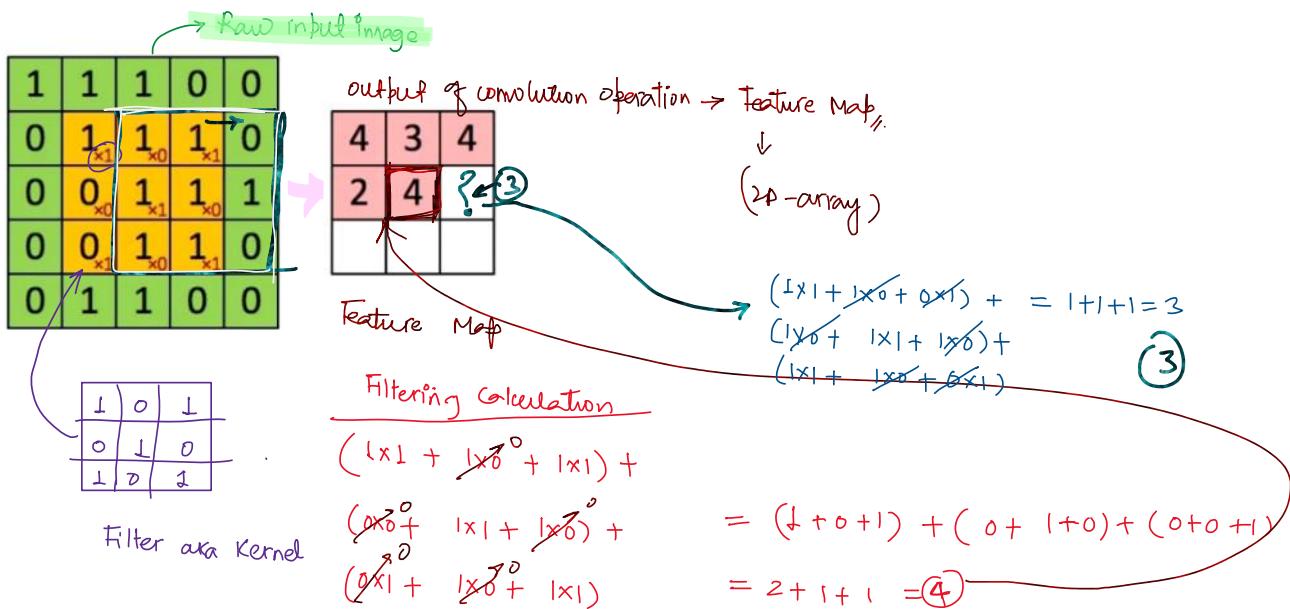
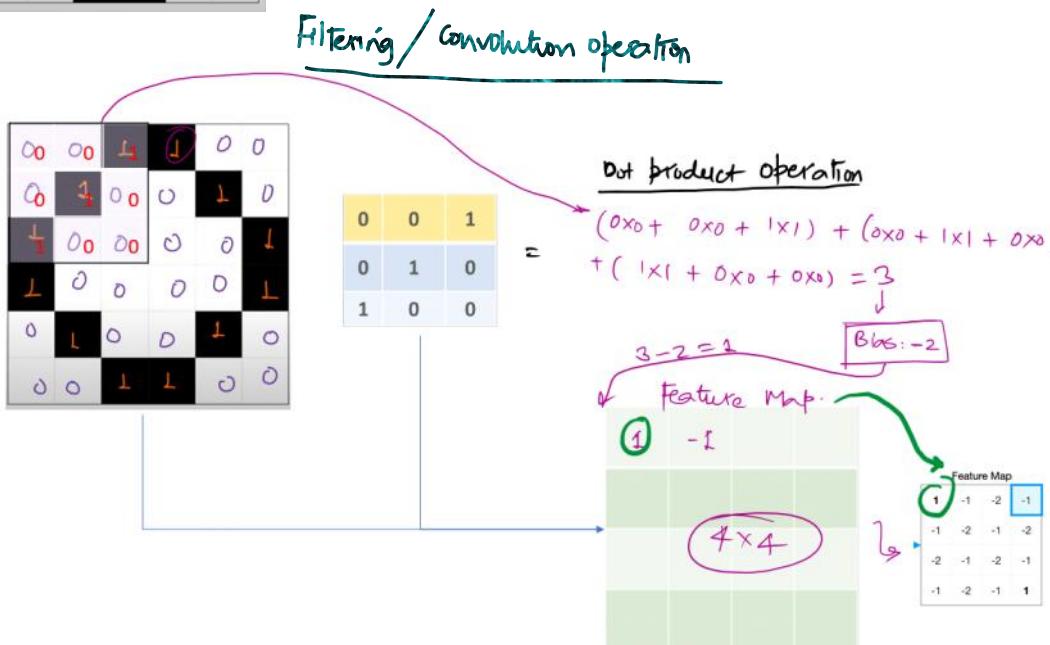
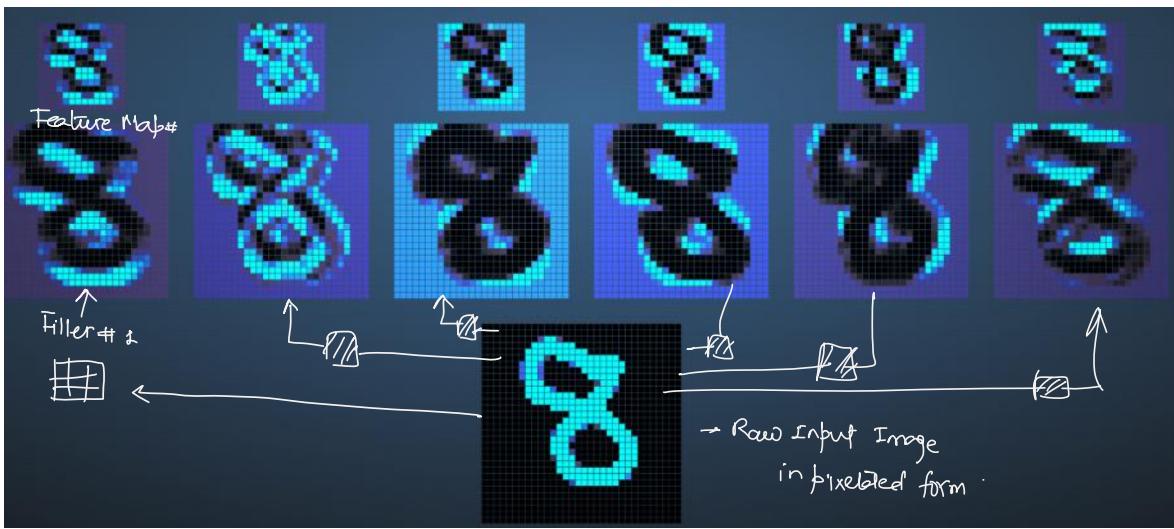


How does convolution work?**Tic-Tac-Toe**

The letter "O", zoomed in.

0	0	1	1	0	0
0	1	0	0	1	0
1	0	0	0	0	1
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0



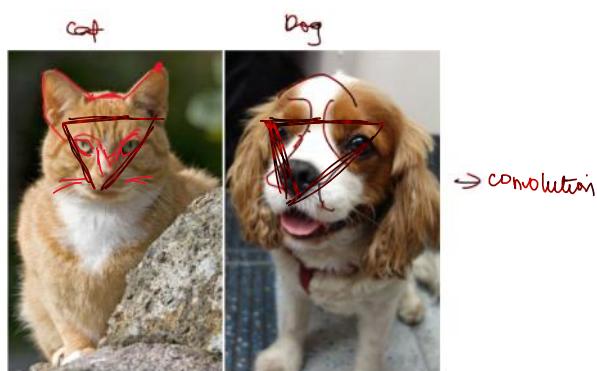
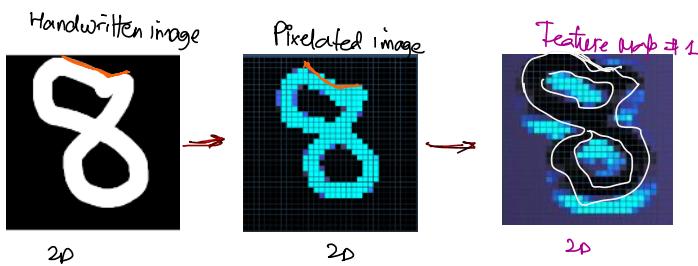


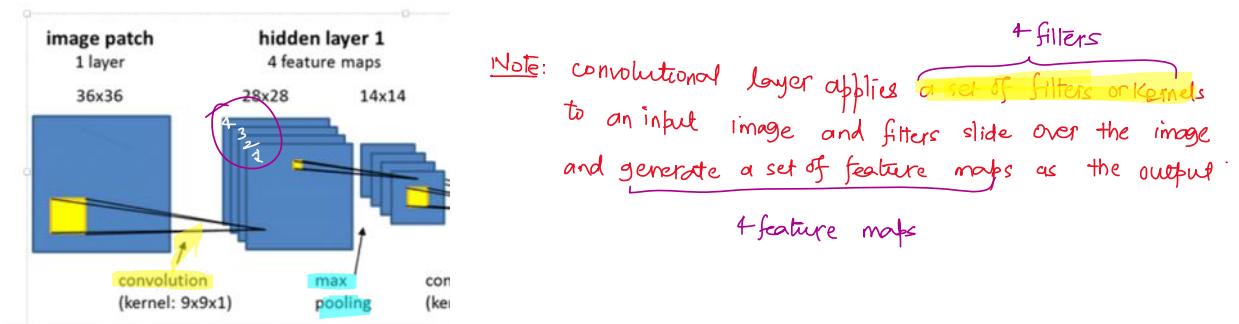
In simple terms, convolution is like sliding a small filter aka kernel over an input image \rightarrow so basically a mathematical operation

[dot product \rightarrow sumproduct of cell overlapped with filter values values]

[to extract specific features such as edges, fine lines, strokes, corners, curves etc.]

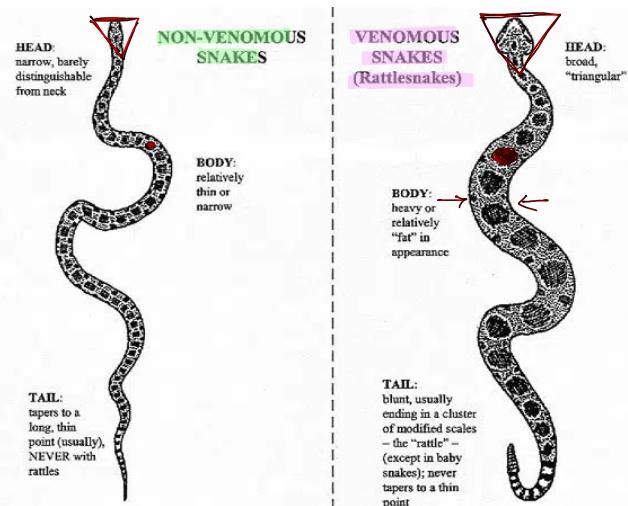
to form shapes \rightarrow patterns





CNN leverages convolution to:

- preserve the **spatial relationship** in the image
- efficiently learn patterns from the **local regions of the image**
- **reduce the computational load** compared to ANNs.



KNOW YOUR SNAKES



COMMON SAND BOA VS RUSSELL'S VIPER

Common Sand Boa
(*Eryx conicus*)

- Non-venomous →
- 1 to 2 ft long
- Relatively small head; neck indistinct
- Conical tail
- Asymmetrical pattern

Russell's Viper
(*Daboia russelii*)

- Venomous →
- 4 to 6 ft long
- Larger, triangular head; distinct neck
- Blunt tail
- Well defined round/oval with pointy ends

INDIAN WOLF SNAKE VS COMMON KRAIT

Indian Wolf Snake
(*Lycodon aulicus*)

- Non-venomous
- 1 to 2 ft long
- Round body, without ridge
- Wide bands; broad band on neck
- Scales similar throughout

Common Krait
(*Bungarus caeruleus*)

- Venomous
- 3 to 4 ft long
- Triangular body; ridge along spine
- Narrow bands; more prominent posteriorly
- Hexagonal vertebral scales

INDIAN RAT SNAKE VS INDIAN COBRA

Indian Rat Snake
(*Ptyas mucosa*)

- Non-venomous
- 6 to 8 ft long
- Doesn't form a hood

Indian Cobra
(*Naja naja*)

- Venomous
- 3 to 5 ft long
- Raises hood when threatened

Intuitive Idea behind CNN

↳ convolution still with downsampling.

Original Image

An excellent illustration of how CNN work! #artificialintelligence
#deeplearning

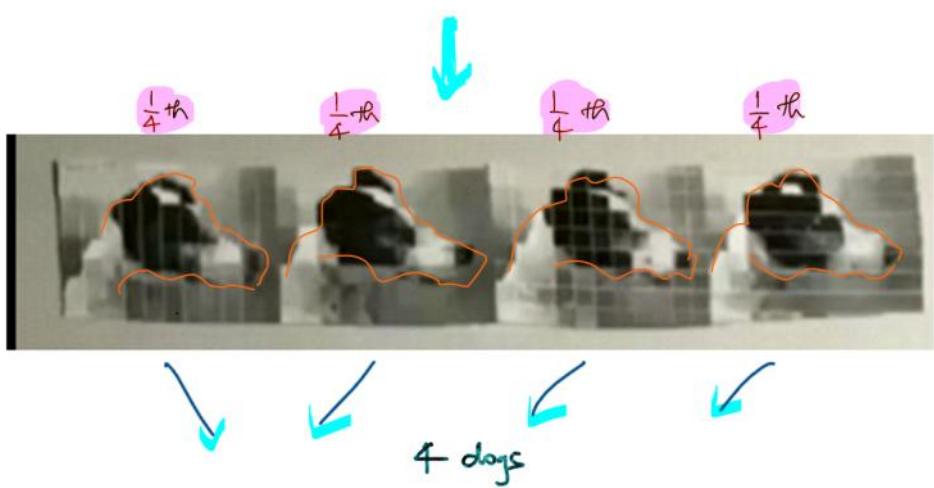
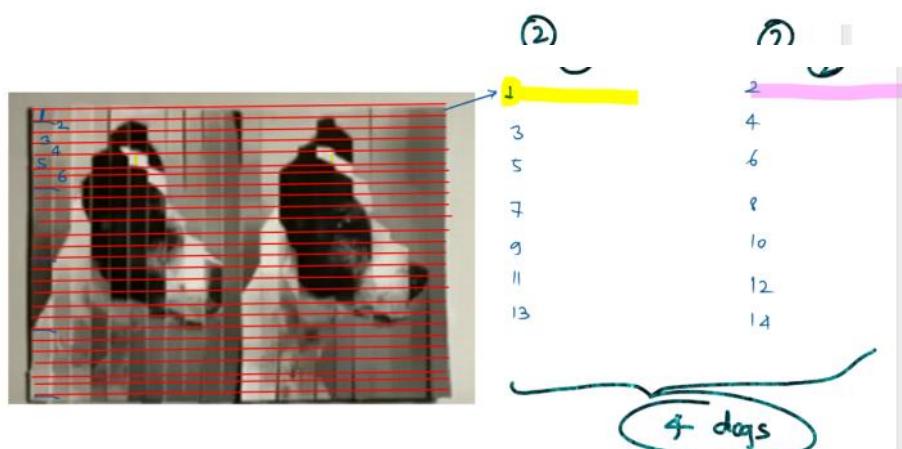
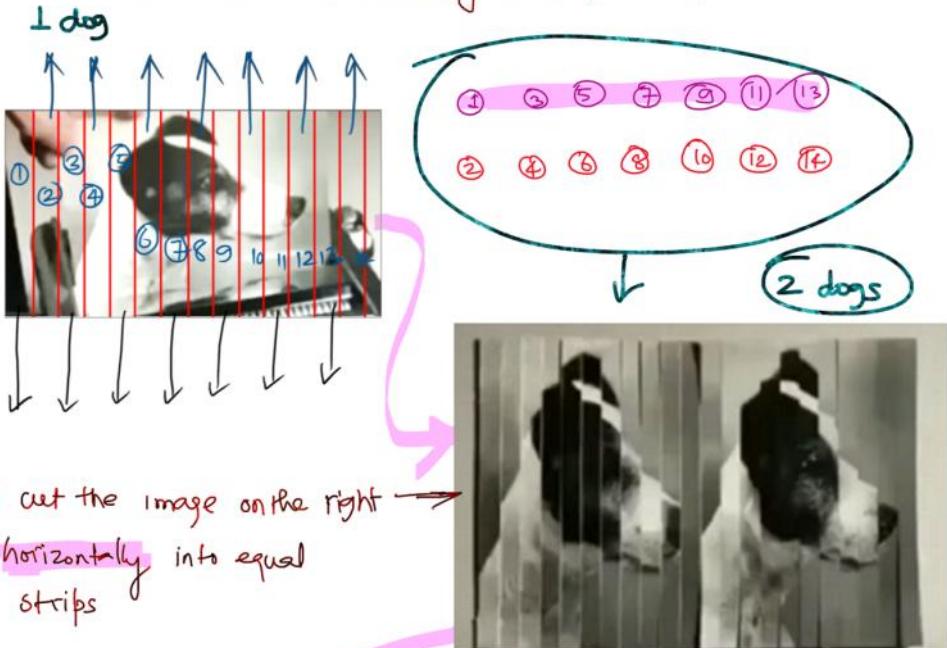
<https://www.youtube.com/shorts/N6NBT-n9mmo>



Original Image



2. Cut the original dog's image vertically into equal strips

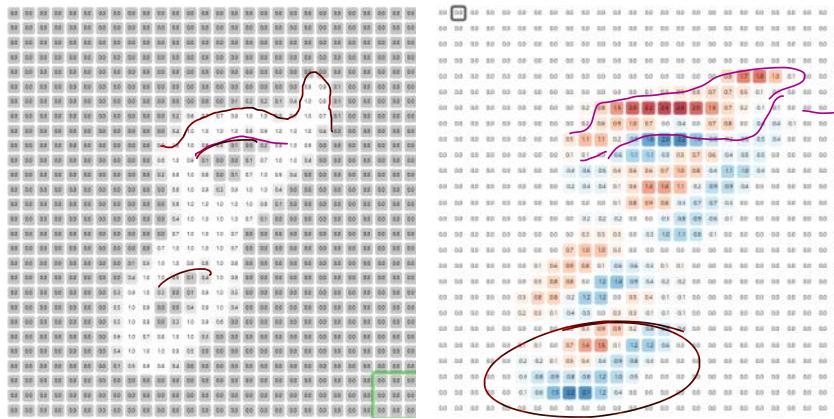


↓
categorized / classified
as a

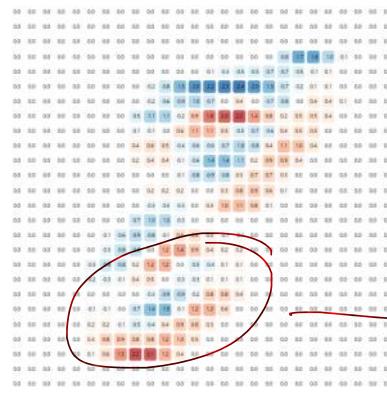
DOG

<https://deplizard.com/resource/pavq7noze2>

[Mathematical Interpretation of filtering operation]

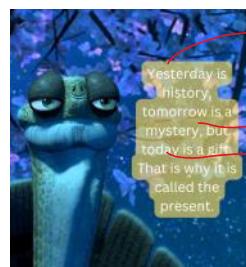
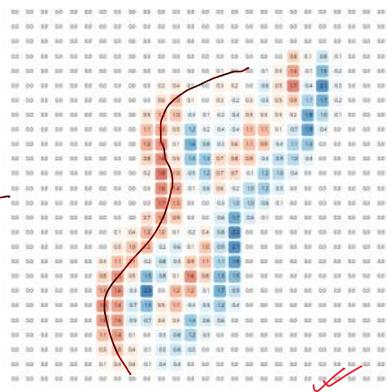


Top Edge getting captured



Bottom Edge getting captured,,

left edge +
getting captured



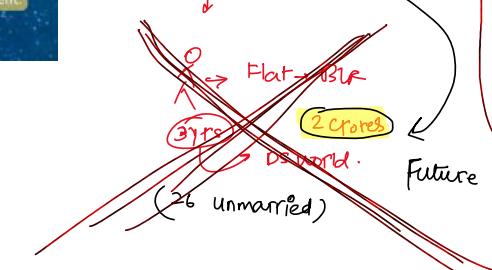
→

past:

Future
Present

(Phone has to be)
in silent

Push
calls



Future

exceptions
↓
allow → cells → filtering

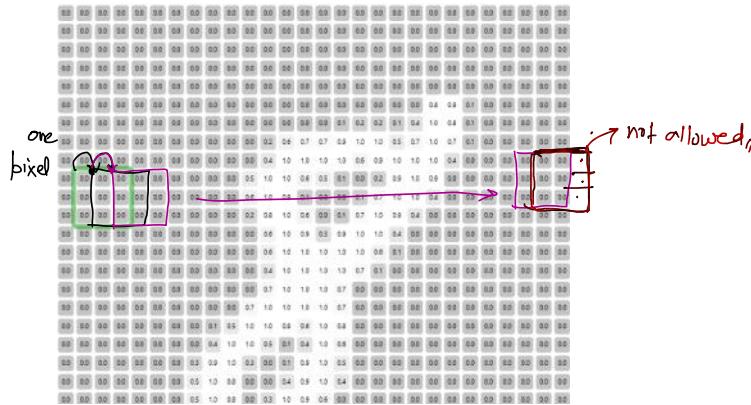
Part P16-T1b

Pro-tip

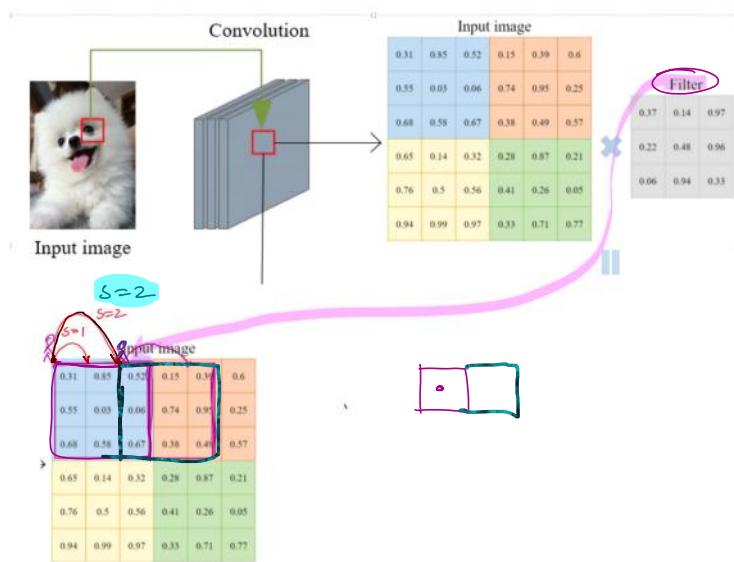
STRIDE & PADDING

- * Stride: Stride is a hyperparameter in CNN that determines the no. of pixels by which the filter (aka kernel) moves across the input image during the convolution operation.

Default setting $S=1$ → Filter moves one pixel at a time



Stride # $S=2$ Filter jumps by 2 pixels at a time → Reducing the overlap and hence the filter map size



Why stride matters?

- ◆ small ($S=1$) → High resolution output with more details captured at the granular level → computation would be slower
- ◆ large ($S=2$ or more)
2, 3 or $\frac{1}{4}$ → small resolution output → feature maps' size would be smaller → better downsampling

It is faster in computation

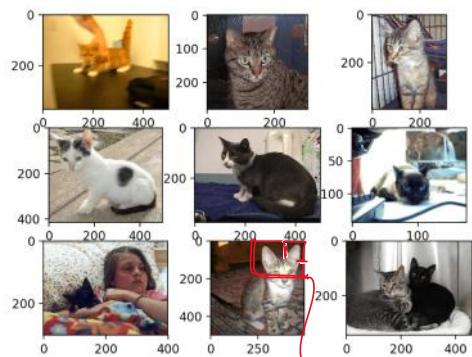
— may loose fine details of the input image

For any small input images (upto 100x100 pixels) → stride #2 is the most recommended.

In some cases or large input images (upto 224x224 pixels) → stride #2 or more can also be used but less frequently and generally in deeper layers to reduce the feature size for computational efficiency while not losing on essential features of the image.

Padding

— margin / some room → to the images

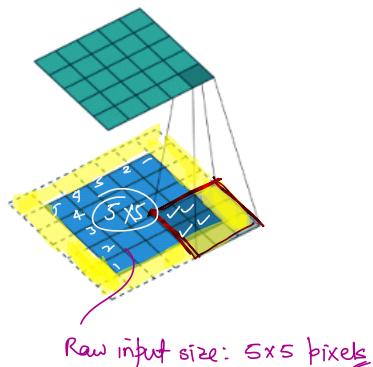


In such cases, it is evident that padding is needed.

Padding is a technique used in CNNs to adjust the spatial dimensions of the input image.

- it involves adding extra row(s) and/or column(s) pixels usually with zero around the border of the input image

padding = 1, stride = 1, transposed



Before padding

$p=0$ and $s=1$

size of the feature map ??

Formula for feature map dimensions

Height of feature map

$$H_{out} = \left[\frac{H_{in} - K + 2P}{S} \right] + 1$$

where $[.] \rightarrow$ Greatest Integer Function
(Floor)

$$[2.3] \rightarrow 2$$

$$[3.6] \rightarrow 3$$

Width of the feature map

$$W_{out} = \left[\frac{W_{in} - K + 2P}{S} \right] + 1$$

where

Input dimensions

H_{in} : Height of the input image

W_{in} : Width → — — —

Filter parameters

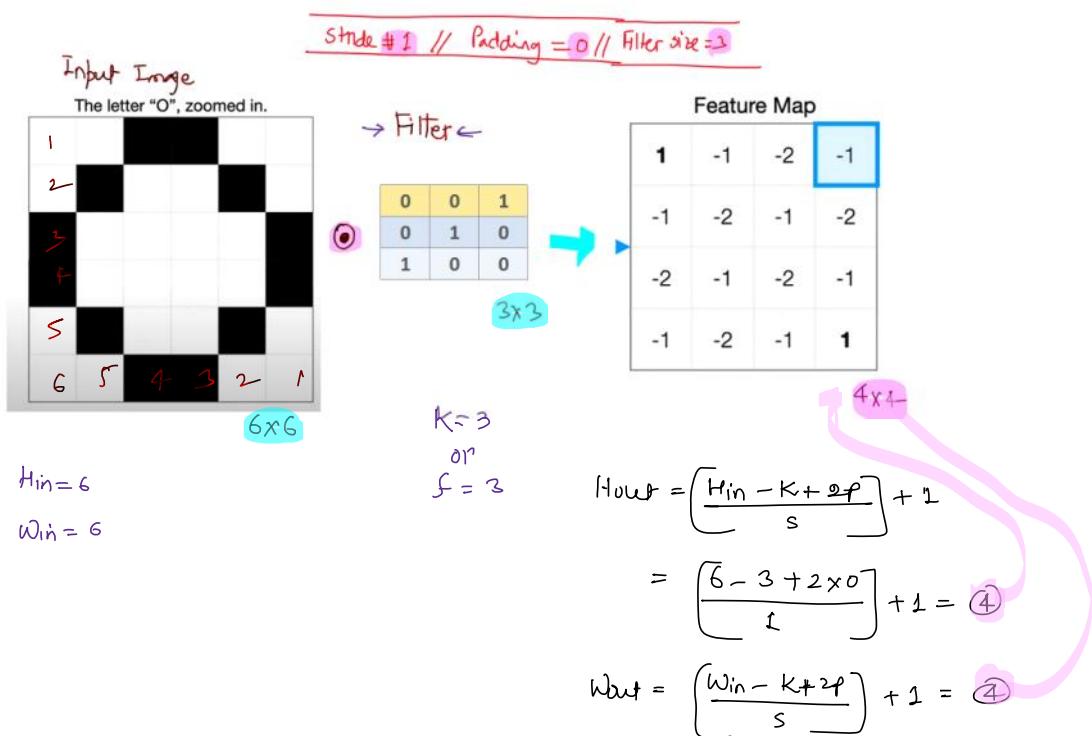
K or f : size of the filter (assuming square matrix of order K)

s : stride of the filter

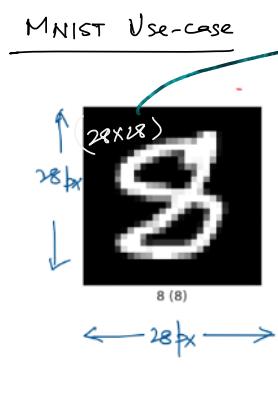
P : padding for the filter

No. of filters

F : no. of filter applied → which determined the depth of the output



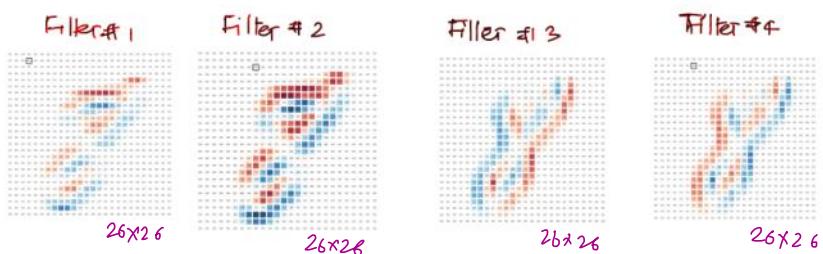
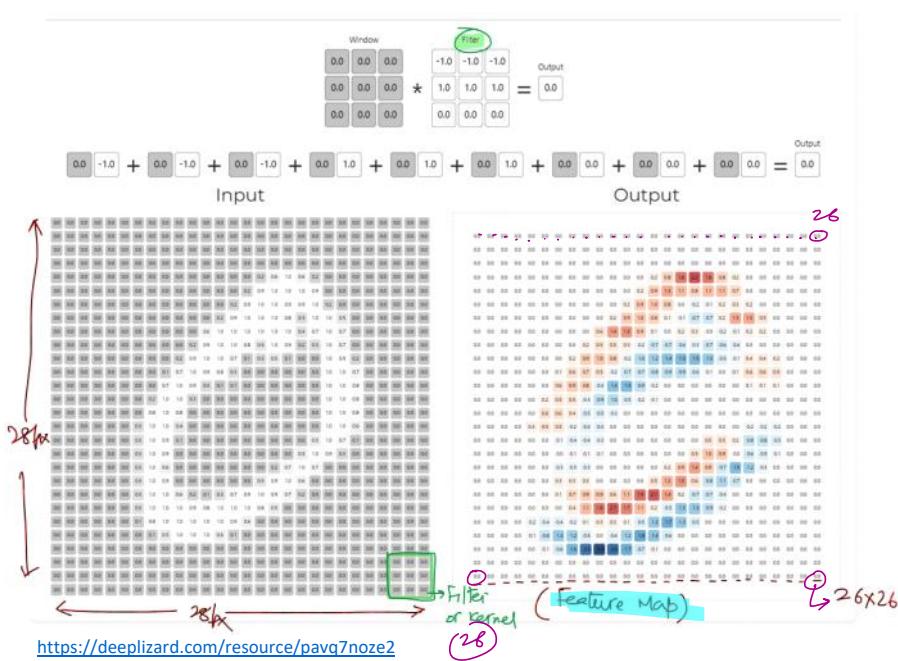
Feature Map dimensions: 4×4



Assume $s=1$ and $p=0$,

$$h_{out} = \left[\frac{28 - 3 + 2 \times 0}{1} \right] + 1 = 26$$

$$w_{out} = \underline{\underline{26}}$$



Why is padding so important?

TASK + U ↗