

Convolutional Neural Networks Assignment

Ahmad Salimi
AI-Med

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1 A convolutional layer with $W \times H$ inputs, $K_1 \times K_2$ kernels, C_{in} input channels, C_{out} output channels, padding P and stride S

1. Number of input elements:

$$W \times H \times C_{in}$$

2. Output width:

$$W_{out} = \lfloor \frac{W + 2P - K_1}{S} \rfloor + 1$$

Output Height:

$$H_{out} = \lfloor \frac{H + 2P - K_2}{S} \rfloor + 1$$

Number of output channels:

$$C_{out}$$

3. Number of parameters:

$$|\theta| = (K_1 \times K_2 \times C_{in} + 1) \times C_{out}$$

4. Number of multiplication:

$$K_1 \times K_2 \times W_{out} \times H_{out} \times C_{out}$$

2 A pooling layer with $K \times K$ kernels, stride S_2 and padding P_2

1. Number of input elements:

$$W \times H \times C_{in}$$

2. Output width:

$$W_{out} = \lfloor \frac{W + 2P_2 - K}{S_2} \rfloor + 1$$

Output Height:

$$H_{out} = \lfloor \frac{H + 2P_2 - K}{S_2} \rfloor + 1$$

Number of output channels:

$$C_{in}$$

3. Number of parameters:

$$0$$

4. Number of multiplication:

$$0$$

3 A fully connected layer with N neurons

1. Number of input elements:

$$W \times H \times C_{in}$$

2. Output size:

$$N$$

3. Number of parameters:

$$|\theta| = (W \times H \times C_{in} + 1) \times N$$

4. Number of multiplication:

$$W \times H \times C_{in} \times N$$

4 Parameters placement

$$W = H = 256$$

$$K_1 = K_2 = 3$$

$$P = 1$$

$$S = 1$$

$$C_{in} = 64$$

$$C_{out} = 128$$

$$K = 2$$

$$S_2 = 2$$

$$P_2 = 0$$

$$N = 1000$$

1. Convolutional layer:

- (a) Number of parameters:

$$|\theta| = (K_1 \times K_2 \times C_{in} + 1) \times C_{out} = (3 \times 3 \times 64 + 1) \times 128 = 73,856$$

- (b) Number of multiplications:

$$K_1 \times K_2 \times W_{out} \times H_{out} \times C_{out} = 3 \times 3 \times \left(\frac{256 + 2 - 3}{1} + 1\right) \times \left(\frac{256 + 2 - 3}{1} + 1\right) \times 128 = 74,908,800$$

- (c) Output size:

$$\left\lfloor \frac{W + 2P - K_1}{S} \right\rfloor + 1 = \left\lfloor \frac{H + 2P - K_2}{S} \right\rfloor + 1 = \frac{256 + 2 - 3}{1} + 1 = 256$$

2. Pooling layer:

- (a) Number of parameters:

$$0$$

- (b) Number of multiplications:

$$0$$

- (c) Output size:

$$\left\lfloor \frac{W + 2P_2 - K}{S_2} \right\rfloor + 1 = \left\lfloor \frac{H + 2P_2 - K}{S_2} \right\rfloor + 1 = \frac{256 + 0 - 2}{2} + 1 = 128$$

3. Fully connected layer:

- (a) Number of parameters:

$$|\theta| = (W \times H \times C_{in} + 1) \times N = (256 \times 256 \times 64 + 1) \times 1000 = 4,194,305,000$$

- (b) Number of multiplications:

$$W \times H \times C_{in} \times N = 256 \times 256 \times 64 \times 1000 = 4,194,304,000$$

- (c) Output size:

$$N = 1000$$

5 Network bottleneck

	Layers	Shape	Size
3	Input: 256 x 256	# B 1 256 256	= B * 65536
4	[64] Conv 3 x 3, s=1, p=1	# B 64 256 256	= B * 4194304
5	[64] Conv 3 x 3, s=1, p=1	# B 64 256 256	= B * 4194304
6	Pool 2 x 2, s=2, p=0	# B 64 128 128	= B * 1048576
7	[128] Conv 3 x 3, s=1, p=1	# B 128 128 128	= B * 2097152
8	[128] Conv 3 x 3, s=1, p=1	# B 128 128 128	= B * 2097152
9	Pool 2 x 2, s=2, p=0	# B 128 64 64	= B * 524288
10	[256] Conv 3 x 3, s=1, p=1	# B 256 64 64	= B * 1048576
11	[256] Conv 3 x 3, s=1, p=1	# B 256 64 64	= B * 1048576
12	Pool 2 x 2, s=2, p=0	# B 256 32 32	= B * 262144
13	[512] Conv 3 x 3, s=1, p=1	# B 512 32 32	= B * 524288
14	[512] Conv 3 x 3, s=1, p=1	# B 512 32 32	= B * 524288
15	Pool 2 x 2, s=2, p=0	# B 512 16 16	= B * 131072
16	[512] Conv 3 x 3, s=1, p=1	# B 512 16 16	= B * 131072
17	[512] Conv 3 x 3, s=1, p=1	# B 512 16 16	= B * 131072
18	Pool 2 x 2, s=2, p=0	# B 512 8 8	= B * 32768
19	Flatten	# B 32768	= B * 32768
20	FC (4096)	# B 4096	= B * 4096
21	FC (4096)	# B 4096	= B * 4096
22	FC (2)	# B 2	= B * 2

It turns out that the largest size is $B \times 4194304$. So, if we assume each number to be `float32`, the size of the largest possible batch will be as follows:

$$B = \lfloor \frac{12GB}{4194304 \times 4B} \rfloor = \lfloor \frac{12 \times 2^{30}}{2^{24}} \rfloor = 12 \times 2^6 = 768$$

6 Receptive Field

For each convolutional and pooling layer with kernel size K , stride S and padding P , the (i, j) neuron of n^{th} layer, represents the following range of $n - 1^{th}$ layer:

$$(Si - P : Si - P + K - 1, Sj - P : Sj - P + K - 1)$$

1	[i : i , j : j]
2	Conv[i-1 : i+1 , j-1 : j+1]
3	Conv[i-2 : i+2 , j-2 : j+2]
4	Pool[2i-4 : 2i+5 , 2j-4 : 2j+5]
5	Conv[2i-5 : 2i+6 , 2j-5 : 2j+6]
6	Conv[2i-4 : 2i+7 , 2j-4 : 2j+7]
7	Pool[4i-8 : 4i+15 , 4j-8 : 4j+15]
8	Conv[4i-9 : 4i+16 , 4j-9 : 4j+16]
9	Conv[4i-10 : 4i+17 , 4j-10 : 4j+17]
10	Pool[8i-20 : 8i+35 , 8j-20 : 8j+35]
11	Conv[8i-21 : 8i+36 , 8j-21 : 8j+36]
12	Conv[8i-22 : 8i+37 , 8j-22 : 8j+37]
13	Pool[16i-44 : 16i+75 , 16j-44 : 16j+75]
14	Conv[16i-45 : 16i+76 , 16j-45 : 16j+76]
15	Conv[16i-46 : 16i+77 , 16j-46 : 16j+77]

So, the (i, j) neuron of last convolutional layer, represents the following range of the input image:

$$(16i - 44 : 16i + 75, 16j - 44 : 16j + 75)$$