

# Deep Learning

Lecture 11: Convolutional Neural Network

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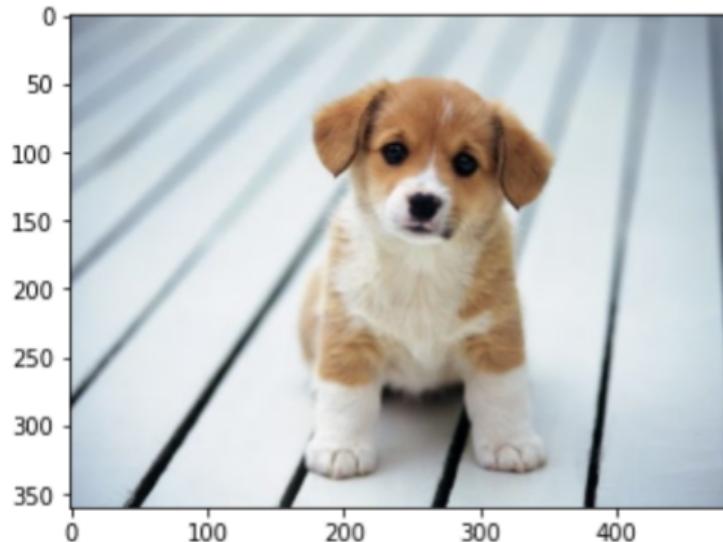
```
1 import matplotlib.pyplot as plt  
2 import numpy as np
```

```
1 dog=plt.imread("dog.jpg")
```

any image in your working directory

```
1 plt.imshow(dog)
```

read image as dog variable



```
1 dog.shape
```

(360, 480, 3)

channel

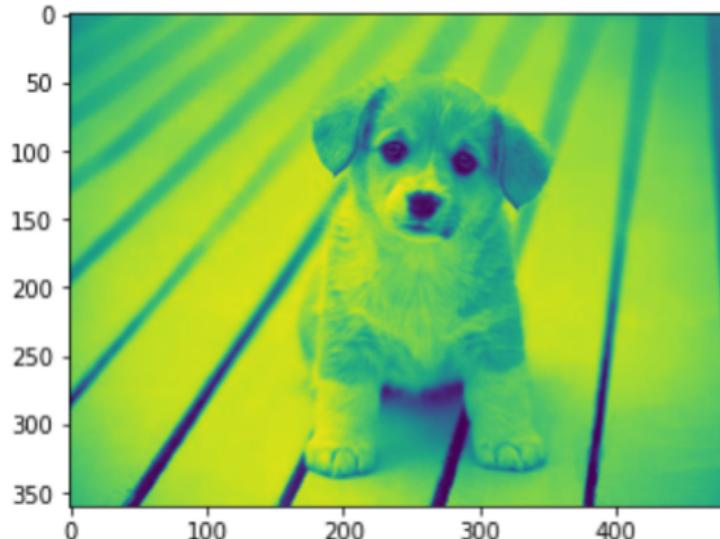
colored image is actually a 3 dimensional array

height

width

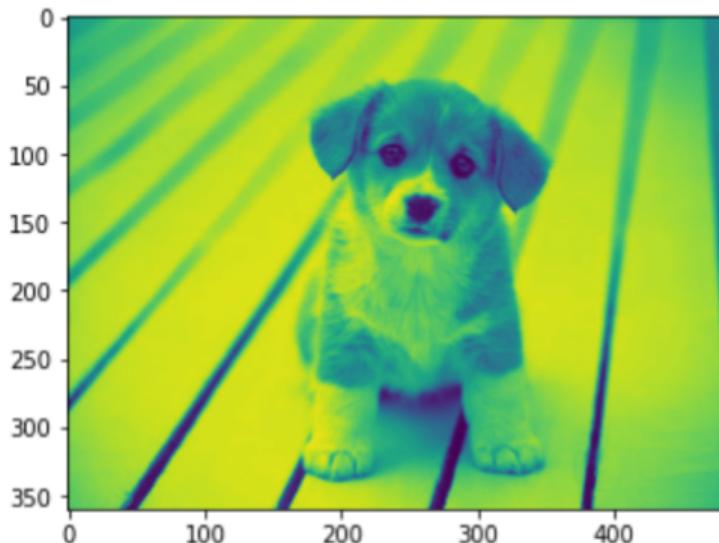
```
1 red_channel=dog[:, :, 0]
```

```
1 plt.imshow(red_channel)
```



```
1 green_channel=dog[:, :, 1] ← select just the second channel, green
```

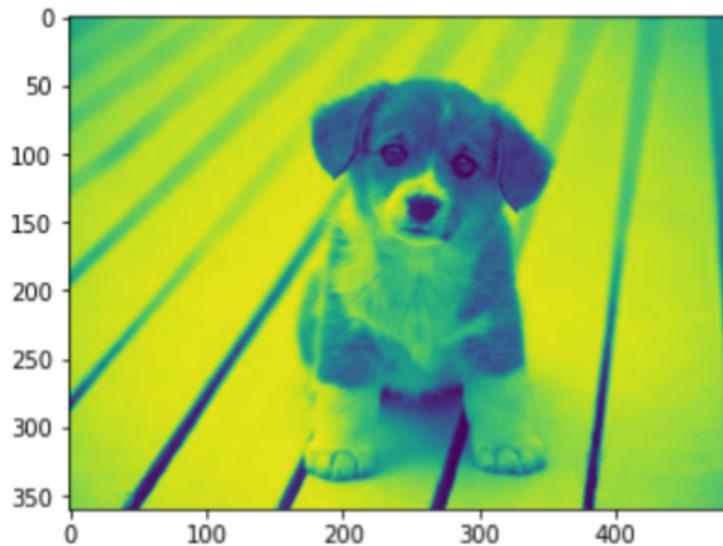
```
1 plt.imshow(green_channel)
```



```
1 blue_channel=dog[:, :, 2]
```

select just the third channel, blue

```
1 plt.imshow(blue_channel)
```



```
1 red_channel.shape
```

```
(360, 480)
```

```
1 green_channel.shape
```

```
(360, 480)
```

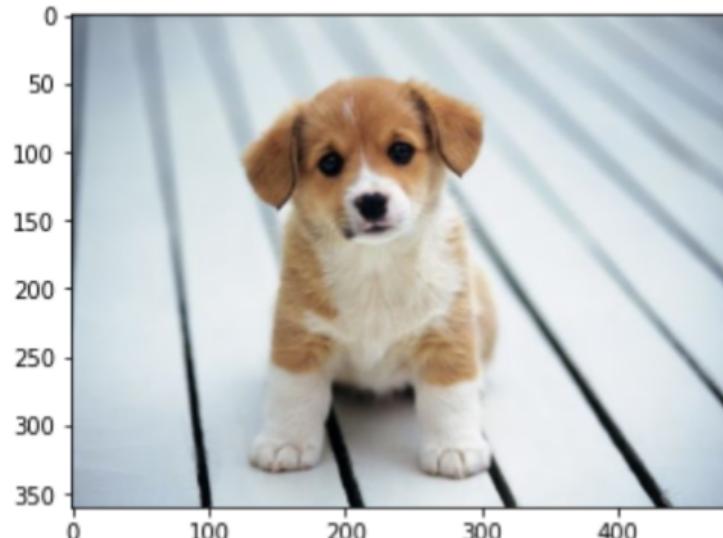
```
1 blue_channel.shape
```

```
(360, 480)
```

dimension of shape reduced  
to a single channel image

```
1 mirror_dog=dog[:,::-1] ← reverse the columnnd of the array
```

```
1 plt.imshow(mirror_dog)
```

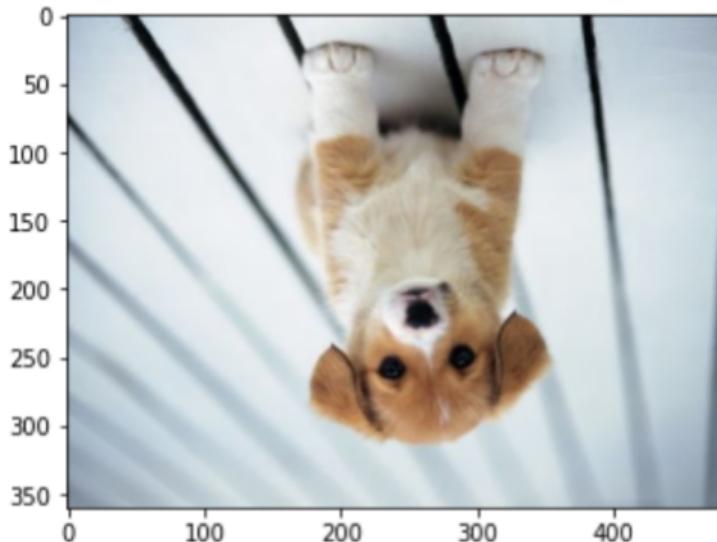


if A is a one-dimensional array  
then A[2:6] gives us A[2] until  
A[5]. But A[2:6:2] gives us A[2]  
and A[4], the third number is  
the jumping length.  
A[6:2:-1] gives us A[6] until A[3]  
(reveresee order)  
A[ : :-1] produce reverse list of A

```
1 reverse_dog=dog[::-1,:,:]
```

reverse rows of the array

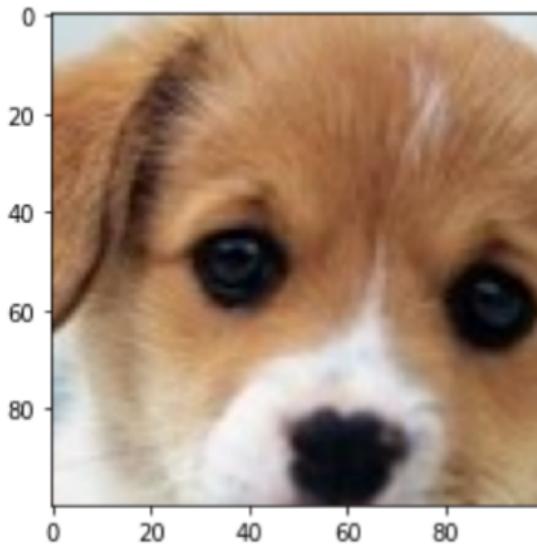
```
1 plt.imshow(reverse_dog)
```



```
1 face_dog=dog[50:150,200:300]
```

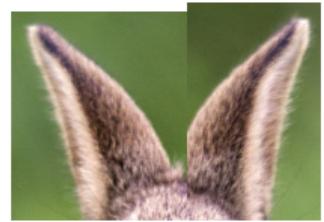
select rows from 50 til 149 and  
columns from 200 til 299

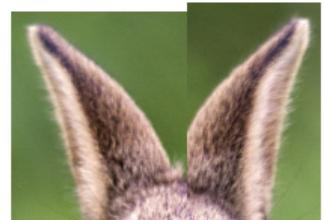
```
1 plt.imshow(face_dog)
```



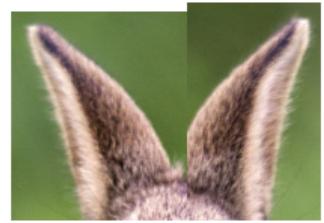












-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1

-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1

Loopy pattern  
filter

-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1

Vertical line  
filter

-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1

-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1

Diagonal line  
filter

-1	<b>1</b>	<b>1</b>	<b>1</b>	-1
-1	<b>1</b>	-1	<b>1</b>	-1
-1	<b>1</b>	<b>1</b>	<b>1</b>	-1
-1	-1	-1	<b>1</b>	-1
-1	-1	-1	<b>1</b>	-1
-1	-1	<b>1</b>	-1	-1
-1	<b>1</b>	-1	-1	-1

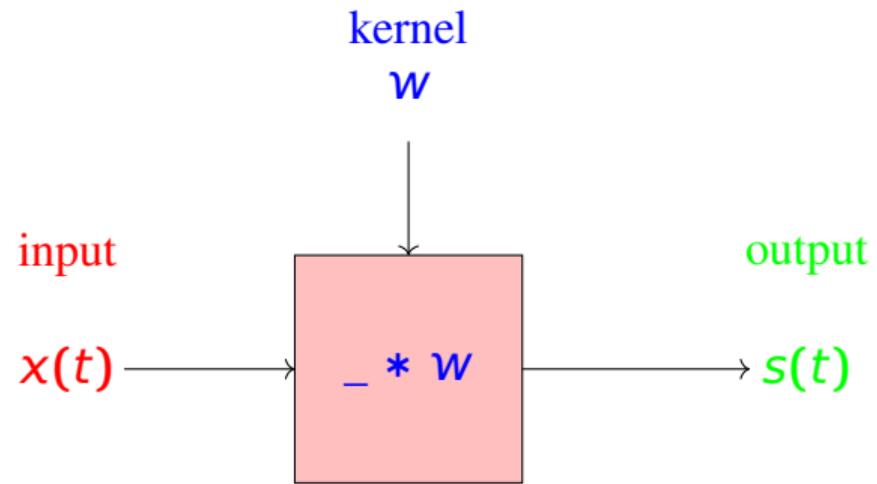
1	1	1
1	-1	1
1	1	1



# Convolution

- ▶ Let  $x(t)$  be a noisy signal of a variable that depend on the time.
- ▶ Let  $w(t')$  be the weight function at time  $t'$ .
- ▶ Then  $s(t) = (x * w)(t)$  is the smoothed signal with respect to the weight  $w$ .

$$s(t) = (x * w)(t) = \int_{-\infty}^{\infty} x(a)w(t-a)da$$



# Discrete Convolution

$$S(i, j) = (X * K)(i, j) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} X(i-m, j-n)K(m, n)$$

This operator has commutative property, i.e.,

$$(X * K)(i, j) = (K * X)(i, j)$$

## Cross-correlation

$$S(i, j) = (X * K)(i, j) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} X(i + m, j + n)K(m, n)$$

This operator does not have the commutative property, i.e.,

$$(X * K)(i, j) \neq (K * X)(i, j)$$

# Why Convolutional Networks

- ▶ Sparse interactions.
- ▶ Parameter sharing.
- ▶ Equivalent representation.

-1	<b>1</b>	<b>1</b>	<b>1</b>	-1
-1	<b>1</b>	-1	<b>1</b>	-1
-1	<b>1</b>	<b>1</b>	<b>1</b>	-1
-1	-1	-1	<b>1</b>	-1
-1	-1	<b>-1</b>	<b>1</b>	-1
-1	-1	<b>1</b>	-1	-1
-1	<b>1</b>	-1	-1	-1

\*

1	1	1
1	-1	1
1	1	1

-0.11	<b>1</b>	-0.11
-0.55	0.11	-0.33
-0.33	0.33	-0.33
-0.22	-0.11	-0.22
-0.33	-0.33	-0.33

Feature Map

9

\*

Loopy pattern  
detector

1	1	1
1	-1	1
1	1	1

=

		1		

6

\*

Loopy pattern  
detector

1	1	1
1	-1	1
1	1	1

=

				1

Loopy pattern  
detector

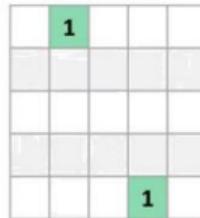
96

\*

## Loopy pattern detector

$$\begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & -1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

二





eye  
detector

\*



=

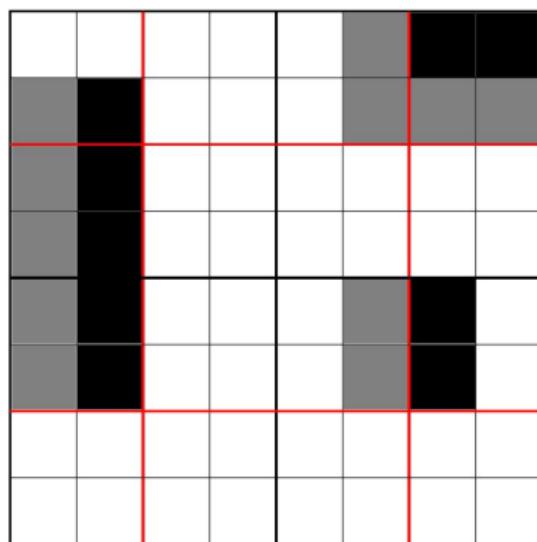


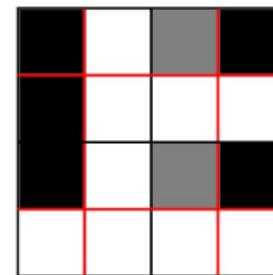
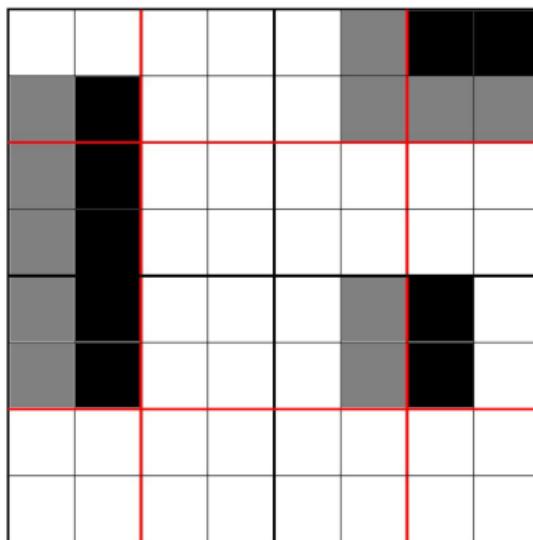


$$\text{eye detector} * \begin{array}{|c|c|c|}\hline & & \\ \hline & & \\ \hline & & \\ \hline\end{array} = \boxed{\begin{array}{ccc} \blacksquare & \blacksquare & \\ & & \\ \blacksquare & \blacksquare & \\ & & \blacksquare \end{array}}$$

# Pooling

- ▶ A pooling function replaces the output of the net at a certain location with a summary statistic of the nearby output.
- ▶ For creating a condensed feature map (reduce dimensionality).
- ▶ The **max pool** report the maximum output within a rectangular neighborhood.





# Padding

- ▶ The shape of input image  $X$  is  $m \times n$ .
- ▶ The shape of kernel  $K$  is  $f \times f$ .
- ▶ Then the shape of output  $S = X * K$  is  $(m - f + 1) \times (n - f + 1)$ .
- ▶ So the output does not have the same shape as input.

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

4		

Convolved feature

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

Image

4	3	4

Convolved feature

4	3	4

Convolved feature

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

Image

4	3	4

Convolved feature

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

Image

4	3	4

Convolved feature

4	3	4

Convolved feature

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

Image

4	3	4

Convolved feature

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

Image

4	3	4

Convolved feature

4	3	4

Convolved feature

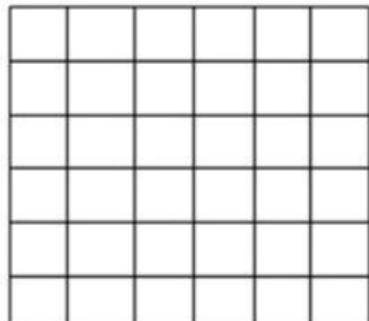
[Sign in to download hi-res image](#)

# Padding

- ▶ The process of adding extra layers to the input image to avoid input/output shape difference is called **padding**.

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6x6 image

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

6x6 image with 1 layer of zero padding

# Types of Padding

1. **Valid padding:** no padding, i.e.,

**input:**  $m \times n$   $\xrightarrow{\text{filter: } f \times f}$  **output:**  $(m - f + 1) \times (n - f + 1)$

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$$\text{input: } m \times n \xrightarrow{\text{filter: } f \times f} \text{output: } (m - f + 1) \times (n - f + 1)$$

2. **Same padding:** output has the same shape as the input if we add  $p$  layers of padding to the border. i.e.,

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$$\text{input: } m \times n \xrightarrow{\text{padding: } p} \text{padded: } (m + 2p) \times (n + 2p) \xrightarrow{\text{filter: } f \times f} \text{output: } m \times n$$

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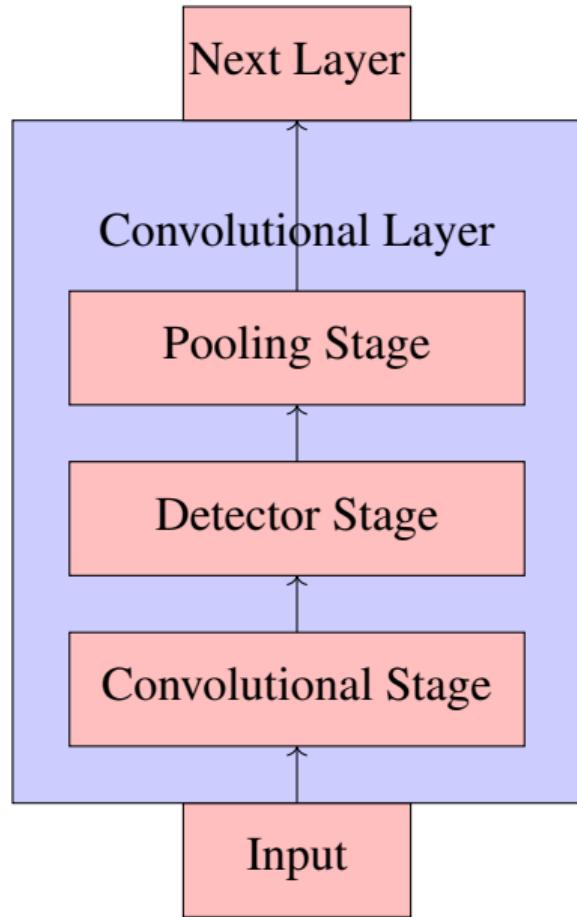
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for same padding  $p$  should be equal to  $\frac{f-1}{2}$ .



*Thank You*