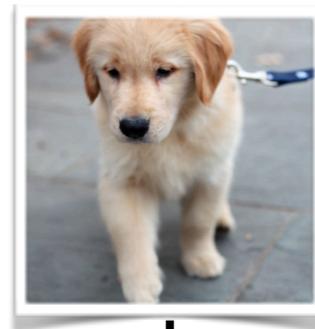


Convolutions

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Images and structure

- Fully connected networks are not shift invariant

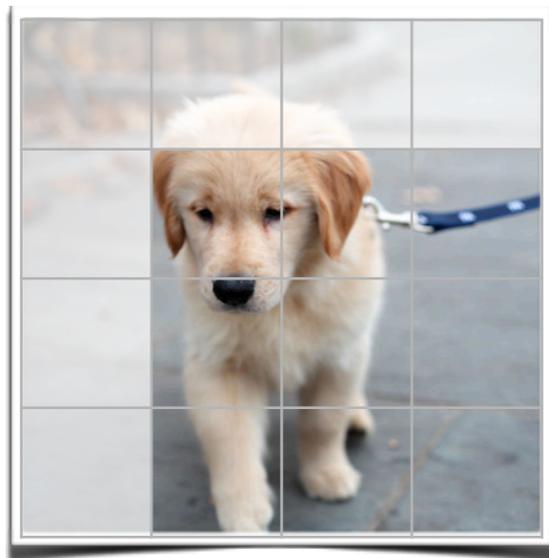


Finding shift-invariant patterns



Convolutions

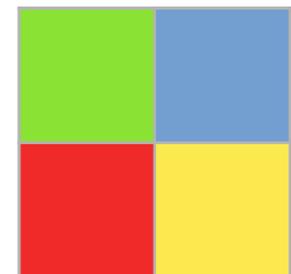
- “Sliding” linear transformation



*

a	b	c
d	e	f
g	h	i

=



Examples of convolutions



Original



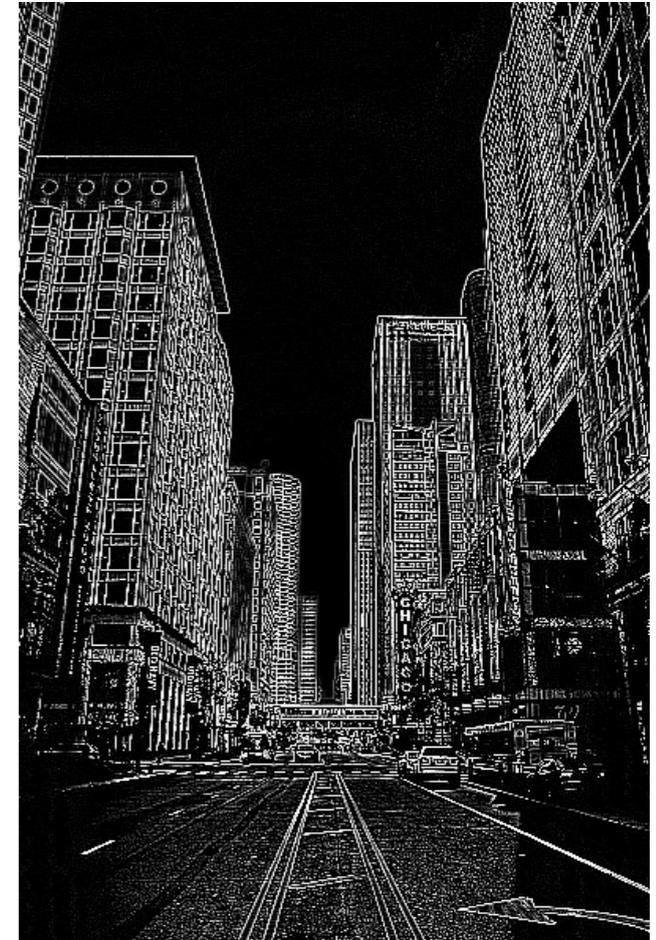
Vertical edges

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



Horizontal edges

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



Laplace filter

-1	-1	-1
-1	8	-1
-1	-1	-1

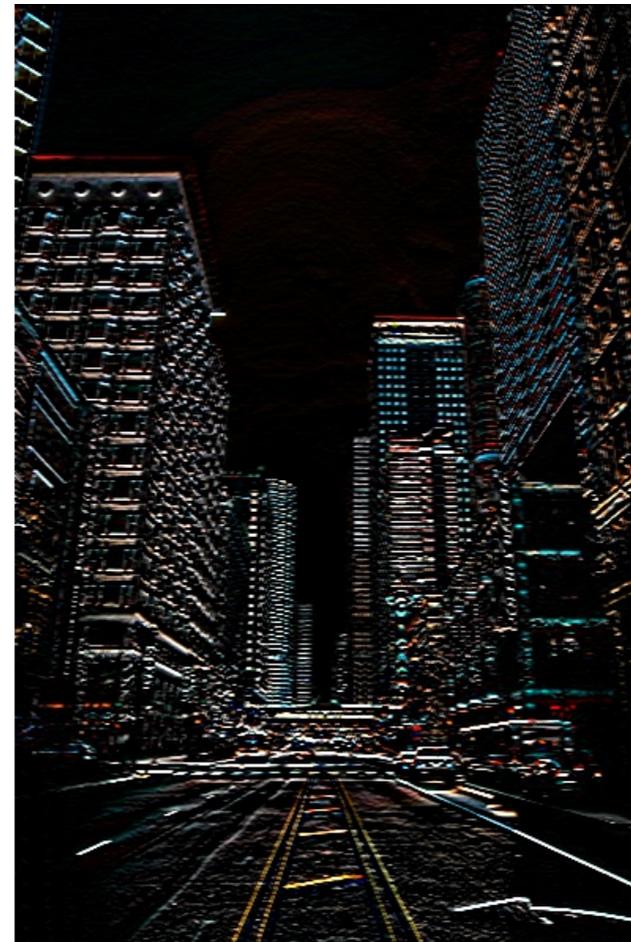
Convolutions on multiple channels



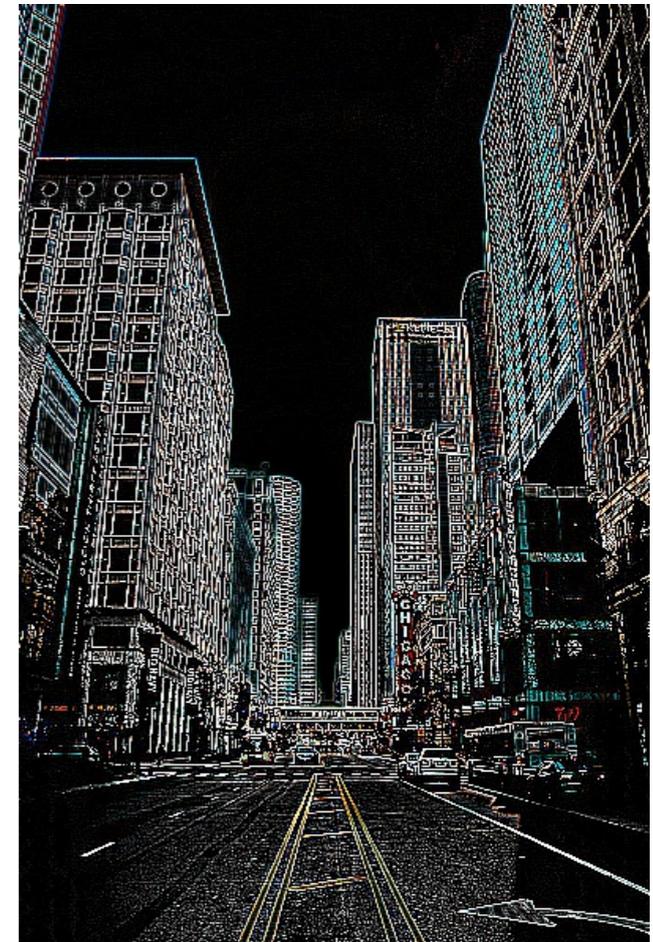
Original



Vertical edges



Horizontal edges



Laplace filter

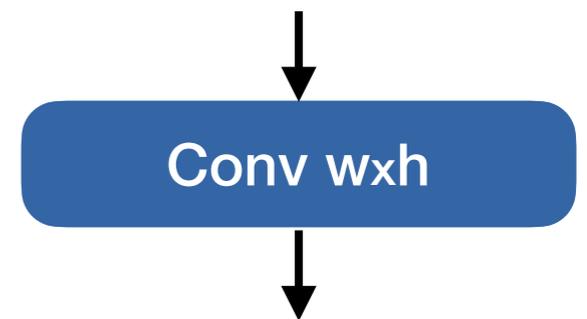
-1	0	1
-1	0	1
-1	0	1

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

-1	-1	-1
-1	8	-1
-1	-1	-1

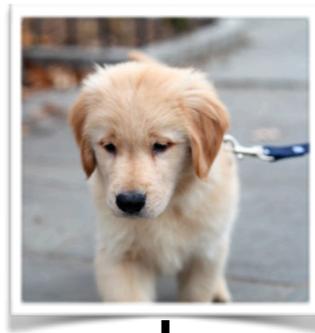
Formal definition

- Input: $\mathbf{X} \in \mathbb{R}^{H \times W \times C_1}$
- Kernel: $\mathbf{w} \in \mathbb{R}^{h \times w \times C_1 \times C_2}$
- Bias: $\mathbf{b} \in \mathbb{R}^{C_2}$
- Output: $\mathbf{Z} \in \mathbb{R}^{(H-h+1) \times (W-w+1) \times C_2}$



$$\mathbf{Z}_{a,b,c} = \mathbf{b}_c + \sum_{i=0}^h \sum_{j=0}^w \sum_{k=0}^{C_1} \mathbf{X}_{a+i,b+j,k} \mathbf{w}_{i,j,k,c}$$

Stacking multiple layers



Conv 3x3

ReLU

Conv 3x3

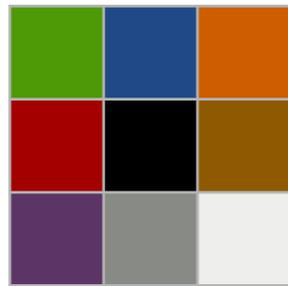
ReLU

Conv 3x3

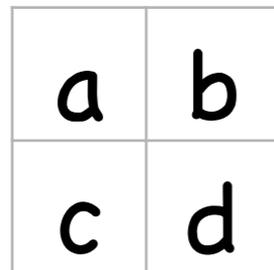
ReLU

Convolution as a linear layer

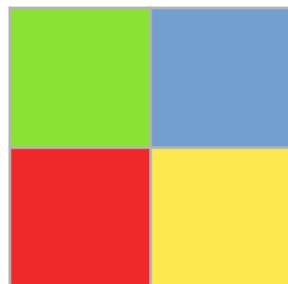
input: $3 \times 3 \times 1$



kernel: $2 \times 2 \times 1 \times 1$



output: $2 \times 2 \times 1$



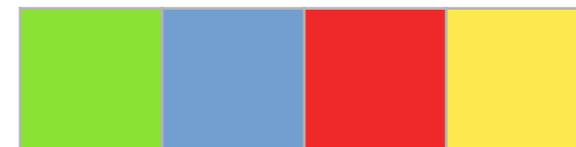
input: 9



weight: 4×9

a	b		c	d				
	a	b		c	d			
			a	b		c	d	
				a	b		c	d

output: 4



Special case: 1x1 convolution

- Pixel-wise linear transformation
- Kernel: $1 \times 1 \times C_1 \times C_2$



*

W =

