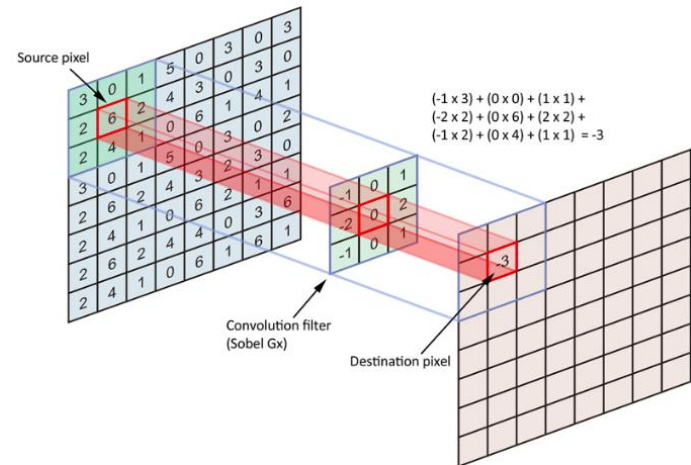
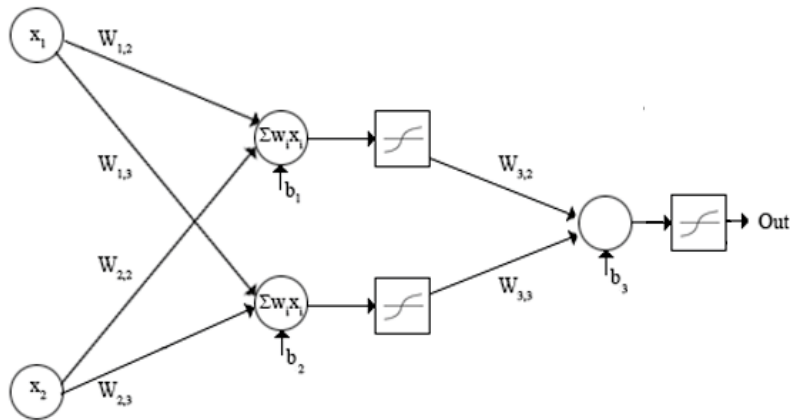


# Course Outline

- TOPICS

1. What is Machine Learning and Image Processing
2. Traditional Features, K-NN classifier
3. Linear Classification
4. Perceptron Algorithm, Sigmoid Activation Function, Gradient Descent
5. Stochastic Gradient Descent, Back-Propagation
6. Multi-Layer Neural Network
7. Convolution and Pooling
8. Mid-Term Examination
9. Mid-Term Examination
10. Convolutional Neural Networks.
11. Training Convolutional Neural Networks: Hyper-Parameters, Activation functions, initialization, dropout, batch normalization
12. Recurrent Neural Networks
13. Applications of Convolutional Neural Networks for Image Segmentation and Object Classification
14. Project Presentations

# Difference Between NN and CNN



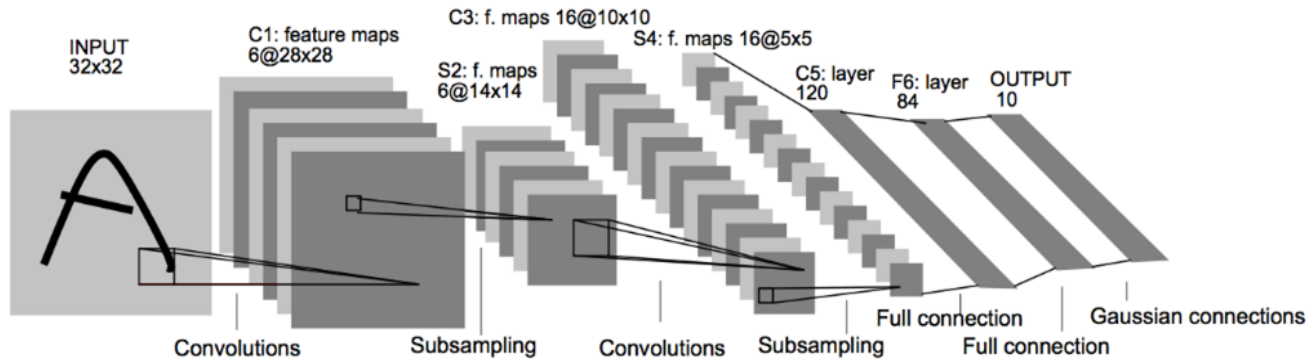
## NN:

- Resemble to human brain: interconnected neurons, transmit signal.
- Input Layer, Hidden Layers, Output Layer.
- **Inputs** are in the **Array** form.
- **Filters** are in the **Array** form

## CNN:

- Similar to NN but convolution exist.
- Convolutional Layer, ReLU Layer (called Activation), Pooling Layer, Fully Connected Layer.
- **Inputs** are in the **Matrix** form.
- **Filters** are in the **Matrix** form

# LeNet5

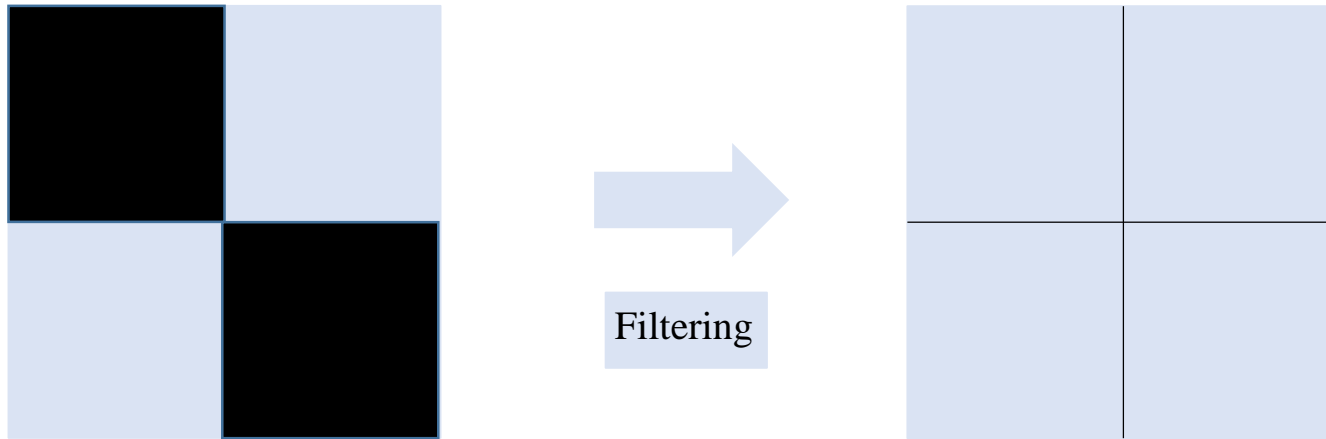


**CNN called LeNet by Yann LeCun (1998)**

**Lenet5:** The first CNN structure was proposed by Yann LeCun in 1998.

- Applied on MNIST and ASCII characters for document classification.
- Specifically, characters and digits are segmented and forwarded to CNN to determine its label.

# Edge Detection



- How can we find the edges in images?
- Answer: Using derivative operation to remove redundant information (homogenous regions).
- Perform derivative operation through  $-x$  axis and  $-y$  axis.

# Edge Detection

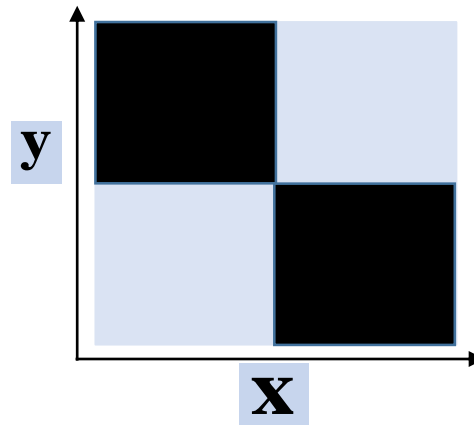


Image: I

Horizontal Edges :  $\frac{dI}{dy} \cong \frac{f(y_i) - f(y_{i-1})}{y_i - y_{i-1}}$



Image: I

Vertical Edges :  $\frac{dI}{dx} \cong \frac{f(x_i) - f(x_{i-1})}{x_i - x_{i-1}}$

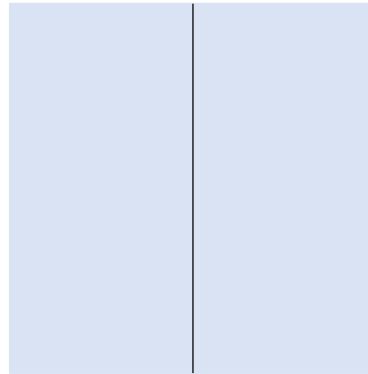
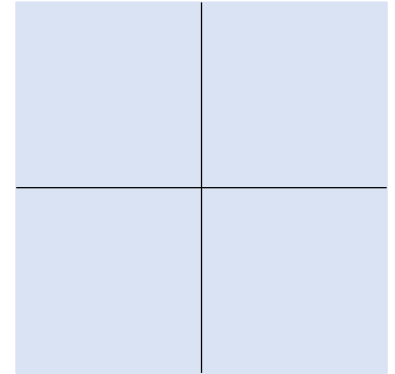
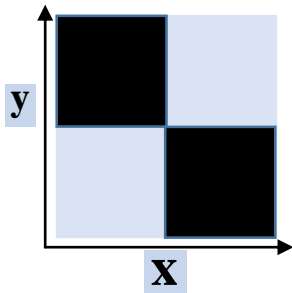


Image: I

EdgeMap =  $\left| \frac{dI}{dx} \right| + \left| \frac{dI}{dy} \right|$



# Edge Detection



**Image: I**

As an alternative way,  
we can convolve the image with filters.

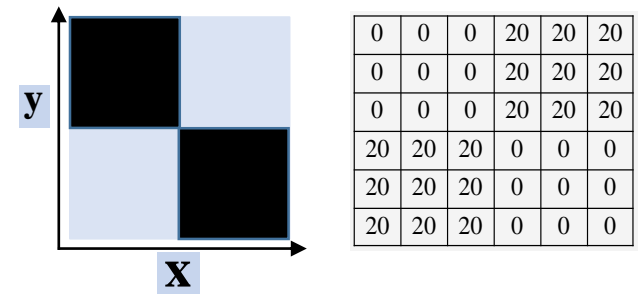
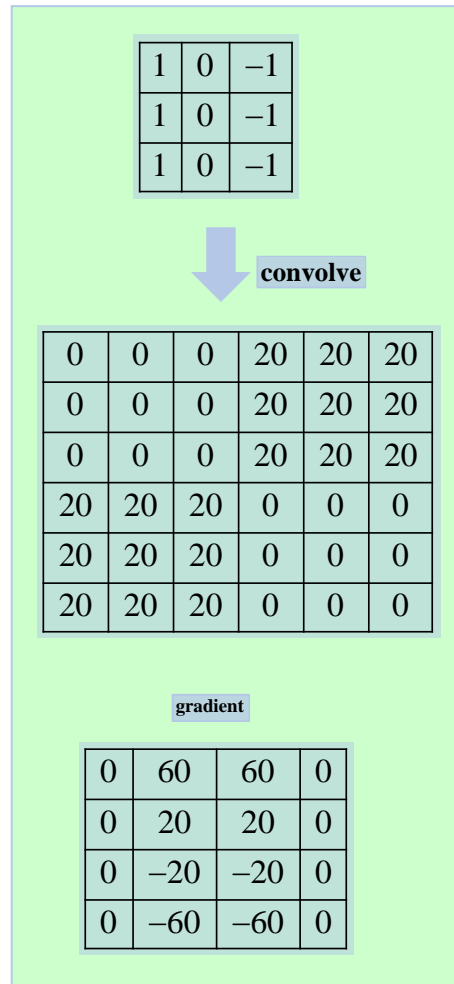
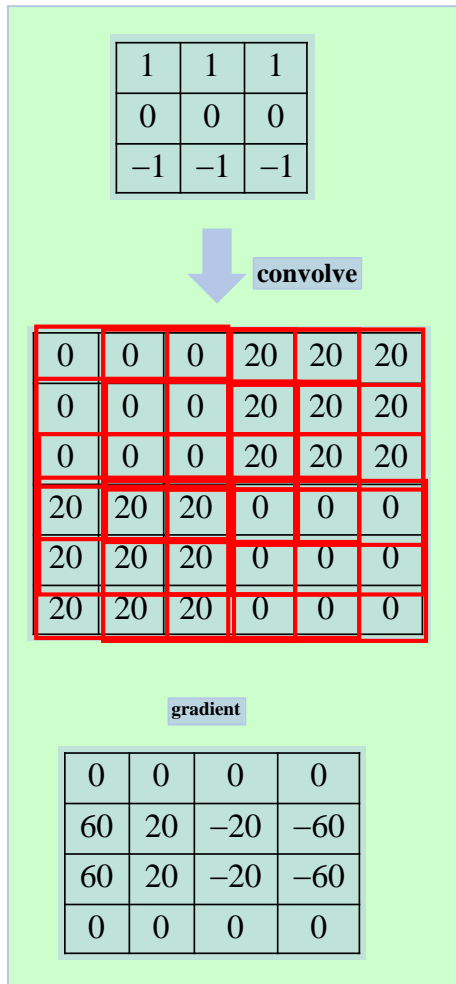
$$\text{Horizontal Filter : } F_x = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

$$\text{Horizontal Edges : } \frac{dI}{dx} \cong I * F_x \quad *: \text{refers convolution}$$

$$\text{Vertical Filter : } F_y = \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix}$$

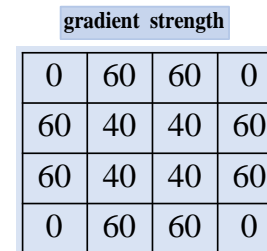
$$\text{Vertical Edges : } \frac{dI}{dy} \cong I * F_y \quad *: \text{refers convolution}$$

# Edge Detection

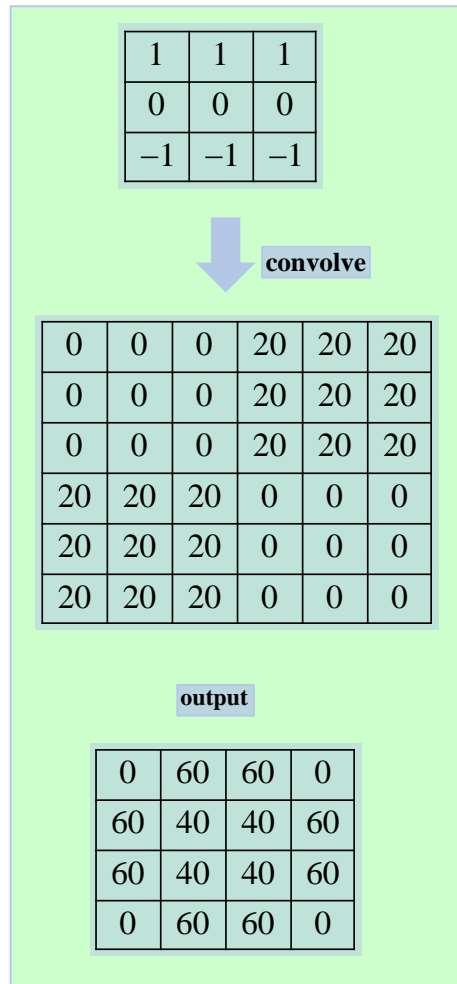


Gradient Strengthness  $\Delta I \cong \left| \frac{dI}{dx} \right| + \left| \frac{dI}{dy} \right|$

Gradient Direction  $\theta = \tan^{-1} \left( \frac{dI}{dy} / \frac{dI}{dx} \right)$

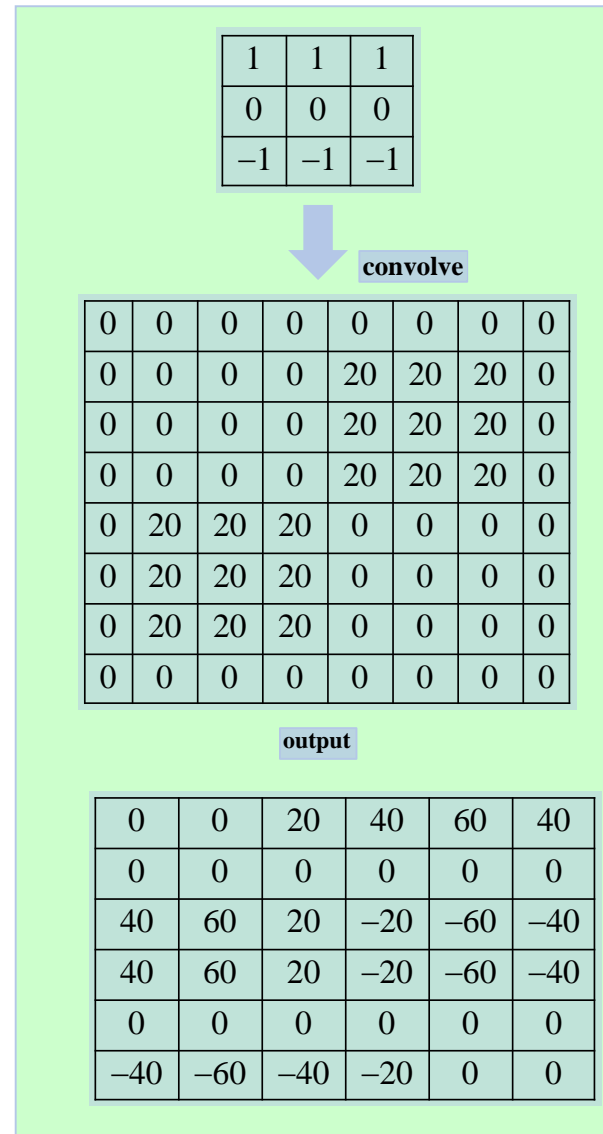


# Padding



valid

padding : 1



same



# Convolution

$$o = \frac{n + 2p - f}{s} + 1$$

**Ex1:**

$$f = 3 \times 3$$

$$n = 6, f = 3, p = 0, s = 1$$

$$\text{out} = \frac{6 + 2 \cdot 0 - 3}{1} + 1 = 4$$

$$\text{out} = 4 \times 4$$

**Ex2:**

$$f = 3 \times 3$$

$$n = 6 \times 6, f = 3, p = 1, s = 1$$

$$\text{out} = \frac{6 + 2 \cdot 1 - 3}{1} + 1 = 6$$

$$\text{out} = 6 \times 6$$

**p : padding**

**h : height**

**w : width**

**f : filter,  $f \times f$  or  $h \times w$**

**I : image  $n \times n$**

**s : stride**

**out : output**

**Ex3:**

$$f = 3 \times 4 = h \times w$$

$$I = 6 \times 6$$

$$n = 6, h = 3, p = 1, s = 1$$

$$h_{\text{out}} = \frac{6 + 2 \cdot 1 - 3}{1} + 1 = 6$$

$$w_{\text{out}} = \frac{6 + 2 \cdot 1 - 4}{1} + 1 = 5$$

$$I_{\text{new}} = 6 \times 5$$

**Ex4:**

$$f = 3 \times 5 = h \times w$$

$$I = 12 \times 8$$

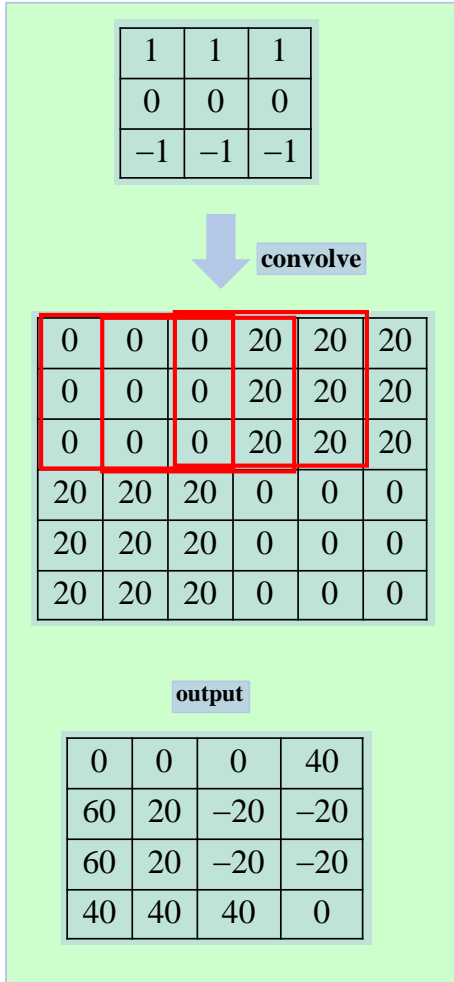
$$n = 6, h = 3, p = 1, s = 1$$

$$h_{\text{out}} = \frac{12 + 2 \cdot 1 - 3}{1} + 1 = 12$$

$$w_{\text{out}} = \frac{8 + 2 \cdot 1 - 5}{1} + 1 = 6$$

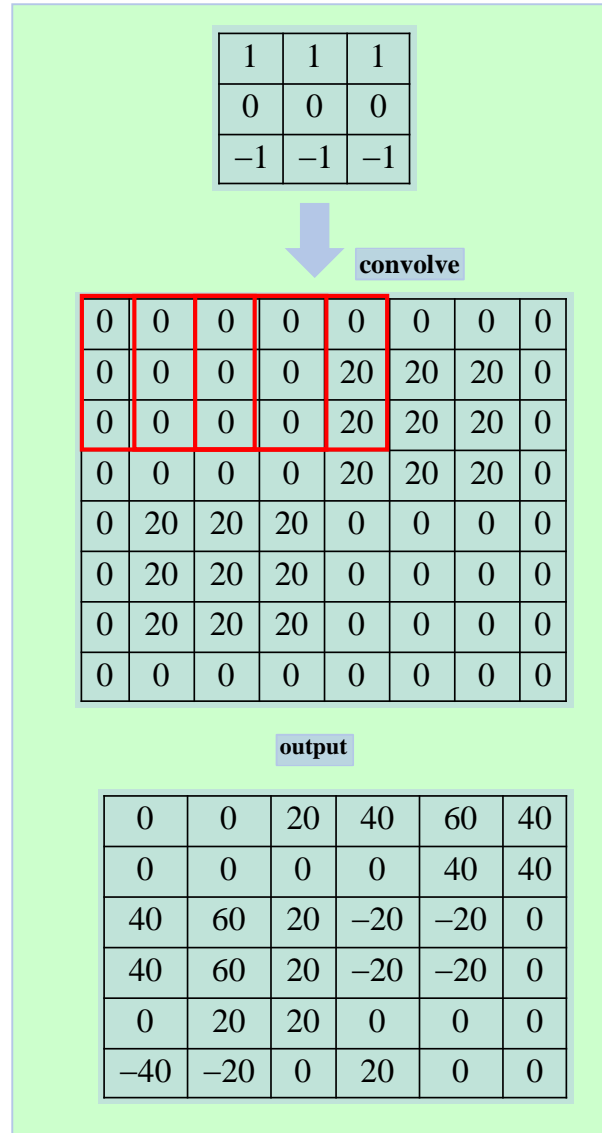
$$I_{\text{new}} = 12 \times 6$$

**padding 0  
stride 1**



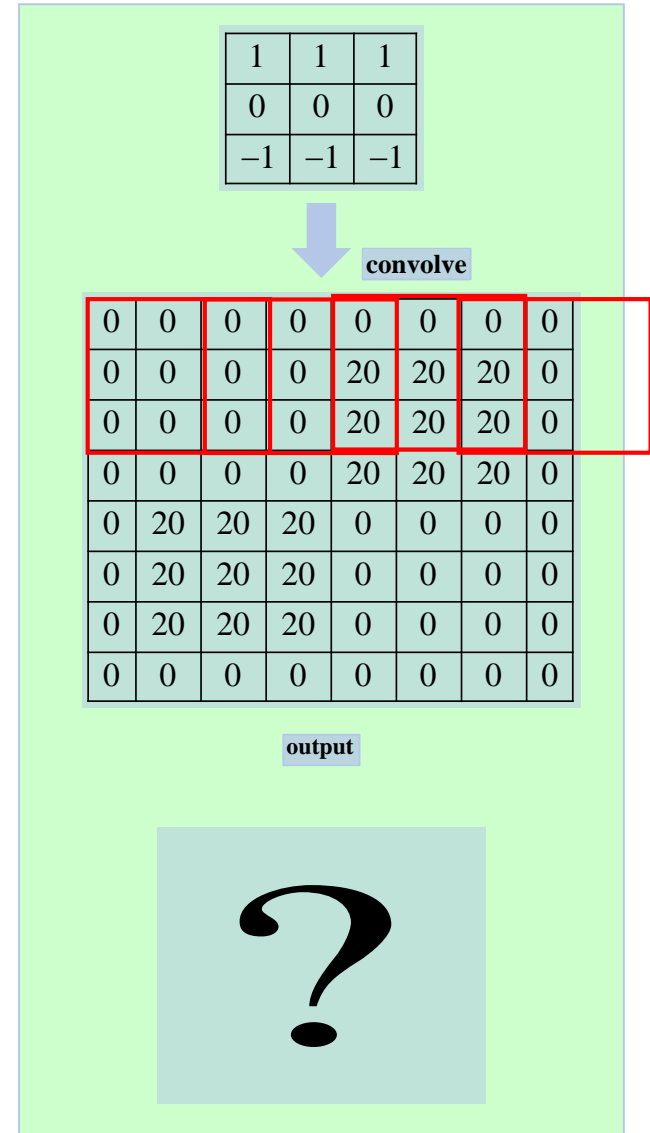
valid

**padding 1  
stride 1**



same

**padding 1  
stride 2**



valid

## padding 1, stride 2

wrong padding

1	1	1
0	0	0
-1	-1	-1



convolve

0	0	0	0	0	0	0	0
0	0	0	0	20	20	20	0
0	0	0	0	20	20	20	0
0	0	0	0	20	20	20	0
0	20	20	20	0	0	0	0
0	20	20	20	0	0	0	0
0	20	20	20	0	0	0	0
0	0	0	0	0	0	0	0

output

0	60	60	0
60	40	40	60
60	40	40	60
0	60	60	0

## padding 3, stride 3

true padding

1	1	1
0	0	0
-1	-1	-1



			0	0	0	20	20	20	
			0	0	0	20	20	20	
			0	0	0	20	20	20	
			20	20	20	0	0	0	
			20	20	20	0	0	0	
			20	20	20	0	0	0	

0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0

$$o = \frac{n + 2p - f}{s} + 1$$

$$6 = \frac{6 + 2 \cdot p - 3}{2} + 1$$

$$10 = 6 + 2 \cdot p - 3$$

$$7 = 2 \cdot p$$

$$p = 3.5$$

wrong padding

$$6 = \frac{6 + 2 \cdot p - 3}{3} + 1$$

$$15 = 6 + 2 \cdot p - 3$$

$$12 = 2 \cdot p$$

$$p = 3$$

true padding

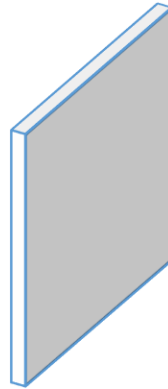
$$p = \frac{f - 1}{2}$$

# Convolution over Volume



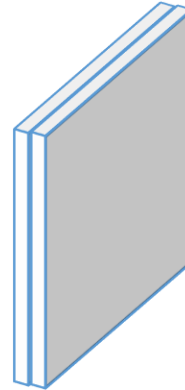
**input**  
 $32 \times 32 \times 3$

**pad : 0**  
**stride : 1**



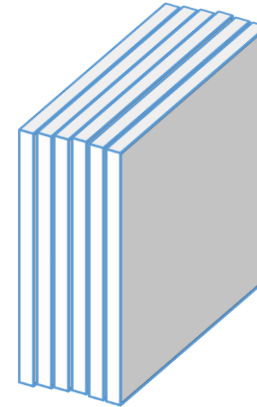
**output**  
 $28 \times 28$

**1 filter**  
 $5 \times 5 \times 3$



**output**  
 $28 \times 28 \times 2$

**2 filter**  
 $5 \times 5 \times 3$



**output**  
 $28 \times 28 \times 6$

**6 filter**  
 $5 \times 5 \times 3$