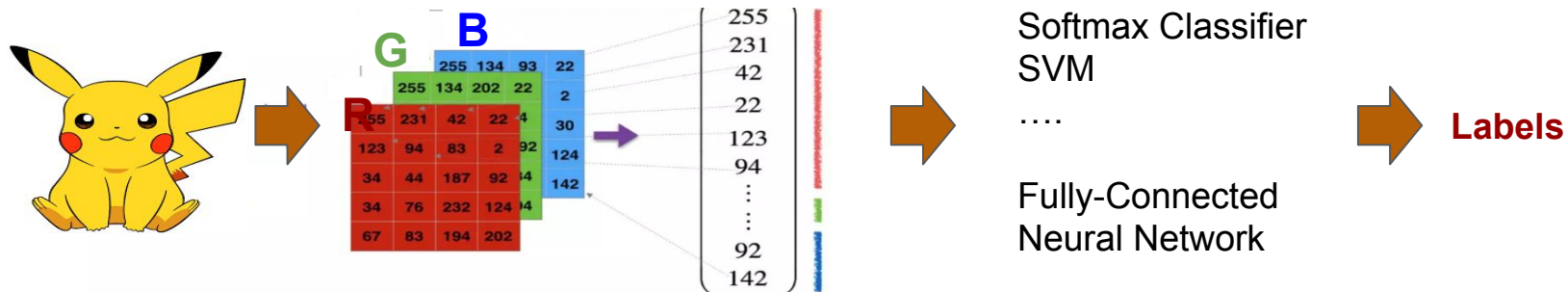


# Convolutional Neural Network

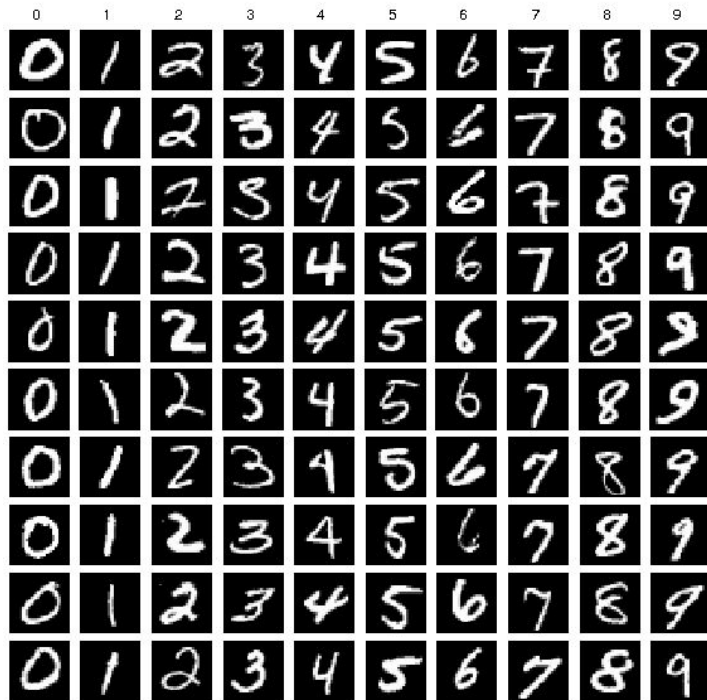
How it “understand” Image and Text

**Before CNN**

# Computers See Image



# Think about MNIST Dataset



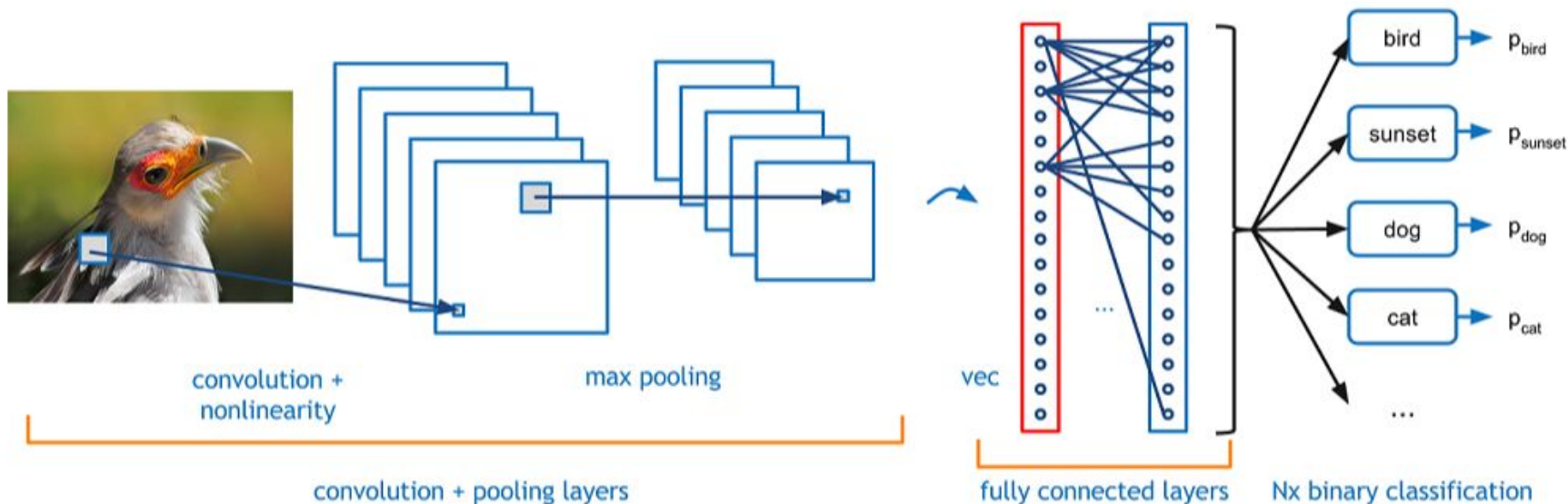
The above model requires the digit should be in the center of the image and it had to be the only thing in the image.

# Intro to CNN



[https://www.youtube.com/watch?v=FwFduRA\\_L6Q](https://www.youtube.com/watch?v=FwFduRA_L6Q)

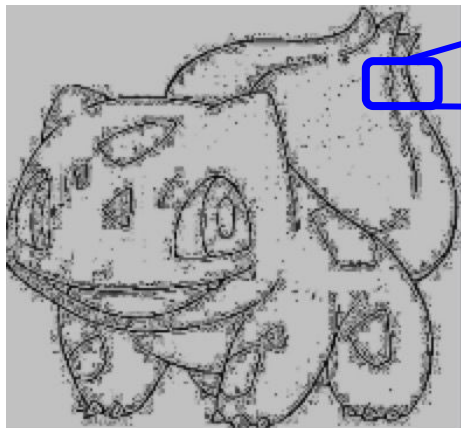
# Convolutional Neural Network



**Extracting useful  
features of data**

**Perform a ML task (like  
classification based on the  
vectorized data)**

# Filter Operation



Consider  
neighbor values

0	32	35
34	203	122
132	223	163

Current Pixel Value is 203

Dot Product



New Pixel Value

$$\begin{aligned} & (-1 * 0) + (0 * 32) + (-2 * 35) + \\ & (.5 * 34) + (4.5 * 203) + (-1.5 * 122) + \\ & (1.5 * 132) + (2 * 223) + (-3 * 163) \end{aligned}$$

Filter (3 by 3)



# Convolutional Operation

- Apply the **same** filter for every pixel in the original image
- Filter Size is the shape of the filter matrix (yellow one)

1 <sub>x1</sub>	1 <sub>x0</sub>	1 <sub>x1</sub>	0	0
0 <sub>x0</sub>	1 <sub>x1</sub>	1 <sub>x0</sub>	1	0
0 <sub>x1</sub>	0 <sub>x0</sub>	1 <sub>x1</sub>	1	1
0	0	1	1	0
0	1	1	0	0

Image

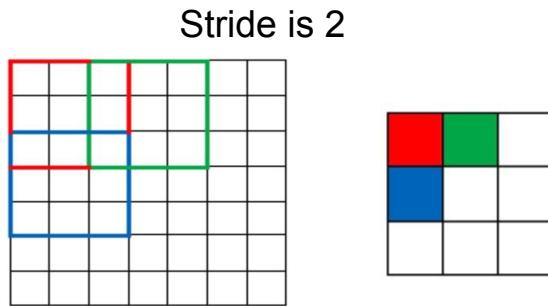
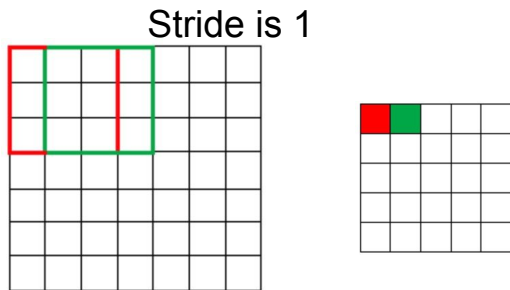
4		

Convolved  
Feature

*Feature  
Map*

# Stride

- Controls how the filter move around the image
- It is the amount by which the filter shifts



# Zero Padding

- Pads the image with zeros around the **border**
- Make the input image and feature map have the same spatial dimensions

0	0	0	0	0	0	0
0	60	113	56	139	85	0
0	73	121	54	84	128	0
0	131	99	70	129	127	0
0	80	57	115	69	134	0
0	104	126	123	95	130	0
0	0	0	0	0	0	0

Kernel

0	-1	0
-1	5	-1
0	-1	0

114				

Stride: 1

Size of zero padding:

$$(k-1)/2$$

<https://stackoverflow.com/questions/52067833/how-to-plot-an-animated-matrix-in-matplotlib>

# Convolutional Operation

- Filter Size:  $K$
- Stride Size:  $S$
- Padding Size:  $P$

1 <sub>x1</sub>	1 <sub>x0</sub>	1 <sub>x1</sub>	0	0
0 <sub>x0</sub>	1 <sub>x1</sub>	1 <sub>x0</sub>	1	0
0 <sub>x1</sub>	0 <sub>x0</sub>	1 <sub>x1</sub>	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved  
Feature

Input size

$$O = \frac{W - K + 2P}{S} + 1$$

Output size

# Multi-Channel CNN

- A color image is a 3-D tensor
- 400 (height) 630 (width) 3 (R,G,B channels)

0	0	0	0	0	0	...
0	156	155	156	158	158	...
0	153	154	157	159	159	...
0	149	151	155	158	159	...
0	146	146	149	153	158	...
0	145	143	143	148	158	...
...	...	...	...	...	...	...

Input Channel #1 (Red)

0	0	0	0	0	0	...
0	167	166	167	169	169	...
0	164	165	168	170	170	...
0	160	162	166	169	170	...
0	156	156	159	163	168	...
0	155	153	153	158	168	...
...	...	...	...	...	...	...

Input Channel #2 (Green)

0	0	0	0	0	0	...
0	163	162	163	165	165	...
0	160	161	164	166	166	...
0	156	158	162	165	166	...
0	155	155	158	162	167	...
0	154	152	152	157	167	...
...	...	...	...	...	...	...

Input Channel #3 (Blue)

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

Kernel Channel #1

308

+

1	0	0
0	1	-1
1	0	-1

Kernel Channel #2

-498

+

0	1	1
0	1	0
1	-1	1

Kernel Channel #3

164

+ 1 = -25

↑  
Bias = 1

-25			...
			...
			...
			...
...	...	...	...

Output

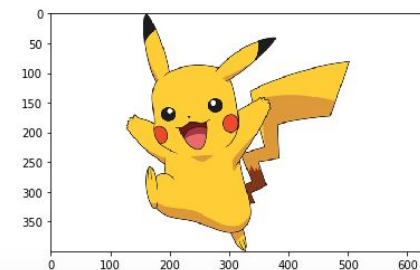
```
from matplotlib.image import imread
import numpy as np
img = imread('pikka_3.jpg')
```

```
print(img.shape)
```

```
(400, 630, 3)
```

```
plt.imshow(img, interpolation='nearest')
```

```
<matplotlib.image.AxesImage at 0x11b404278>
```



## From Keras Layers Conv2D

Input shape

4D tensor with shape: (batch, channels, rows, cols) if data\_format is "channels\_first" or 4D tensor with shape: (batch, rows, cols, channels) if data\_format is "channels\_last".

Output shape

4D tensor with shape: (batch, filters, new\_rows, new\_cols) if data\_format is "channels\_first" or 4D tensor with shape: (batch, new\_rows, new\_cols, filters) if data\_format is "channels\_last". rows and cols values might have changed due to padding.

[https://www.researchgate.net/post/How\\_will\\_channels\\_RGB\\_effect\\_convolutional\\_neural\\_network](https://www.researchgate.net/post/How_will_channels_RGB_effect_convolutional_neural_network)

# How Filter Works



Image

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



Convolved  
Features

**Only Keep Vertical Lines**

# How Filter Works



Image

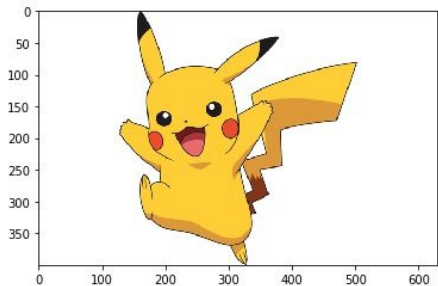
-1	-2	-1
0	0	0
-1	2	1



Convolved  
Features

**Only Keep Horizontal Lines**

# Filter comes from “Image Processing”

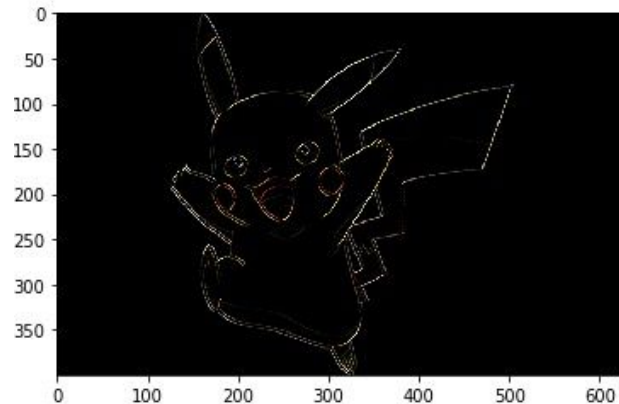


Image

```
print(kernel)
```

```
[[ 1  0 -1]  
 [ 0  0  0]  
 [-1  0  1]]
```

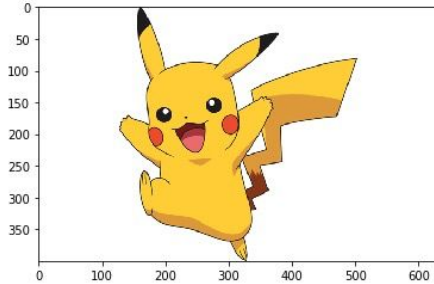
Edge  
Detection



Convolved  
Features



# Filter comes from “Image Processing”

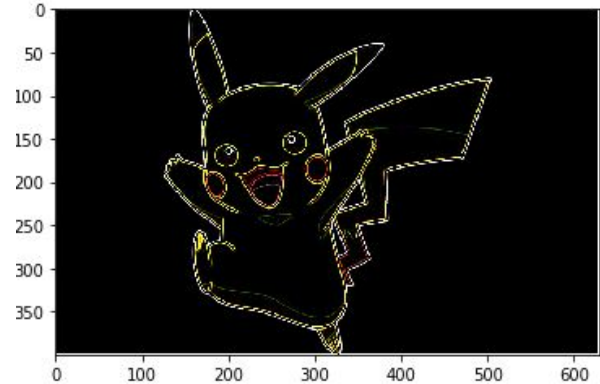


Image

```
print(kernel)
```

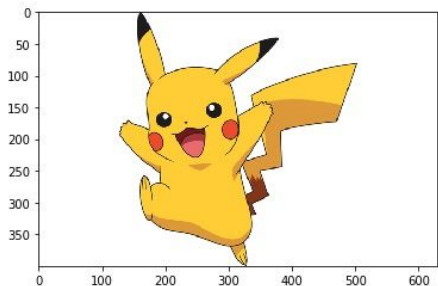
```
[[-1 -1 -1]  
 [-1  8 -1]  
 [-1 -1 -1]]
```

Edge  
Detection



Convolved  
Features

# Filter comes from “Image Processing”

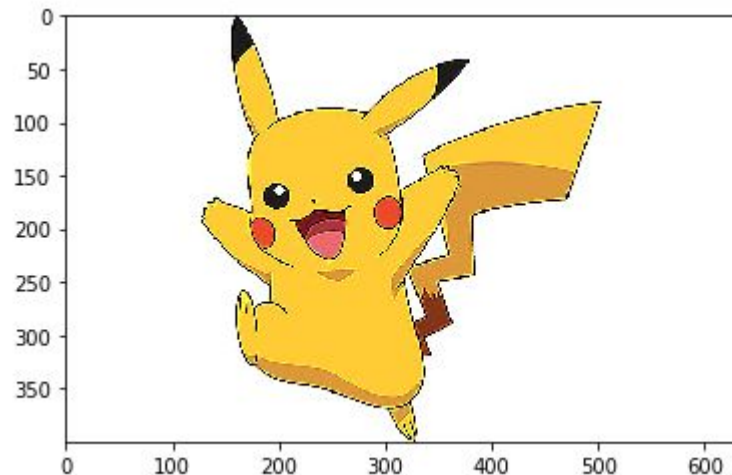


Image

```
print(kernel)
```

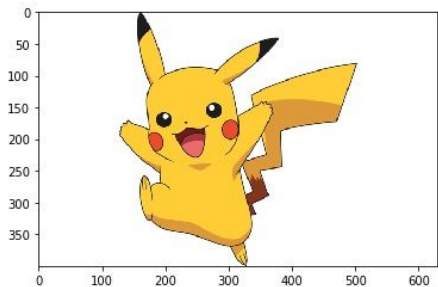
```
[[ 0 -1  0]  
 [-1 5 -1]  
 [ 0 -1  0]]
```

**Sharpen**



**Convolved  
Features**

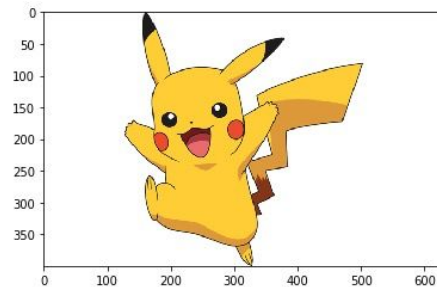
# Filter comes from “Image Processing”



**Image**



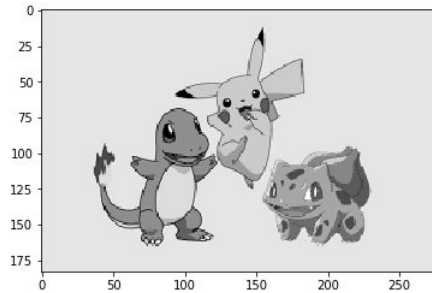
**Identity**



**Convolved  
Features**

# Non-linear Activation

- In nature, filter operation is dot product.
- In deep learning, we need to have non-linear transformation.
- Add non-linear activation



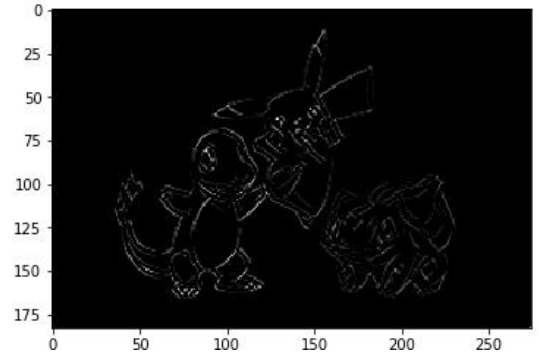
Image

```
print(kernel)
```

```
[[ 1  0 -1]  
 [ 0  0  0]  
 [-1  0  1]]
```



non-linear

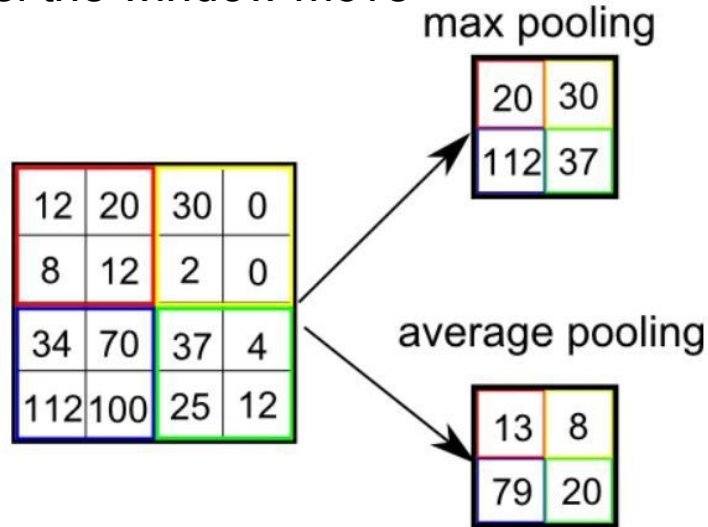


**The First Task in Assignment II**

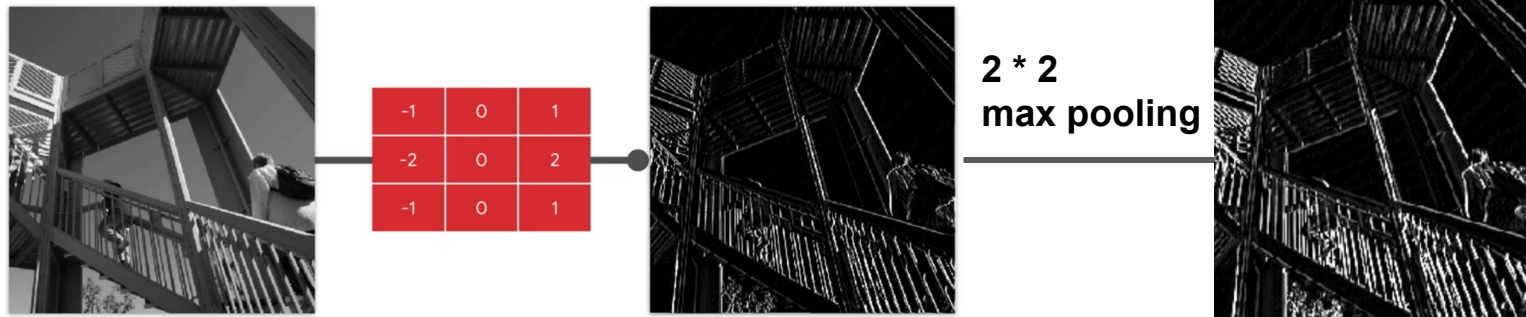
# Pooling Operation

- Pooling Size: the box size. Here is  $2 \times 2$
- Stride Size: how much pixel the window move

What is stride size here ?

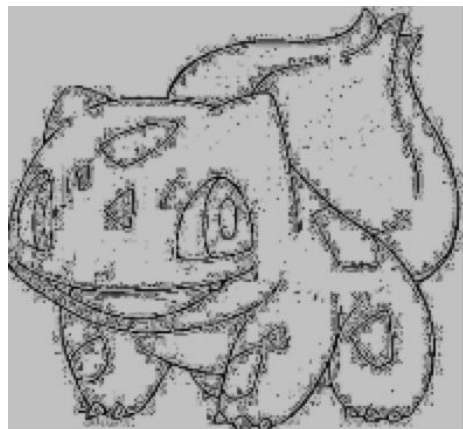


# Filter then Pool



1. The size is **one quarter** the original size
2. The **vertical line** features are **enhanced**.

# Conv-Pool



Conv-Pool

$$\begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{pmatrix}_{n \times m}$$

$$\begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{pmatrix}_{n \times m}$$

○  
○  
○

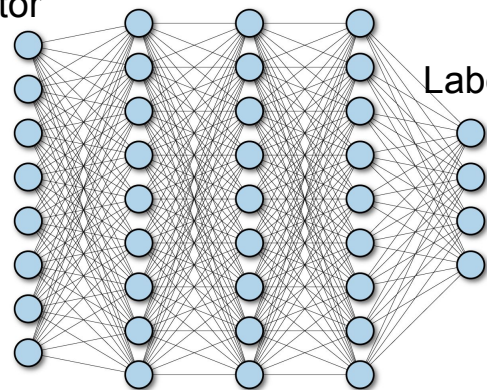
$$\begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{pmatrix}_{n \times m}$$

Flatten

Concatenate

vector

Labels



# Where are these filters from?

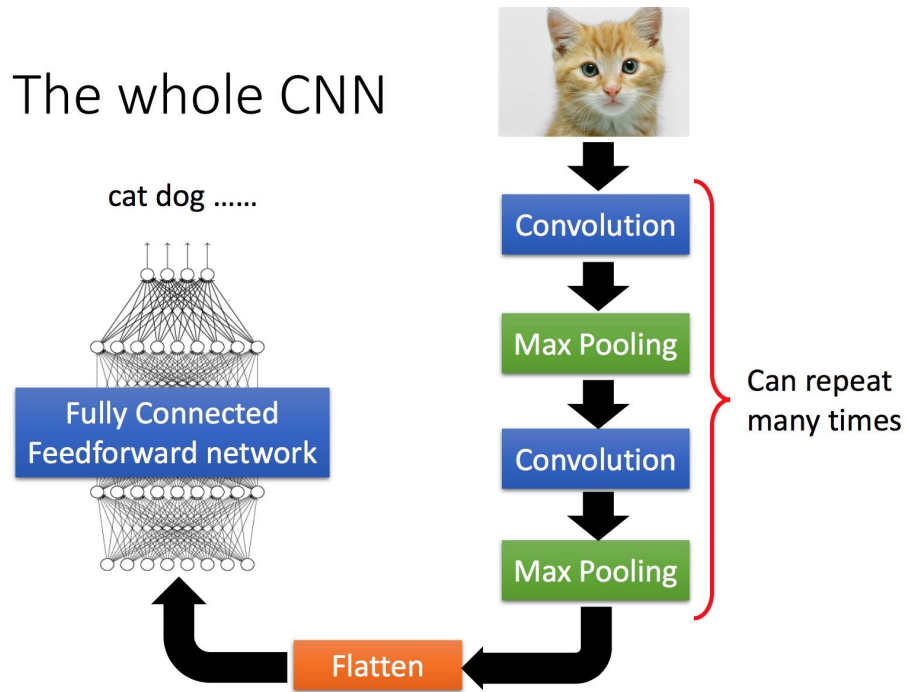
- Filters, in nature, are model parameters, which can be **learned** by backpropagation.
- These filters weights are firstly randomly initialized, and then updated during training process.
- End-to-End optimization: Backpropagation.
- More details:  
<https://towardsdatascience.com/training-a-convolutional-neural-network-from-scratch-2235c2a25754>



# CNN Can be Deep

- Convolution-Pooling can be followed by another Convolution-Pooling
- At the end, after flatten operation, fully connected layers are used to map the outputs.

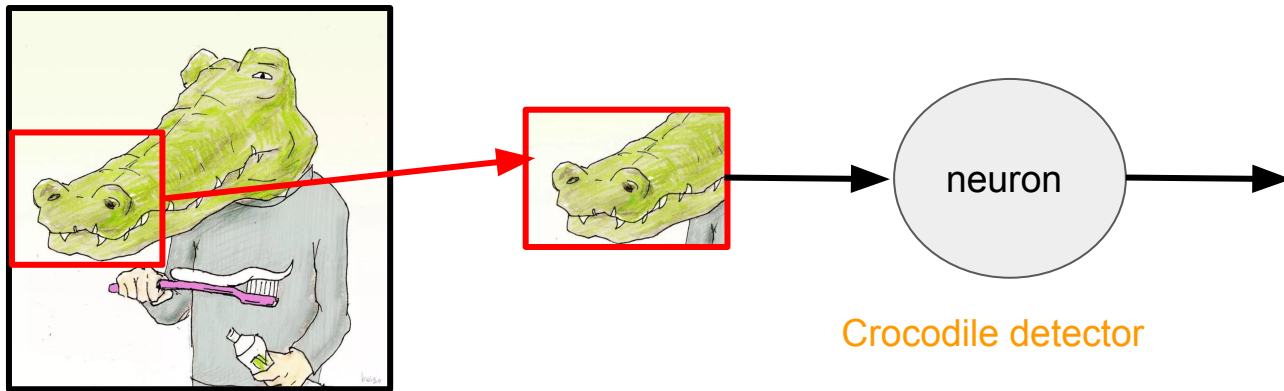
The whole CNN



# Why CNN is Suitable for Images

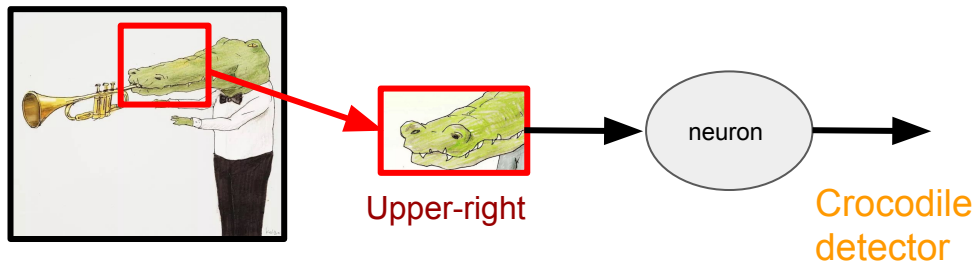
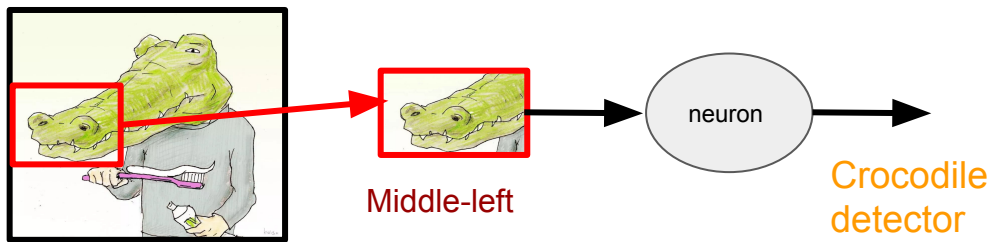
# Local Features Matter

- Discriminative patterns are much smaller than the whole image
- A neuron does not have to see the whole image
- Less parameters required



# Location Insensitive

- The same patterns appear in different regions
- A neuron should be location insensitive.



# Subsampling Works

- Subsampling the pixels will not change the object
- We can subsample the pixels to make images smaller -> less parameters required

Crocodile



**subsampling**

Crocodile



# Limitations of CNN

# CNN is different human vision

- CNN can handle translations. But they can not cope with the effects of **changing viewpoints such as rotation and scaling**
- Human is able to generalize knowledge.

neatly positioned

ImageNet

Chairs



Real world

ObjectNet

Chairs by rotation



Chairs by background



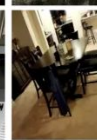
Chairs by viewpoint




Teapots



T-shirts



# CNN is different human vision



$x$   
"panda"  
57.7% confidence

$+ .007 \times$

$\text{sign}(\nabla_x J(\theta, x, y))$   
"nematode"  
8.2% confidence

$=$

$x + \epsilon \text{sign}(\nabla_x J(\theta, x, y))$   
"gibbon"  
99.3 % confidence

*Adversarial examples can cause neural networks to misclassify images while appearing unchanged to the human eye*



# Solutions

- Use 4D or 6D maps to train machine learning model
  - Too expensive
- Get huge-size training data that cover all positions of objects.
  - Data augmentation: flip the image or rotate it by some angle. Then, CNN will be trained on multiple copies of every image, each being slightly different.
  - It will never cover all of corner cases.



Enlarge your Dataset

<https://www.kdnuggets.com/2018/05/data-augmentation-deep-learning-limited-data.html>

# CNN is different human vision

- CNN may get confused by seeing this bizarre teapot, since they can not understand images in terms of objects and their parts.
- Human is able to decompose an object into parts and then we can understand its nature.



# CNN for Text

# CNN works for Text

## Images

- Local Features Matter
- Locations Insensitive
- Subsampling Works

## Texts

- Key n-grams define semantics  
*Pulp fiction's director is Quentin. I **am obsessed of** it.*
- Locations of key n-grams Insensitive?  
*I **am obsessed of** Pulp fiction, whose director is Quentin.*  
*Pulp fiction's director is Quentin. I **am obsessed of** it.*  
  
I owe **you** ten dollars  
You owe **me** ten dollars.
- Doc. Summarization

# Combinations

*E.g., I hate this movie*

- Compute vectors for every possible phrase
  - *I hate this movie* ----> I hate; hate this; this movie
- Compute these vectors for these phrases

# Convolution Operation

Word Vectors

I  
like  
this  
movie  
very  
much  
!

0.6	0.5	0.2	-0.1	0.4
0.8	0.9	0.1	0.5	0.1
0.4	0.6	0.1	-0.1	0.7
...	...	...	...	...
...	...	...	...	...
...	...	...	...	...
...	...	...	...	...

0.2	0.1	0.2	0.1	0.1
0.1	0.1	0.4	0.1	0.1

Filters updated  
during training

0.51

I  
like  
this  
movie  
very  
much  
!

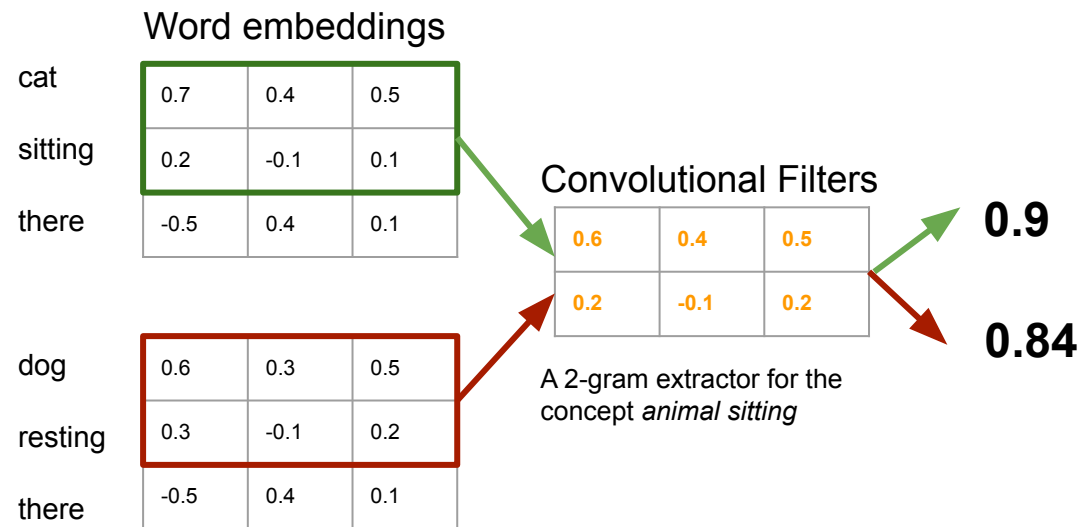
0.6	0.5	0.2	-0.1	0.4
0.8	0.9	0.1	0.5	0.1
0.4	0.6	0.1	-0.1	0.7
...	...	...	...	...
...	...	...	...	...
...	...	...	...	...
...	...	...	...	...

0.2	0.1	0.2	0.1	0.1
0.1	0.1	0.4	0.1	0.1

Feature Maps

0.51
0.53

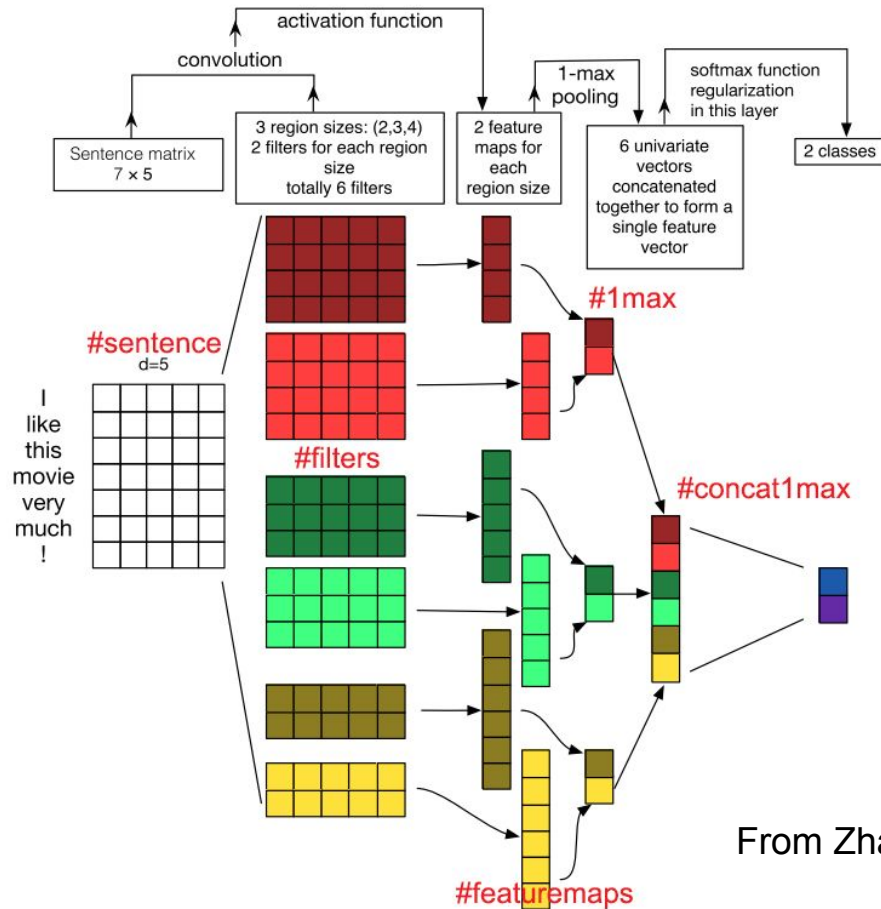
# Toy Example



- This convolution provides high activations for 2-grams with certain meaning
- Can be extended to 3-grams, 4-grams, etc.
- Can have various filters, need to track many n-grams.
- They are called 1D since we only slice the windows only in one direction

**Why is it better than BoW?**

# CNN Framework



From Zhang 2015



# Multiple Channels

- Like image, CNN is applied on R-G-B channels
- For NLP, different word embeddings can be regarded as different channels

# CNN for NLP

1. n-grams features are important (window size)
2. Location of **key** n-grams are trivial (pooling)
3. Stack of Convolutional layer or large window size can also capture long-range information