



CS 4104 APPLIED MACHINE LEARNING

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CONVOLUTIONAL NEURAL NETWORK

- Neural Networks that use convolution in place of general matrix multiplication in at least one layer
- There are three types of layers in the convolutional network,
 - Convolution layer (Conv)
 - Pooling layer (Pool)
 - Fully connected layer (FC)

Cross-correlation

- \Box Let f be the image,
- \square w be the kernel of size $m \times n$
 - o where m=2a+1 and n=2b+1), a and b are the positive integers.
- g be the output image

$$g(x, y) = \sum_{s=-at=-b}^{a} \sum_{t=-b}^{b} w(s, t) f(x+s, y+t)$$

This is called a **cross-correlation** operation:

$$g = w \otimes f$$

Cross-correlation

$$g(x, y) = \sum_{s=-at=-b}^{a} \sum_{t=-b}^{b} w(s, t) f(x+s, y+t)$$

At any point (x, y), the response g(x, y) of the filter is the sum of product of filter coefficient and the image pixels

$$g(x, y) = w(-1,-1) f(x-1, y-1) +$$

$$w(-1,0) f(x-1, y) + ...$$

$$w(0,0) f(x, y) + ...$$

$$w(1,1) f(x+1, y+1)$$

 Same as cross-correlation, except that the kernel is "flipped" (horizontally and vertically)

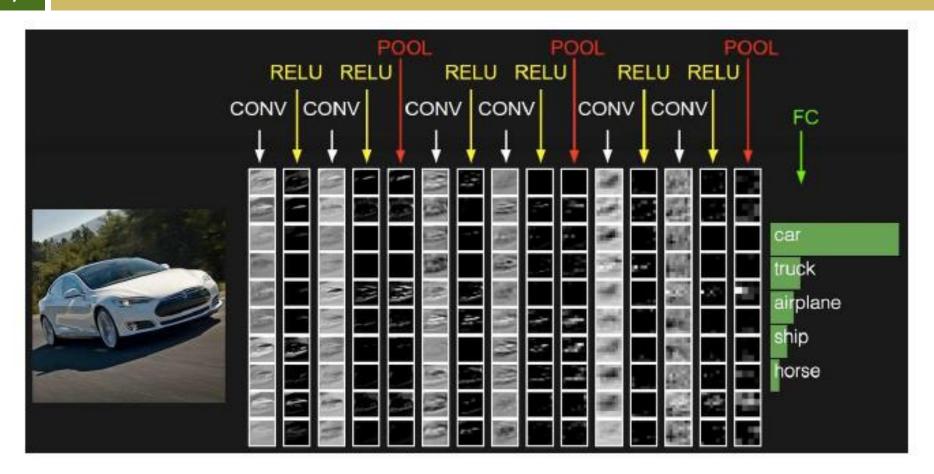
$$g(x, y) = \sum_{s=-at=-b}^{a} \sum_{t=-b}^{b} w(s, t) f(x - s, y - t)$$

This is called a **convolution** operation:

$$g = w * f$$

Convolution is commutative and associative

CNN ... Example



CNN ... EDGE DETECTION

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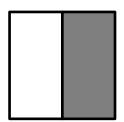
White to Dark pixels

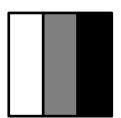
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

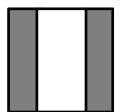
*

•	1	0	-1
•]	0	-1
•	1	0	-1

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





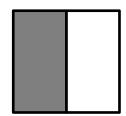


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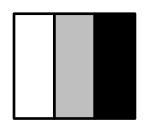
Dark to White pixels

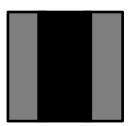
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10

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



*





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

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

Prewitt Filter

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

Sobel Filter

*

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

Scharr Filter

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

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

 $egin{array}{c|cccc} w_1 & w_2 & w_3 \\ \hline w_4 & w_5 & w_6 \\ \hline w_7 & w_8 & w_9 \\ \hline \end{array}$

Horizontal Edges Vertical Edges 45° Degree Edges 70° Degree Edges

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

$$n-f+1 \times n-f+1$$

CNN ... PADDING

CNN ... Padding

Convolution without Padding

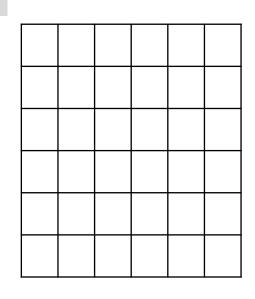
- □ Shrinking output
 - □ If we have a hundred layers of deep net and it'll shrink a bit on every layer, then after a hundred layers we end up with a very small image.
- □ Throwing away a lot of information
 - The information on the edges are thrown away every time

CNN ... Padding

0	0	0	0	0	0	0	0
0	3	0	٦	2	7	4	0
0	1	5	8	9	က	1	0
0	2	7	2	5	1	3	0
0	0	1	3	1	7	8	0
0	4	2	1	6	2	8	0
0	2	4	5	2	3	9	0
0	0	0	0	0	0	0	0

Padding =
$$p = 1$$

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



$$n + 2p - f + 1 \times n + 2p - f + 1$$

CNN ... Padding

Valid Convolution

$$n \times n$$

$$f \times f$$

$$n-f+1 \times n-f+1$$

Same Convolution

Pad so that output size is the same size as the input size.

$$n + 2p - f + 1 \times n + 2p - f + 1$$

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

CNN ... STRIDE

CNN ... Stride

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

Padding: p = 0

Stride: s = 2

က	4	4
1	0	2
-1	0	3

91	100	83
69	91	127
44	72	74

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

CNN ... Stride

 $n \times n$,

 $f \times f$

padding p,

stride s

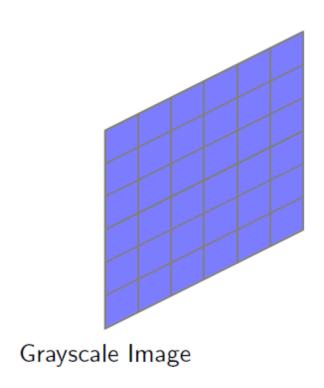
$$\left\lfloor \frac{n+2p-f}{s} + 1 \right\rfloor$$



$$\left| \frac{n+2p-f}{s} + 1 \right|$$

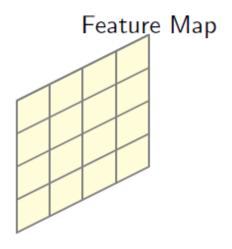
CNN ... Example

□ Convolve image with kernel having weights w

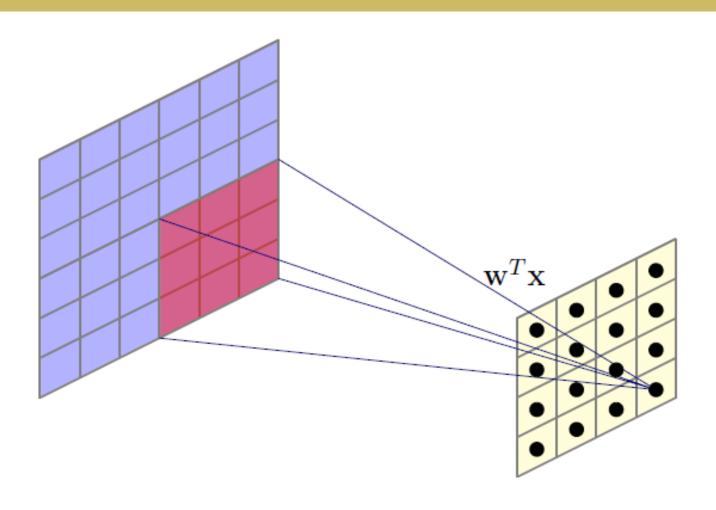


Kernel

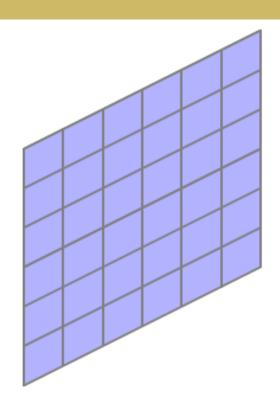
w_7	w_8	w_9
w_4	w_5	w_6
w_1	w_2	w_3

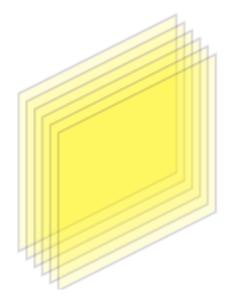


CNN ... Example



CNN ... Multiple Filters



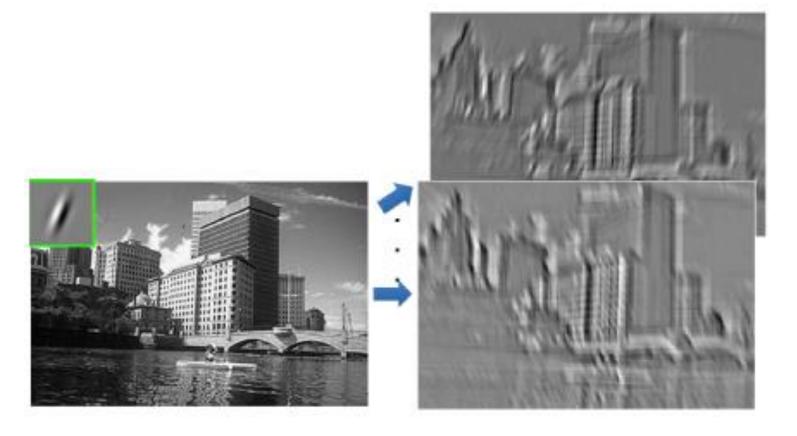


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Applied Machine Learning (CS4104)

CNN ... Multiple Filters (Example)

□ If we use 100 filters, we get 100 feature maps



Acknowledgements

Stuart J. Russell and Peter Norvig, Tom M. Mitchell, Jiwon Jeong, Floydhub, Andrej Karpathy