

6-12-2021

Week #15 Lecture #19
CNN

Monday

we could consider 1 filter as one Neuron

we won't reshape the image when sending into a filter layer / Convolution layer.

Dilated Convolution:

Dilation = 1

w_1		w_2		w_3
w_4		w_5		w_6
w_7		w_8		w_9

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

5x5 image

before dilation = 0

Now

Resultant

Image

size gets small size

i) with small filter we scan bigger Image.

ii) Less Computation

iii) bcz neighbour pixels would be same, we scan quickly.

1x1 Convolution:

1x1 filter size

No padding required

with more channels

1x1x3 filter size

Used to reduce or enhance input size.

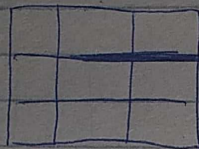
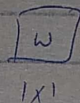


Image
3x3



1x1

Here no size reduction.

e.g.:

consider $224 \times 224 \times 70$ = ~~input~~ output size of one

convolutional layer.

we can convert it to

$224 \times 224 \times 1$

by using filter

$1 \times 1 \times 70$.

to increase size

$32 \times 32 \times 3$

convert to

$32 \times 32 \times N$

by using filter

$1 \times 1 \times 3$

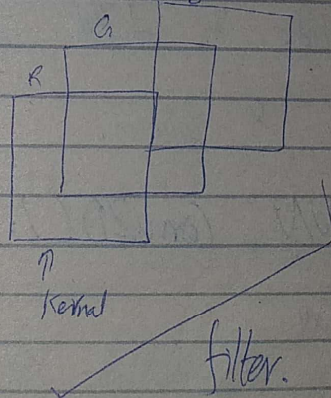
8 No. of filters N in one convolution layer.

we increase or decrease depth of input.

No. of filters = kernel

1 filter of 2D is called kernel

1 filter of 3D have 3 ^{2D} kernels



Conv1D () ; 1D filter

Conv2D () ; 2D filter

Conv3D () ;

↓

if input had size $32 \times 32 \times 20$

Then filter size will be $3 \times 3 \times 20$

instead ~~of~~ in this we use

$3 \times 3 \times 3$ stride in channels ^{depth} as well

Stride was already in rows & columns in image.

when input \neq filter size depth, then automatically we use

Conv3D

first make stride in depth dimension & we

stride in row & column.

Code of CNN Conv2D ():

image size = 4×4

filter size = 3×3

Stride=1
padding=0

Conv2D (Image I, filter f):

$$\text{Feature Map} = \text{np.zeros}((I.\text{height} - f.\text{height} + 1, I.\text{width} - f.\text{width} + 1))$$

~~for i in range~~

$$I_r, I_c = I.\text{shape}[0], I.\text{shape}[1]$$

$$f_r, f_c = f.\text{shape}[0], f.\text{shape}[1]$$

$$\text{out} = \text{np.zeros}((I_r - f_r + 1, I_c - f_c + 1))$$

for i in range(I_r - f_r + 1):

for j in range(I_c - f_c + 1):

$$\text{out}[i][j] = \text{np.sum}(f * I[i:i+f_r, j:j+f_c])$$

$$\# \text{out}[i][j] = \text{np.sum}(f * I[i:i+f_r, j:j+f_c, :])$$

all
channels
for more than
channels

$$f * I[i:i+f_r, j:j+f_c, :]$$

Zero strides in channels/depth

Gradients for filters.

a	b	c	d
e	f	g	h
i	j	k	l
m	n	o	p

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

first time gradients

dw	a	b	c
	ed	af	g
	i	j	k

Second time gradients

dw	b	c	d
	f	g	h
	n	o	l

Now add these dw .

Code:-

grade $W[]$

grade $W.append(I part)$

if Image size = 4×4 & filter size = 3×3

then we have 4 gradients & At the end we

Darknet

"YOLO v1 Implementation" Project

add all values in these to one 2×2 grid.

Correlation:

when we multiply filter with image part this process is called correlation

Convolution:

first rotate filter ~~90 degrees~~ 180 degrees then do correlation, This concept is called convolution

reverse order multiplication is called convolution

Assumption that filter is 180 degrees rotated

already & we only do correlation