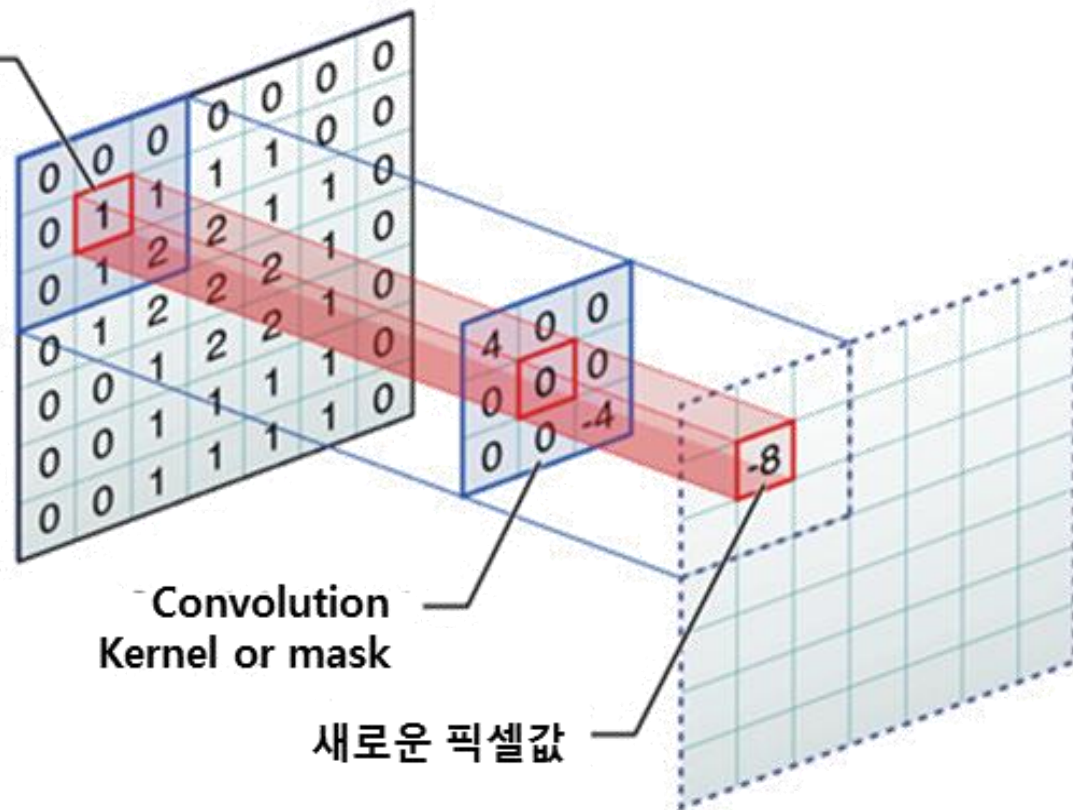


# Convolution and Pooling

# Convolution and Pooling


- Convolution
- Channel
- Stride
- Padding
- Pooling


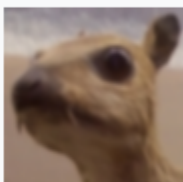
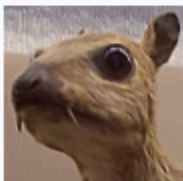
이미지 픽셀값



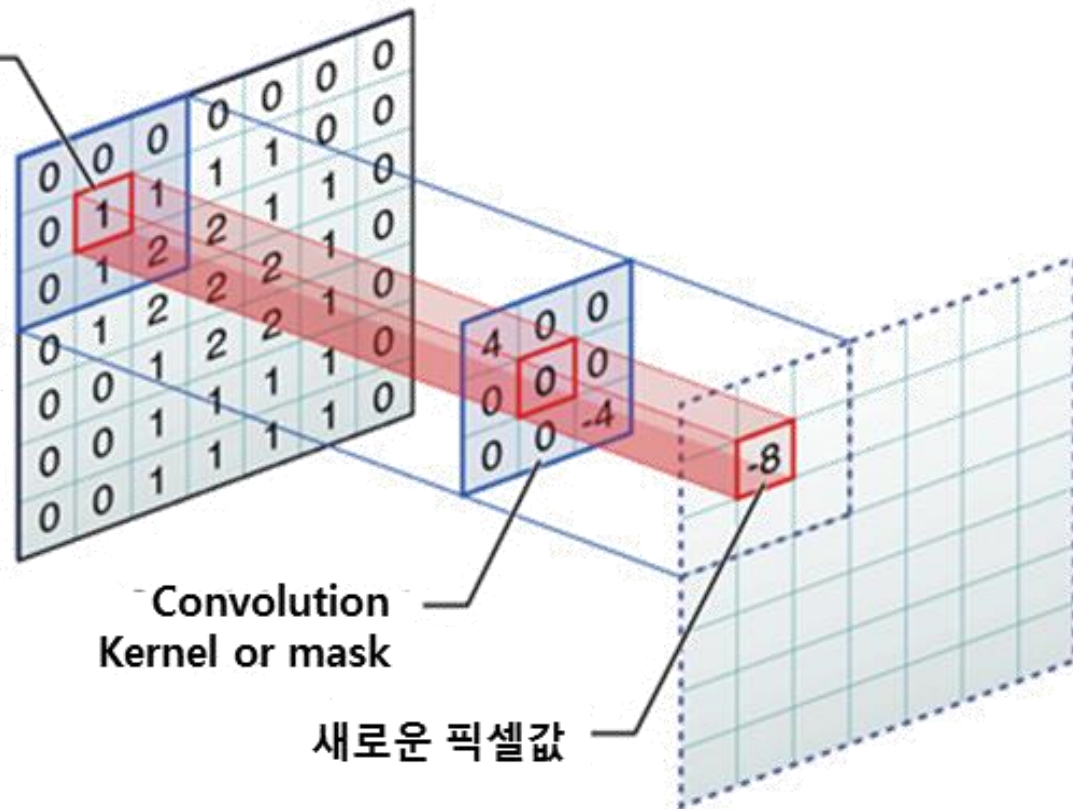
Convolution  
Kernel or mask

새로운 픽셀값

Operation	Kernel	Image result
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	

Gaussian blur $3 \times 3$ (approximation)	$\frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	
Gaussian blur $5 \times 5$ (approximation)	$\frac{1}{256} \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$	
Unsharp masking $5 \times 5$ Based on Gaussian blur with amount as 1 and threshold as 0 (with no image mask)	$\frac{-1}{256} \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & -476 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$	

이미지 픽셀값



Convolution  
Kernel or mask

새로운 픽셀값

이미지 픽셀값

0	0	0	0
0	1	1	2
0	1	2	2
0	1	2	2
0	0	1	1
0	0	1	1
0	0	1	1
0	0	1	1

Kernel mask

새로운 픽셀값

image

1	2	3
4	5	6
7	8	9

$\otimes$

kernel

A	B	C
D	E	F
G	H	I

$$(1 * A) + (2 * B) + (3 * C) + (4 * D) + \dots + (9 * I)$$

image

1	2	3
4	5	6
7	8	9

\*

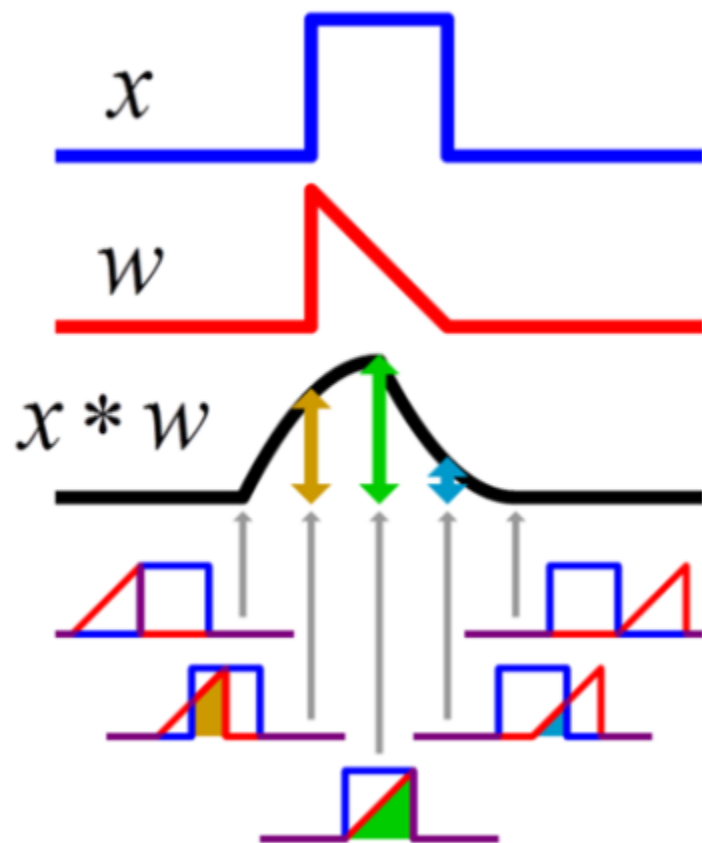
kernel

A	B	C
D	E	F
G	H	I

$$(1 * I) + (2 * H) + (3 * G) + (4 * F) + \dots + (9 * A)$$

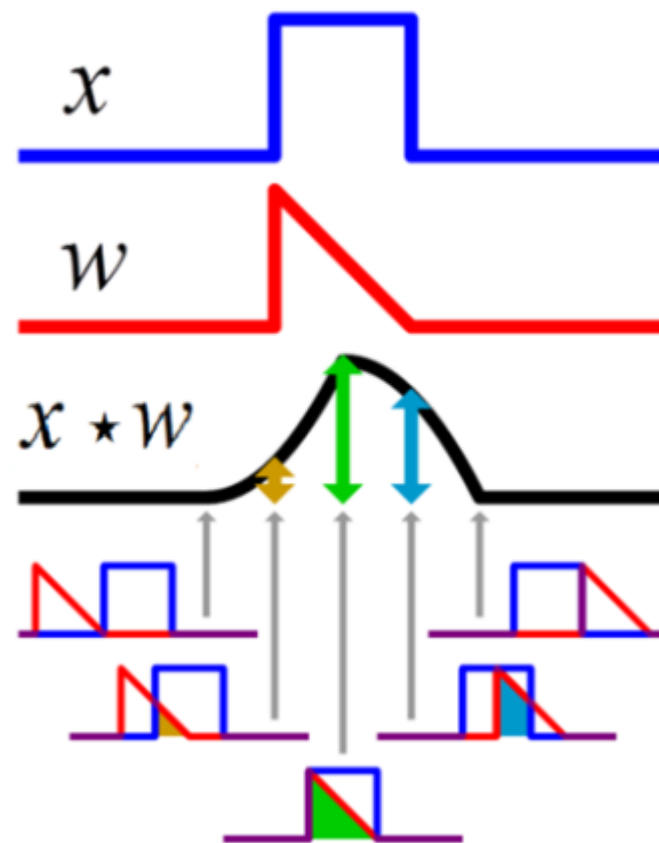


*Convolution*



$$x * w$$

*Cross-Correlation*



$$x \otimes w$$

# 합성곱

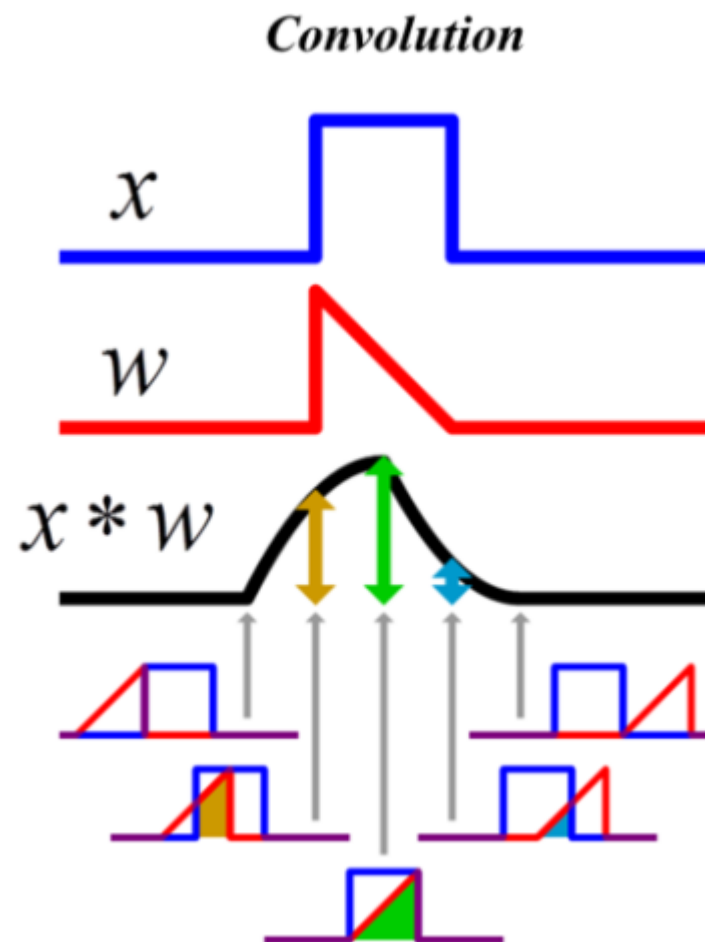
위키백과, 우리 모두의 백과사전.

**합성곱**(合成-, convolution, 콘벌루션)은 하나의 함수와 또 다른 함수를 반전 이동한 값을 곱한 다음, 구간에 대해 적분하여 새로운 함수를 구하는 수학 연산자이다.

$$y(t) = (x * w)(t)$$

$$= \int_{-\infty}^{\infty} x(a)w(t-a)da$$

$$y[n] = \sum_{a=-\infty}^{\infty} x[a]w[n-a]$$



$$y(i,j) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} image[m,n] kernel[i-m,j-n]$$

image

1	2	3
4	5	6
7	8	9

\*

kernel

A	B	C
D	E	F
G	H	I

$$(1 * I) + (2 * H) + (3 * G) + (4 * F) + \dots + (9 * A)$$

$$y(i,j) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} image[m,n] \, kernel[i-m,j-n]$$

image

1	2	3
4	5	6
7	8	9

\*

kernel

A	B	C
D	E	F
G	H	I

\*

-1,-1	0,-1	1,-1
-1,0	0,0	1,0
-1,1	0,1	1,1

i-1, j-1	i, j-1	i+1, j-1
i-1, j	i, j	i+1, j
i-1, j+1	i, j+1	i+1, j+1

Ex) m = -1, n = -1

-1,-1	0,-1	1,-1
-1,0	0,0	1,0
-1,1	0,1	1,1

i-1, j-1	i, j-1	i+1, j-1
i-1, j	i, j	i+1, j
i-1, j+1	i, j+1	i+1, j+1

-1,-1	0,-1	1,-1
-1,0	0,0	1,0
-1,1	0,1	1,1

i-1, j-1	i, j-1	i+1, j-1
i-1, j	i, j	i+1, j
i-1, j+1	i, j+1	i+1, j+1

Ex) m = 1, n = -1

$$y(i,j) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} image[m,n] kernel[i+m,j+n]$$

image

1	2	3
4	5	6
7	8	9

 $\otimes$ 

kernel

A	B	C
D	E	F
G	H	I

$$(1 * A) + (2 * B) + (3 * C) + (4 * D) + \dots + (9 * I)$$

$$y(i,j) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} \text{image}[m,n] \text{kernel}[i+m,j+n]$$

image

1	2	3
4	5	6
7	8	9

⊗

kernel

A	B	C
D	E	F
G	H	I

⊗

-1,-1	0,-1	1,-1
-1,0	0,0	1,0
-1,1	0,1	1,1

i-1, j-1	i, j-1	i+1, j-1
i-1, j	i, j	i+1, j
i-1, j+1	i, j+1	i+1, j+1

Ex) m = -1, n = -1

-1,-1	0,-1	1,-1
-1,0	0,0	1,0
-1,1	0,1	1,1

i-1, j-1	i, j-1	i+1, j-1
i-1, j	i, j	i+1, j
i-1, j+1	i, j+1	i+1, j+1

-1,-1	0,-1	1,-1
-1,0	0,0	1,0
-1,1	0,1	1,1

Ex) m = 1, n = -1

i-1, j-1	i, j-1	i+1, j-1
i-1, j	i, j	i+1, j
i-1, j+1	i, j+1	i+1, j+1

**RED Channel**



**Green Channel**



**Blue Channel**



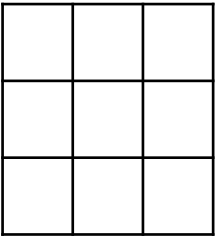
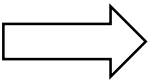
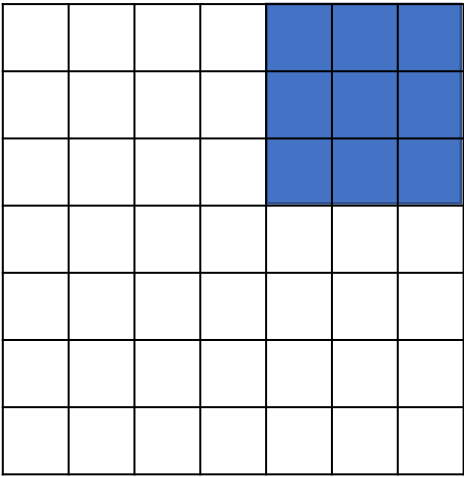
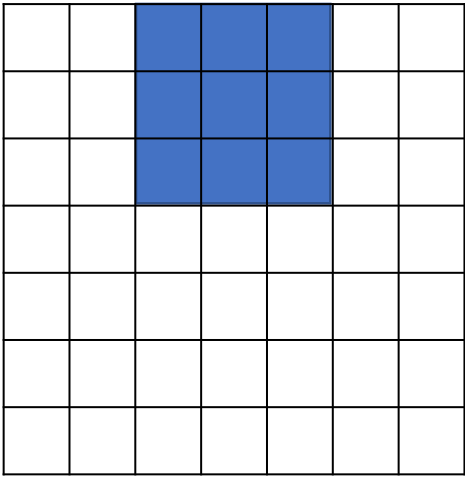
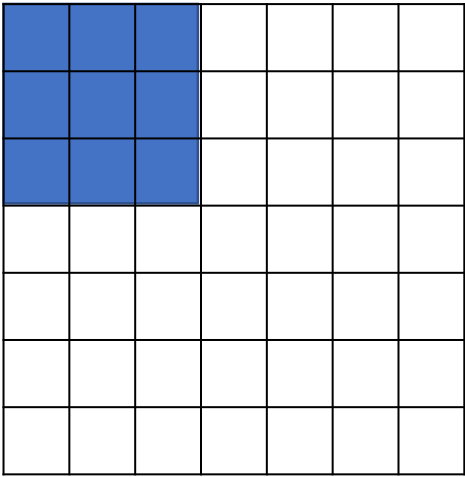
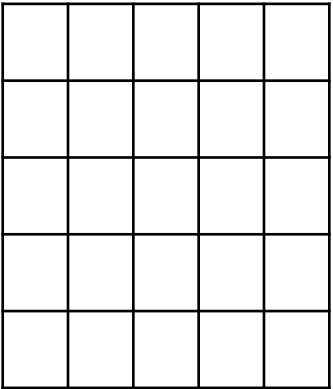
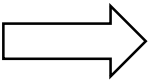
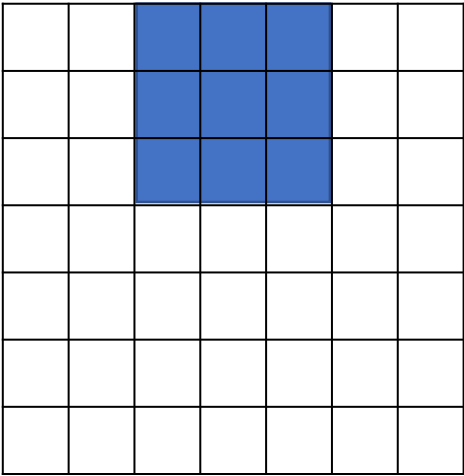
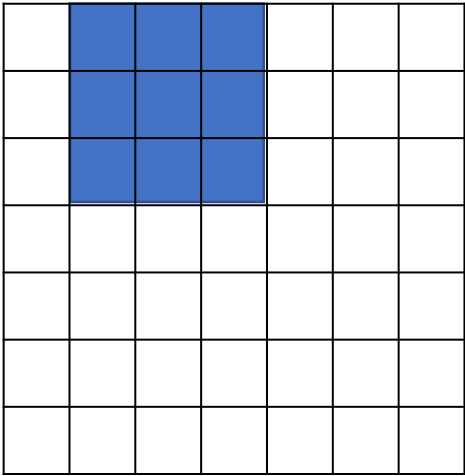
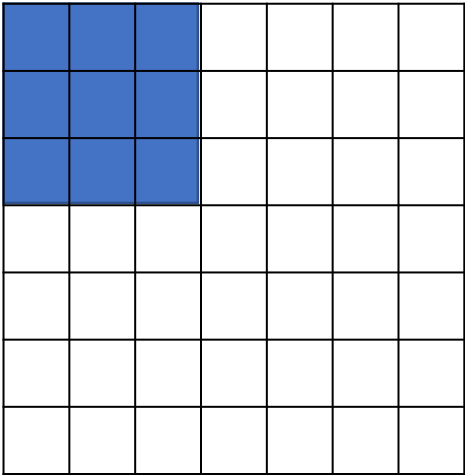
RGB image -> 3 channels

Gray image -> 1 channel

$n$  filters in conv. layer ->  $n$  channels output

 : image     : filter

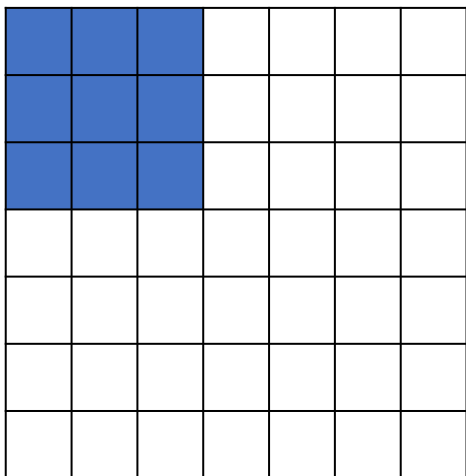
**Stride** : Convolution을 진행할 때, 필터의 이동 간격.





**Padding** : image의 모서리 부분 정보 손실 방지

Zero Padding = X

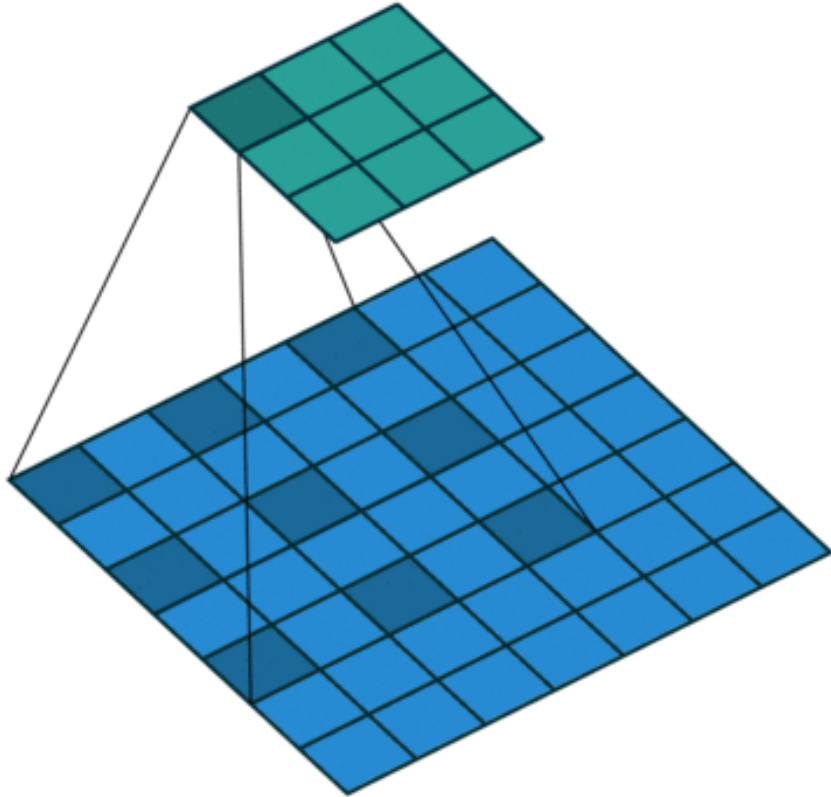


$7 \times 7 \xrightarrow{\text{conv}} 5 \times 5$

Zero Padding = O

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

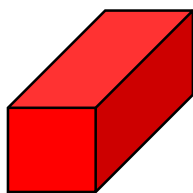
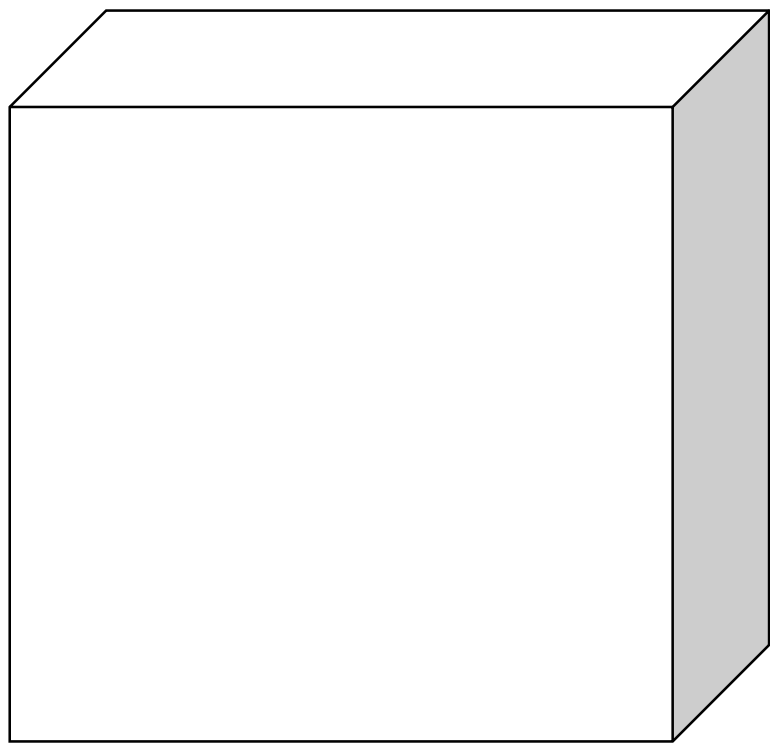
$7 \times 7 \xrightarrow{\text{conv}} 7 \times 7$

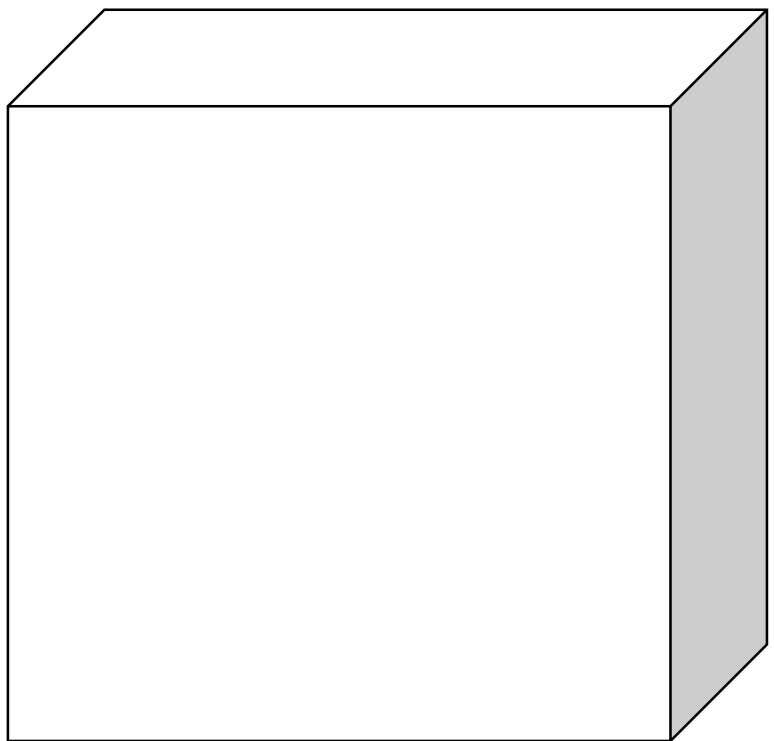


# Dilated Convolutions

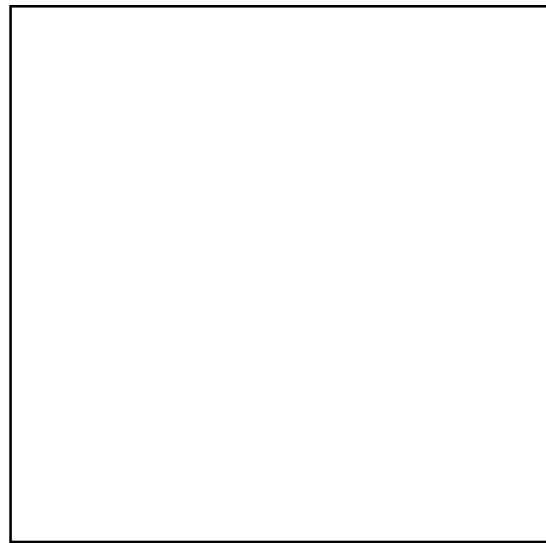
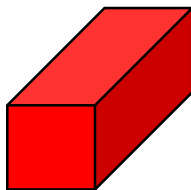
dilation rate : 커널 사이의 간격  
ex) dilation rate = 2

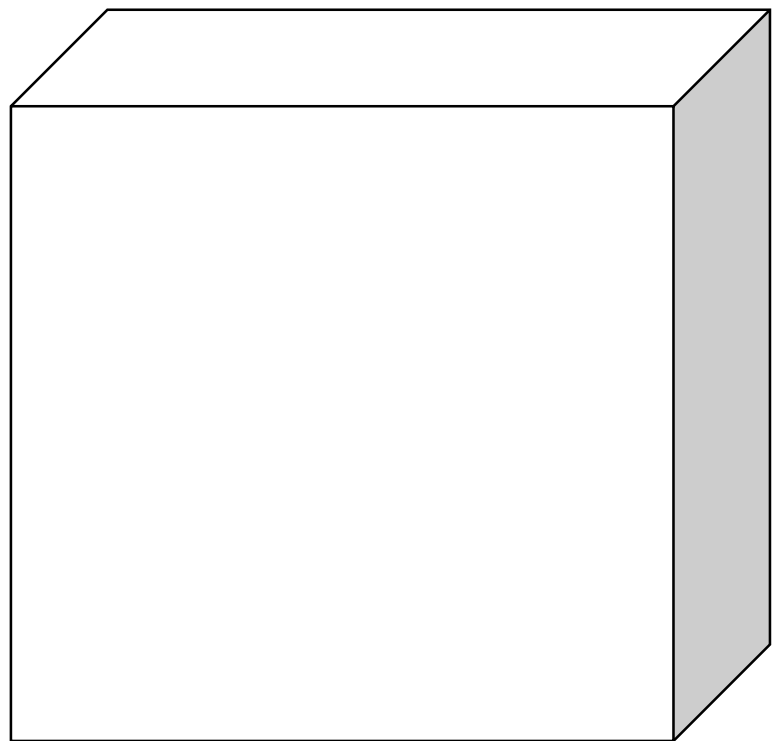
넓은 시야가 필요할 때 용이  
필터 내부에 zero padding을 추가  
연산의 효율 좋다



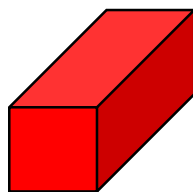


\*

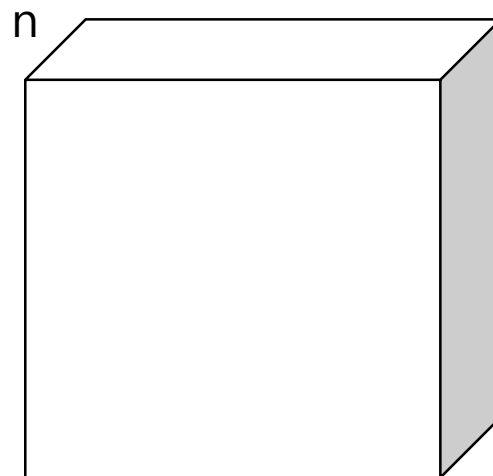




\*



$\times n$



## Sampling (Pooling)

- 이동 불변성.
- 이미지의 크기를 줄이기 때문에 학습할 노드의 수가 줄어들어 **학습속도를 높**이는 효과.
- 하지만 **정보 손실**이 일어남.

Feature Map

3	0	4	3
4	1	2	3
1	1	8	7
2	0	6	4



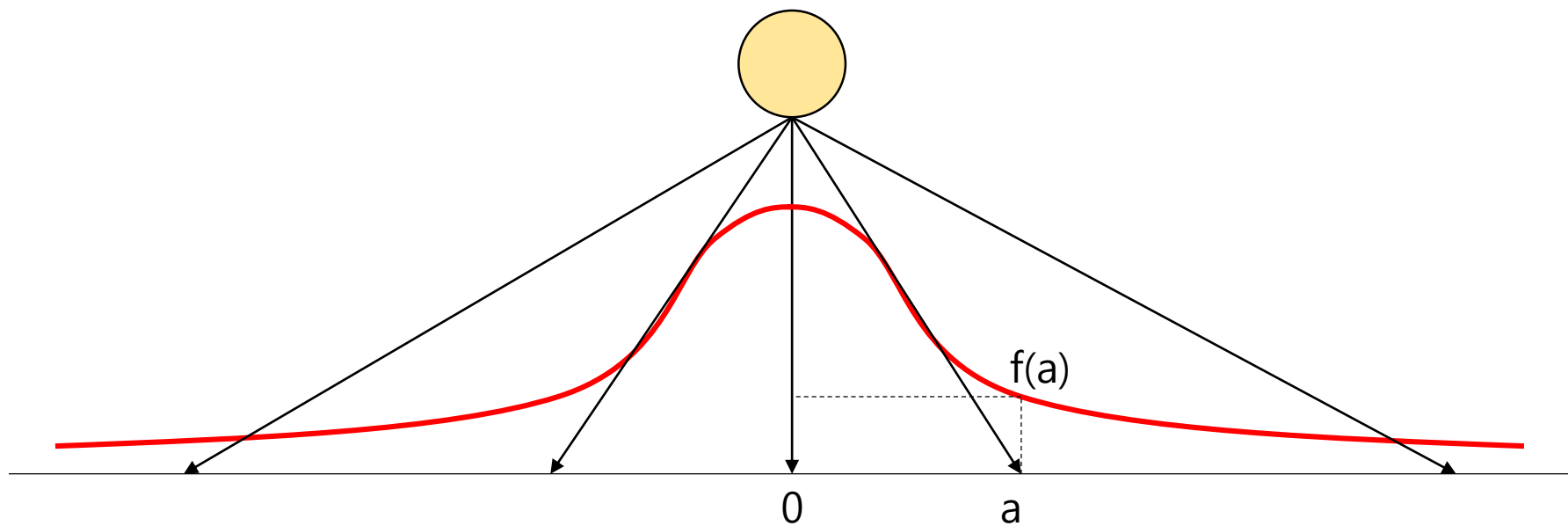
4	4
2	8

1	3	0	4
2	4	1	2
1	1	1	8
1	2	0	6

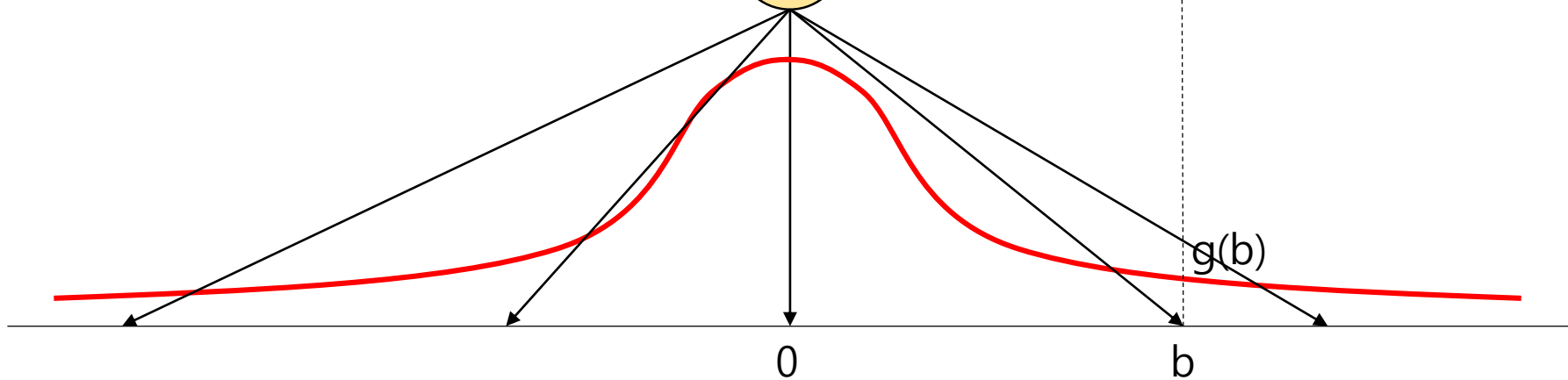
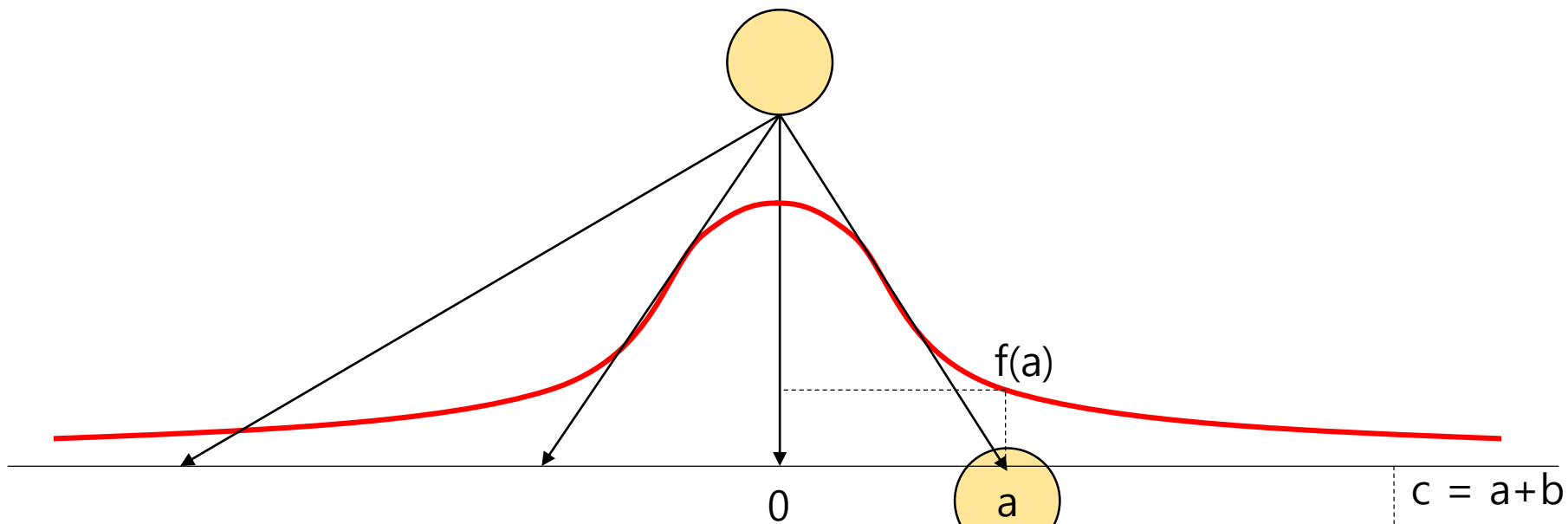


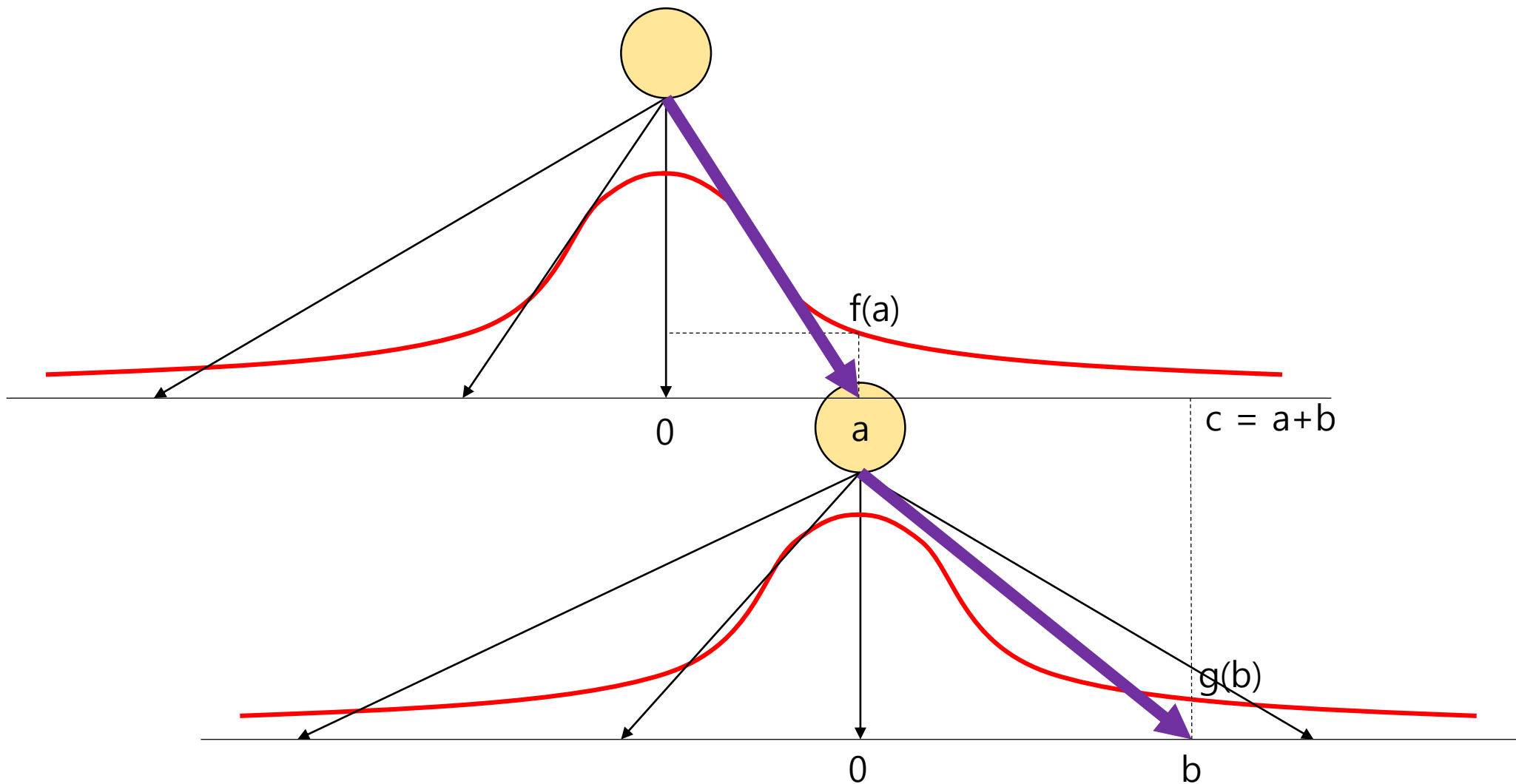
4	4
2	8

Appendix.



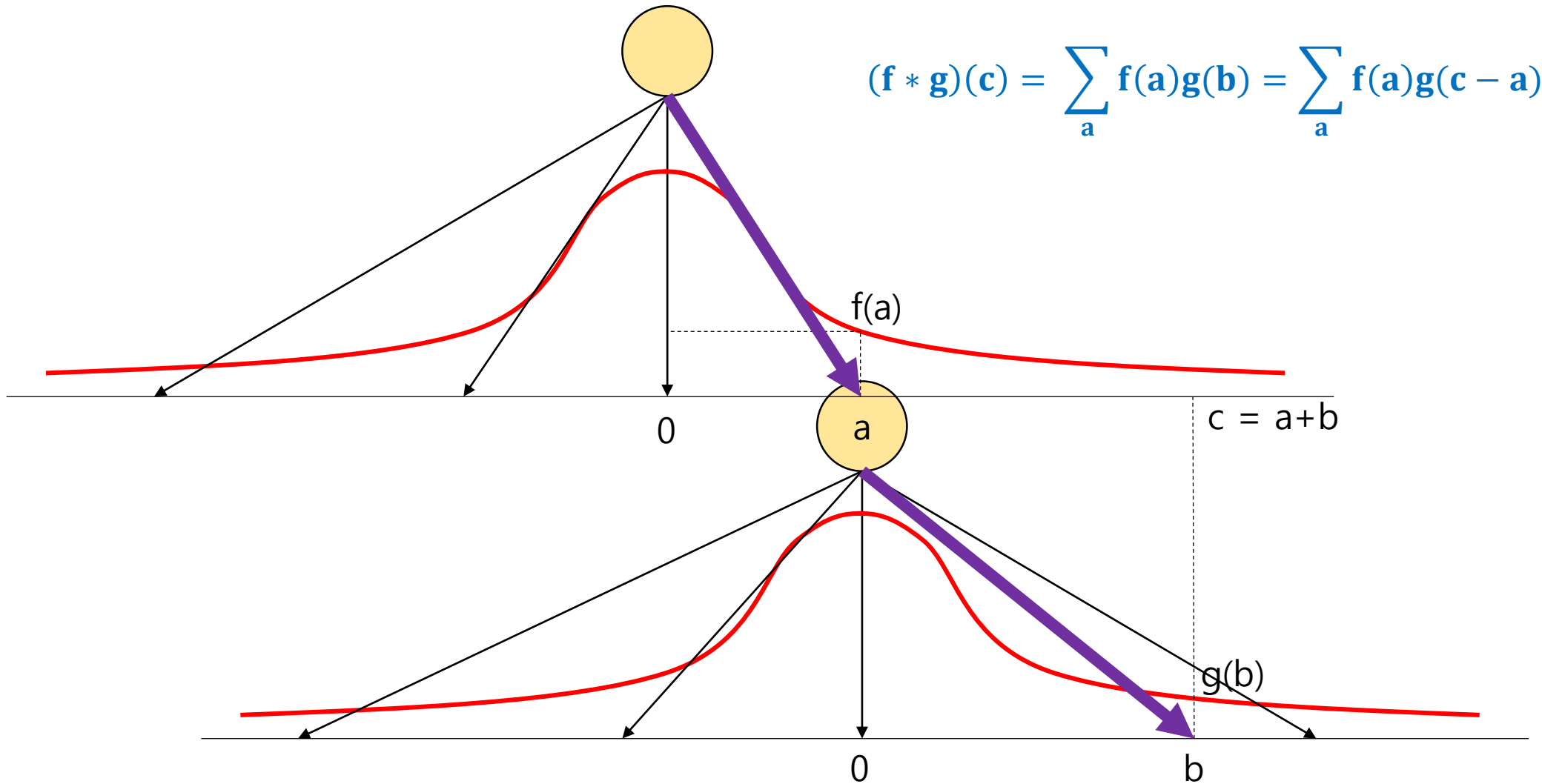






$$f(a)g(b) = f(a)g(c-a)$$

$$(f * g)(c) = \sum_a f(a)g(b) = \sum_a f(a)g(c - a)$$



$$f(a)g(b) = f(a)g(c-a)$$