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15주차 발표

컴퓨터비전 ~ 입체형 이미지에서의 합성곱



목치

#01 Computer Visions

#02 CNN

#03 Convolutions over Volumes

#04 퀴즈 리뷰

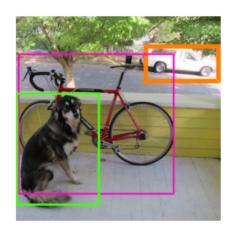




1.1 Computer Vision Problems



Image Classification



Object detection

content image



Ancient city of Persepolis

style image



The Starry Night (Van Gogh)

generated image

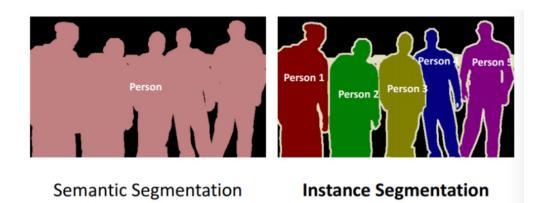


Persepolis in Van Gogh style

Neural Style Transfer



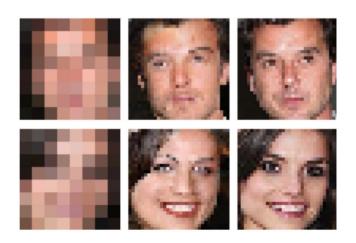
1.1 Computer Vision Problems



Vision Language Shopping at an outdoor market.

There are many vegetables at the fruit stand.

Image Segmentation

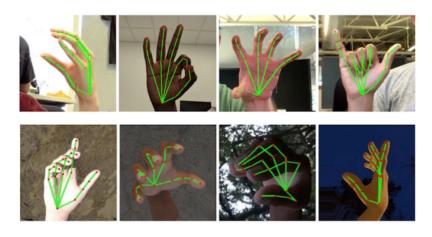


Super Resolution



Text Detection & OCR

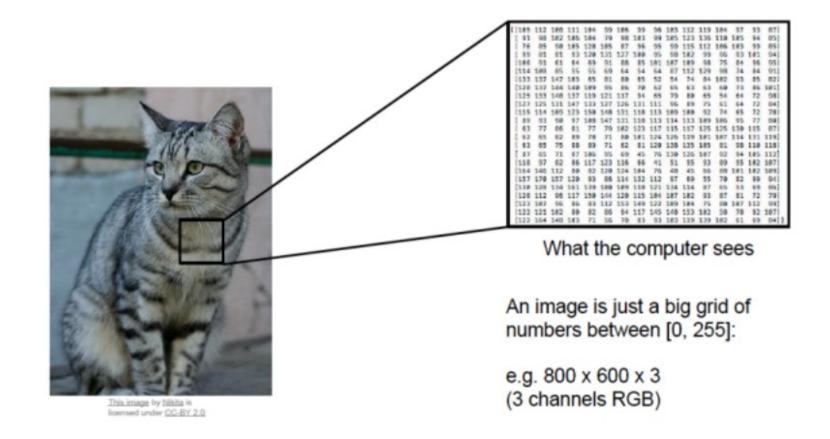
Image Captioning



Keypoint Detection

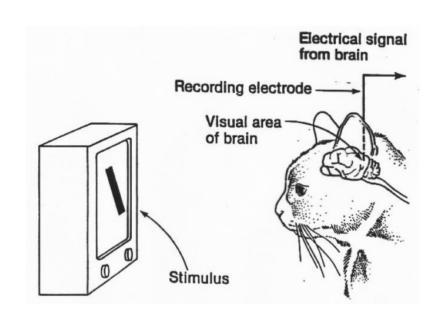


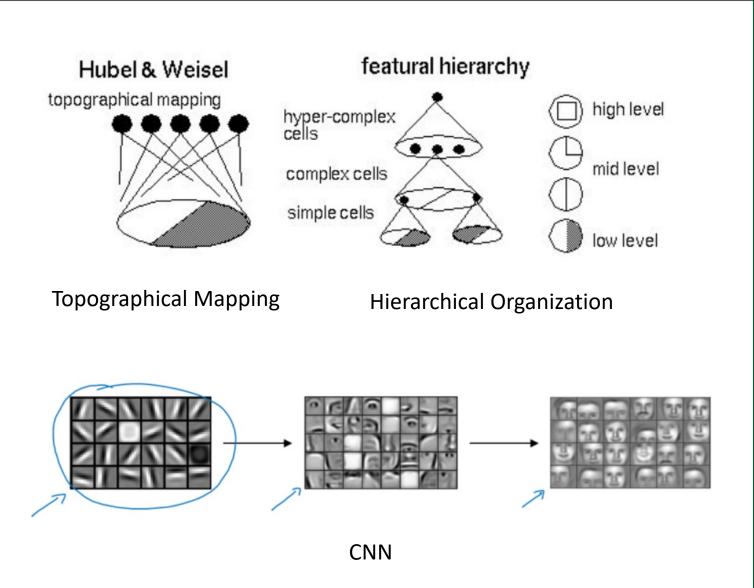
1.2 Deep Learning on Large images



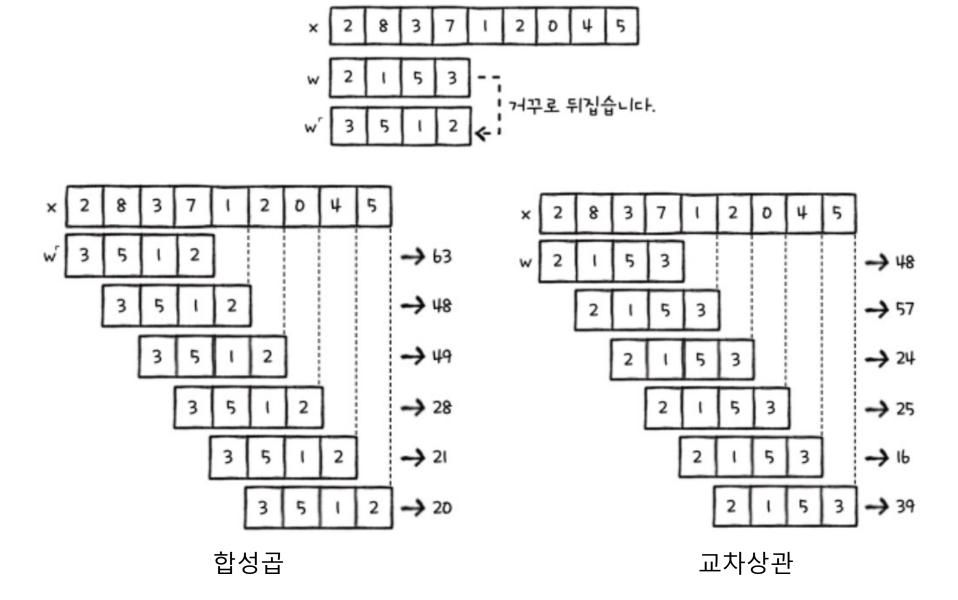


2.1 CNN Introduction





2.2 CNN - Convolution





2.2 CNN - Convolution

		6	x 6		
3	0 ¹	1°	2-1	7	4
1	5 ¹	8°	9.1	3	1
2	7 <mark>1</mark>	2°	5 ¹	1	3
0	1	3	1	7	8
4	2	1	6	2	8
4	2	5	2	3	9

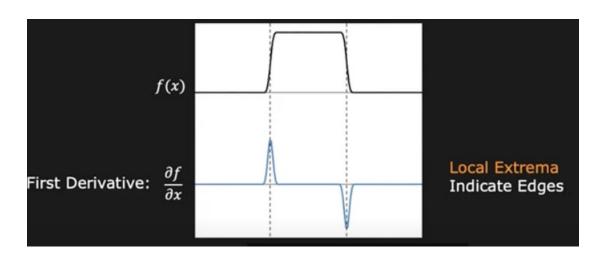
	3 X 3	
1	0	-1
1	0	-1
1	0	-1

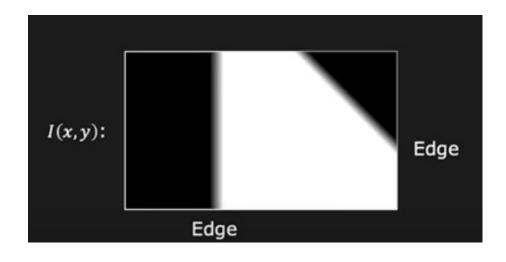
4 x 4						
-5	-4					

$$0x1 + 1x0 + 2x-1 + 5x1 + 8x0 + 9x-1 + 7x1 + 2x0 + 5x-1 = -4$$



수학적 이해



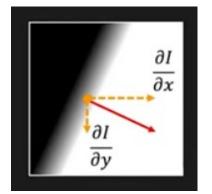


1D Edge Detection

Gradient Magnitude
$$S = \|\nabla I\| = \sqrt{\left(\frac{\partial I}{\partial x}\right)^2 + \left(\frac{\partial I}{\partial y}\right)^2}$$

Gradient Orientation $\theta = \tan^{-1}\left(\frac{\partial I}{\partial y}/\frac{\partial I}{\partial x}\right)$

2D Edge Detection





$$f'(x)pprox rac{f(x+h)-f(x-h)}{2h}$$

유한 차분 근사 기법

Finite difference approximations:

$$\frac{\partial I}{\partial x} \approx \frac{1}{2\varepsilon} \left(\left(I_{i+1,j+1} - I_{i,j+1} \right) + \left(I_{i+1,j} - I_{i,j} \right) \right)$$

$$\frac{\partial I}{\partial y} \approx \frac{1}{2\varepsilon} \left(\left(I_{i+1,j+1} - I_{i+1,j} \right) + \left(I_{i,j+1} - I_{i,j} \right) \right)$$

$$I_{i,j+1} = I_{i+1,j+1}$$

$$I_{i,j+1} = I_{i+1,j+1}$$

Can be implemented as Convolution!

$$\frac{\partial}{\partial x} \approx \frac{1}{2\varepsilon} \begin{bmatrix} -1 & 1 \\ -1 & 1 \end{bmatrix} \qquad \frac{\partial}{\partial y} \approx \frac{1}{2\varepsilon}$$

$$\frac{\partial}{\partial y} \approx \frac{1}{2\varepsilon} \begin{bmatrix} 1 & 1 \\ -1 & -1 \end{bmatrix}$$

$$G_{\chi} = \begin{bmatrix} -1 & 0 & +1 \\ -1 & 0 & +1 \\ -1 & 0 & +1 \end{bmatrix}$$

$$G_{y} = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ +1 & +1 & +1 \end{bmatrix}$$

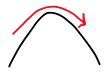
Prewitt Filter



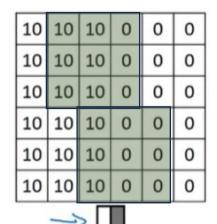
Gradient	Roberts	Prewitt	Sobel (3x3)
$\frac{\partial I}{\partial x}$	0 1 -1 0	-1 0 1 -1 0 1 -1 0 1	-1 0 1 -2 0 2 -1 0 1
<u>∂I</u> ∂y	1 0 0 -1	1 1 1 0 0 0 -1 -1 -1	1 2 1 0 0 0 -1 -2 -1

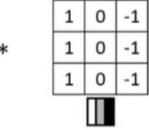


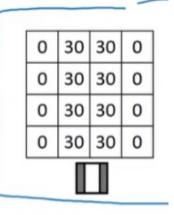




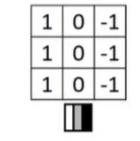
Vertical edge detection





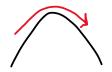


0	0	0	10	10	10	
0	0	0	10	10	10	
0	0	0	10	10	10	
0	0	0	10	10	10	
0	0	0	10	10	10	
0	0	0	10	10	10	

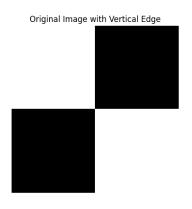


0	-30	-30	0
0	-30	-30	0
0	-30	-30	0
0	-30	-30	0
	-30	-30	-

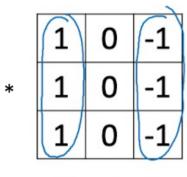




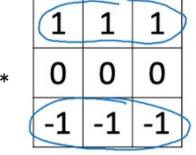
Vertical and Horizontal edge detection



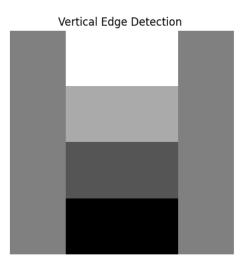
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10



Vertical



Horizontal



Horizontal Edge Detection



다양한 필터들

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

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

sobel

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

scharr

vertical

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

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

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

horizontal

sobel

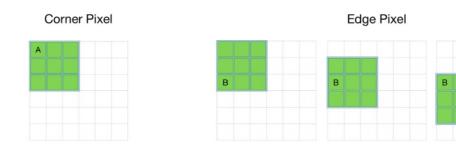
scharr

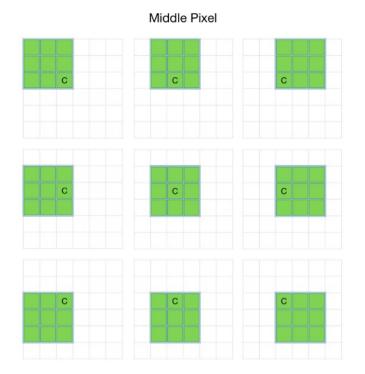
적합한 필터 탐색

w_1	w_2	w_3
W_4	w_5	w_6
w_7	w ₈	W ₉



2.4 CNN – Padding





< 기존 방식 단점 >

- 1) 합성곱 연산을 반복하면 이미지가 축소
- 2) 가장 자리 픽셀 -> 단 한번 사용



Padding



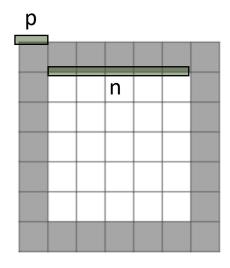
2.4 CNN – Padding

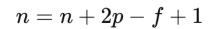
zero padding of size 2

0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0						0	0
0	0						0	0
0	0						0	0
0	0						0	0
0	0						0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0

Padding의 종류

- 1. Valid Padding : padding하지 않는 것
- 2. Same Padding : output image 크기 = input image의 크기







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

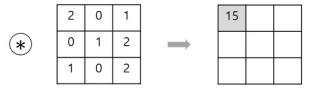
- n: 입력 이미지 한변 길이
- f: 필터의 크기
- p: 패딩의 크기



2.5 CNN - Stride

Stride = 2인 합성곱 연산

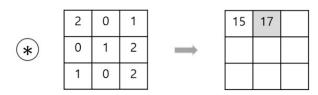
1	2	3	0	1	2	3	
0	1	2	3	0	1	2	
3	0	1	2	3	0	1	
2	3	0	1	2	3	0	
1	2	3	0	1	2	3	
0	1	2	3	0	1	2	
3	0	1	2	3	0	1	
	3 2 1 0	0 1 3 0 2 3 1 2 0 1	0 1 2 3 0 1 2 3 0 1 2 3 0 1 2	0 1 2 3 3 0 1 2 2 3 0 1 1 2 3 0 0 1 2 3	0 1 2 3 0 3 0 1 2 3 2 3 0 1 2 1 2 3 0 1 0 1 2 3 0	0 1 2 3 0 1 3 0 1 2 3 0 2 3 0 1 2 3 1 2 3 0 1 2 0 1 2 3 0 1	



 $n \times n$ image $f \times f$ filter padding p stride s

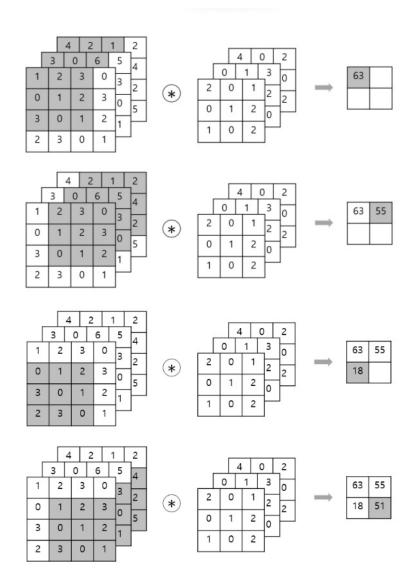


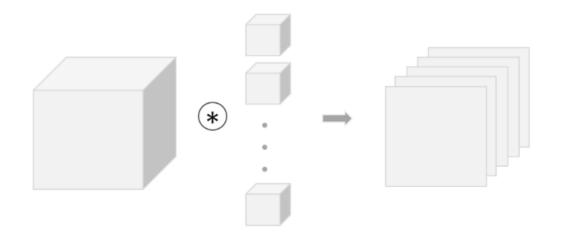
4		7	-				
	1	2	3	0	1	2	3
	0	1	2	3	0	1	2
	3	0	1	2	3	0	1
	2	3	0	1	2	3	0
	1	2	3	0	1	2	3
	0	1	2	3	0	1	2
	3	0	1	2	3	0	1



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

3. CNN - Convolutions Over Volumes





3차원의 필터 n개

 $(n imes n imes n_c) * (f imes f imes n_c) = (n-f+1) imes (n-f+1) imes n_{c'}$ 형태가 됩니다.

채널이 n개인 3차원의 출력 데이터

。 n:이미지의 크기

3차원의 입력 데이터

 n_c : 채널의 개수

 \circ f : 필터의 크기

 \circ $n_{c'}$: 사용된 필터의 개수



4. 퀴즈 리뷰

- 1. 합성곱 연산에 대한 설명 중 틀린 것은 무엇인가요? *
- 필터와 이미지의 각 픽셀에 대해 곱하고 모두 더해 결과를 얻습니다.
- 합성곱 연산은 주로 이미지의 특징을 추출하는 데 사용됩니다.
- 작은 필터는 큰 특징을, 큰 필터는 작은 특징을 찾는 데 도움이 됩니다.

- 2. 패딩을 사용하는 이유는 무엇인가요? *
- 이미지를 더 작게 만들기 위해서
- 이미지의 가장자리 정보를 유지하기 위해서
- 연산 속도를 높이기 위해서



THANK YOU



