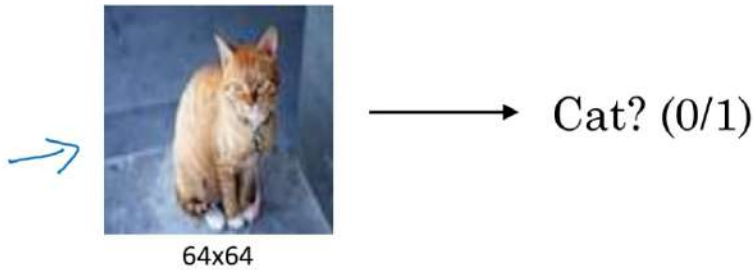


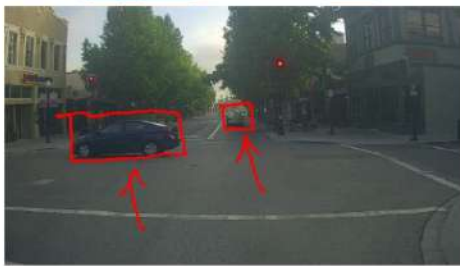


Computer Vision Problems

Image Classification



Object detection



차의 머리와 옆면
박스도 식별

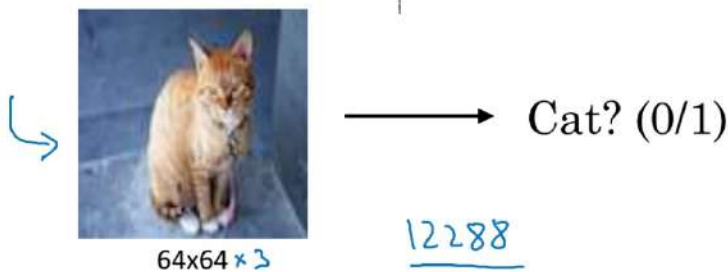
Neural Style Transfer



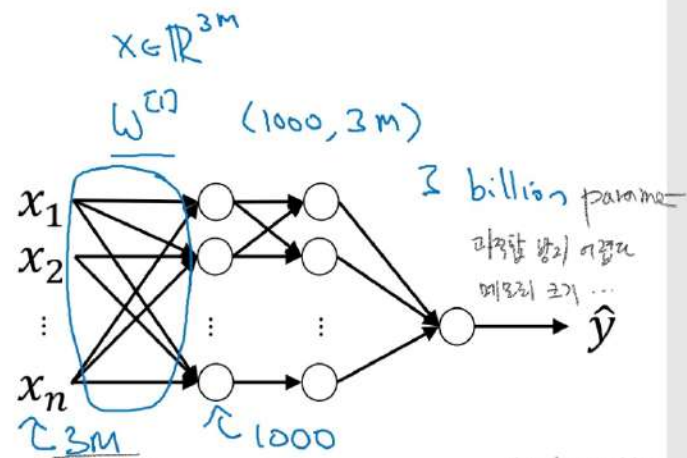
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Deep Learning on large images

input이 크다!



RGB 채널
 $1000 \times 1000 \times 3$
= 3 million



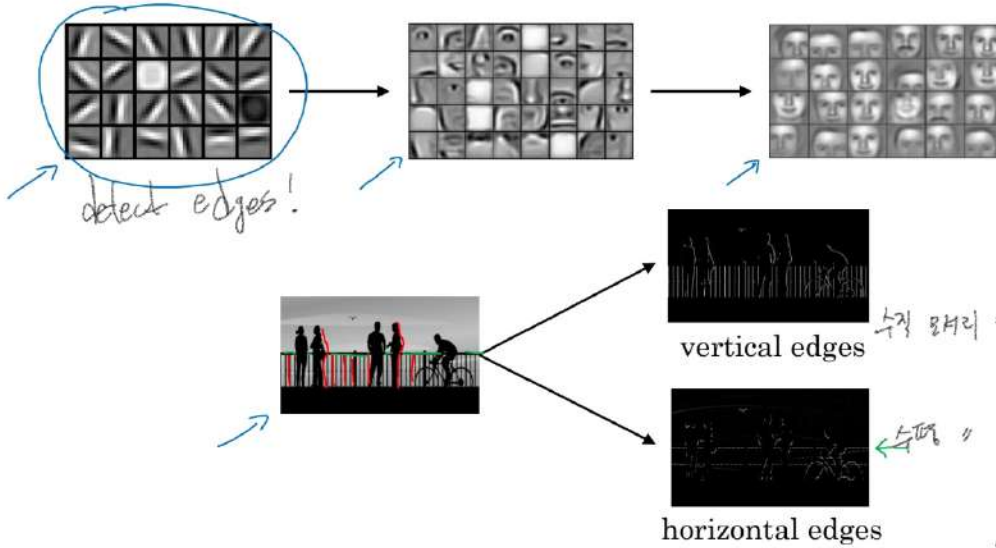
Andrew Ng



Edge detection example

"한글자 작업"

Computer Vision Problem



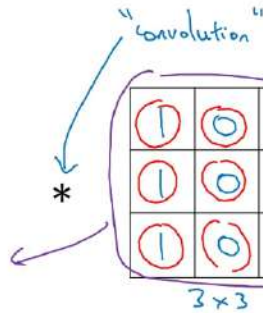
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Vertical edge detection

$$\rightarrow 3 \times 1 + 1 \times 1 + 2 \times 1 + 0 \times 0 + 5 \times 0 + 7 \times 0 + 1 \times -1 + 8 \times -1 + 2 \times -1 = -5$$

3	0	1	2	7	4
1	5	8	3	3	1
2	7	2	1	3	
0	1	3	1	7	8
4	2	1	6	2	8
2	4	5	2	3	9

6x6



-5	-4	0	8
-10	-2	2	3
0	-2	-4	-7
-3	-2	-3	-16

4x4

filter
(kernel)

python: `Conv Forward`

Vertical edge detection

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

6x6

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

3x3

tensorflow: `tf.nn.conv2d`
keras: `Conv2D`

0	30	30	0
0	30	30	0
0	30	30	0
0	30	30	0

4x4

Q
-1 라 1 위치를
바꿔야하면?



Andrew Ng



More edge detection

Vertical edge detection examples

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

$$\begin{matrix} * \\ \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} \end{matrix}$$

=

0	30	30	0
0	30	30	0
0	30	30	0
0	30	30	0

0 → 0

0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10

$$\begin{matrix} * \\ \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} \end{matrix}$$

=

0	-30	-30	0
0	-30	-30	0
0	-30	-30	0
0	-30	-30	0

0 → 0

Vertical and Horizontal Edge Detection

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

Vertical

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

Horizontal

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10

6x6

*

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

=

0	0	0	0
30	10	-10	-30
30	10	-10	-30
0	0	0	0

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Learning to detect edges

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

↑

3	0	1	2	7	4
1	5	8	9	3	1
2	7	2	5	1	3
0	1	3	1	7	8
4	2	1	6	2	8
2	4	5	2	3	9

중간값으로

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

Sobel filter

3	0	-3
10	0	-10
3	0	-3

Scharr filter

convolution

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

3x3

45°
70°
73°

Andrew Ng



deeplearning.ai

Convolutional Neural Networks

Padding

Padding

해결
이/2/2
padding

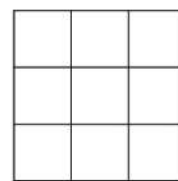
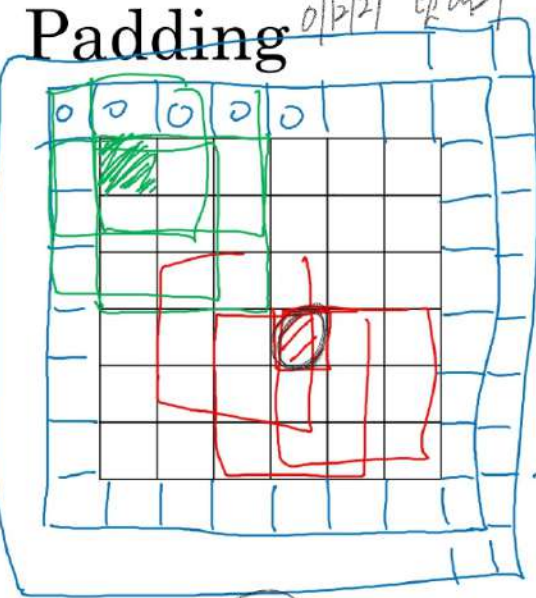
<2단점>

- shrinking output
- throw away info from edge

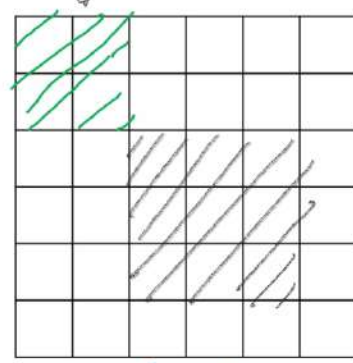
이/2/2 축소

가장자리 정보 사용

가장자리 정보를 더 가져오는 것은 중요하다!



3x3
f x f



6x6 (기존 크기 유지)

6x6 → 8x8
n x n

$$\frac{(n-f+1) \times (n-f+1)}{6-3+1=4}$$

$$\frac{(n+2p-f+1) \times (n+2p-f+1)}{6+2-3+1=6}$$

P = padding = 1
padding of 2

Andrew Ng

Valid and Same convolutions

no padding

테스트를 할 때만 할 것임

"Valid": $n \times n * f \times f \rightarrow n-f+1 \times n-f+1$
 $6 \times 6 * 3 \times 3 \rightarrow 4 \times 4$

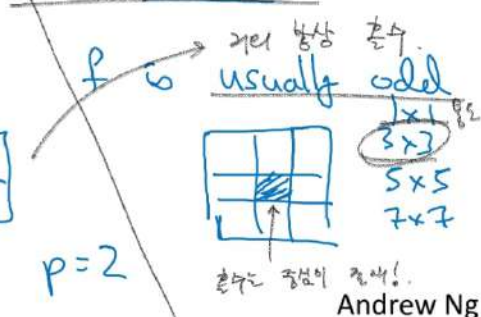
무엇도 안함

"Same": Pad so that output size is the same as the input size.

동일 함

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

ex 3×3 $p = \frac{3-1}{2} = 1$ 5×5 $f=5$ $p=2$

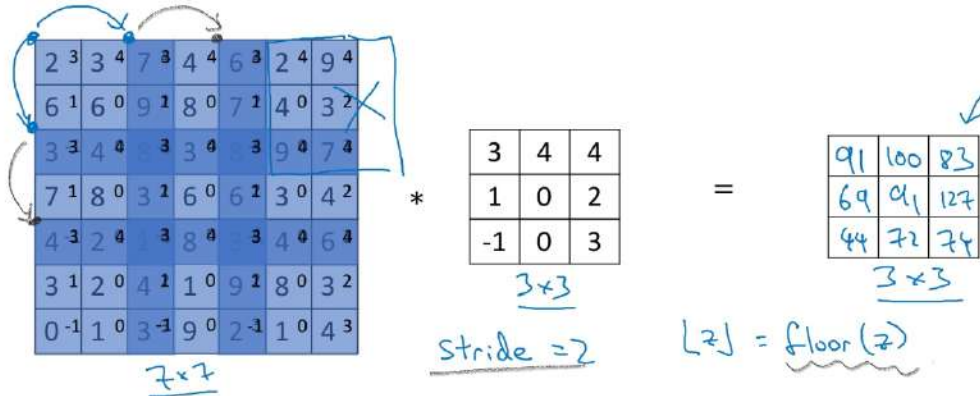


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Strided convolutions

Strided convolution



$$n \times n \text{ image} * f \times f \text{ filter}$$

padding p stride s

$s=2$

$$\left\lfloor \frac{n+2p-f}{s} + 1 \right\rfloor \times \left\lfloor \frac{n+2p-f}{s} + 1 \right\rfloor$$

$\frac{7+0-3}{2} + 1 = \frac{4}{2} + 1 = 3$

$\lfloor x \rfloor = \text{floor}(x)$

정확히 아날 시
세임을 한다.

Andrew Ng

Summary of convolutions

$n \times n$ image $f \times f$ filter

padding p stride s

Output size:

$$\left\lfloor \frac{n+2p-f}{s} + 1 \right\rfloor \times \left\lfloor \frac{n+2p-f}{s} + 1 \right\rfloor$$

Technical note on cross-correlation vs. convolution

교차상관

Convolution in math textbook:

2	3	7	4	6	2
6	6	9	8	7	4
3	4	8	3	8	9
7	8	3	6	6	3
4	2	1	8	3	4
3	2	4	1	9	8

3	4	5
1	0	2
-1	9	7

$$(A * B) * C = A * (B * C)$$

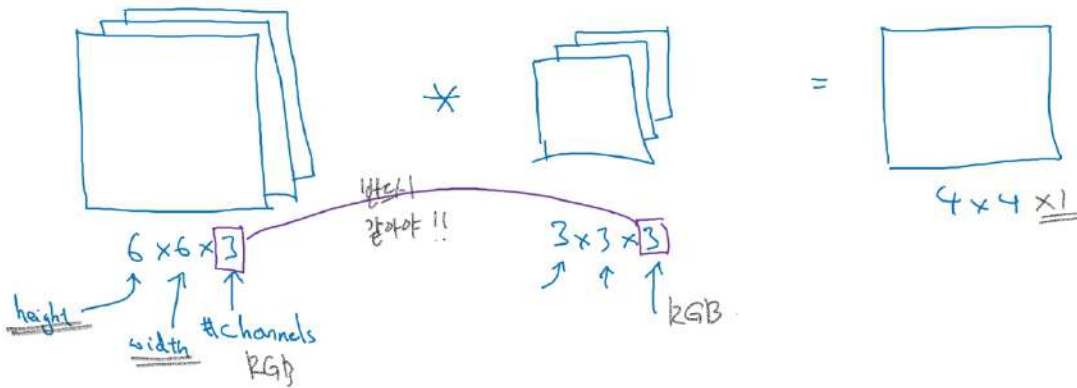
비어있는 것은 생략!!

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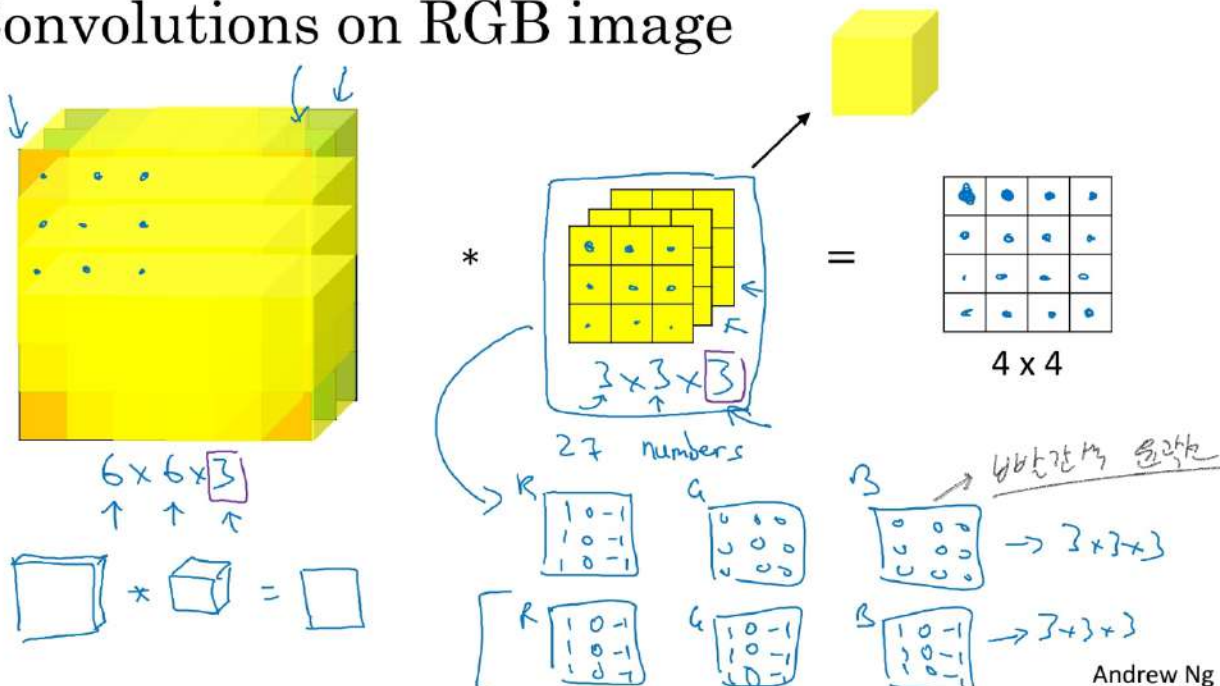


Convolutions over volumes

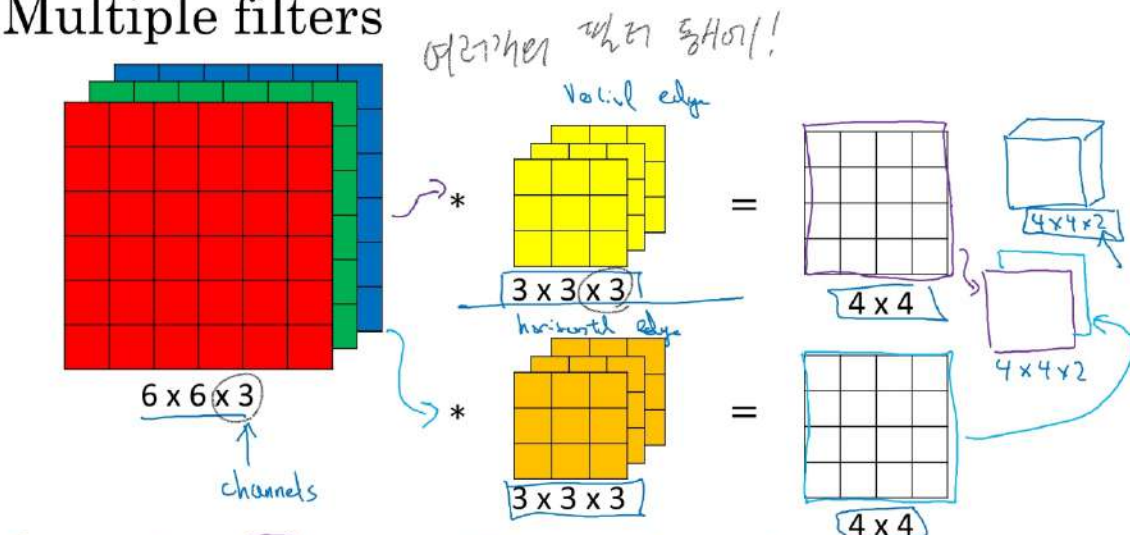
Convolutions on RGB images



Convolutions on RGB image



Multiple filters



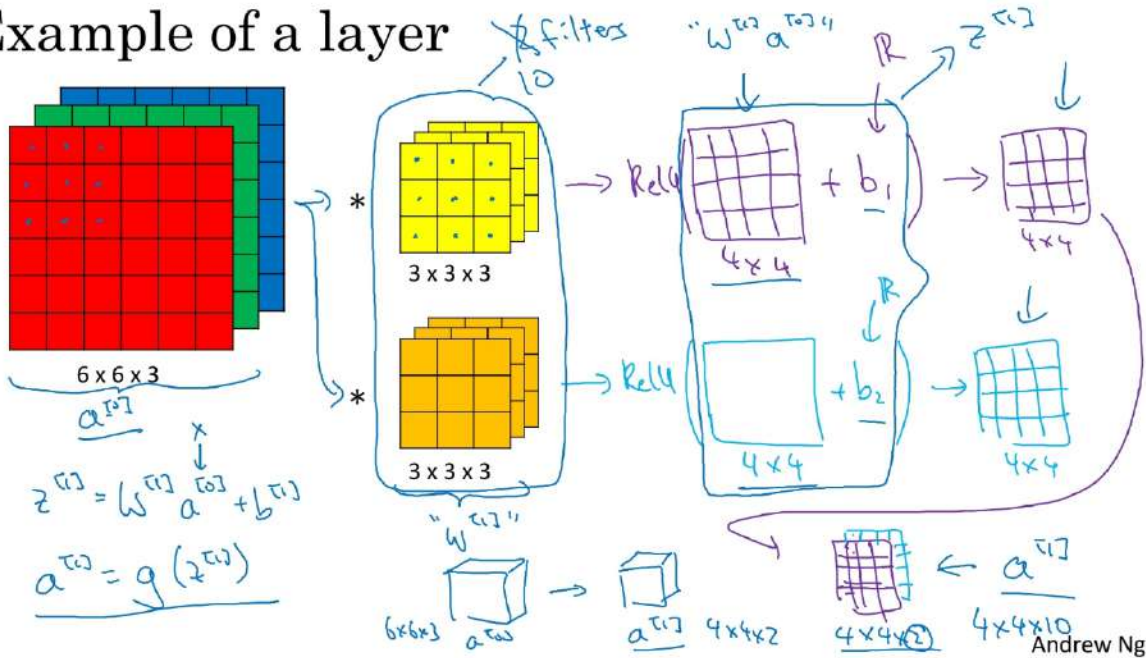
Summary: $n \times n \times n_c \times f \times f \times n_c \rightarrow \frac{n-f+1}{4} \times \frac{n-f+1}{4} \times n_c \times \#filters$



Convolutional Neural Networks

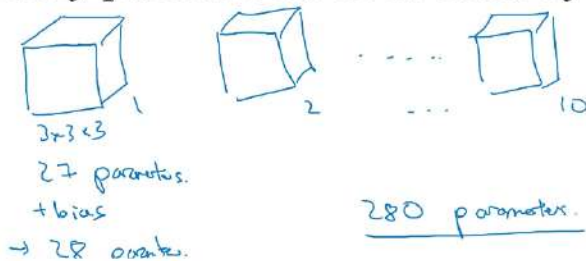
One layer of a convolutional network

Example of a layer



Number of parameters in one layer

If you have 10 filters that are $3 \times 3 \times 3$ in one layer of a neural network, how many parameters does that layer have?



Summary of notation

If layer l is a convolution layer:

$f^{[l]}$ = filter size

$p^{[l]}$ = padding

$s^{[l]}$ = stride

$n_c^{[l]}$ = number of filters

→ Each filter is: $f^{[l]} \times f^{[l]} \times n_c^{[l-1]}$

Activations: $a^{[l-1]} \rightarrow n_H \times n_W \times n_C^{[l-1]}$

Weights: $f^{[l]} \times f^{[l]} \times n_c^{[l-1]} \times n_c^{[l]}$

bias: $n_c^{[l]} - (1, 1, 1, n_c^{[l]})$ ← #filters in layer l .

Input: $n_H^{[l-1]} \times n_W^{[l-1]} \times n_C^{[l-1]}$
Output: $n_H^{[l]} \times n_W^{[l]} \times n_C^{[l]}$

$$n_H^{[l]} = \left\lfloor \frac{n_H^{[l-1]} + 2p^{[l]} - f^{[l]}}{s^{[l]}} + 1 \right\rfloor$$

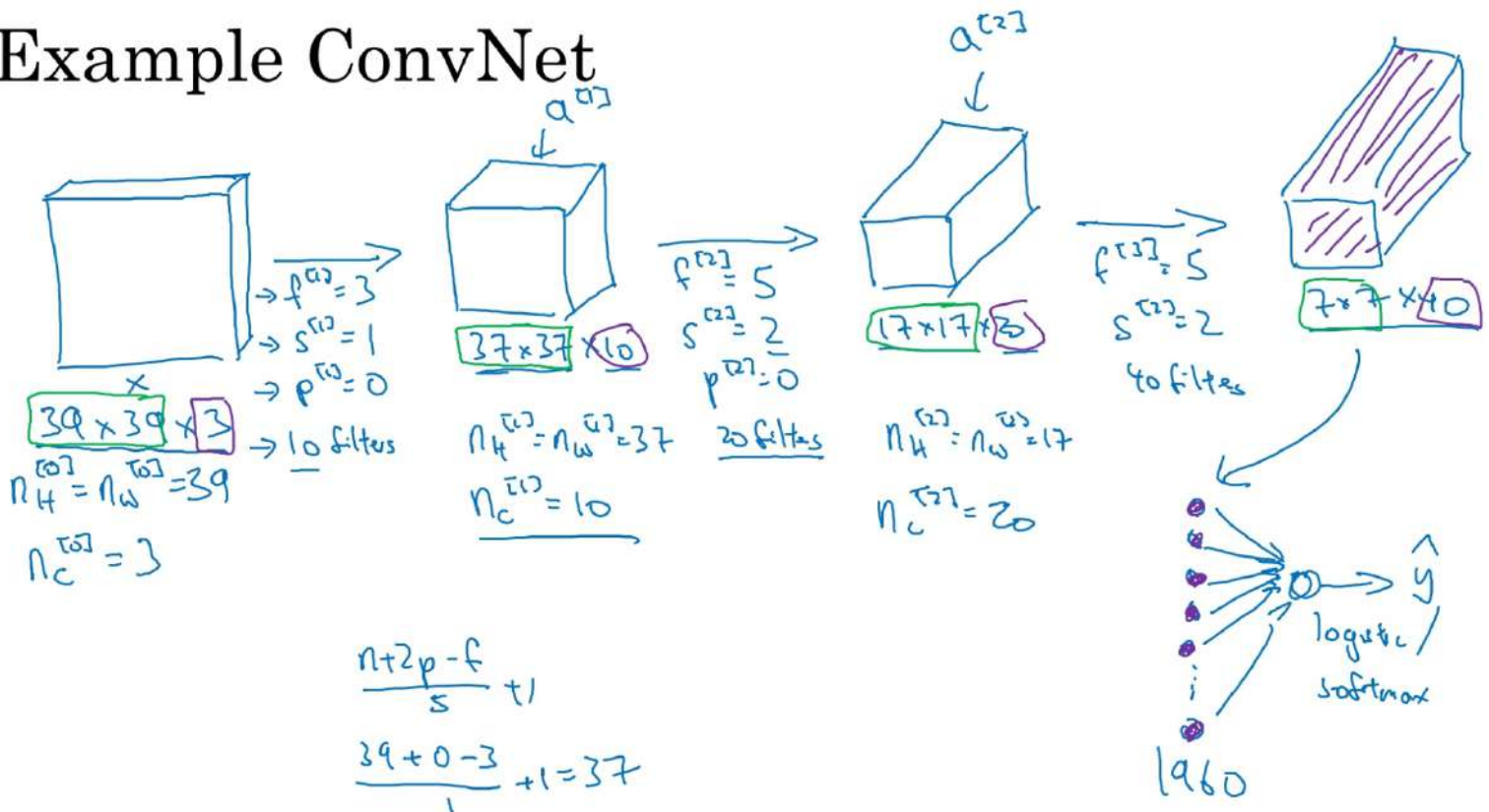
$$A^{[l]} \rightarrow n_H^{[l]} \times n_W^{[l]} \times n_C^{[l]}$$



합성곱 연산 → 편향 추가 → 활성화 함수

합성곱 신경망의 크기는 깊어질수록 줄어든다!

Example ConvNet



Types of layer in a convolutional network:

- Convolution (CONV) ←
- Pooling (POOL) ←
- Fully connected (FC) ←

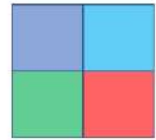


Convolutional Neural Networks

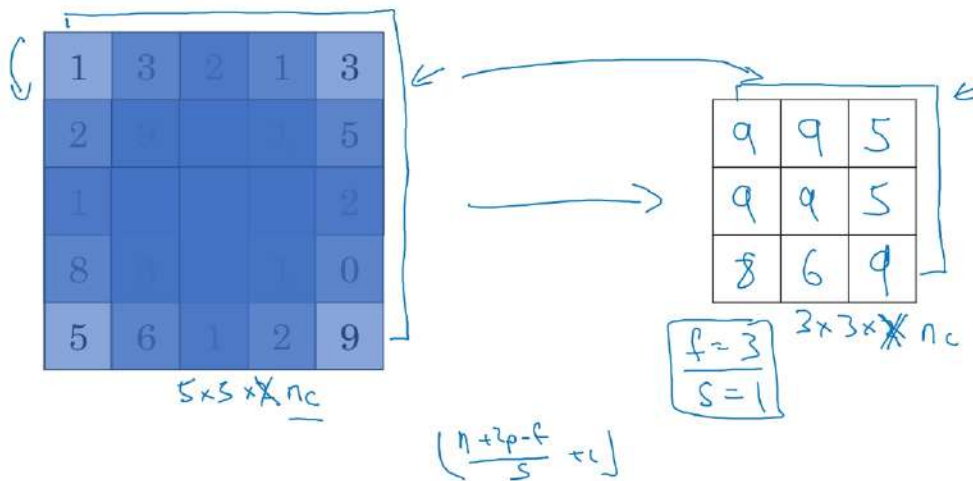
Pooling layers

Pooling layer: Max pooling

1	3	2	1
2	9	1	1
1	3	2	3
5	6	1	2

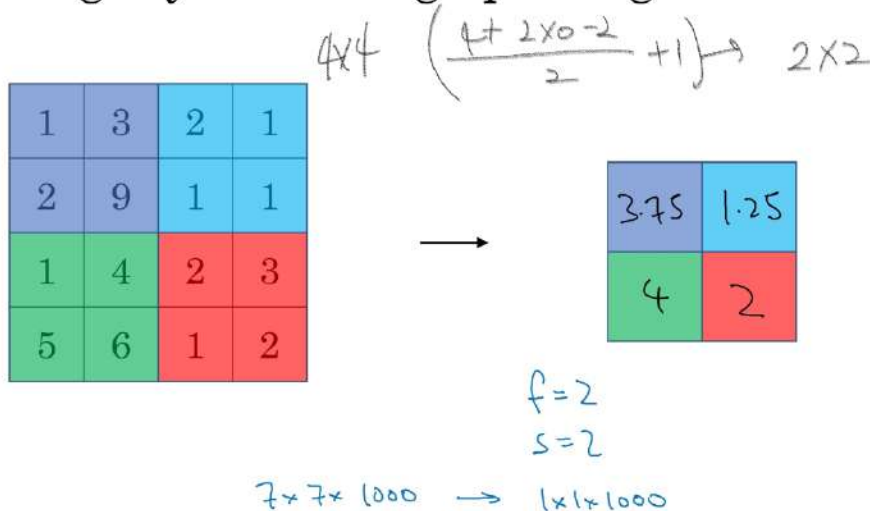


Pooling layer: Max pooling



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Pooling layer: Average pooling



Summary of pooling

Hyperparameters:

- f : filter size
- s : stride
- Max or average pooling

$$n_H \times n_W \times n_C$$

$$\downarrow$$

$$\left\lfloor \frac{n_H - f}{s} + 1 \right\rfloor \times \left\lfloor \frac{n_W - f}{s} + 1 \right\rfloor \times n_C$$

~~p: padding~~

No parameters to learn!

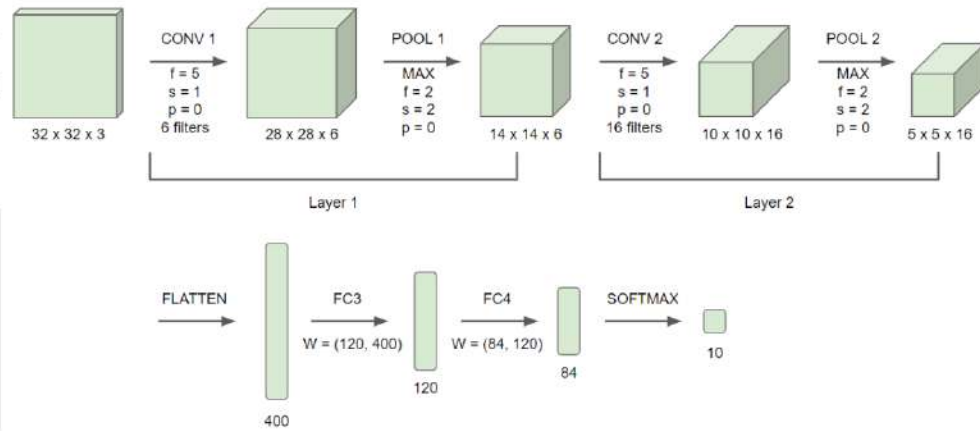
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Convolutional Neural Networks

Convolutional neural network example

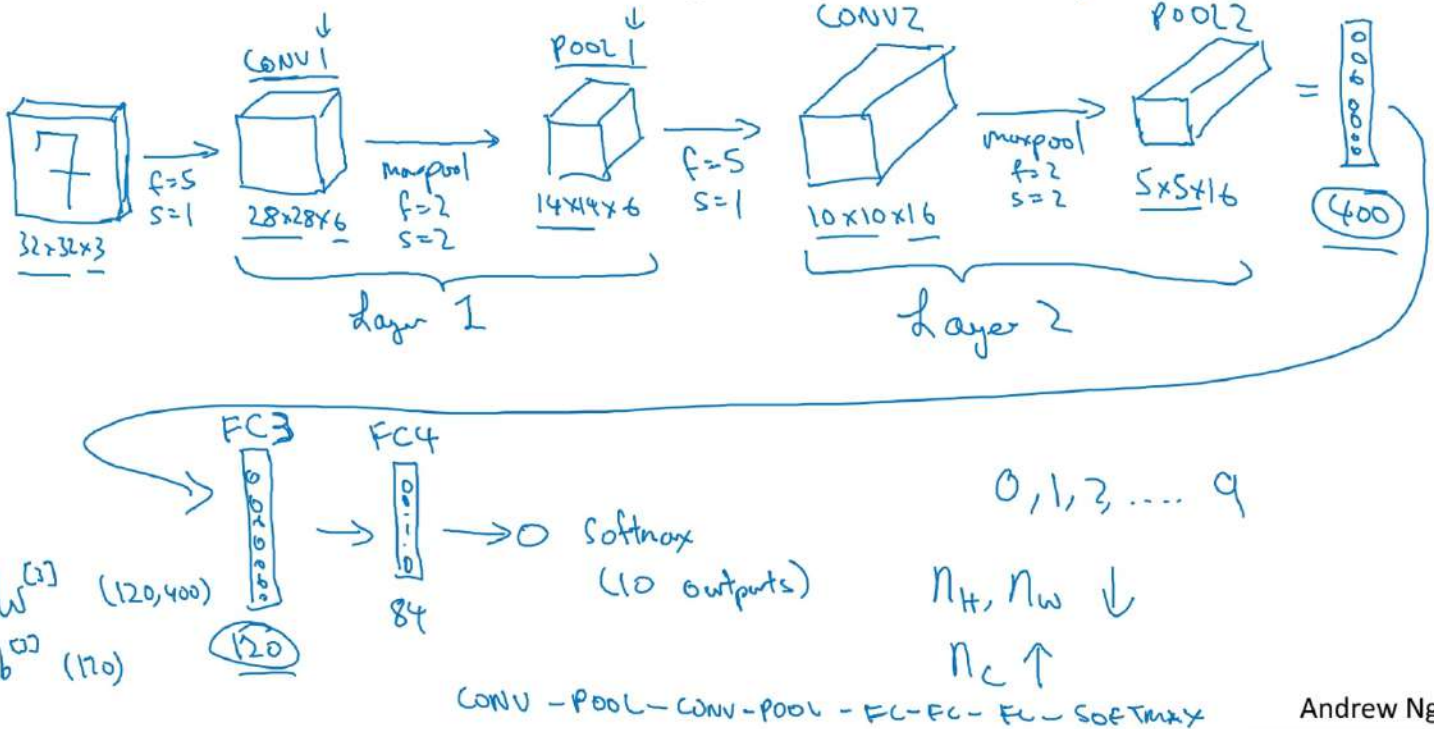
LeNet - 5



합계 608, 풀링층
 출력층
 각각의 층은 2

Neural network example

(LeNet-5)



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Neural network example

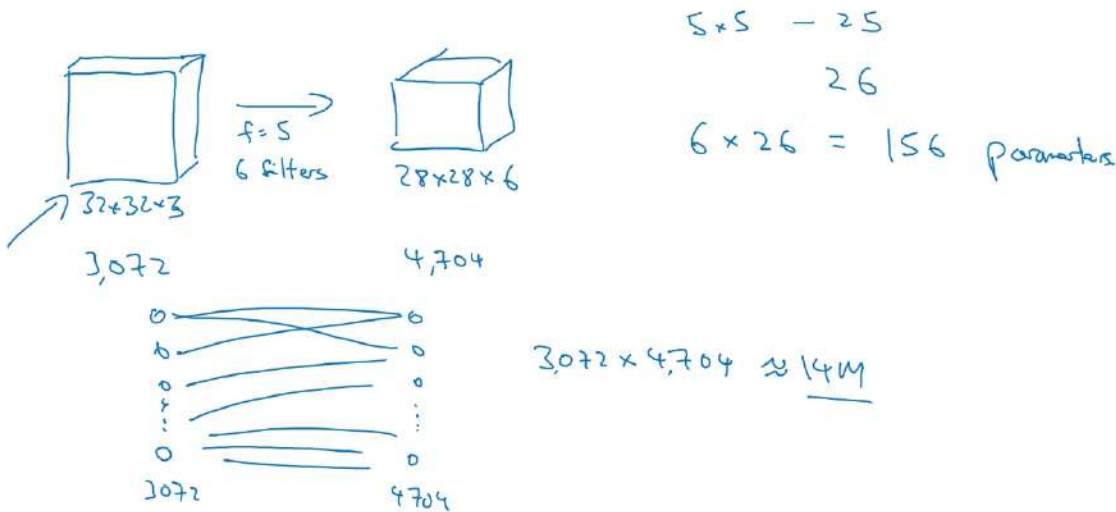
	Activation shape	Activation Size	# parameters
Input:	(32,32,3)	3,072 $a^{[0]}$	0
CONV1 (f=5, s=1)	(28,28,8)	6,272	608 ←
POOL1	(14,14,8)	1,568	0 ←
CONV2 (f=5, s=1)	(10,10,16)	1,600	3216 ←
POOL2	(5,5,16)	400	0 ←
FC3	(120,1)	120	48120 }
FC4	(84,1)	84	
Softmax	(10,1)	10	850

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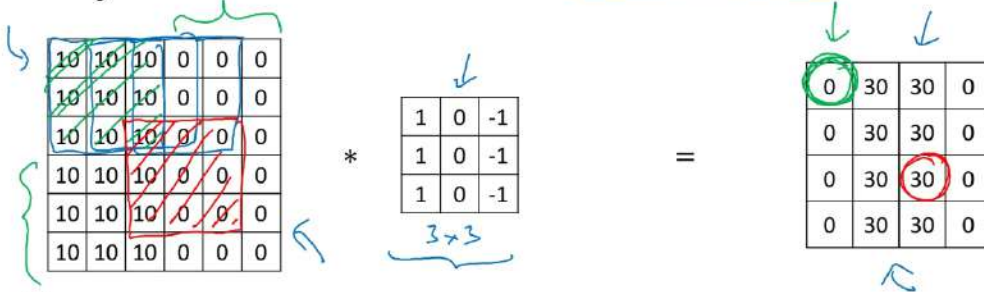


Why convolutions?

Why convolutions



Why convolutions



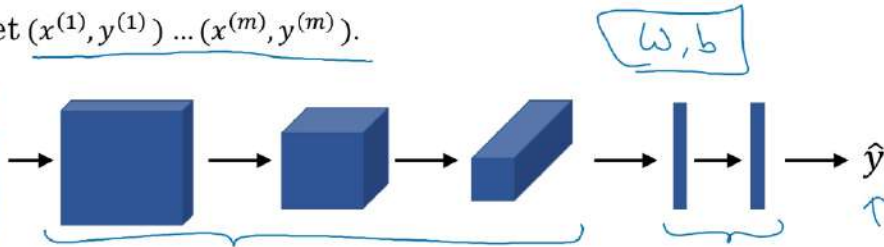
① **Parameter sharing:** A feature detector (such as a vertical edge detector) that's useful in one part of the image is probably useful in another part of the image.

② **Sparsity of connections:** In each layer, each output value depends only on a small number of inputs.

Putting it together

Training set $(x^{(1)}, y^{(1)}) \dots (x^{(m)}, y^{(m)})$.

이동 불변성을 포착하는 데에도 용이하다



$$\text{Cost } J = \frac{1}{m} \sum_{i=1}^m \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

Use gradient descent to optimize parameters to reduce J