Questions

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DaSCI

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Data Science and Computational Intelligence

Correlation vs Convolution

Cross-correlation

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0
0	1	0
0	0	0

Cross-correlation

Kernel H

	2	3
4	5	6
7	8	9

0	0	0
0	1	0
0	0	0

1	2	3

4	5	6	U
7	80	91	0

9	

Cross-correlation

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0	
0	1	0	
0	0	0	

1	2	3

4 0	5 0	6 0
------------	------------	------------

0	0	
---	---	--

9	8	

Cross-correlation

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0	
0	1	0	:
0	0	0	

	1	2	3
0	40	5 0	6
0	71	80	9
0	0	0	

9	8	7

Cross-correlation

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0
0	1	0
0	0	0

9	8	7
6		

Cross-correlation

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0
0	1	0
0	0	0

1 0	2 0	3 0
40	5 1	60
70	80	90

9	8	7
6	5	

Cross-correlation

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0	
0	1	0	
0	0	0	

0	1 0	2 0	3
0	41	5 0	6
0	7 0	80	9

9	8	7
6	5	4

Cross-correlation

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0
0	1	0
0	0	0

	9	8	7
=	6	5	4
	3		

Cross-correlation

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0
0	1	0
0	0	0

0	0	0
1 0	2 1	3 0
40	5 0	60
7	8	9

	9	8	7
=	6	5	4
	3	2	

Cross-correlation

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0
0	1	0
0	0	0

0	0	0	
0	1 1	20	3
0	40	5 0	6
	7	8	9

9	8	7
6	5	4
3	2	1

Cross-correlation

Kernel H

0	0	0
0	1	0
0	0	0

	1	2	3
4	4	5	6
	7	8	9

Cross-correlation

Kernel H

0	0	0
0	1	0
0	0	0

1	2	3
4	5	6
7	8	9

	0	0	0	
	0	11	02	3
=	0	04	05	6
		7	8	9

1	

Cross-correlation

Kernel H

0	0	0
0	1	0
0	0	0

1	2	3
4	5	6
7	8	9

0	0	0
01	1 2	03
04	05	06
7	8	9

1	2	

Cross-correlation

Kernel H

0	0	0
0	1	0
0	0	0

	2	3
4	5	6
7	8	9

	0	0	0
1	02	1 3	0

4	05	06	0
7	8	9	

1	2	3

Cross-correlation

Kernel H

0	0	0
0	1	0
0	0	0

1	2	3
4	5	6
7	8	9

	0	01	02	3
=	0	1 4	0 5	6
	0	07	08	9

1	2	3
4		

Cross-correlation

Kernel H

0	0	0
0	1	0
0	0	0

1	2	3
4	5	6
7	8	9

01	02	03
04	1 5	06
07	08	09

1	2	3
4	5	

Cross-correlation

Kernel H

0	0	0
0	1	0
0	0	0

1	2	3
4	5	6
7	8	9

1	02	03	0
4	05	1 6	0
7	08	09	0

1	2	3
4	5	6

Cross-correlation

Kernel H

0	0	0
0	1	0
0	0	0

1	2	3
4	5	6
7	8	9

		1	2	3
=	0	04	05	6
	0	1 7	08	9
	0	0	0	

	1	2	3
=	4	5	6
	7		

Cross-correlation

Kernel H

0	0	0
0	1	0
0	0	0

1	2	3
4	5	6
7	8	9

1	2	3
04	05	06
07	18	09
0	0	0

	1	2	3
=	4	5	6
	7	8	

Cross-correlation

Kernel H

0	0	0
0	1	0
0	0	0

1	2	3
4	5	6
7	8	9

1	2	3	
4	05	06	0
7	08	1 9	0
	0	0	0

1	2	3
4	5	6
7	8	9

Cross-correlation

Kernel H

1	2	ന
4	5	6
7	8	9

Image F

0	0	0
0	1	0
0	0	0

9	8	7
6	5	4
3	2	1

Kernel H

0	0	0
0	1	0
0	0	0

Image F

1	2	3
4	5	6
7	8	9

No commutative!!!!

Convolution

Ke	rne	I F	+
			•

1	2	3
4	5	6
7	8	9

0	0	0
0	1	0
0	0	0

Convolution

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0
0	1	0
0	0	0

9	8	7

b	50	40	0
3	2 0	1 1	0

1	

Convolution

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0	
0	1	0	
0	0	0	

	9	8	7
	60	5 0	40
	3 0	2 1	10
1			

1	2	

Convolution

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0	
0	1	0	
0	0	0	

_			<u> </u>
	9	8	7

0	60	5 0	4
0	3 1	20	1
0	0	0	

1	2	3

Convolution

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0
0	1	0
0	0	0

	9	80	7 0	0
=	6	5 0	4 1	0
	3	20	10	0

1	2	3
4		

Convolution

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0
0	1	0
0	0	0

90	80	7 0
60	5 1	40
3 0	20	1 0

1	2	3
4	5	

Convolution

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0	
0	1	0	
0	0	0	

0	90	80	7
0	6 1	5 0	4
0	3 0	20	1

1	2	3
4	5	6

Convolution

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0
0	1	0
0	0	0

		0	0	0
=	9	80	7 1	0
	6	5 0	4 0	0
	3	2	1	

1	2	3
4	5	6
7		

Convolution

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0	
0	1	0	
0	0	0	

0	0	0
90	8 1	70
60	5 0	40
3	2	1

	1	2	3
=	4	5	6
	7	8	

Convolution

Kernel H

1	2	3
4	5	6
7	8	9

0	0	0	
0	1	0	
0	0	0	

	0	0	0	
	0	91	80	7
	0	6 0	5 0	4
•		3	2	1

1	2	3
4	5	6
7	8	9

Convolution

Kernel H

0	0	0
0	1	0
0	0	0

1	2	3
4	5	6
7	8	9

Convolution

Kernel H

0	0	0
0	1	0
0	0	0

1	2	3
4	5	6
7	8	9

0	0	0	
0	1 1	02	3
0	04	0 5	6
		·	

1	

Convolution

Kernel H

0	0	0
0	1	0
0	0	0

1	2	3	
4	5	6	
7	8	9	

0	0	0
01	1 2	03
04	05	06
7	8	9

1	2	

Convolution

Kernel H

0	0	0
0	1	0
0	0	0

*

1	2	3	
4	5	6	=
7	8	9	

	0	0	0
1	02	1 3	0
4	05	06	0
7	Q	a	

1	2	3

Convolution

Kernel H

0	0	0
0	1	0
0	0	0

1	2	3	
4	5	6	
7	8	9	

	0	01	02	3
=	0	1 4	0 5	6
	0	07	08	9

1	2	3
4		

Convolution

Kernel H

0	0	0
0	1	0
0	0	0

1	2	3	
4	5	6	
7	8	9	

01	02	03
04	1 5	06
07	08	09

1	2	3
4	5	

Convolution

Kernel H

0	0	0
0	1	0
0	0	0

1	2	3	
4	5	6	:
7	8	9	

1	02	03	0
4	05	1 6	0
7	08	09	0

1	2	3
4	5	6

Convolution

Kernel H

0	0	0
0	1	0
0	0	0

1	2	3
4	5	6
7	8	9

		1	2	3
=	0	04	05	6
	0	1 7	08	9
	0	0	0	

1	2	3
4	5	6
7		

Convolution

Kernel H

0	0	0
0	1	0
0	0	0

1	2	3	
4	5	6	
7	8	9	

1	2	3
04	05	06
07	18	09
0	0	0

1	2	3
4	5	6
7	8	

Convolution

Kernel H

0	0	0
0	1	0
0	0	0

	2	3	
4	5	6	
7	8	9	

1	2	3	
4	05	06	0
7	08	1 9	0
	0	0	0

1	2	3
4	5	6
7	8	9

Convolution

Kernel H			
1	2	3	
4	5	6	
7	8	9	





0	0	0
0	1	0
0	0	0

1	2	3
4	5	6
7	8	9

Kernel H

0	0	0
0	1	0
0	0	0

Image F

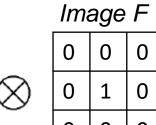
1	2	3
4	5	6
7	8	9

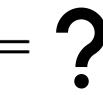
Commutative!!!!

Cross-correlation

Kernel H







Convolution

Kernel H



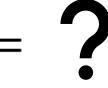
0 0 * 0

Kernel H (rotated 180°)



Image F		
0	0	0
0	1	0

)	0	0	
C	1	0	=
)	0	0	

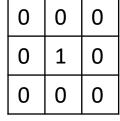


Cross-correlation

Kernel H



Image F



 \otimes

*

=

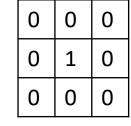


Convolution

Kernel H



Image F



Kernel H (rotated 180°)

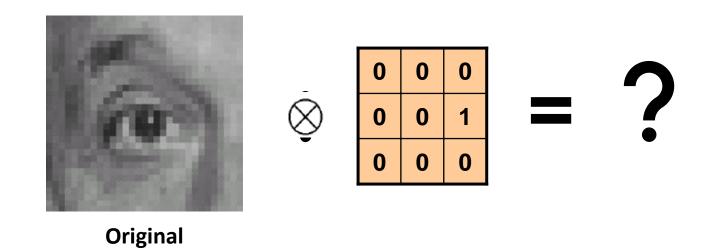


Image F

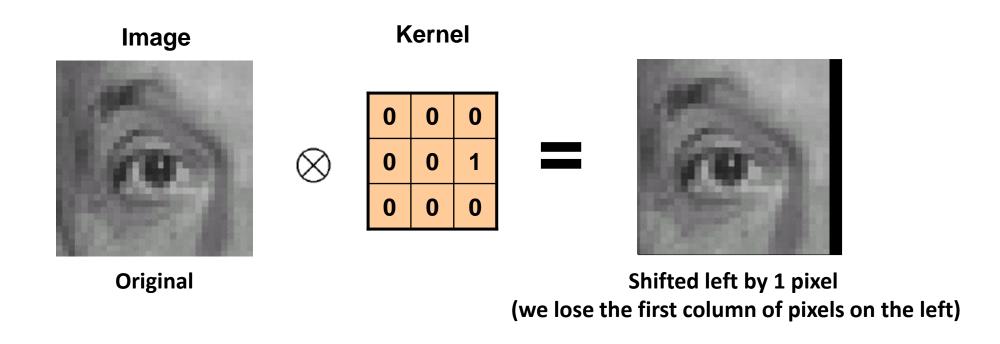
	0	0	0
)	0	1	0
	0	0	0

<u>—</u>

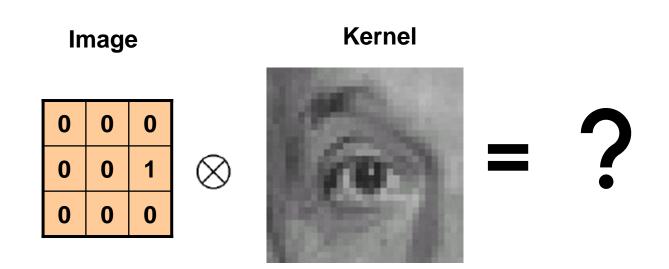


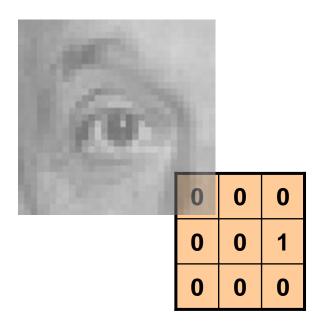


Slide 46 of 2.1.ImageFiltering actually shows correlation not convolution!!!!!



Slide 46 of 2.1.ImageFiltering actually shows correlation not convolution!!!!!



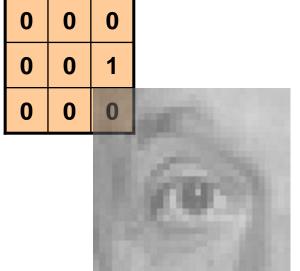


15			
10			
	0	0	0
	0	0	1
	0	0	0

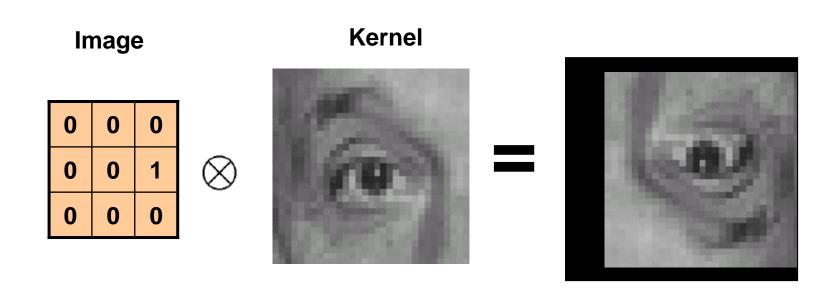
œ.		
Ľ,	۷,	
0	0	0
0	0	1

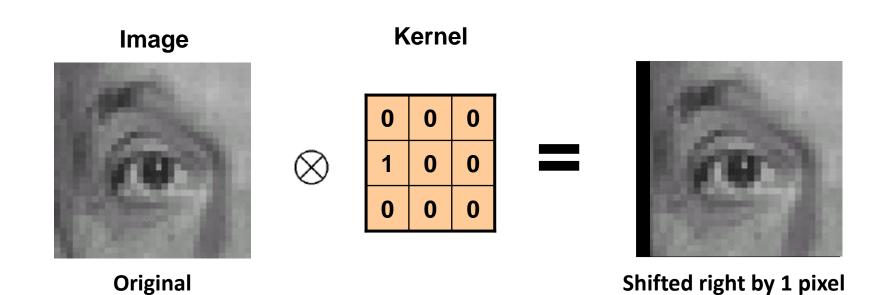
0 0 0	0 0 0 0 0 0 0 1
0 0 0	Contract Contract
	0 0 1

0	0	0
0	0	1
0	0	0

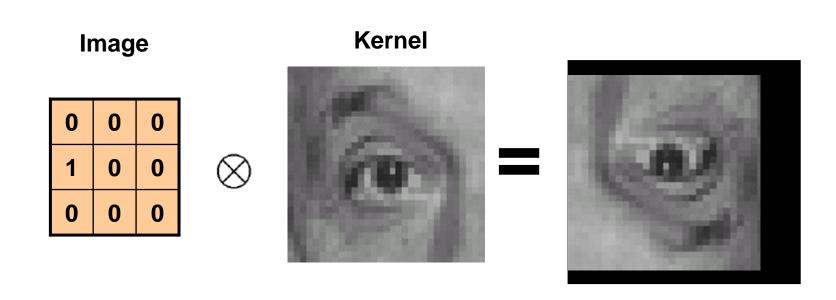


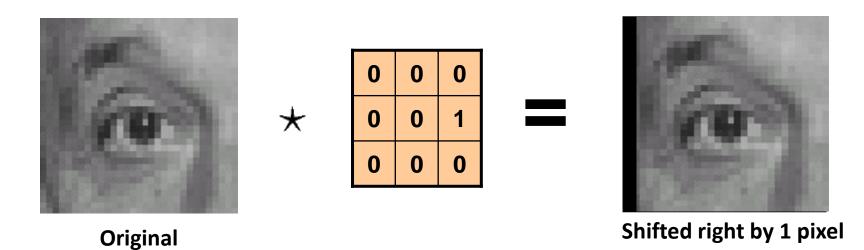
This visual representation tries to convey the main intuition behind the operation carried out. It is not made to scale (where each position of the kernel (Einstein's eye) should coincide with a single pixel of the image)





(we lose the first column of pixels on the right)





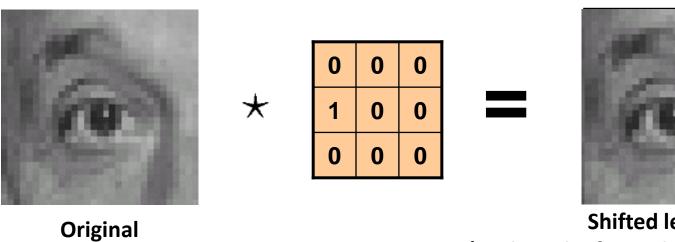


 0
 0

 1
 0

 0
 0

(we lose the first column of pixels on the right)



Shifted left by 1 pixel (we lose the first column of pixels on the left)



Original

Cross-correlation vs Convolution (technical note)

In case you want to check those results:

```
import scipy.signal as sp
import cv2
sp.convolve2d()
https://docs.scipy.org/doc/scipy/reference/generated/scipy.signal.convolve2
d.html
sp.correlate2d()
https://docs.scipy.org/doc/scipy/reference/generated/scipy.signal.correlate
2d.html
cv2.filter2D()
https://docs.opencv.org/4.x/d4/d86/group imgproc filter.html#ga27c049795c
e870216ddfb366086b5a04
```

Gaussian kernels and separability

Separability

First derivative of 2D Gaussian is separable:

$$G(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(\frac{-(x^2 + y^2)}{2\sigma^2}\right)$$

$$= \left(\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{x^2}{2\sigma^2}\right)\right) \cdot \left(\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{y^2}{2\sigma^2}\right)\right)$$

$$= G_h(x) \cdot G_v(y)$$

$$= -\frac{x}{\sigma^2} \cdot \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2}{2\sigma^2}\right) \exp\left(-\frac{y^2}{2\sigma^2}\right)$$

$$= G'_h(x) \cdot G_v(y)$$

horizontal 1D Gaussian

derivative kernel

vertical 1D Gaussian

kernel

How are the product and convolution related? Why do we assume that this product is equivalent to the convolution?



smooth in one direction, differentiate in the other

This allows us to know which 1D kernels to apply to calculate the derivatives of an image.

In the previous example, the first derivative on X.

Separability

1. We know that the 1st derivative of a 2D Gaussian is separable.

$$\frac{\partial G(x,y)}{\partial x} = -\frac{x}{\sigma^2} \cdot \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2}{2\sigma^2}\right) \exp\left(-\frac{y^2}{2\sigma^2}\right)$$
$$= G'_h(x) \cdot G_v(y)$$

The partial derivative of a Gaussian is composed of the derivative in that direction and the Gaussian in the other.

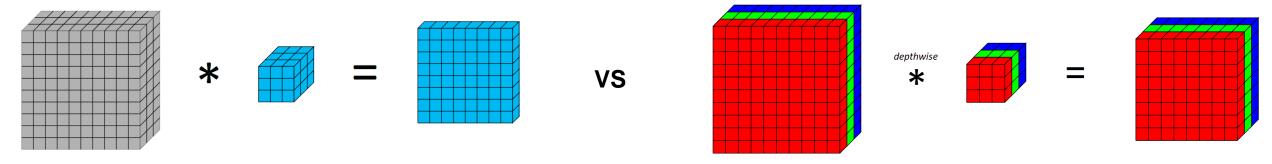
2. From a practical point of view, we are interested in implicitly smoothing the signal to avoid magnifying the noise. So, we smooth in one direction and differentiate in the other.

3. Mathematically, a separable kernel function leads to a separable convolution. See http://www.songho.ca/dsp/convolution/convolution2d separable.html

Convolutional Neural Networks and Separable Filters

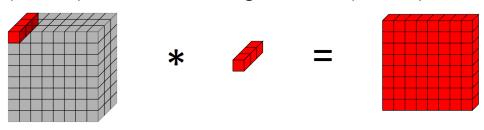
ConvNets and Separable Convolutions

Depthwise Separable Convolutions



We apply a kernel (3x3x3) over the whole input volume (10x10x3)

We apply one kernel (3x3x1) per channel in the input volume (10x10x3). We then apply a pointwise convolutional layer (1x1x3) on the resulting volume (8x8x3):



Number of parameters (if we want to apply 64 convolutional filters to our RGB image):

3x3x3x64 + 64 = 1792 parameters

(3x3x1x3 + 3) + (1x1x3x64 + 64) = 286 parameters

ConvNets and Separable Convolutions

- Depthwise Separable Convolutions
 - They have been shown to yield similar performance while using less parameters and less floating point operations.
- SVD is sometimes used to decompose/approximate the weight matrices and reduce the number of parameters in the model (regularization; light-weight DL models deployment)
 - Note: it is costly to use SVD on every training step
- Apart from this, I don't have the impression that ConvNets generally use any filter factorization (e.g., SVD) to apply the separable convolution of smaller kernels...

Questions

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