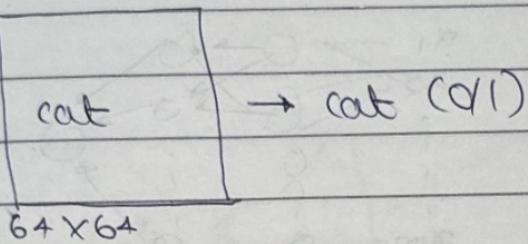


WEEK 1:-

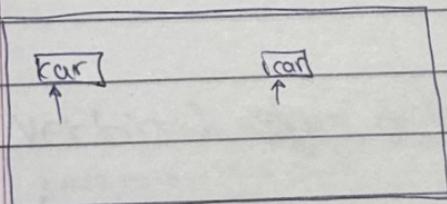
COMPUTER VISION:-

CV problems

1] Image classification

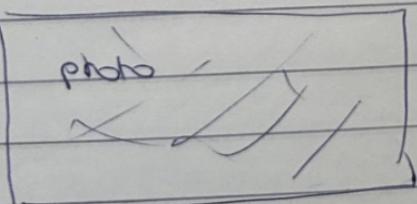
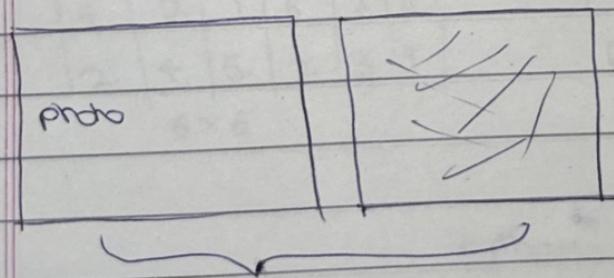


2] Object detection

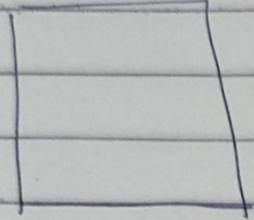


position of car?

3] Neural style transfer

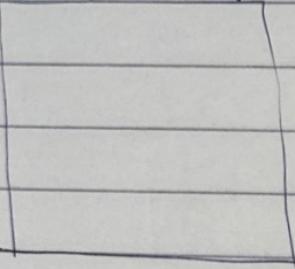


64x64 image

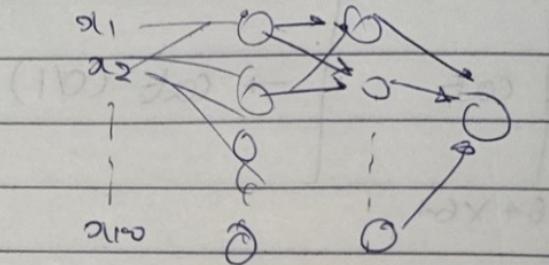


$$64 \times 64 \times 3 = 12288$$

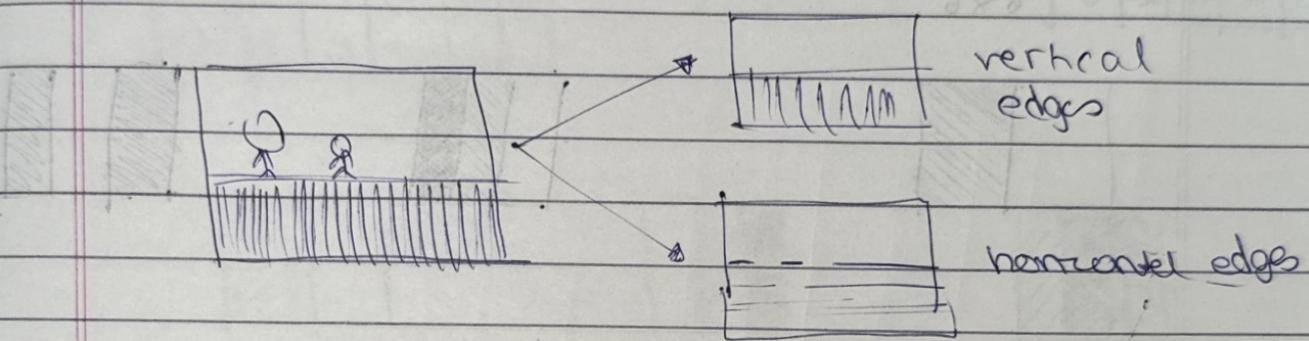
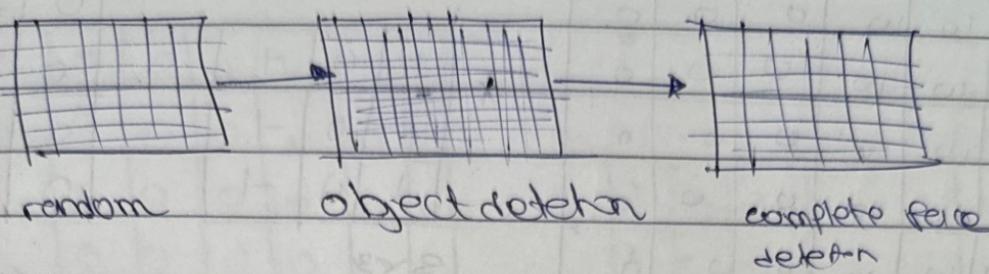
1000x1000 image



$$1000 \times 1000 \times 3 = 3 \text{ million}$$



EDGE-DETECTION (ON EXAMPLE!)

→ Vertical edge detection!

$$3+12+0+10-1-8-2 = -5$$

| | | | | | |
|---|---|---|---|---|---|
| 1 | 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 |

6×6

"convolutional operator"

| | | | |
|---|---|----|----|
| * | 1 | 0 | -1 |
| 1 | 0 | -1 | = |
| 1 | 1 | 1 | |

Filter Kernel

3×3 4×2

python: conv-forward

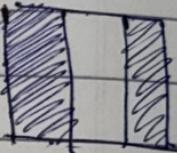
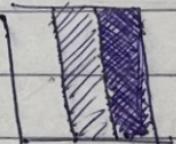
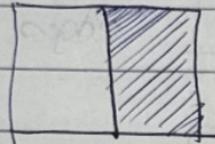
tensorflow: tf.nn.conv2d

$$\begin{array}{|c|c|c|c|c|c|c|} \hline
 10 & 10 & 10 & 0 & 0 & 0 \\ \hline
 10 & 10 & 10 & 0 & 0 & 0 \\ \hline
 10 & 10 & 10 & 0 & 0 & 0 \\ \hline
 10 & 10 & 10 & 0 & 0 & 0 \\ \hline
 10 & 10 & 10 & 0 & 0 & 0 \\ \hline
 10 & 10 & 10 & 0 & 0 & 0 \\ \hline
 \end{array}
 \times
 \begin{array}{|c|c|c|} \hline
 1 & 0 & -1 \\ \hline
 1 & 0 & -1 \\ \hline
 1 & 0 & -1 \\ \hline
 \end{array}
 =
 \begin{array}{|c|c|c|c|c|c|} \hline
 0 & 30 & 30 & 0 \\ \hline
 0 & 30 & 30 & 0 \\ \hline
 0 & 30 & 30 & 0 \\ \hline
 0 & 30 & 30 & 0 \\ \hline
 \end{array}$$

3×3

6×6

4×9



Matriz de transformación

Matriz de transformación

$\begin{pmatrix} 8 & 0 & -12 \\ 8 & c & 0 \\ 5 & 2 & 0 \\ 3 & 2 & 8 \end{pmatrix}$

$\begin{pmatrix} 1 & 0 & 1 \\ 4 & 0 & 1 \\ 1 & 0 & 1 \\ 2 & 0 & 1 \end{pmatrix}$

$\begin{pmatrix} 1 & 0 & 1 \\ 8 & 1 & 0 \\ 8 & 2 & 0 \\ 8 & 2 & 0 \end{pmatrix}$

$=$

$\begin{pmatrix} 8 & 0 & 1 \\ 32 & 1 & 0 \\ 16 & 2 & 0 \\ 16 & 2 & 0 \end{pmatrix}$

$\begin{pmatrix} 1 & 0 & 1 \\ 8 & 1 & 0 \\ 8 & 2 & 0 \\ 8 & 2 & 0 \end{pmatrix}$

\times

$\begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$

$\begin{pmatrix} 1 & 0 & 1 \\ 8 & 1 & 0 \\ 8 & 2 & 0 \\ 8 & 2 & 0 \end{pmatrix}$

$\begin{pmatrix} 8 & 0 & 1 \\ 32 & 1 & 0 \\ 16 & 2 & 0 \\ 16 & 2 & 0 \end{pmatrix}$

$\begin{pmatrix} 1 & 0 & 1 \\ 8 & 1 & 0 \\ 8 & 2 & 0 \\ 8 & 2 & 0 \end{pmatrix}$

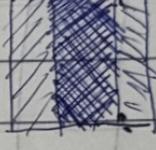
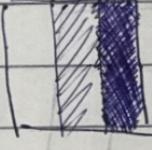
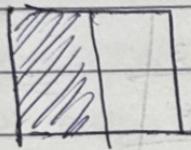
Transformación
de la recta en el eje

MORE 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 |

| | | | |
|---|---|----|----|
| * | 1 | 0 | -1 |
| 1 | 0 | -1 | |
| 1 | 0 | -1 | |

| | | | |
|---|-----|-----|---|
| 0 | -30 | -30 | 0 |
| 0 | -30 | -30 | 0 |
| 0 | -30 | -30 | 0 |
| 0 | -30 | -30 | 0 |



| | | |
|---|---|----|
| 1 | 0 | -1 |
| 1 | 0 | -1 |
| 1 | 0 | -1 |

| | | |
|----|----|----|
| 1 | 1 | 1 |
| 0 | 0 | 0 |
| -1 | -1 | -1 |

Vertical

Horizontal

| | | | | | |
|----|----|----|----|----|----|
| 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 |

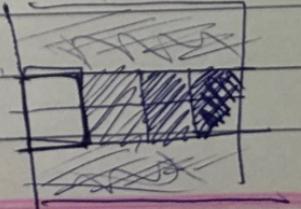
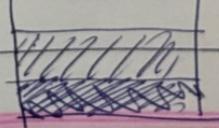
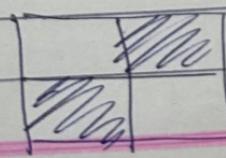
6x6

| | | | |
|----|----|----|---|
| * | 1 | 1 | 1 |
| 0 | 0 | 0 | |
| -1 | -1 | -1 | |

3x3

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

4x4



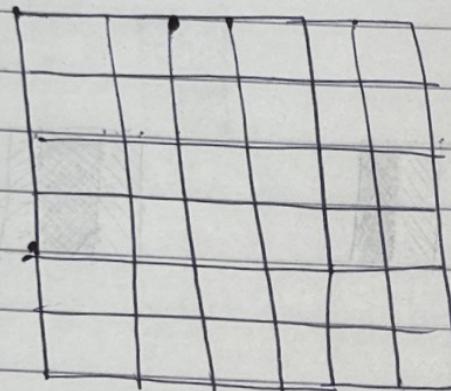
LEARNING TO DETECT EDGES

| | | |
|---|---|----|
| 1 | 0 | -1 |
| 1 | 0 | -1 |
| 1 | 0 | -1 |

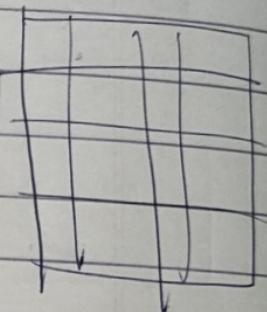
| | | |
|---|---|---|
| 1 | 0 | 1 |
| 2 | 0 | 2 |
| 1 | 0 | 1 |

| | | |
|----|---|----|
| 3 | 0 | -3 |
| 0 | 0 | 0 |
| -3 | 0 | -3 |

Sobel filter



$$\begin{matrix} w_1 & w_2 & w_3 \\ w_4 & w_5 & w_6 \\ w_7 & w_8 & w_9 \end{matrix}$$



letting numbers ^{be} parameters

Iteration

Iteration

0 0 0 0

0 0 0 0

0 0 0 0

0 0 0 0

dx1

dy1

0 0 0 0

0 0 0 0

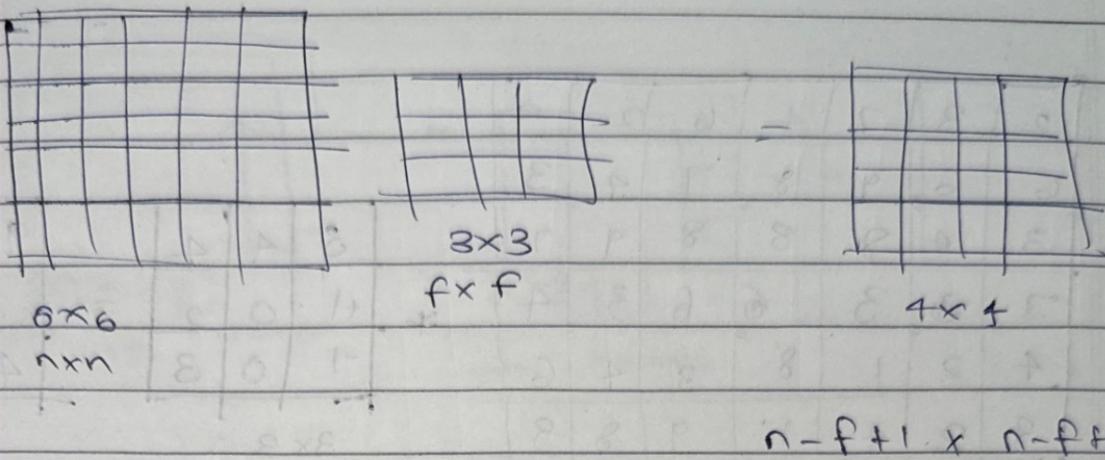
0 0 0 0

0 0 0 0

dx2

dy2

PADDING



two downsides

- image shrinks
- corner edges are used in only one output

so you pad the 6×6 image

it becomes 8×8 and after convolving it with 3×3
we get 6×6 image.

p = padding amount

we pad it with ~~0~~ 0

Valid and Same convolutions

$$\begin{aligned} \text{"Valid"} &= n \times n \times f \times f \Rightarrow n - f + 1 \times n - f + 1 \\ 6 \times 6 \times 3 \times 3 &\Rightarrow 4 \times 4 \end{aligned}$$

"Same": pad so that output size is the same as the input size

STRIDED CONVOLUTIONS:-

| | | | | | | |
|---|---|---|---|---|---|---|
| 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 | 9 |

7x7
stride = 2

| | | |
|----|---|---|
| 3 | 4 | 4 |
| +1 | 0 | 2 |
| -1 | 0 | 3 |

3x3

| | | |
|----|-----|-----|
| 91 | 100 | 83 |
| 69 | 91 | 127 |
| 44 | 71 | 14 |

$$n \times p * f \times f = \left[\frac{n+2p-f}{s} + 1 \right] \times \left[\frac{D+2p-f}{s} + 1 \right]$$

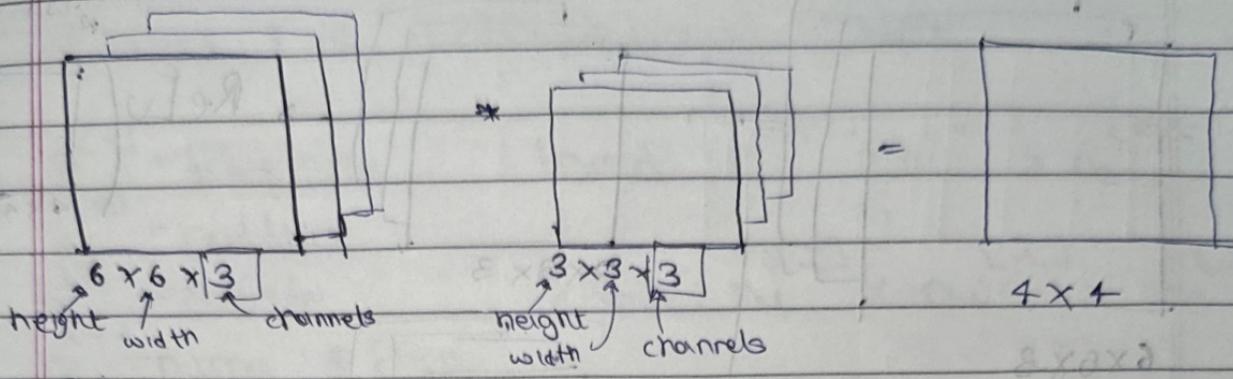
Technical note on cross-correlation vs. convolution
 Convolution in math textbook

| | | | |
|----|---|---|---|
| * | 3 | 4 | 5 |
| 1 | 0 | 2 | |
| -1 | 9 | 7 | |

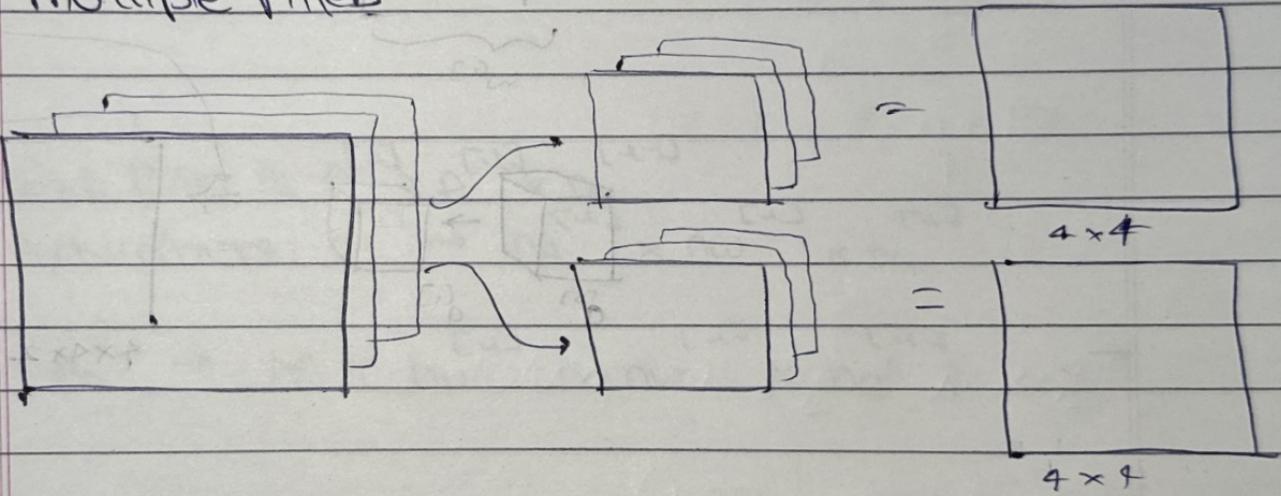
| | | |
|---|---|----|
| 7 | 9 | -1 |
| 2 | 0 | 1 |
| 5 | 4 | 3 |

$$(A * B) * C = A * (B * C)$$

CONVOLUTIONS OVER VOLUME



multiple filters



$$\begin{matrix} f_1 \\ f_2 \end{matrix} + \begin{matrix} f_3 \\ f_4 \end{matrix} \rightarrow \begin{matrix} f_1 \\ f_2 \\ f_3 \\ f_4 \end{matrix}$$

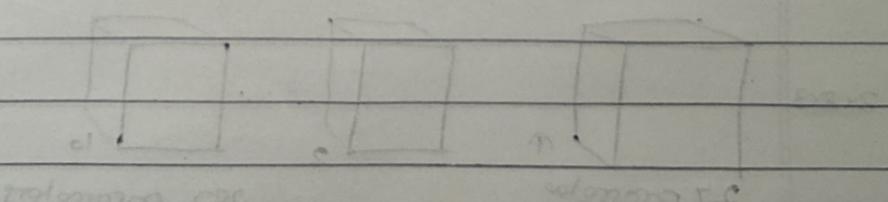
$4 \times 4 \times 2$

result of concatenating both

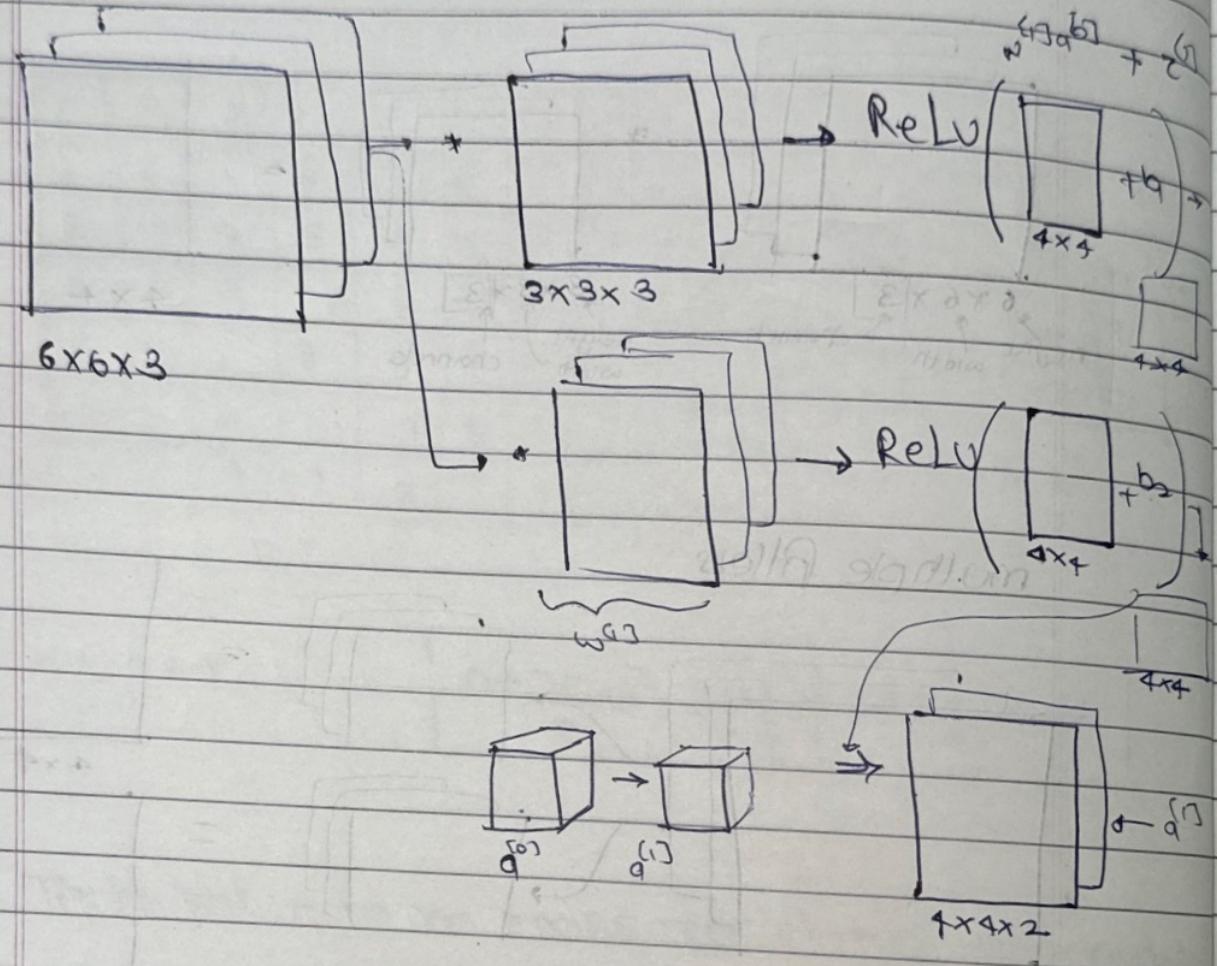
Summary

$$n \times n \times n_c \quad * \quad f \times f \times n_c \Rightarrow n-f+1 \times n-f+1 \times n_c$$

(and sym. for)



ONE LAYER OF CONVOLUTIONAL NN

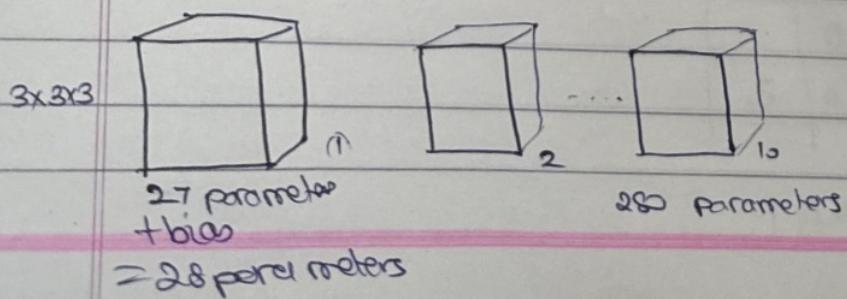


$$f_{ij}^{(l)} = w_{ij}^{(l)} f_{ij}^{(l-1)} + b_{ij}^{(l)}$$

$$g^{(l)} = g(f^{(l)})$$

Number of parameters in one layer

If you have 10 filters that are $3 \times 3 \times 3$ in one layer of a neural network, how many parameters does that layer have?



Summary of notation

If layer l is a convolutional layer:

$f^{[l]}$ = filter size

$p^{[l]}$ = padding

$s^{[l]}$ = stride

$n_c^{[l]}$ = number of filters

Input: $n^{[l-1]} \times n^{[l-1]} \times n_c^{[l-1]}$

Output: $n_H^{[l]} \times n_W^{[l]} \times n_c^{[l]}$

$$\frac{n_H^{[l-1]} + 2p^{[l]} - f^{[l]}}{s^{[l]}} + 1$$

Each filter is: $f^{[l]} \times f^{[l]} \times n_c^{[l]}$

Activations: $a^{[l]} \rightarrow n_H^{[l]} \times n_W^{[l]} \times n_c^{[l]}$

$A^{[l]} \rightarrow M \times n_H^{[l]} \times n_W^{[l]} \times n_c^{[l]}$

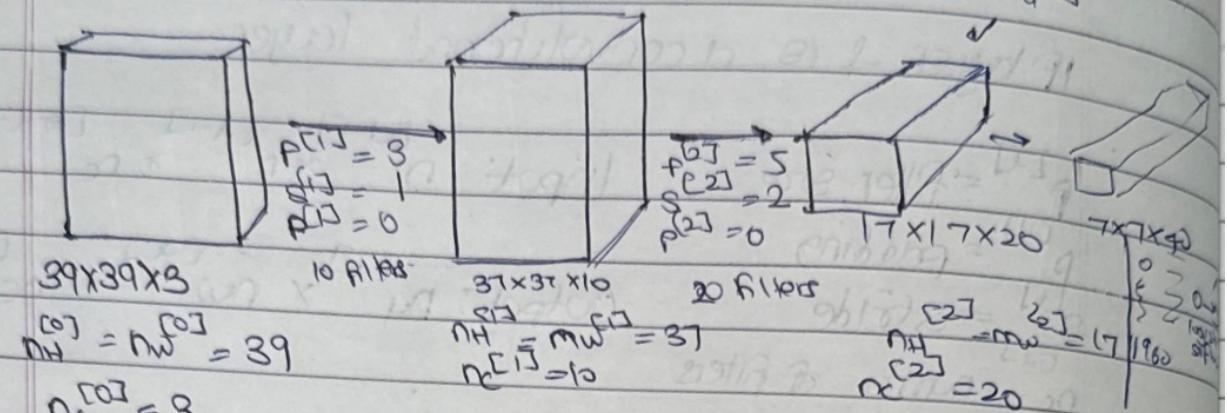
Weights: $f^{[l]} \times f^{[l]} \times n_c^{[l-1]} \times n_c^{[l]}$ # Filters in layer l

bias: $n_c^{[l]} - (b_1, b_2, \dots, b_{n_c^{[l]}})$

SIMPLE CONVOLUTIONAL NETWORK EXAMPLE:

(for 1st layer)

Conv Net



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

$$\frac{39+0-3+1}{1} = 37$$

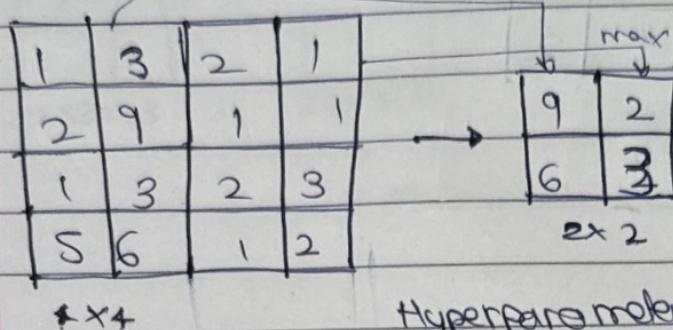
Types of layer in convolutional network:

- Convolution (conv)
- Pooling (POOL)
- fully connected (FC)

POOLING LAYERS

Date _____
Page _____

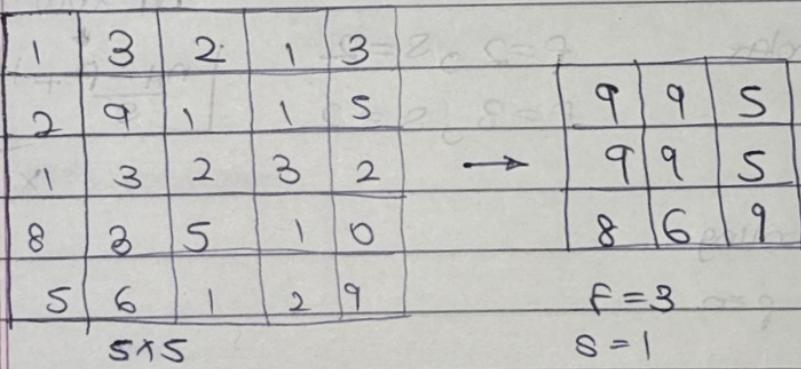
Pooling layer: Max pooling



Hyperparameters

$$f = 2$$

$$s = 2$$

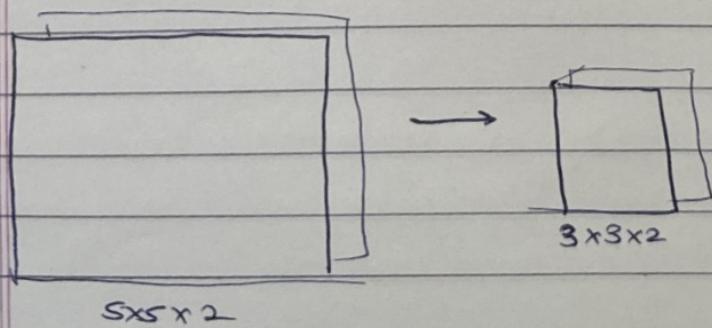


$$f = 3$$

$$s = 1$$

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

multiple layer



Average pooling

297VA1 04/15/09 #

| | | | |
|---|---|---|---|
| 1 | 3 | 2 | 1 |
| 2 | 9 | 1 | 1 |
| 1 | 4 | 2 | 3 |
| 5 | 6 | 1 | 2 |

| | |
|------|------|
| 3.75 | 1.25 |
| 4 | 2 |

$$f=2$$

$$s=2$$

$$7 \times 7 \times 1000 \rightarrow 1 \times 1 \times 1000$$

$$c=4$$

max pooling uses more MN than avg pooling

Hyperparameters

f: filter size

s: stride

Max or avg pooling

p: padding

p=0

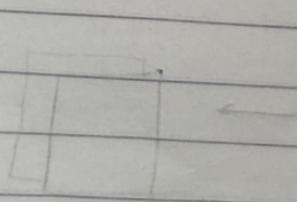
$$f=2, s=2$$

$$f=3, s=2$$

$n_H \times n_W \times n_C$

$$\left[\frac{n_H - f + 1}{s} \right] \times \left[\frac{n_W - f + 1}{s} \right] \times n_C$$

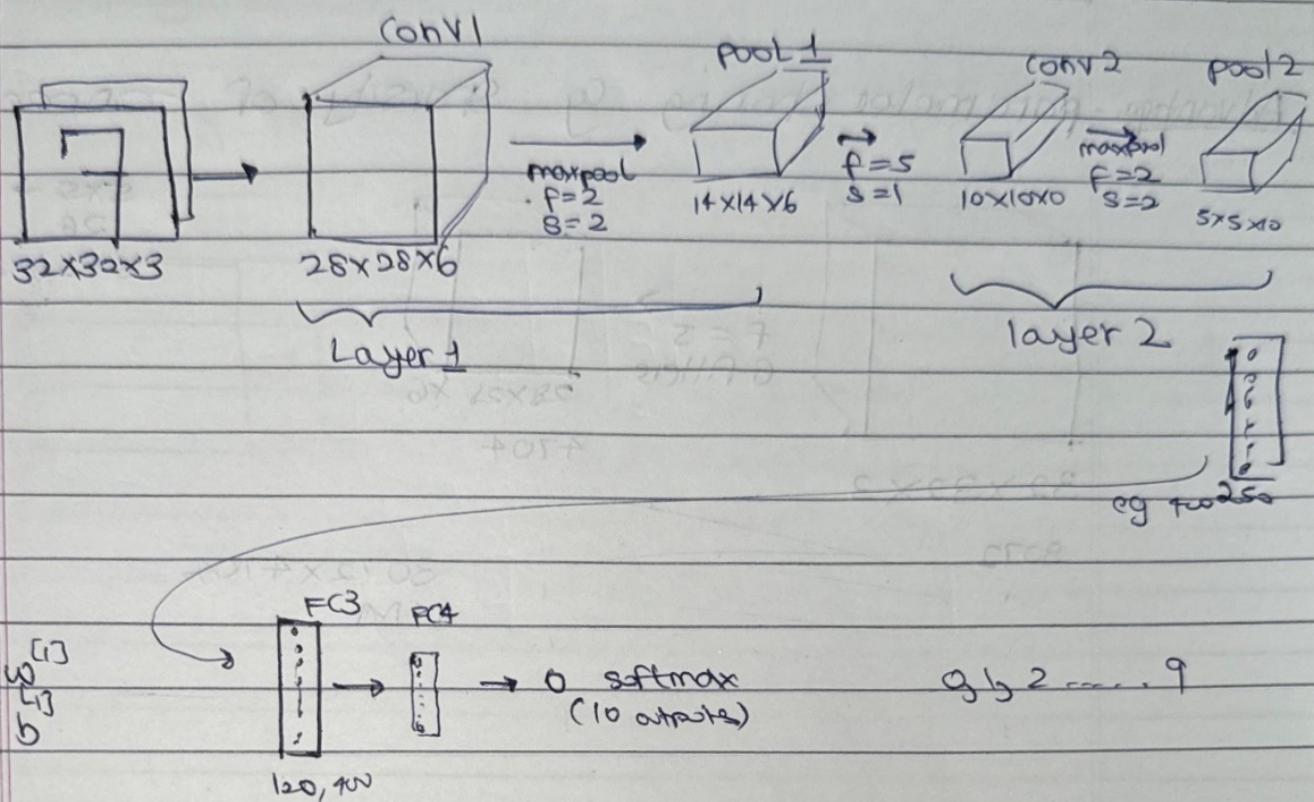
no parameters to learn!



1x2x2

CNN EXAMPLE

(LeNet-5)



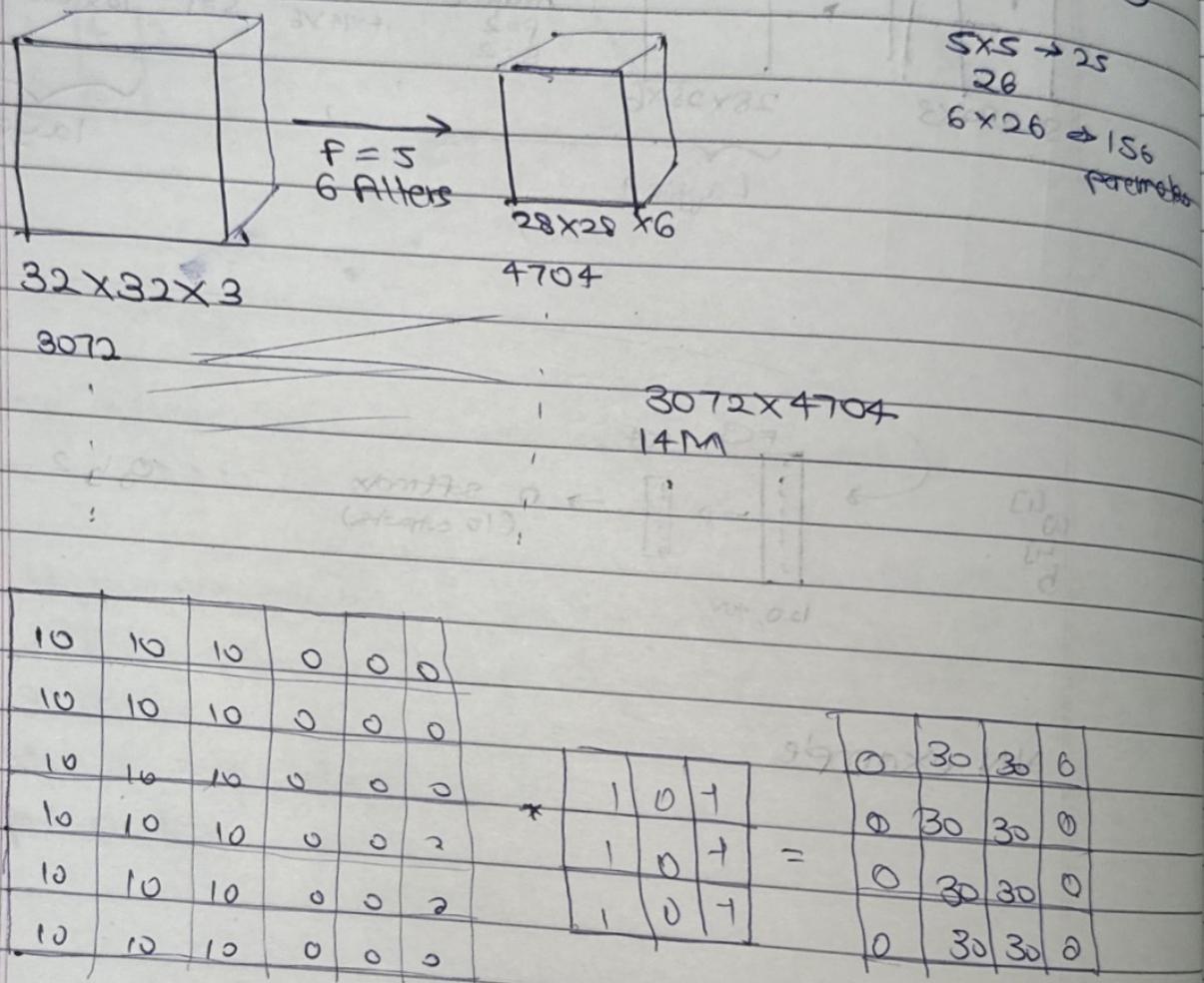
NN example

in this) what's going on? A - ignore planning
 like start (what's going on in this
 I would say is that we do
 In this section in layer 1
 so now

+ more about what's going on in layer 1
 so as what's going on in this
 enough to make it work

WHY CONVOLUTIONS?

Advantage: - parameter sharing, by sparsity of connections



Parameter sharing:- A feature detector (such as a vertical edge detector) that's useful in one part of the image is probably useful in another part of image

Sparsity of connections:- In each layer, each output value depends only on a small number of inputs.

Putting it together

Training set $(x^{(1)}, y^{(1)}) \dots (x^{(m)}, y^{(m)})$.

