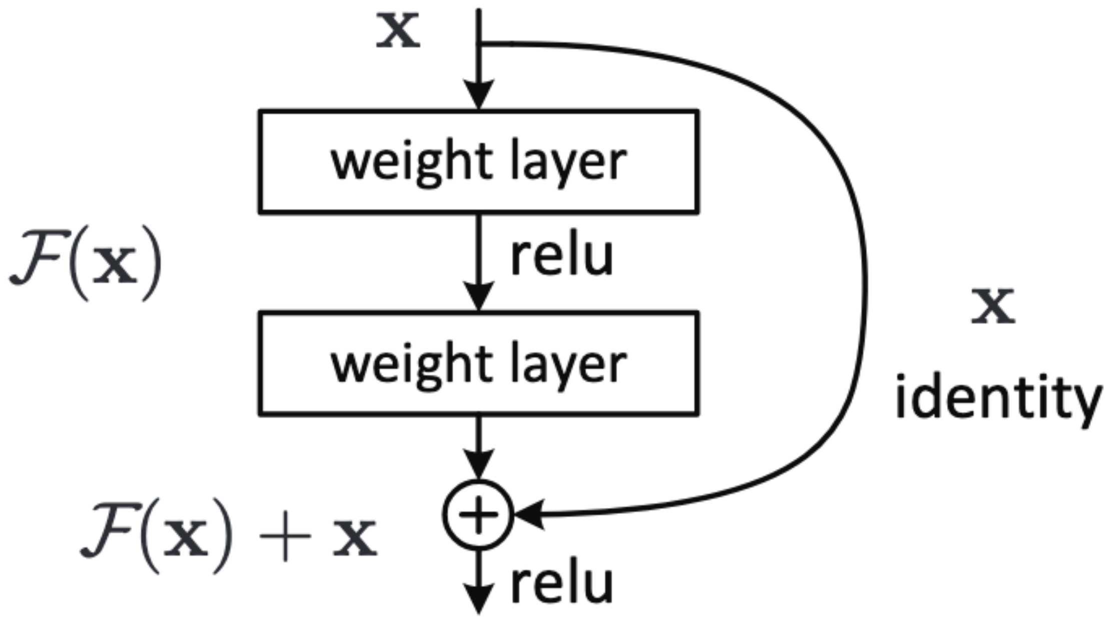




https://arxiv.org/abs/1512.03385

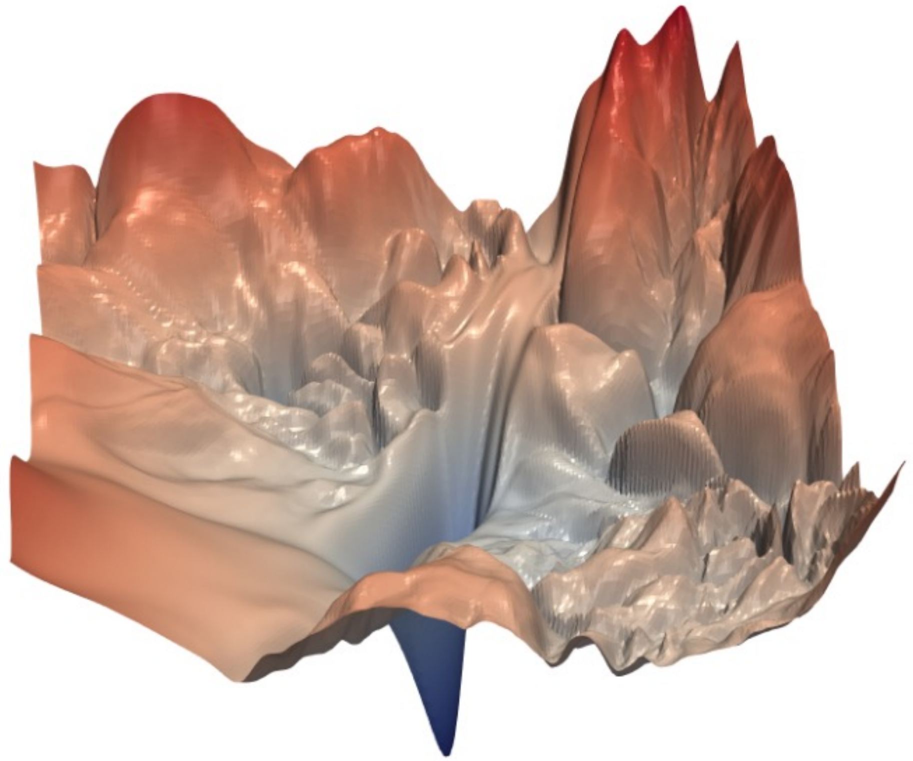
## Skip Connection: Tutorial!!

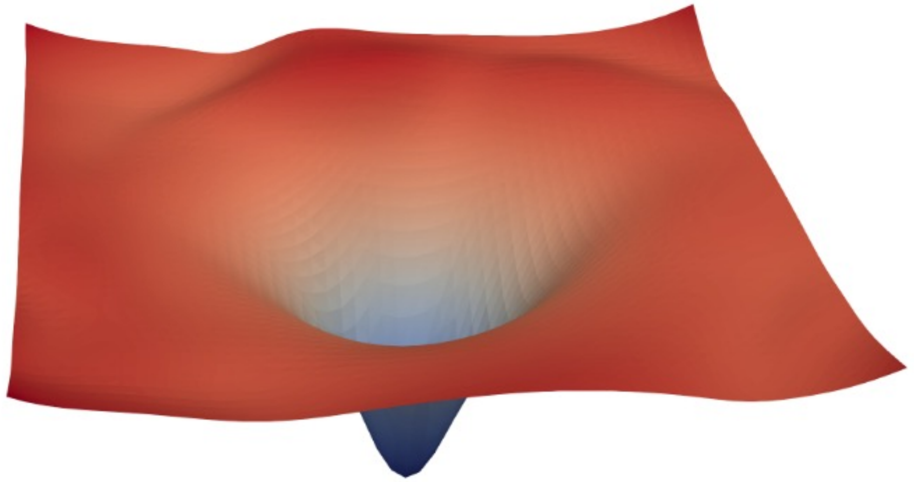
aka Residual Connection



Basic building block of residual learning

# Skip Connections


(a) without skip connections


(b) with skip connections