

CNN

● Natural language processing
Topic

● Convolutional neural network
Topic

+ Add comparison

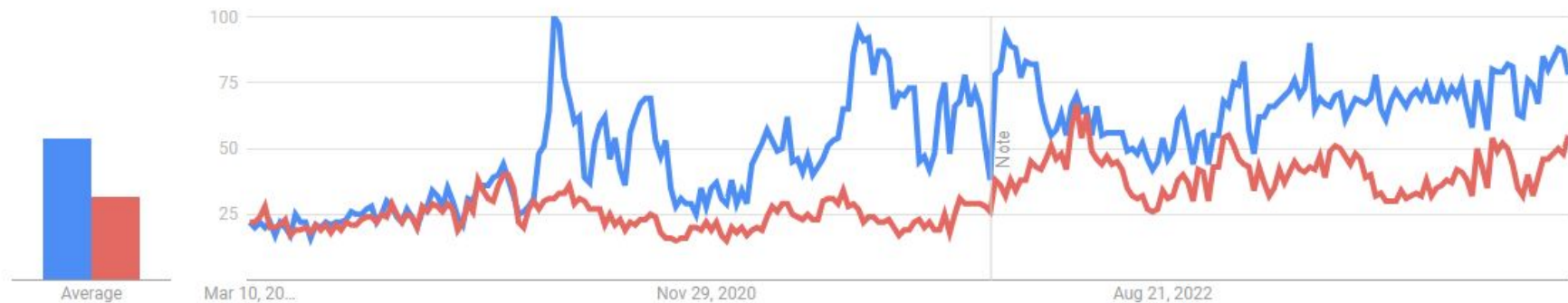
India ▼

Past 5 years ▼

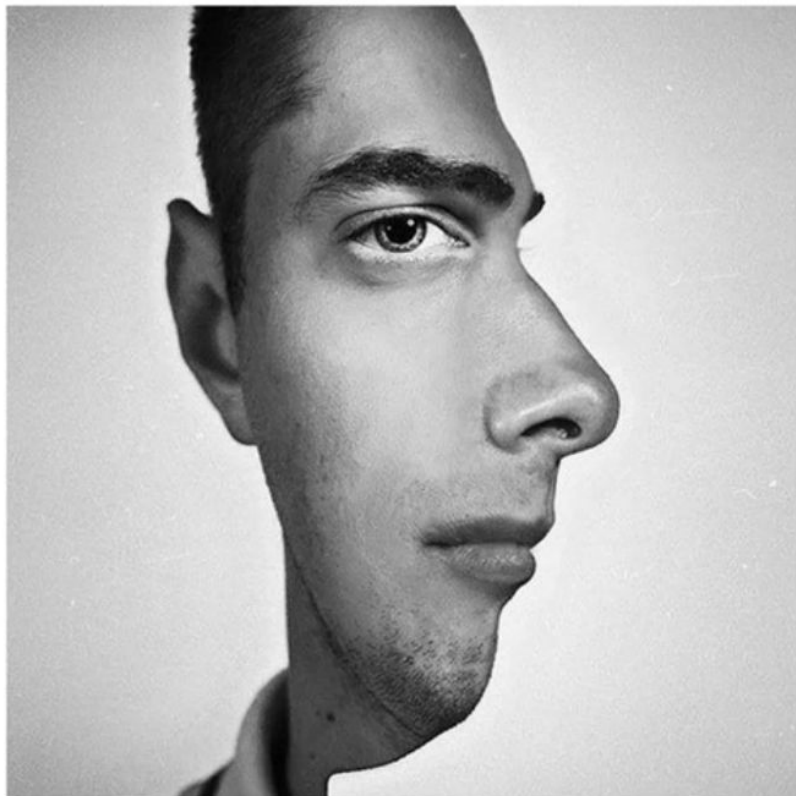
All categories ▼

Web Search ▼

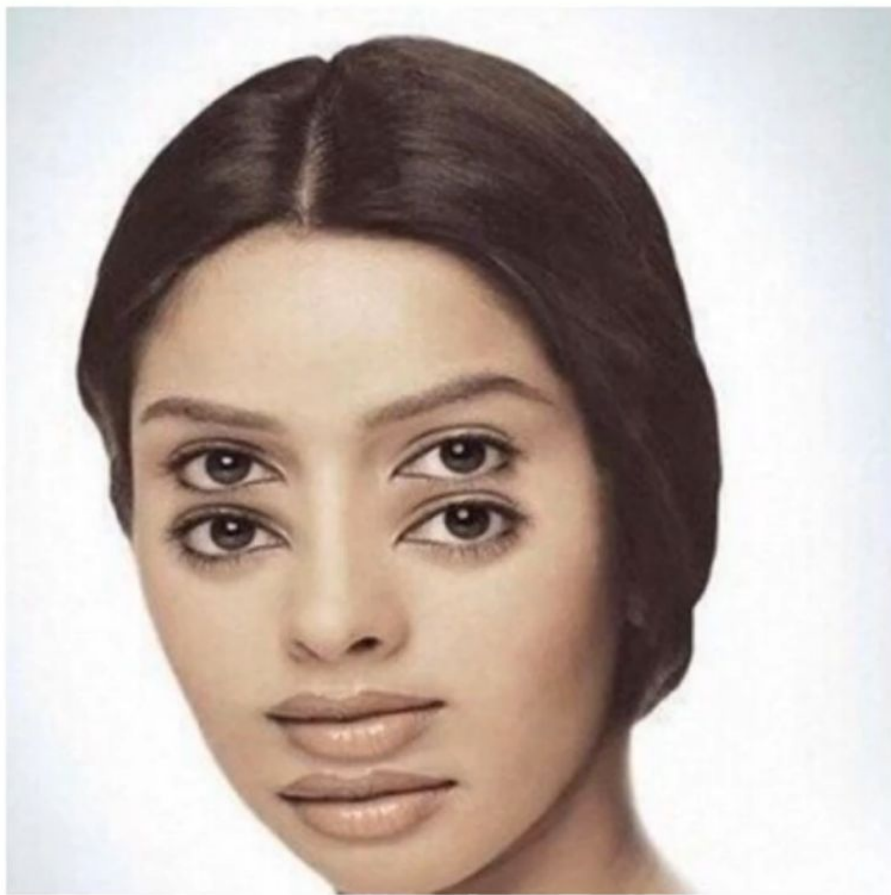
Interest over time ⓘ



Convolutional Neural Networks

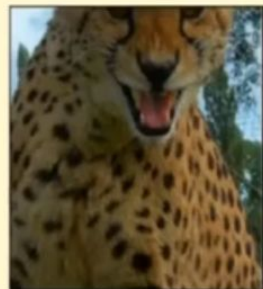


Convolutional Neural Networks



Convolutional Neural Networks

Examples from the test set
(with the network's guesses)



cheetah

cheetah

leopard

snow leopard

Egyptian cat



bullet train

bullet train

passenger car

subway train

electric locomotive



hand glass

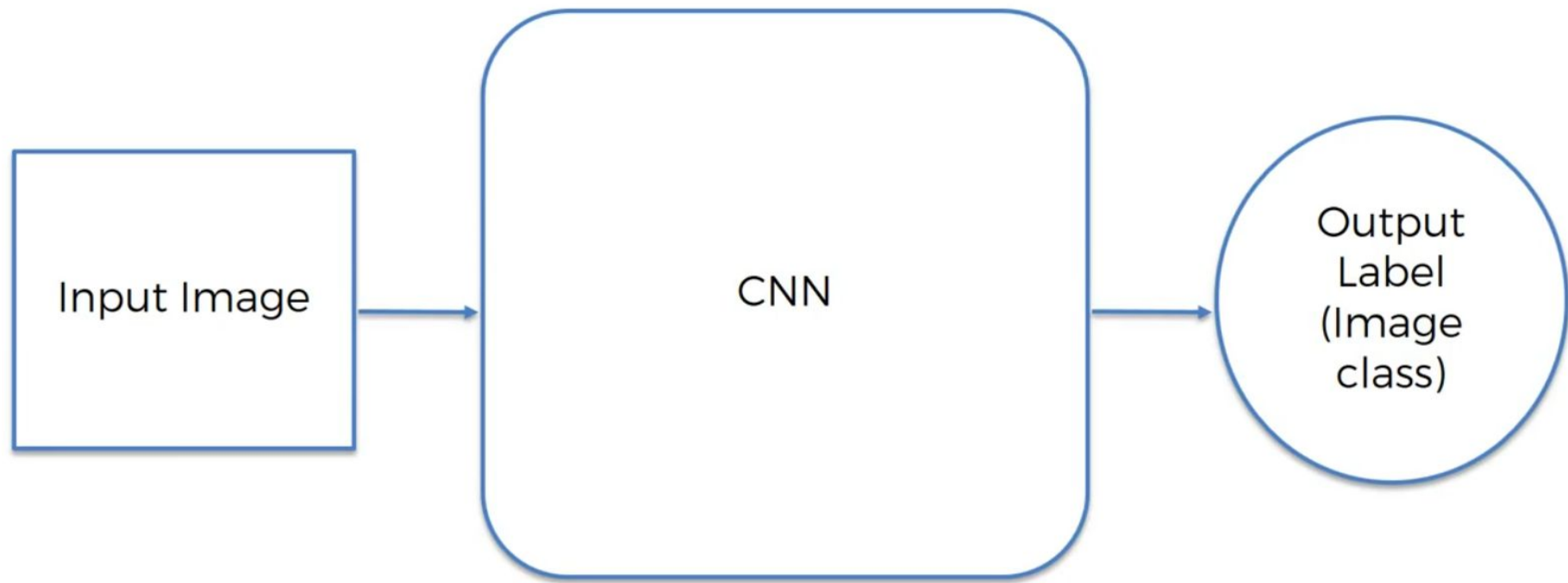
scissors

hand glass

frying pan

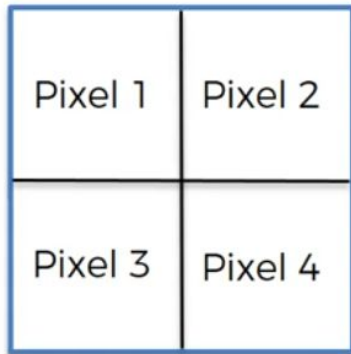
stethoscope

Convolutional Neural Networks

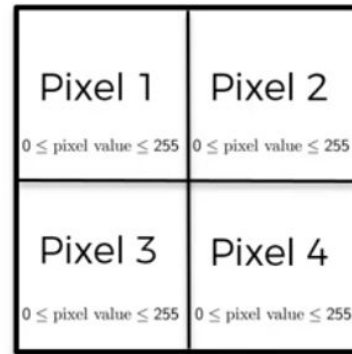


Convolutional Neural Networks

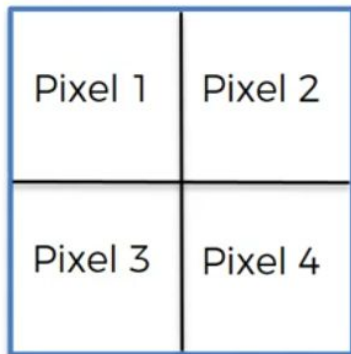
B / W Image 2x2px



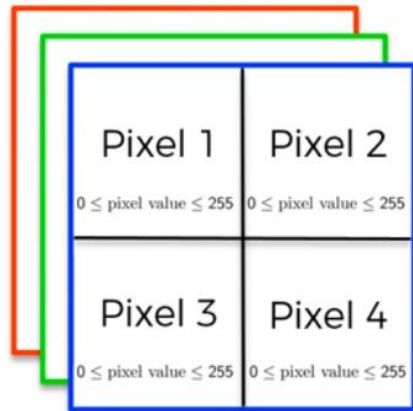
2d array



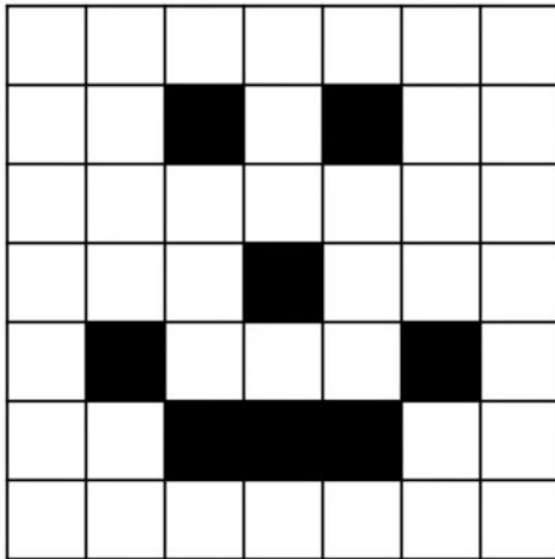
Colored Image 2x2px



3d array



Convolutional Neural Networks



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

<http://yann.lecun.com/exdb/publis/pdf/lecun-01a.pdf>

Convolutional Neural Networks

STEP 1: Convolution



STEP 2: Max Pooling



STEP 3: Flattening



STEP 4: Full Connection

Introduction to Convolutional Neural Networks

<https://cs.nju.edu.cn/wujx/>

<https://cs.nju.edu.cn/wujx/paper/CNN.pdf>

$$(f * g)(t) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} f(\tau) g(t - \tau) d\tau$$

Step 1 - Convolution

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

Input Image



0	0	1
1	0	0
0	1	1

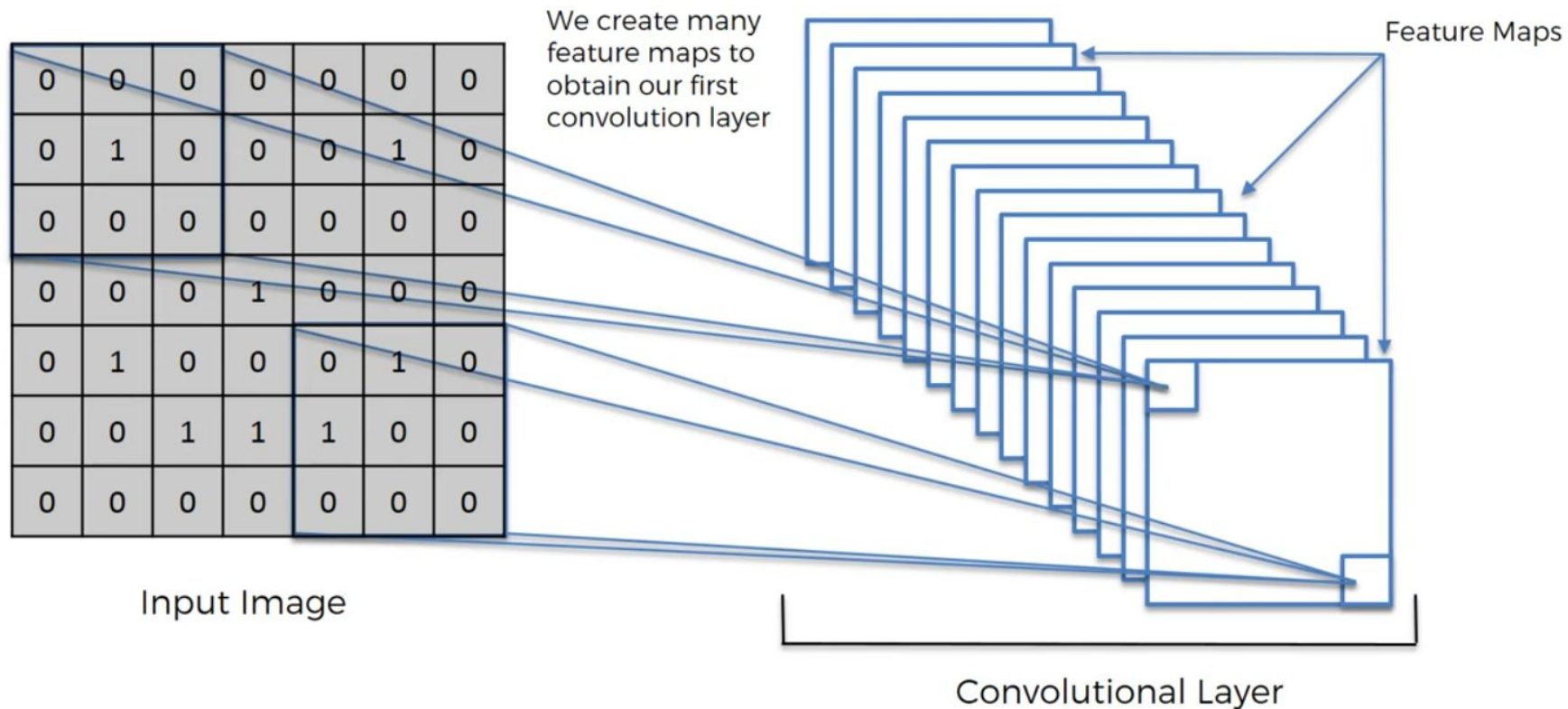
Feature
Detector



0	1	0	0	0
0	1	1	1	0

Feature Map

Step 1 - Convolution



Filters - How they work

<https://docs.gimp.org/2.10/en/>

Step 1 - Convolution

Sharpen:

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



Step 1 - Convolution

Blur:

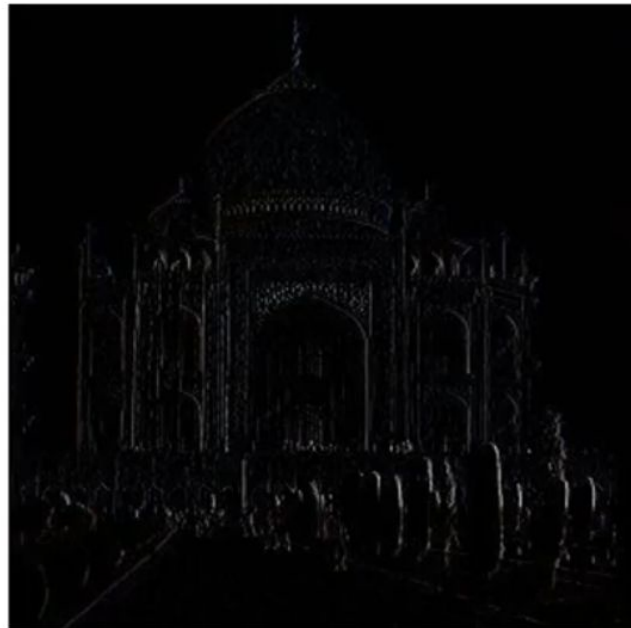
0	0	0	0	0
0	1	1	1	0
0	1	1	1	0
0	1	1	1	0
0	0	0	0	0



Step 1 - Convolution

Edge Enhance:

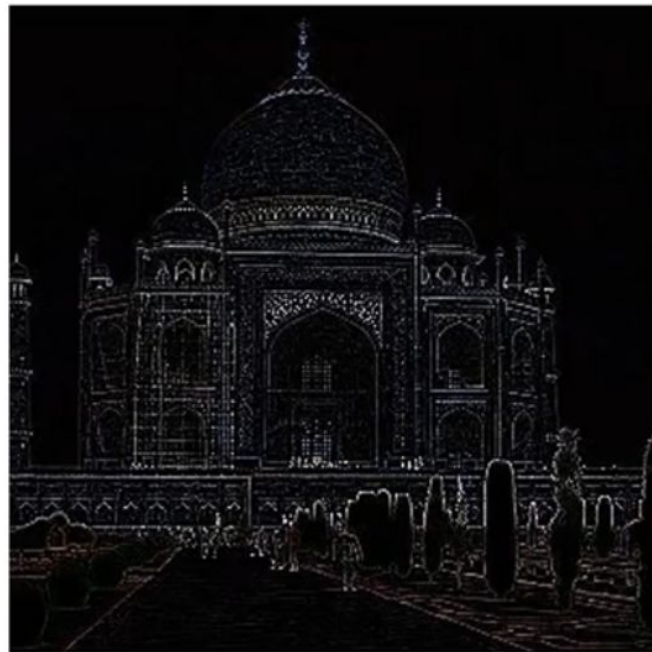
	0	0	0	
	-1	1	0	
	0	0	0	



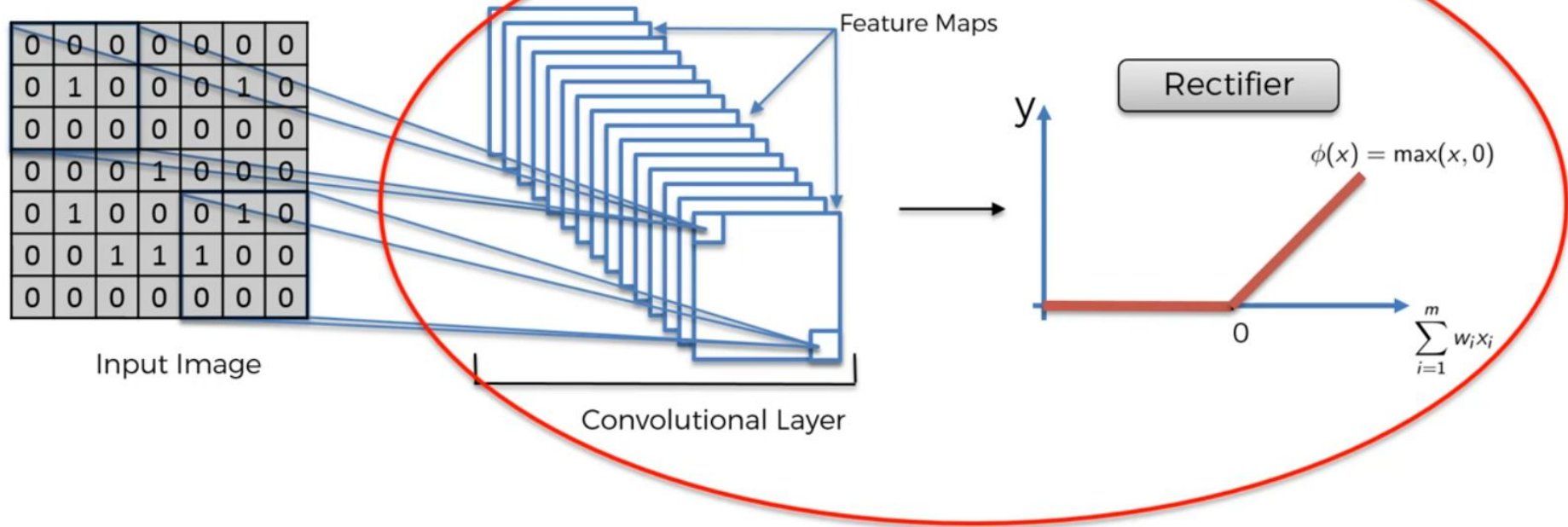
Step 1 - Convolution

Edge Detect:

	0	1	0	
	1	-4	1	
	0	1	0	



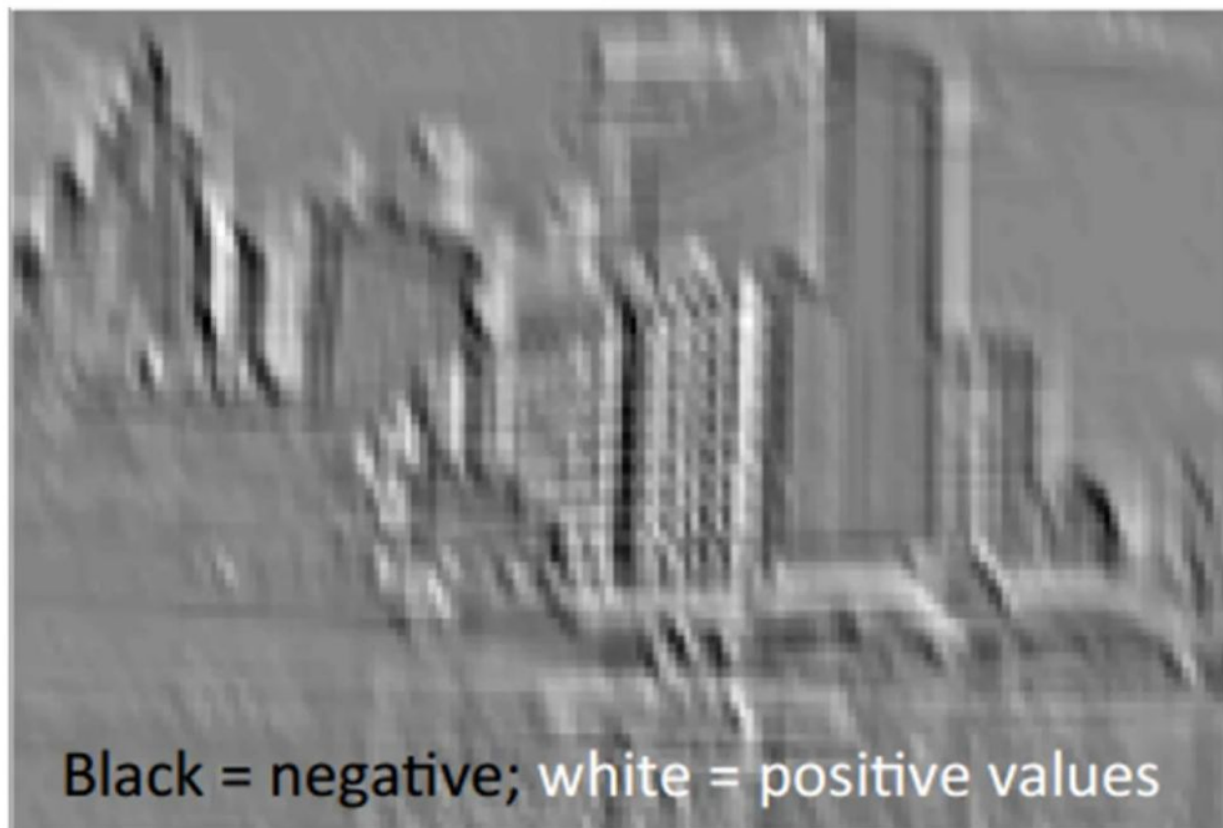
Step 1 (B) – ReLU Layer



Step 1 (B) – ReLU Layer



Step 1 (B) – ReLU Layer



Step 1 (B) – ReLU Layer



<https://arxiv.org/pdf/1609.04112.pdf>

Step 2 - Max Pooling



Step 2 - Max Pooling



Step 2 - Max Pooling

0	1	0	0	0
0	1	1	1	0
1	0	1	2	1
1	4	2	1	0
0	0	1	2	1

Feature Map

Max Pooling



1	1	0
4		

Pooled Feature Map

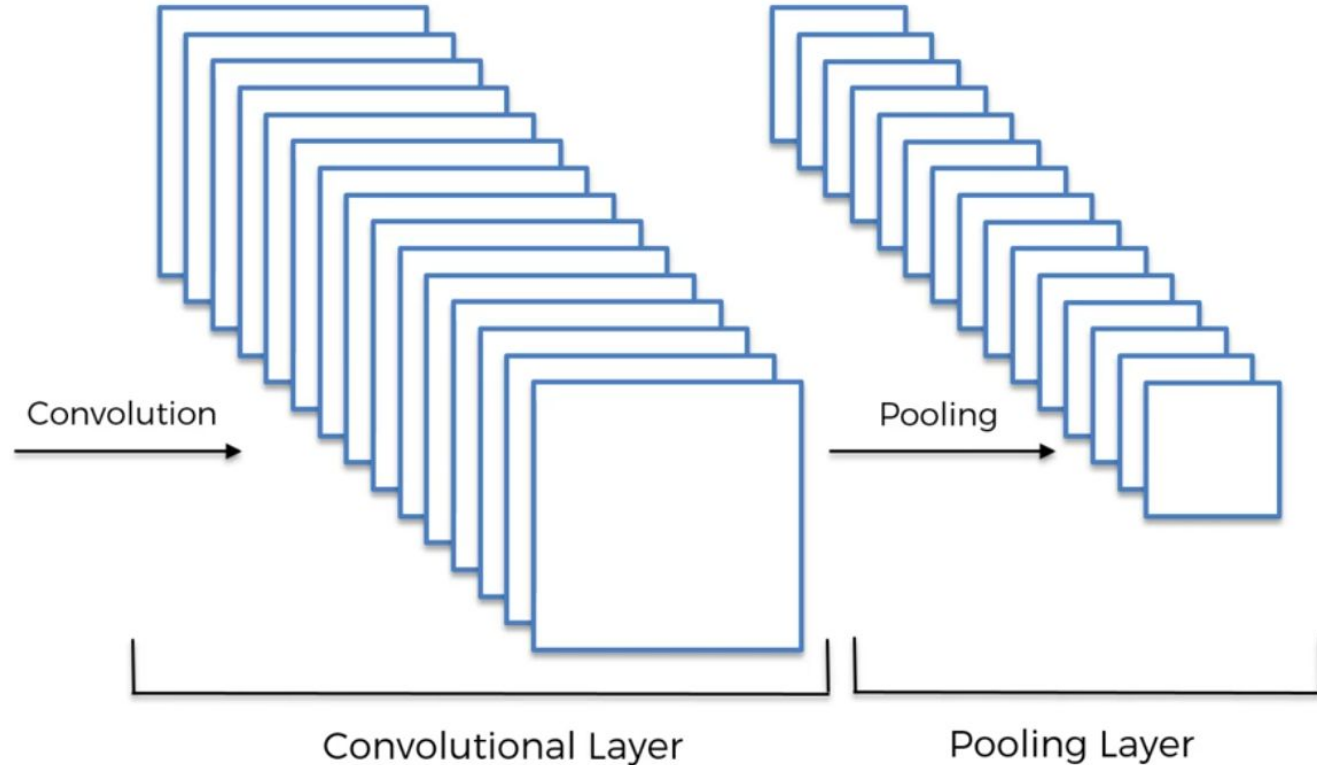
Evaluation of Pooling Operations in
Convolutional Architectures for Object
Recognition

<https://cs.nju.edu.cn/wujx/paper/CNN.pdf>

Step 2 - Max Pooling

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

Input Image



<https://www.cs.ryerson.ca/~aharley/vis/conv/flat.html>

Step 3 - Flattening

1	1	0
4	2	1
0	2	1

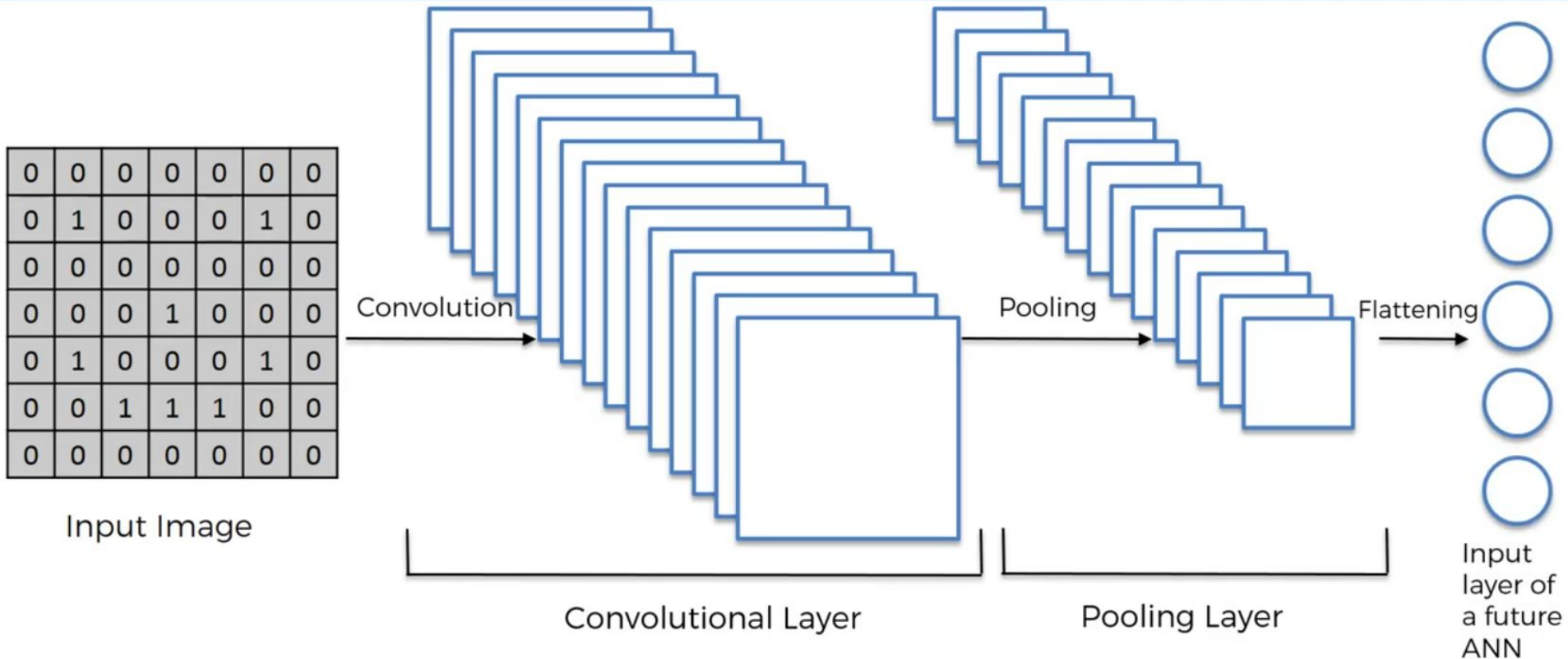
Pooled Feature Map

Flattening

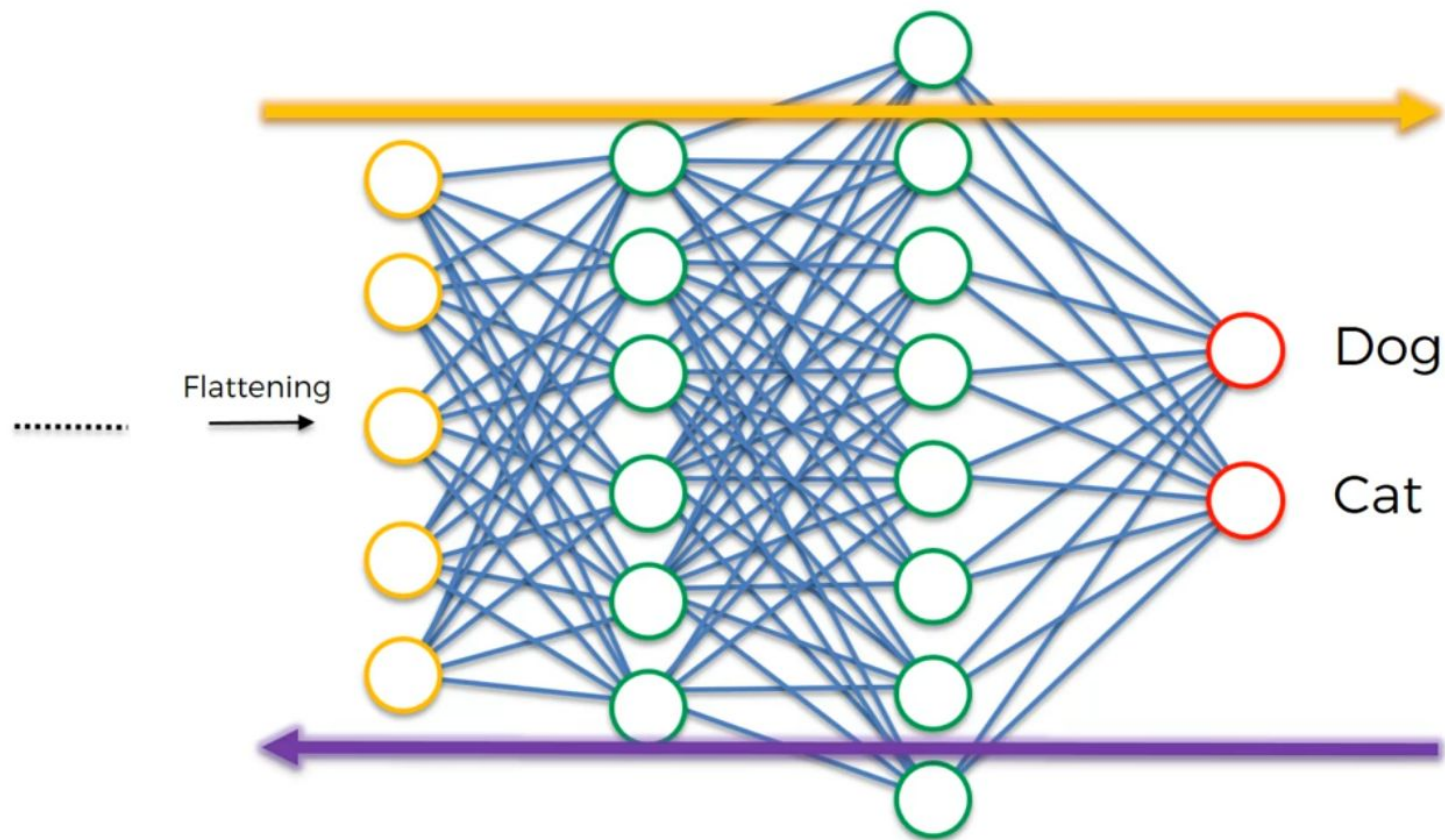


1
1
0
4
2
1
0
2
1

Step 3 - Flattening



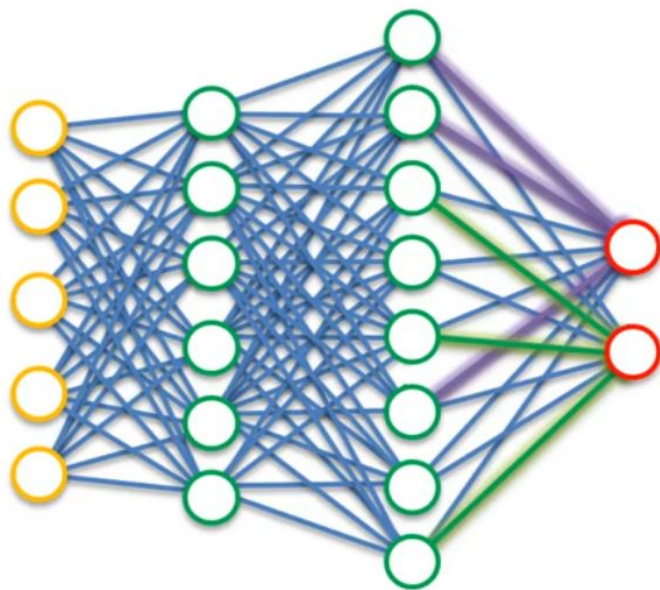
Step 4 - Full Connection



Softmax & Cross-Entropy



.....
→ Flattening →



Dog → z_1 → 0.95

Cat → z_2 → 0.05

$$f_j(z) = \frac{e^{z_j}}{\sum_k e^{z_k}}$$



Categorizing Listing Photos at Airbnb

<https://medium.com/airbnb-engineering/categorizing-listing-photos-at-airbnb-f9483f3ab7e3>

Airbnb is a marketplace featuring millions of homes

Factors for decision-making during a guest's search journey

location

Price

listing photos

Problem Statement

had no way to help guests find the most informative images,

No way to ensure the information conveyed in the photos was accurate

No way to advise hosts about how to improve the appeal of their images in a scalable way

How categorizing listing photos is useful to Airbnb

- same room type can be grouped together

- categorization makes it much easier to validate the number of certain rooms

- check whether the basic room information is correct

On the guest side

it facilitates re-ranking and re-layout of photos based on distinct room types so that the ones people are most interested in will be surfaced first

On the host side

it helps automatically review listings to ensure they abide by marketplace's high standards

Model used - ResNet50

Why ResNet50

Due to its good balance between model performance and computation time

To make it compatible with use case,

- added two extra fully connected layers
- a Softmax activation in the end

Re-training ResNet50

- Keep the base ResNet50 model fixed
- only re-train the added two layers using using massive data

two major challenges in Training ResNet50

- Even though there were lots of listing photos uploaded by hosts, it didn't have accurate room-type labels associated with them
- Re-training a DNN like ResNet50 is highly non-trivial — There were more than 25 million parameters to train and this required substantial GPU support

For the first challenge

- asked vendors to label relatively small number of photos, usually in thousands or tens of thousands
- leveraged image captions created by hosts for room-type information and extracted labels out of it