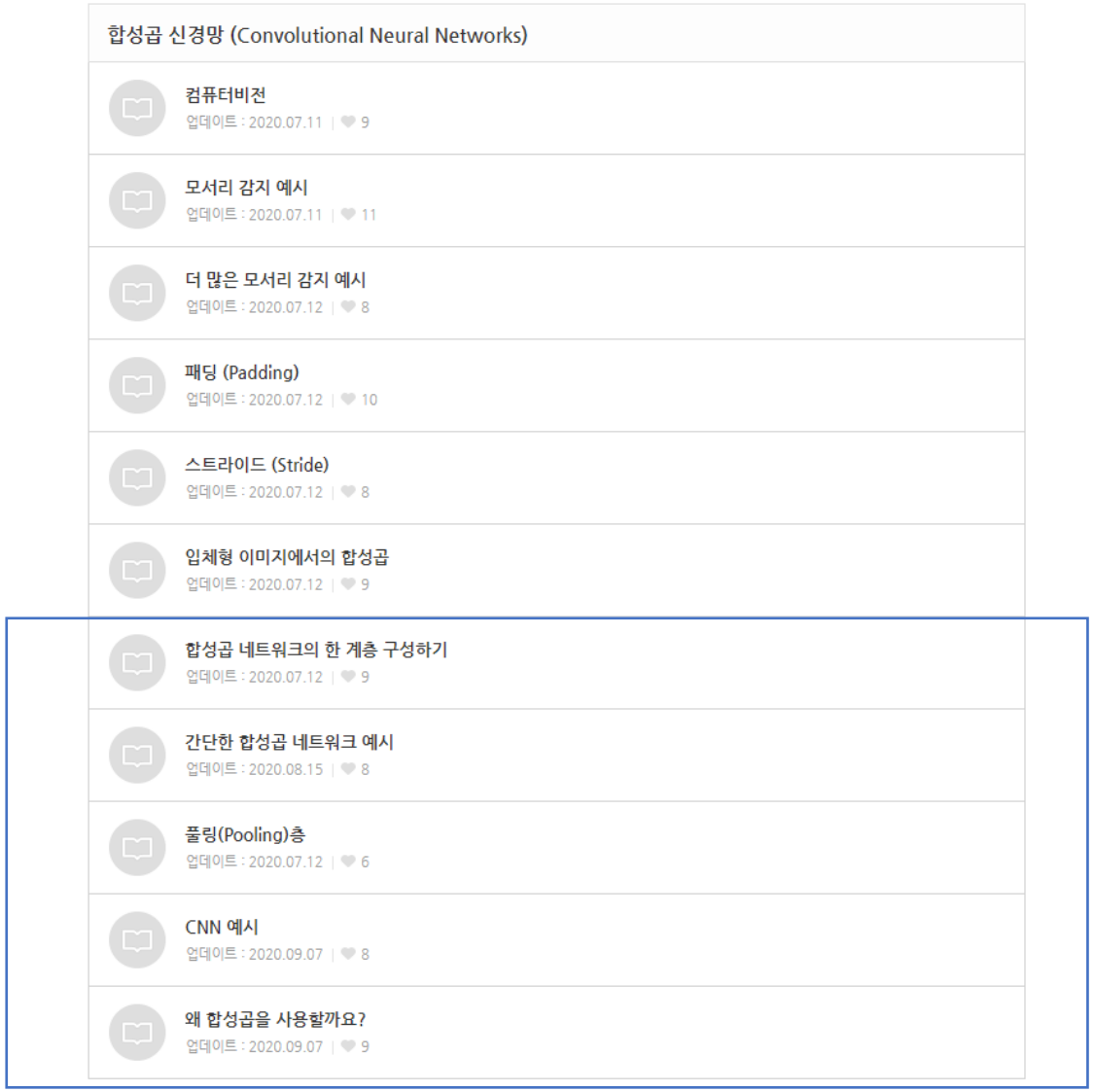
Deep Learning Study

2020/09/08

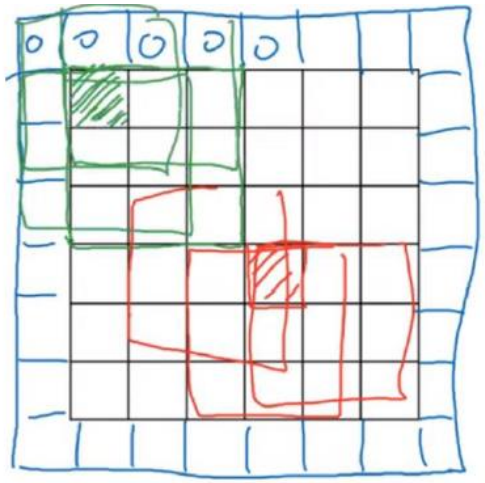
Byungchan Lee

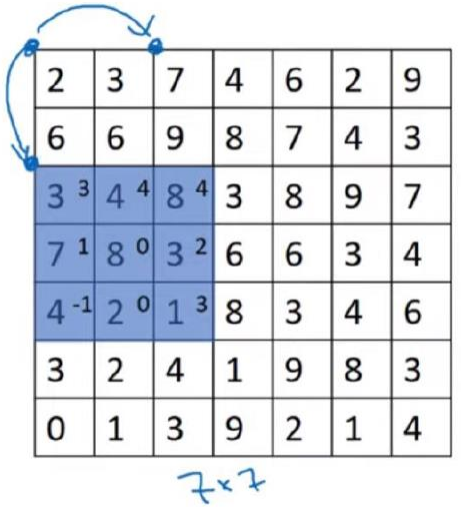
딥러닝 3단계 : 머신러닝 프로젝트 구조화하기



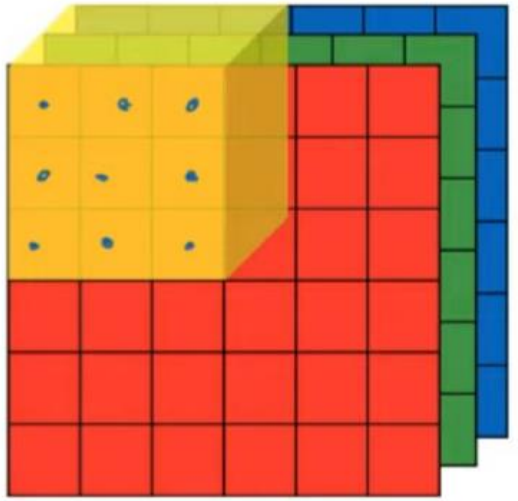
CNN

- Filter
- Padding
- Stride
- Channel

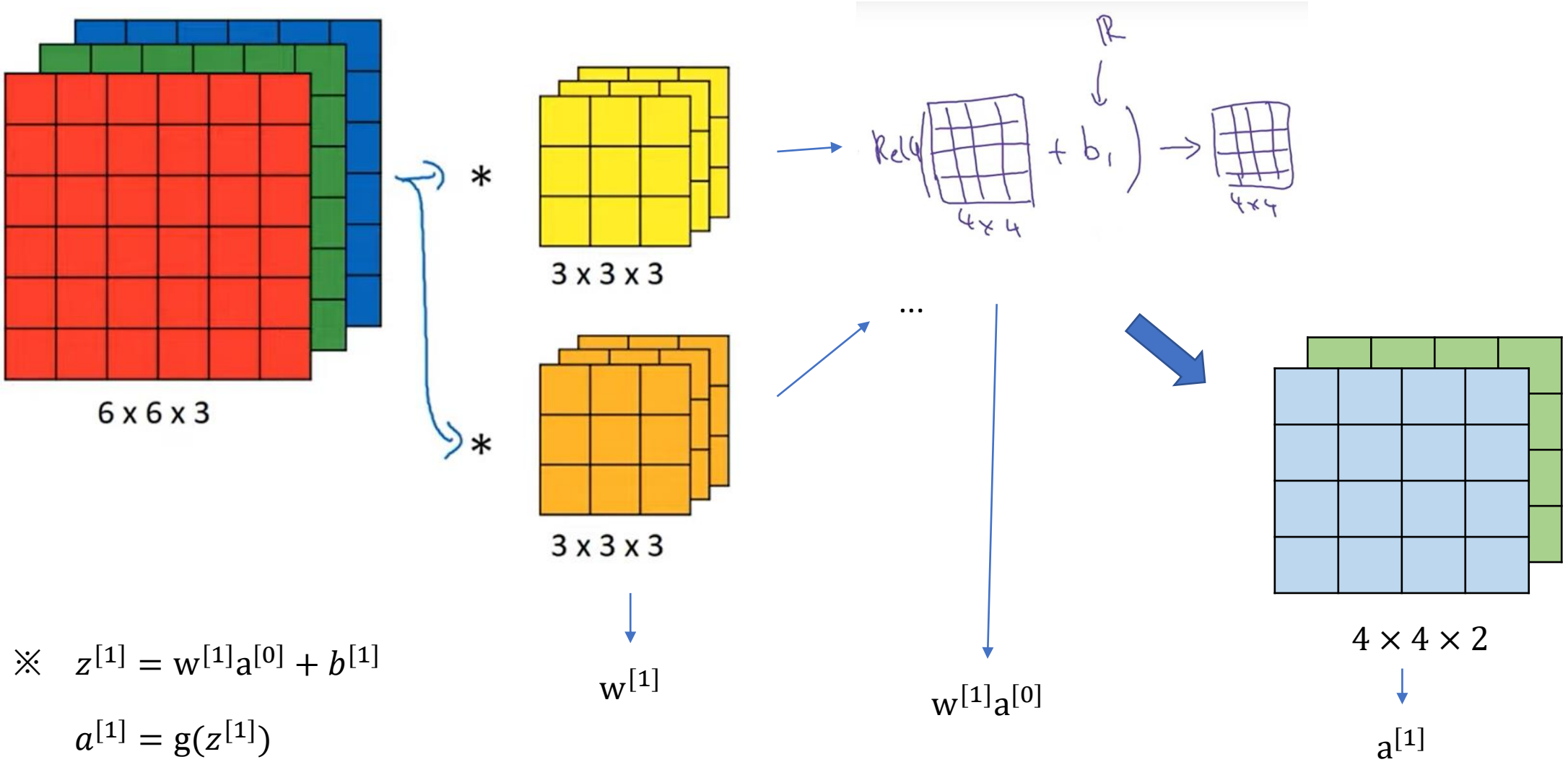




- 입력 $n \times n \times n_c$
- 필터 $f \times f \times n_c \times n_c'$
- 출력 $\left(\frac{n+2p-f}{s}+1\right) \times \left(\frac{n+2p-f}{s}+1\right) \times n_c'$



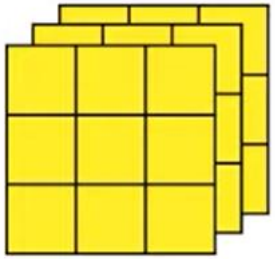
One Layer of a Convolutional Network



※ $z^{[1]} = w^{[1]}a^{[0]} + b^{[1]}$

$a^{[1]} = g(z^{[1]})$

Number of Parameters in one Layer



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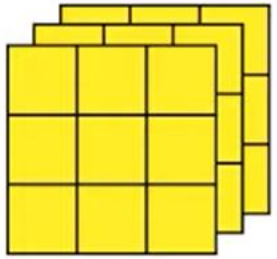

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- 10 filter, $3 \times 3 \times 3$
- How many parameters does that layer have?

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: $a^{[l]} \rightarrow n_H^{[l]} \times n_W^{[l]} \times n_c^{[l]}$

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

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: $n_H^{[l]} \times n_W^{[l]} \times n_c^{[l]}$ ←

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

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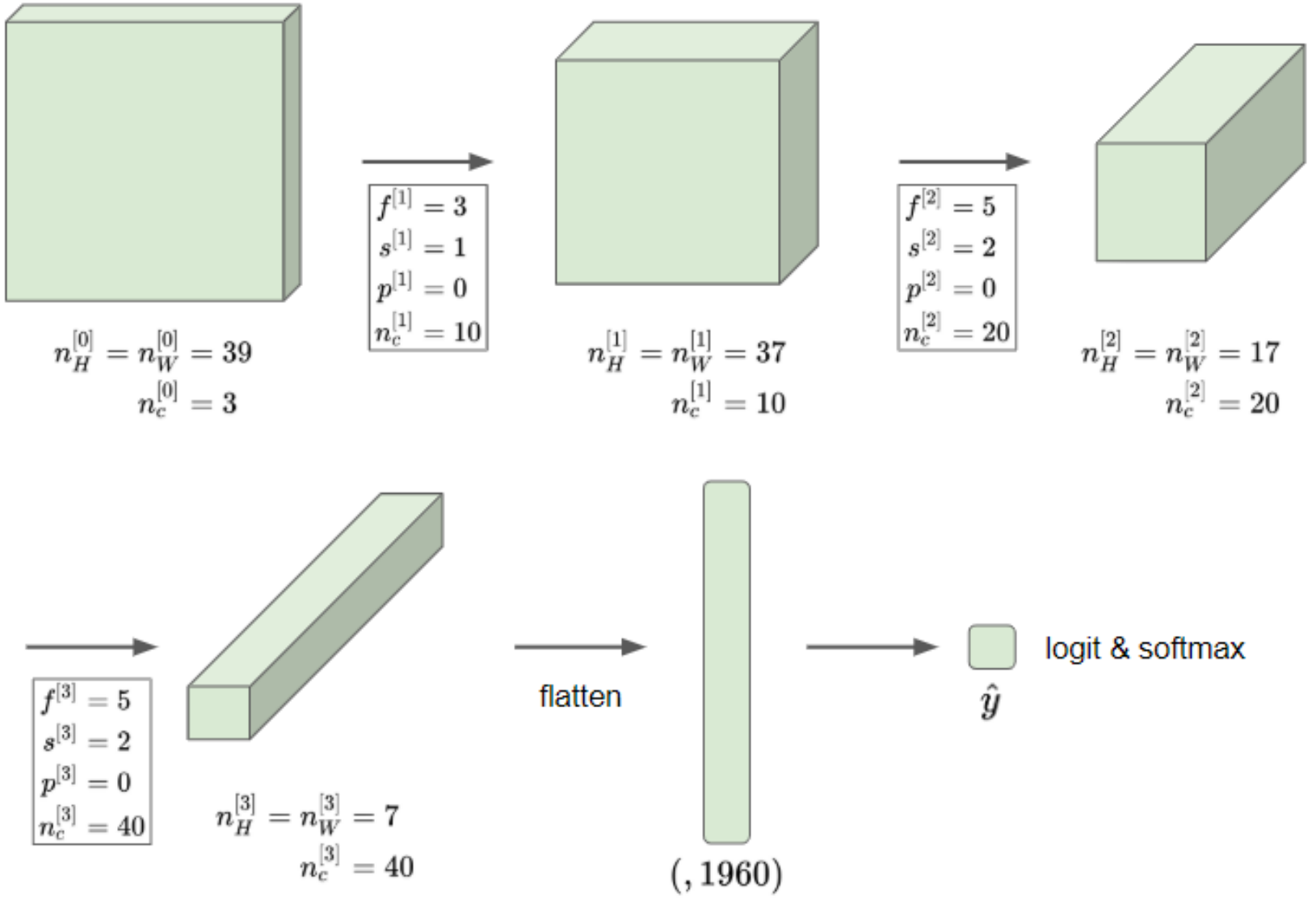
Simple CNN Example



Pooling Layers

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

Max Pooling

9	2
6	3

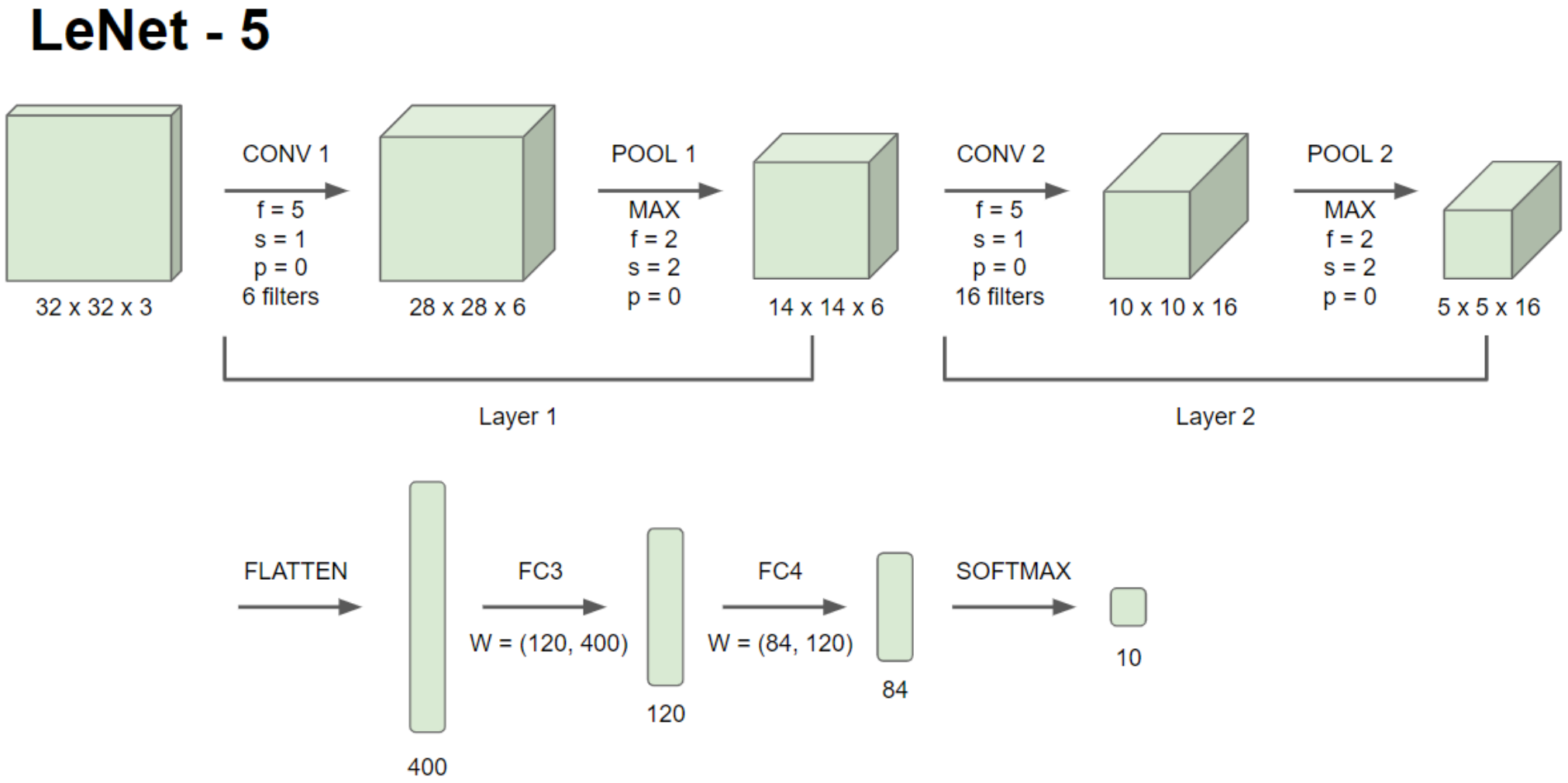
1	3	2	1
2	9	1	1
1	3	2	3
5	6	1	2

Average Pooling

3.75	1.25
3.75	2.0

- f = 2, s = 2, p = 0
- No parameters to learn!

CNN Example



http://yann.lecun.com/exdb/publis/pdf/lecun-01a.pdf

CNN Example

	Activation shape	Activation Size	# parameters
Input:	(32,32,3)	3,072	0
CONV1 (f=5, s=1)	(28,28,8)	6,272	208
POOL1	(14,14,8)	1,568	0
CONV2 (f=5, s=1)	(10,10,16)	1,600	416
POOL2	(5,5,16)	400	0
FC3	(120,1)	120	48,001
FC4	(84,1)	84	10,081
Softmax	(10,1)	10	841

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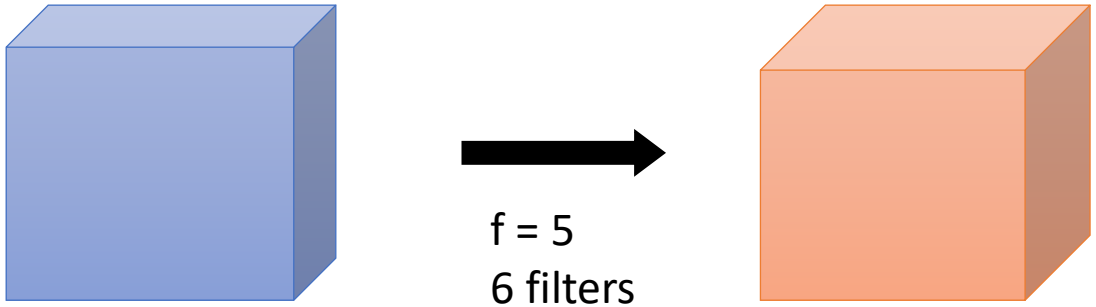
Why Convolutions?



$32 \times 32 \times 3$ $28 \times 28 \times 6$

# of parameters

- Fully Connected : 3072 * 4704 ~ 14M
- Convolution : (5*5 + 1) *6 = 156

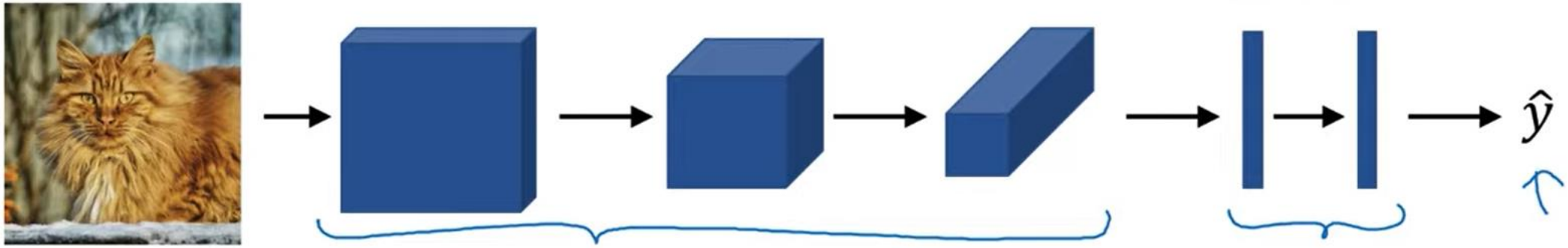
- Parameter sharing : A feature detector (such as a vertical edge detector) that's useful in one part of the image is probably useful in another part of the image
- Sparsity of connections : In each layer, each output value depends only on a small number of inputs

  → Translation Invariance

Why Convolutions?

Putting it together

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



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

Use gradient descent to optimize parameters to reduce J