KMI 한국기상산업기술원
Korea Meteorological Institute

빅파이 크래프트
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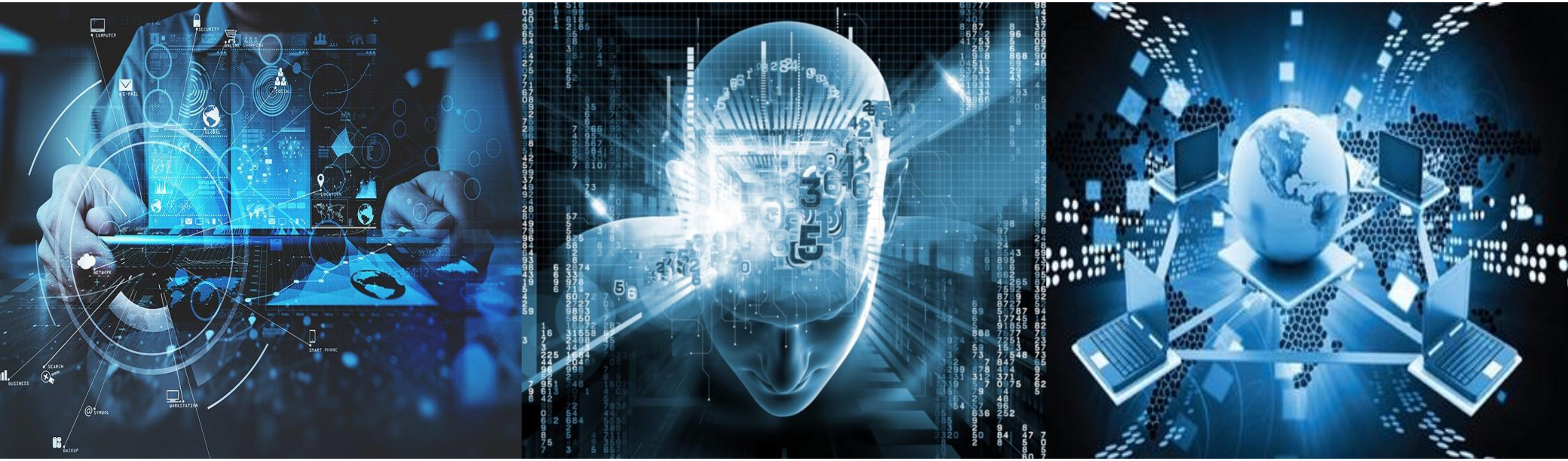


기상기후 빅데이터와 지능정보기술 활용과정

AI핵심기술 - CNN(Convolution Neural Networks)

Training BigData Experts & Empowering AI Technology

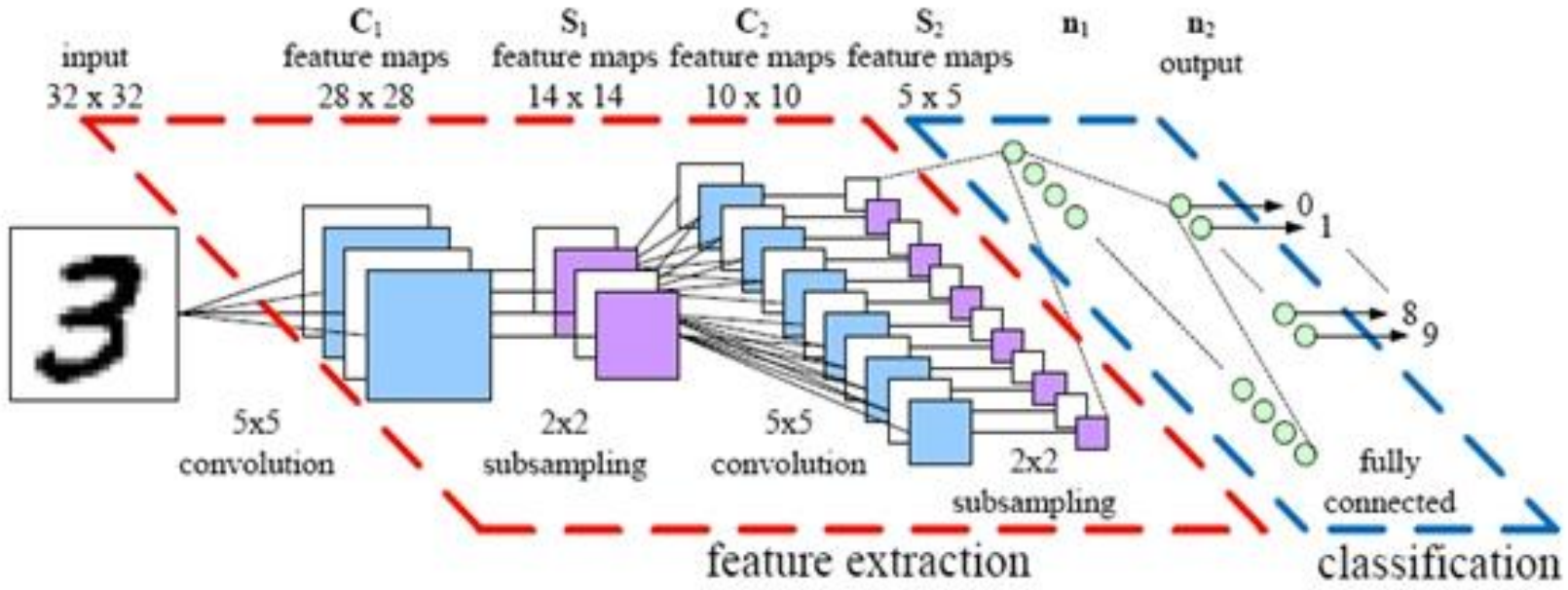
Kim Jin Soo

학습내용

- CNN(Convolution Neural Networks) Overview
- Step 1 – Convolution Operation
- Step 1 – ReLU Layer
- Step 2 – Pooling
- Step 3 – Flattening
- Step 4 – Full Connection
- Summary

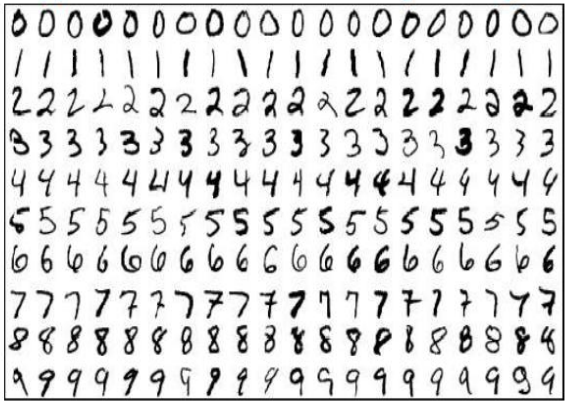
CNN (Convolutional Neural Network)

- 최근 신경망 연구에서 가장 두드러진 변화를 일으키고 있는 딥러닝의 핵심분야이다.
- 특히, 컴퓨터비전, 컴퓨터오디션, 강화학습 등에서 최첨단의 성과를 도출
- 컨볼루션넷은 새로운 서비스와 기능을 통해 기술기반의 회사에 널리 적용되고 있다.

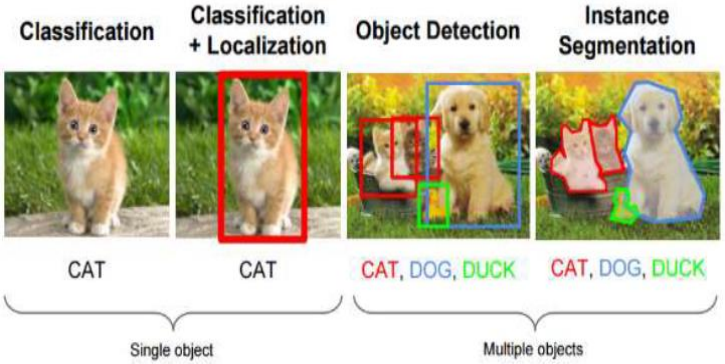


CNN 적용분야

CNN application in Handwritten Digit Recognizer



Object recognition and classification using Convolutional Networks



CNN application in Self Driving Cars

- 이미지 캡션, 이미지 인식, 다양한 시각 시스템 처리
- 이미지 기반의 물체 혹은 사람, 위치, 탐지 및 구분
- 음성의 문자변환, 오디오 합성
- 자연어로 이미지 및 동영상 묘사
- 무인차량에서 장애물 탐지 및 자율주행
- 생성모델을 통해 이미지, 사운드, 텍스트에 대한 홀루시네이팅(hallucinating)

CNN (Convolutional Neural Network)

Yann Lecun

CNN의 역사

Hubel & Wiesel,

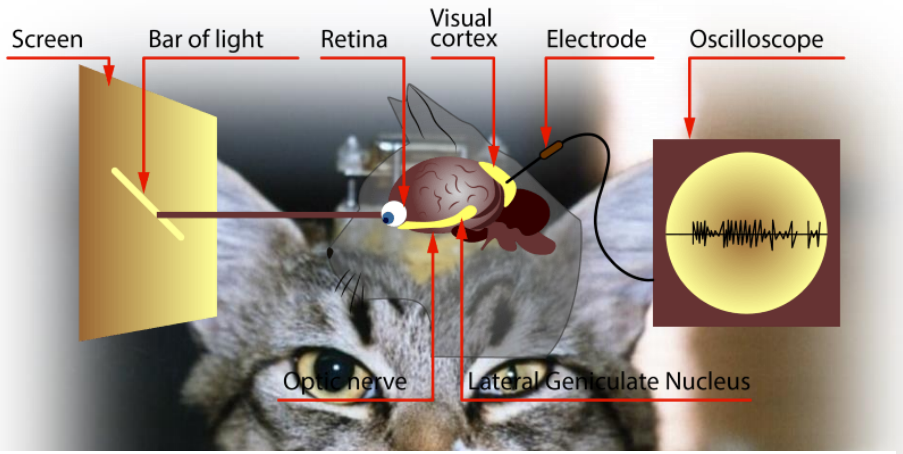
1959

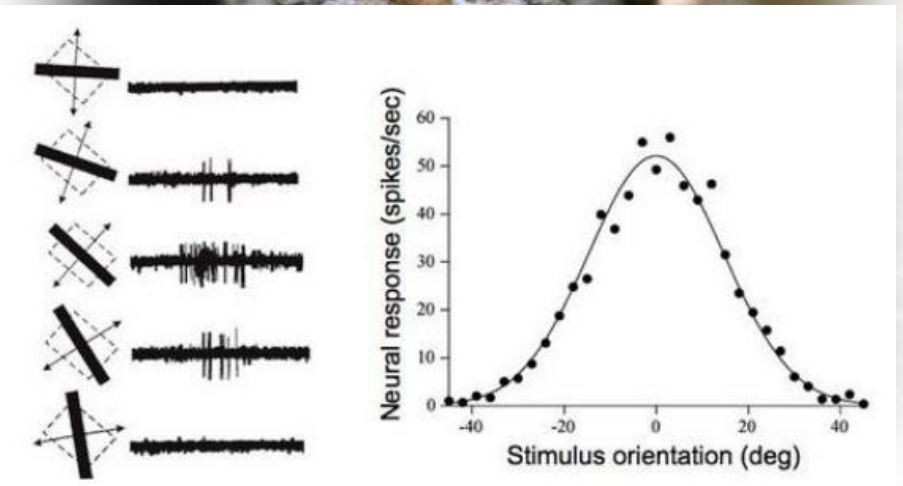
RECEPTIVE FIELDS OF SINGLE NEURONES IN THE CAT'S STRIATE CORTEX

1962

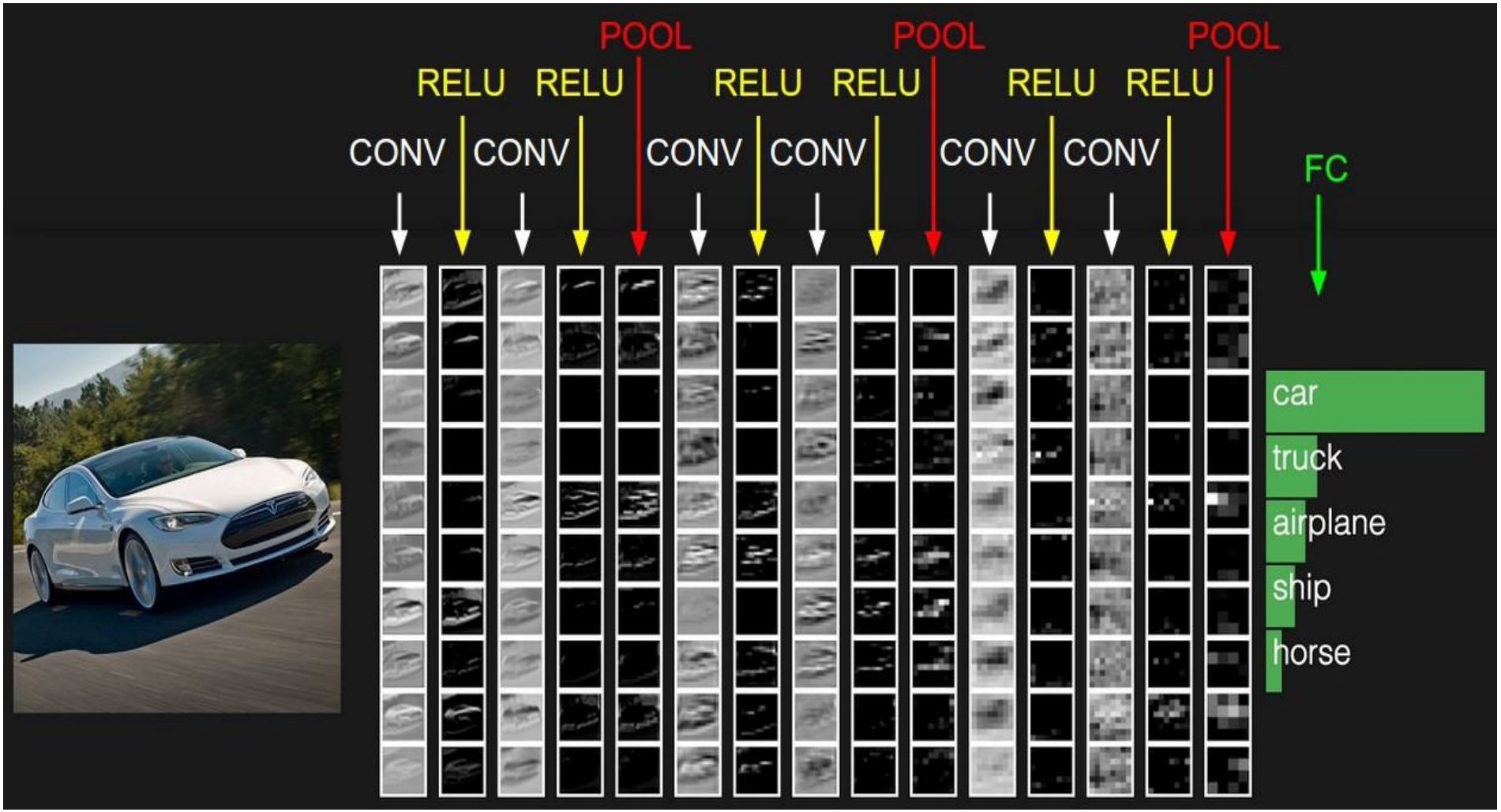
RECEPTIVE FIELDS, BINOCULAR INTERACTION AND FUNCTIONAL ARCHITECTURE IN THE CAT'S VISUAL CORTEX

1968





CNN DEMO



[ITP-NYU, CNN] https://ml4a.github.io/classes/itp-S16/03/

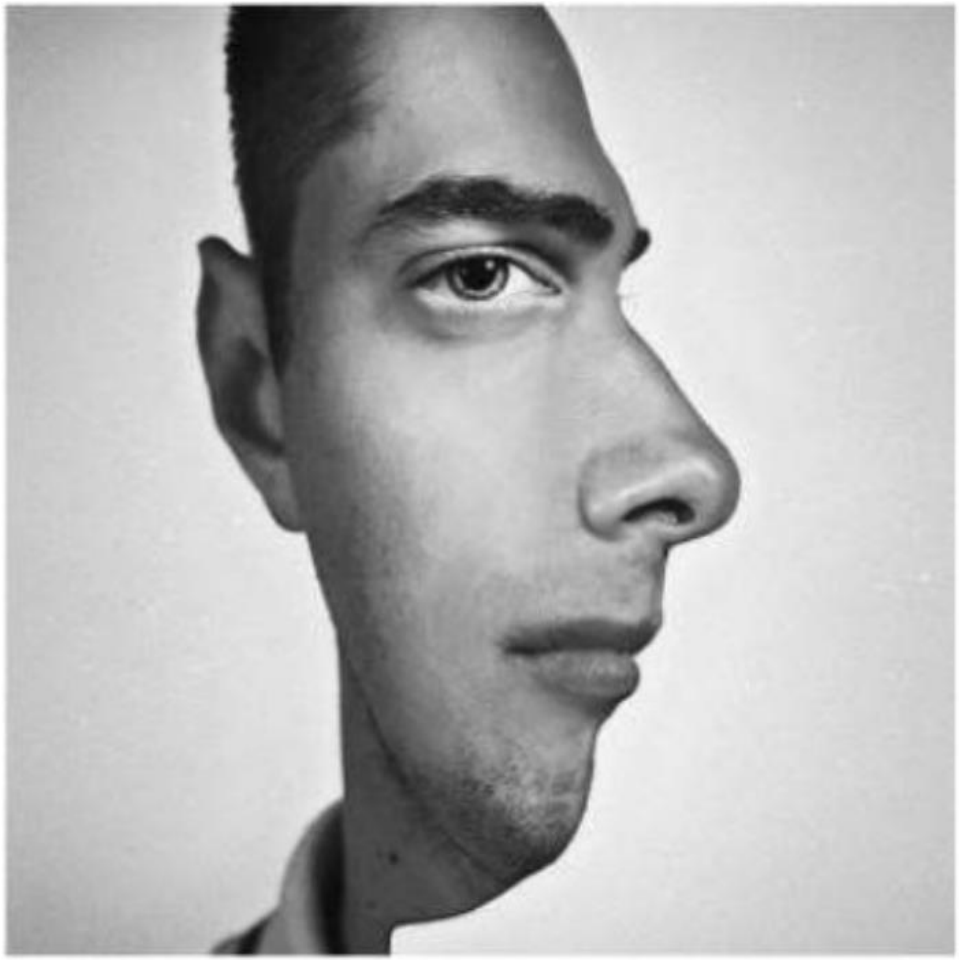
CNN (Convolutional Neural Network)

What we will learn in this section:

- What are Convolutional Neural Networks?
- Step 1 - Convolution Operation
- Step 1(b) - ReLU Layer
- Step 2 - Pooling
- Step 3 - Flattening
- Step 4 - Full Connection
- Summary

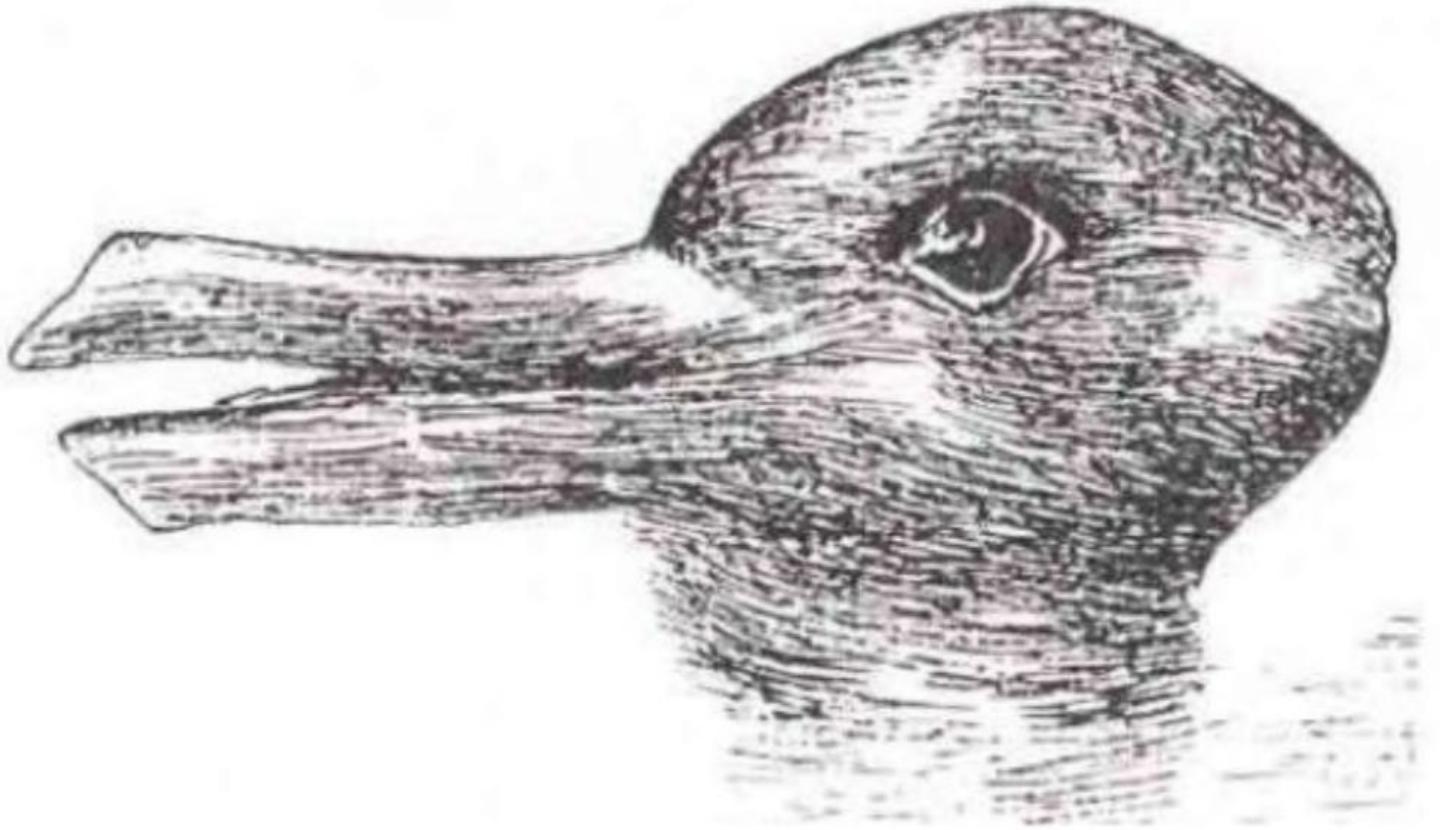
- EXTRA: Softmax & Cross-Entropy

CNN (Convolutional Neural Network)

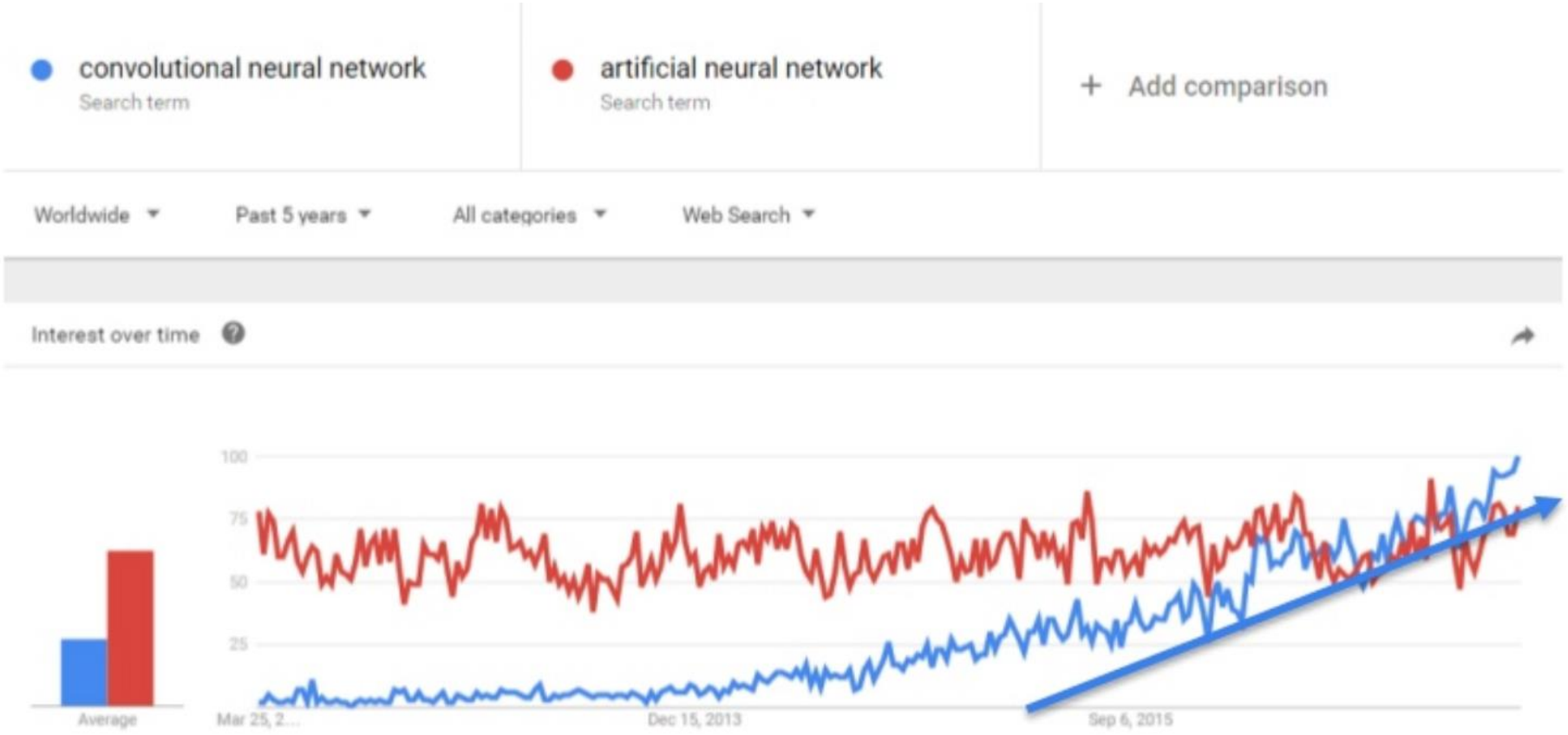


CNN (Convolutional Neural Network)

CNN (Convolutional Neural Network)



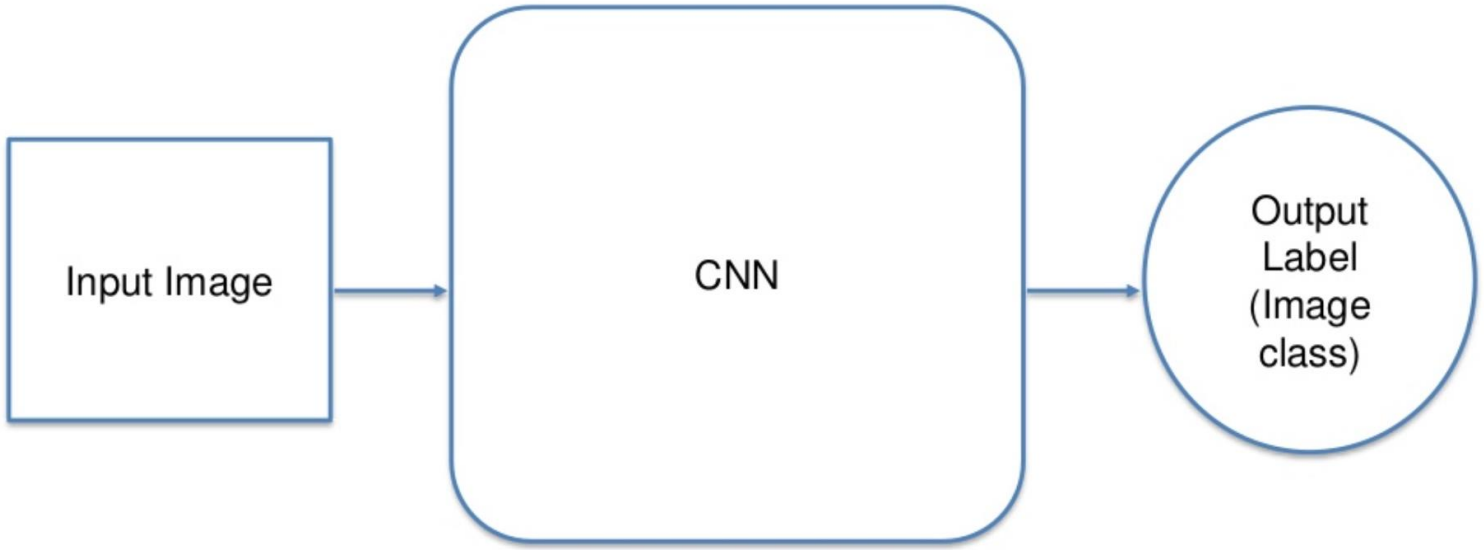
CNN (Convolutional Neural Network)



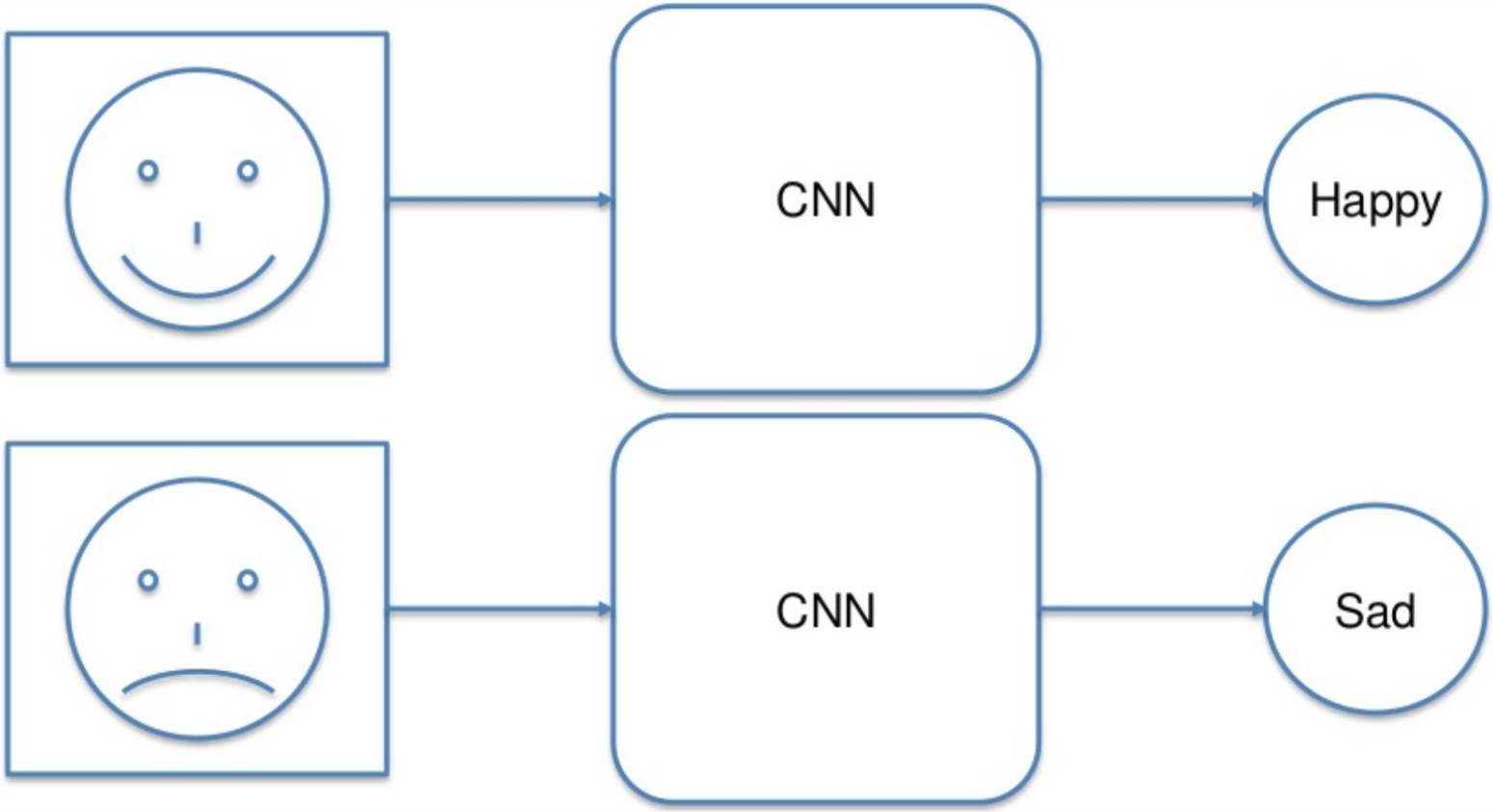
CNN (Convolutional Neural Network)

Yann Lecun

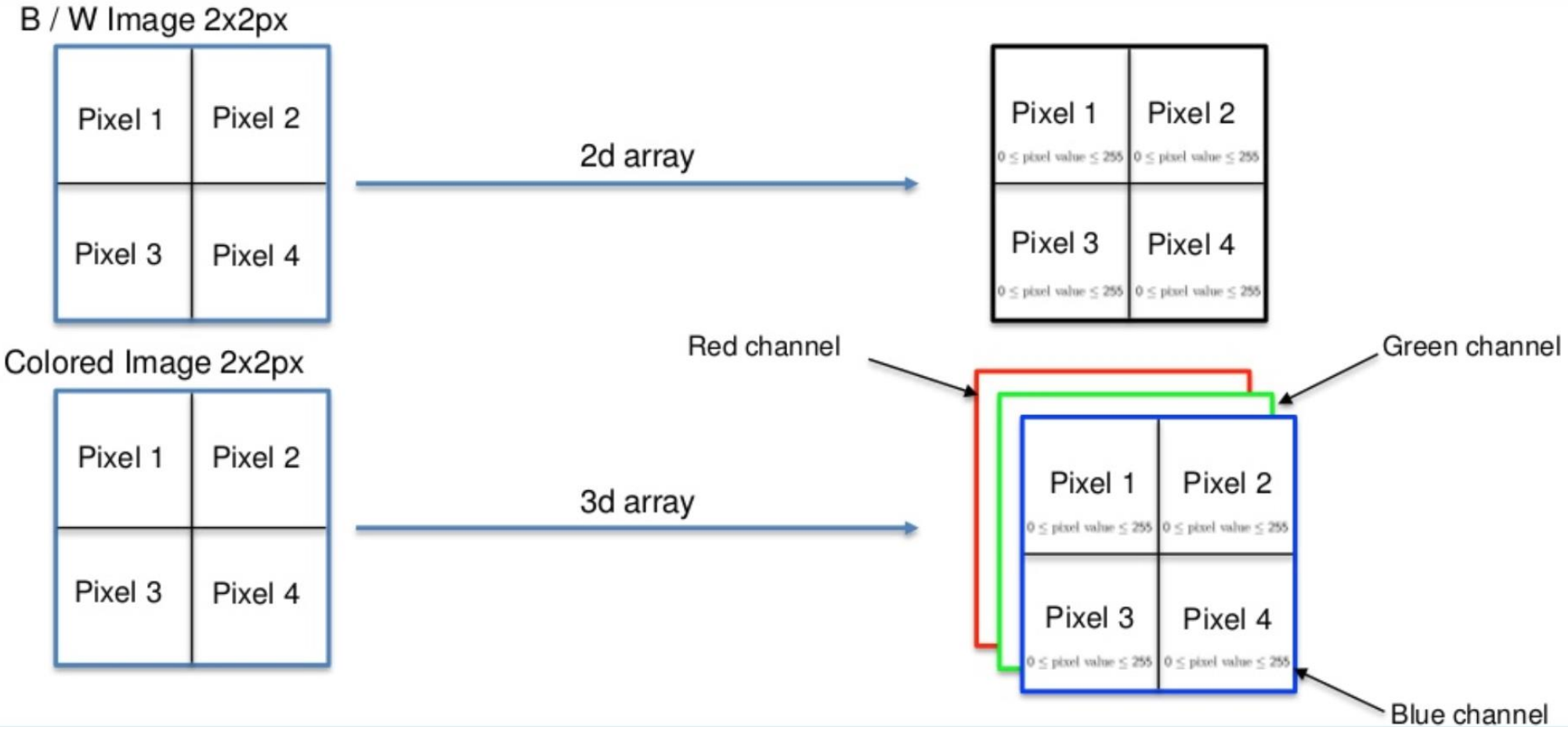
CNN (Convolutional Neural Network)



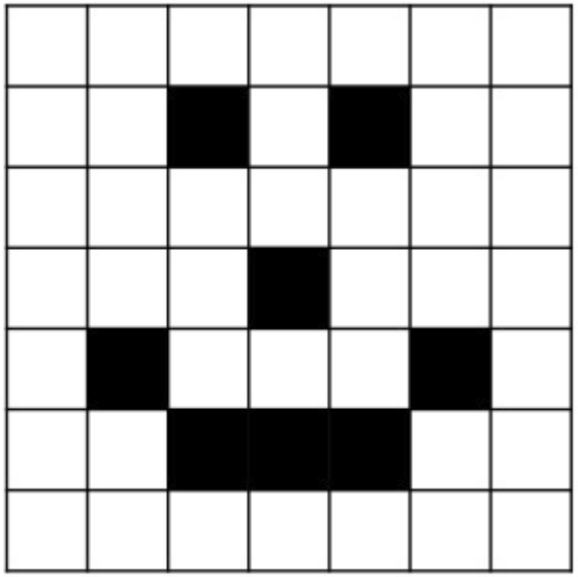
CNN (Convolutional Neural Network)



CNN (Convolutional Neural Network)



CNN (Convolutional Neural Network)



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

CNN (Convolutional Neural Network)

STEP 1: Convolution

STEP 2: Max Pooling

STEP 3: Flattening

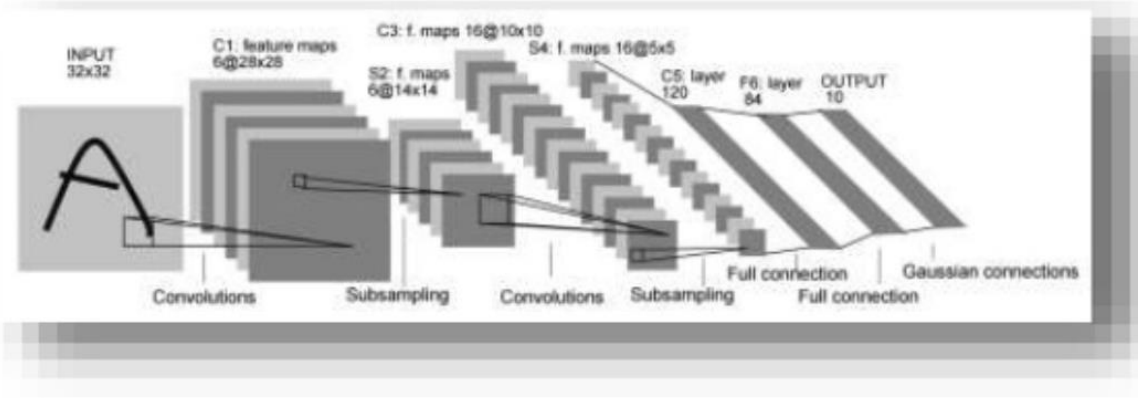
STEP 4: Full Connection

CNN (Convolutional Neural Network)

Additional Reading:

Gradient-Based Learning Applied to Document Recognition

By Yann LeCun et al. (1998)



Link:

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

CNN : Step 1 - Convolution

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

CNN : Step 1 - Convolution

Additional Reading:

Introduction to Convolutional Neural Networks

By Jianxin Wu (2017)

$$\begin{aligned}\frac{\partial z}{\partial(\mathrm{vec}(\boldsymbol{y})^T)}(F^T \otimes I) &= \left((F \otimes I)\frac{\partial z}{\partial \mathrm{vec}(\boldsymbol{y})}\right)^T \\ &= \left((F \otimes I)\,\mathrm{vec}\left(\frac{\partial z}{\partial Y}\right)\right)^T \\ &= \mathrm{vec}\left(I\frac{\partial z}{\partial Y}F^T\right)^T \\ &= \mathrm{vec}\left(\frac{\partial z}{\partial Y}F^T\right)^T,\end{aligned}$$

Link:

http://cs.nju.edu.cn/wujx/paper/CNN.pdf

CNN : Step 1 - Convolution

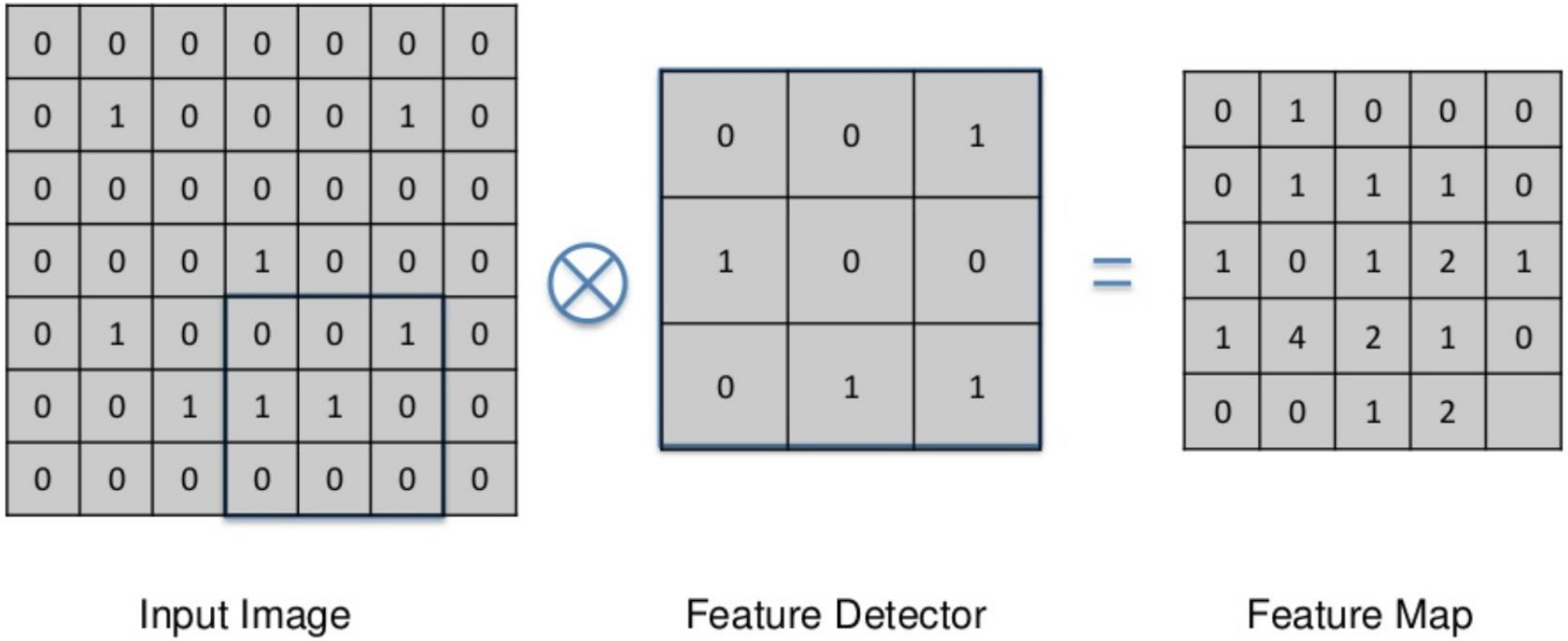
0	0	0	0	0	0	0
0	1	0	0	0	1	0
0	0	0	0	0	0	0
0	0	0	1	0	0	0
0	1	0	0	0	1	0
0	0	1	1	1	0	0
0	0	0	0	0	0	0

Input Image

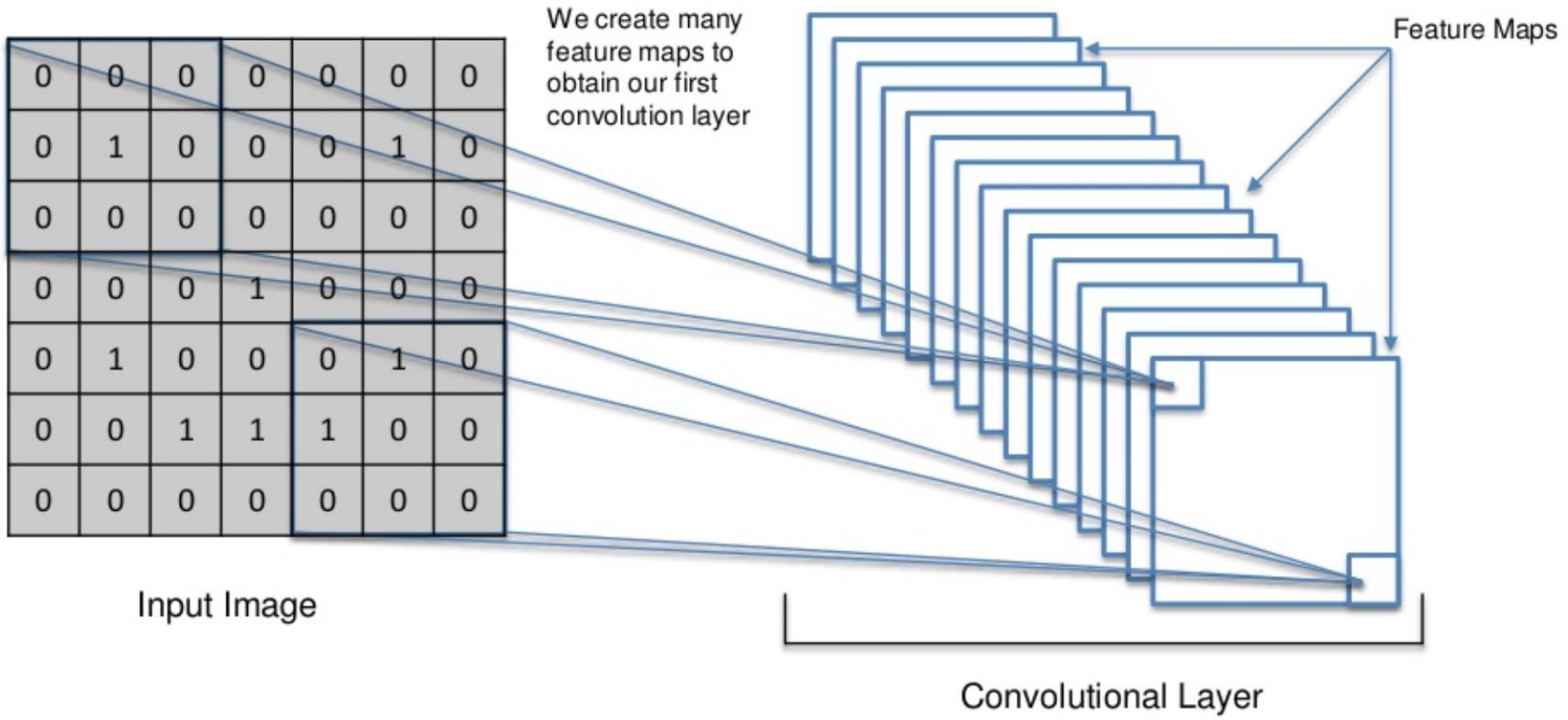
0	0	1
1	0	0
0	1	1

Feature Detector

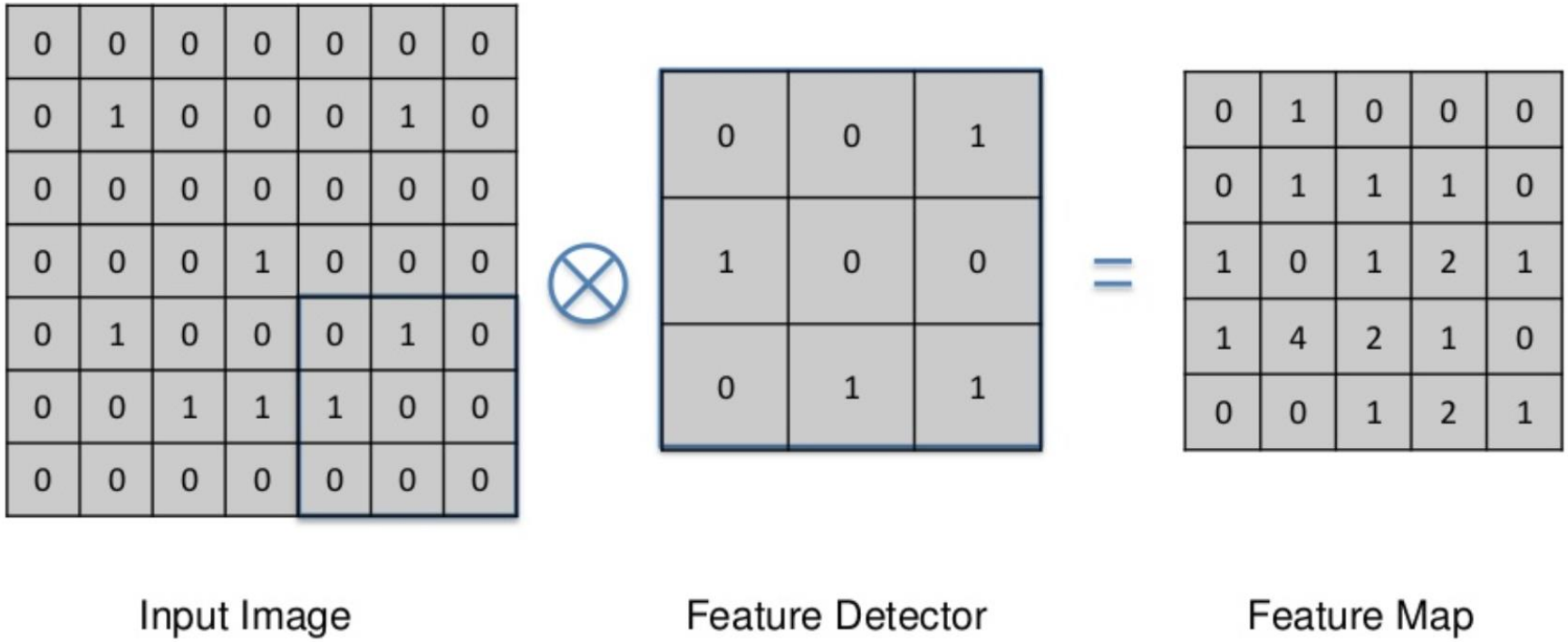
CNN : Step 1 - Convolution



CNN : Step 1 - Convolution



CNN : Step 1 - Convolution



CNN : Step 1 - Convolution

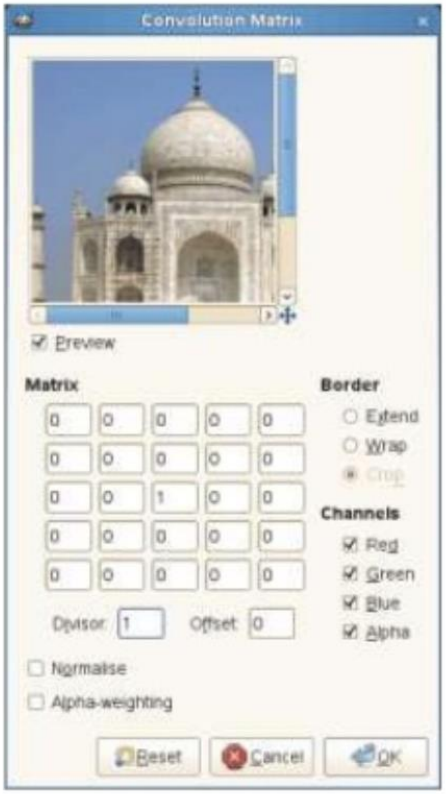


Image Source: docs.gimp.org/en/plug-in-convmatrix.html

CNN : 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

Image Source: docs.gimp.org/en/plug-in-convmatrix.html

CNN : 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

Image Source: docs.gimp.org/en/plug-in-convmatrix.html

CNN : Step 1 - Convolution

Edge Enhance:

	0	0	0	
	-1	1	0	
	0	0	0	

Image Source: docs.gimp.org/en/plug-in-convmatrix.html

CNN : Step 1 - Convolution

Emboss:

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

Image Source: docs.gimp.org/en/plug-in-convmatrix.html

CNN : Step 1 - Convolution

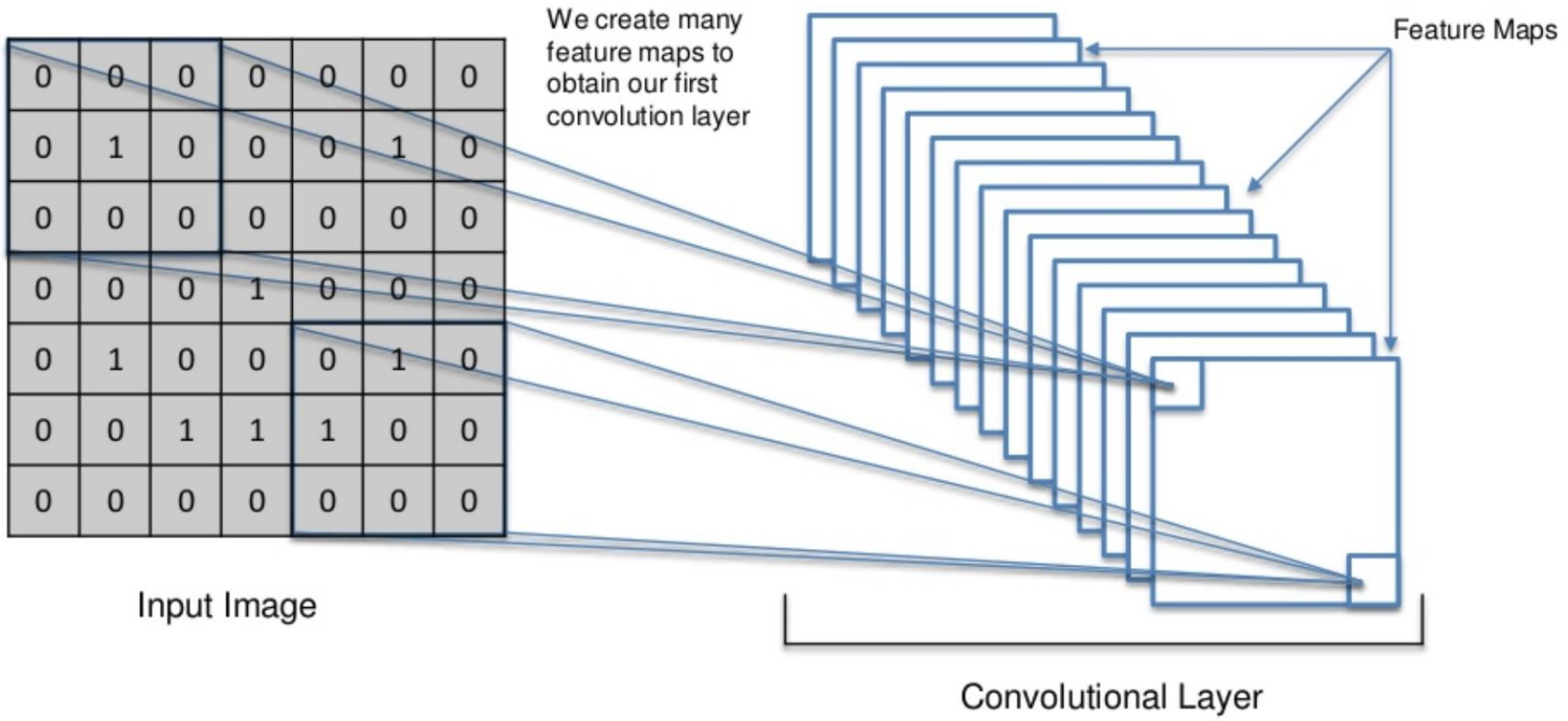
$*$

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

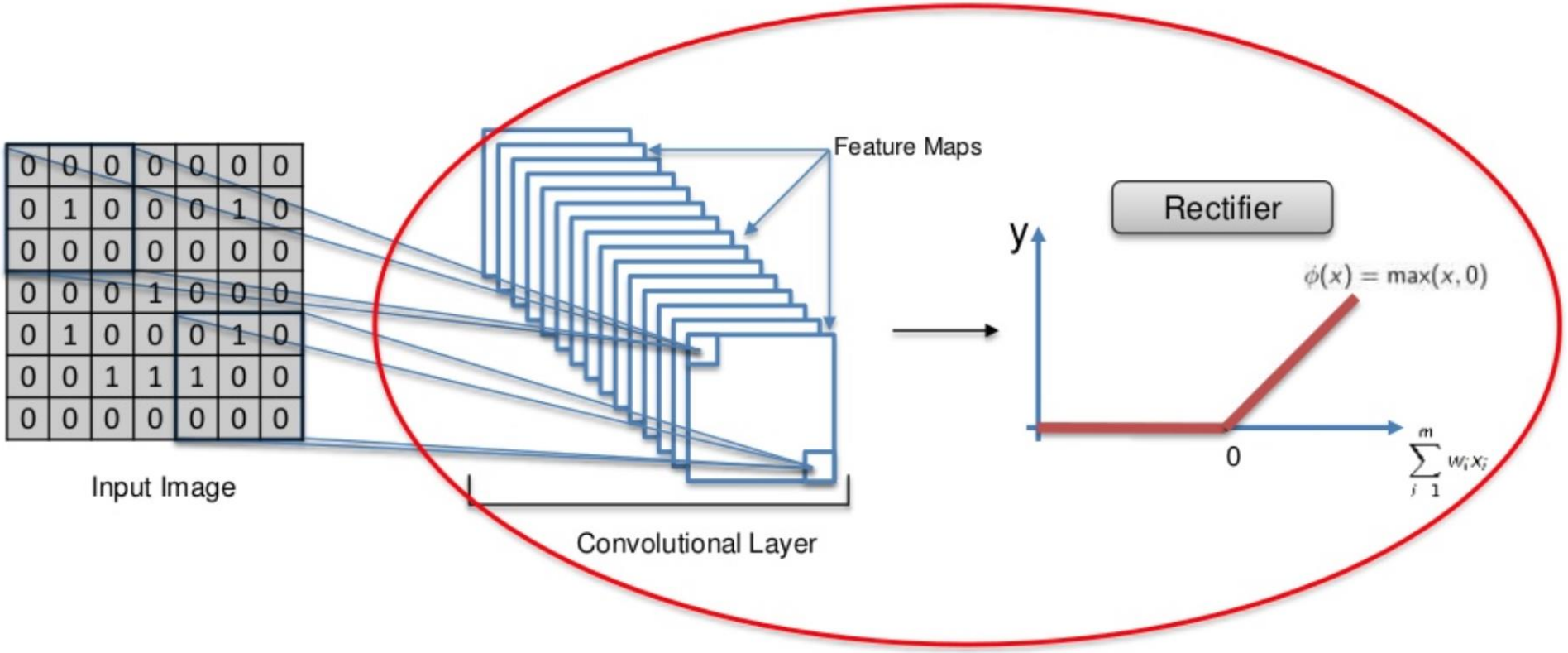
Image Source: eonardoaraujosantos.gitbooks.io

Step 1(B) – ReLU Layer

CNN : Step 1 – ReLU Layer



CNN : Step 1 – ReLU Layer



CNN : Step 1 – ReLU Layer

Image Source: http://mlss.tuebingen.mpg.de/2015/slides/fergus/Fergus_1.pdf

CNN : Step 1 – ReLU Layer

Image Source: http://mlss.tuebingen.mpg.de/2015/slides/fergus/Fergus_1.pdf

CNN : Step 1 – ReLU Layer

Image Source: http://mlss.tuebingen.mpg.de/2015/slides/fergus/Fergus_1.pdf

CNN : Step 1 – ReLU Layer

Image Source: http://mlss.tuebingen.mpg.de/2015/slides/fergus/Fergus_1.pdf

CNN : Step 1 – ReLU Layer

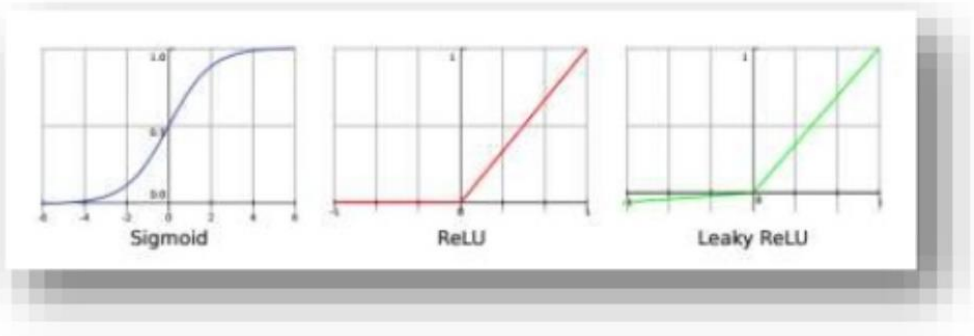
Additional Reading:

Understanding Convolutional Neural Networks with A Mathematical Model

By C.-C. Jay Kuo (2016)

Link:

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



CNN : Step 1 – ReLU Layer

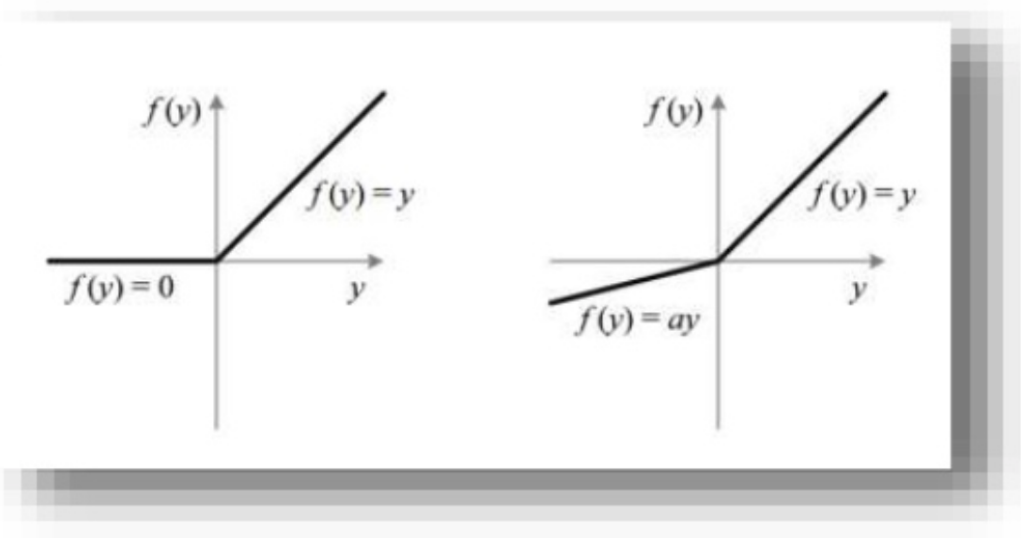
Additional Reading:

Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification

By Kaiming He et al. (2015)

Link:

https://arxiv.org/pdf/1502.01852.pdf



Step 2 – Max Pooling

CNN : Step 2 – Max Pooling

Image Source: Wikipedia

CNN : Step 2 – Max Pooling

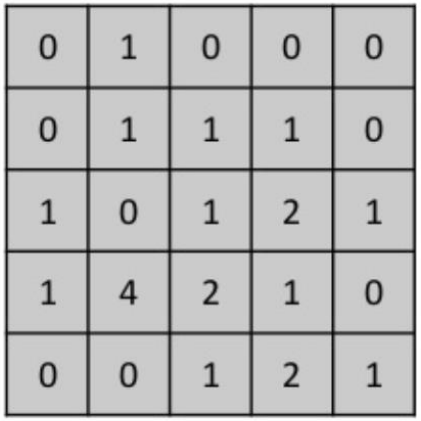
Image Source: Wikipedia

CNN : 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

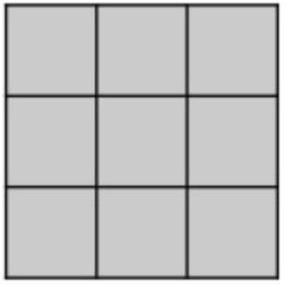
Feature Map

CNN : Step 2 – Max Pooling



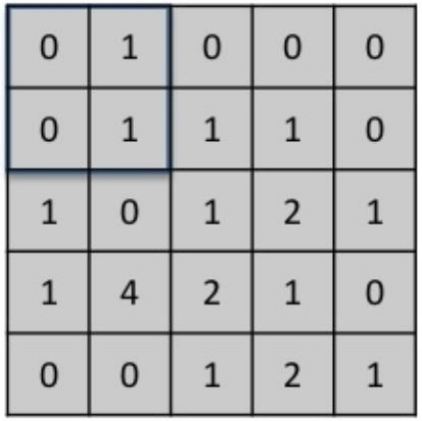
Feature Map

Max Pooling



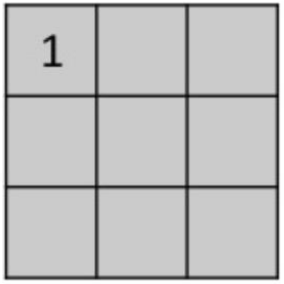
Pooled Feature Map

CNN : Step 2 – Max Pooling



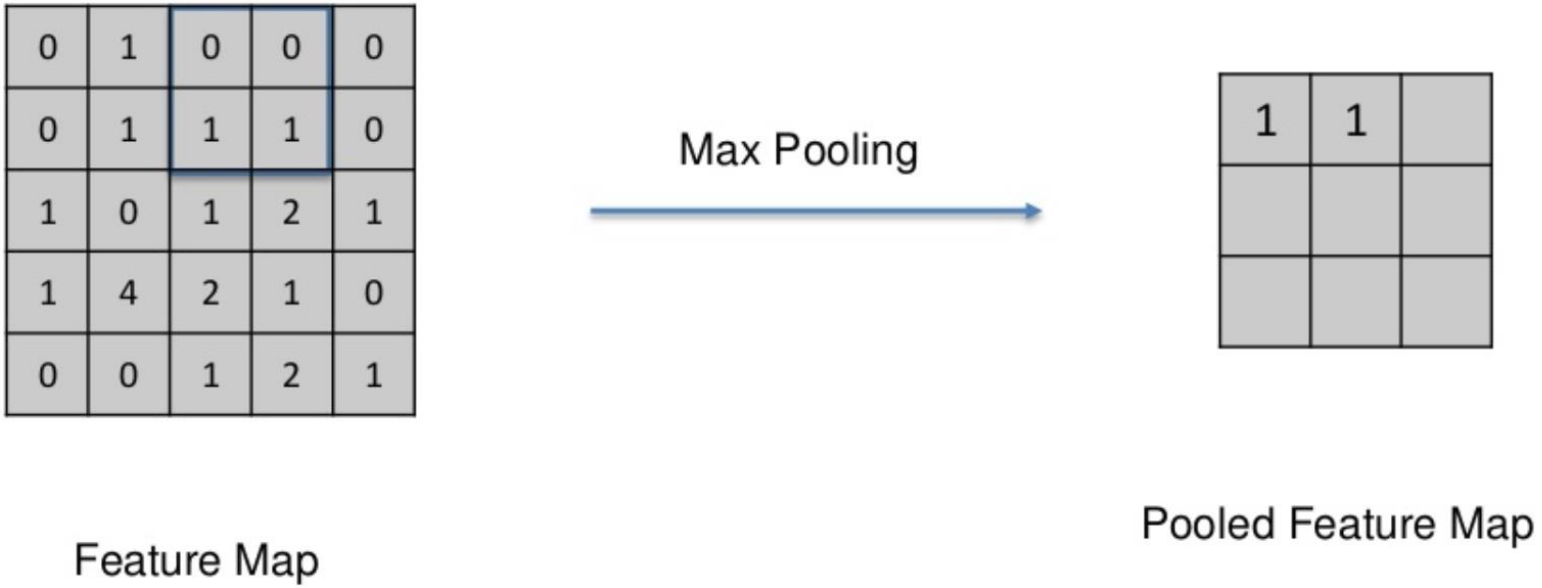
Feature Map

Max Pooling

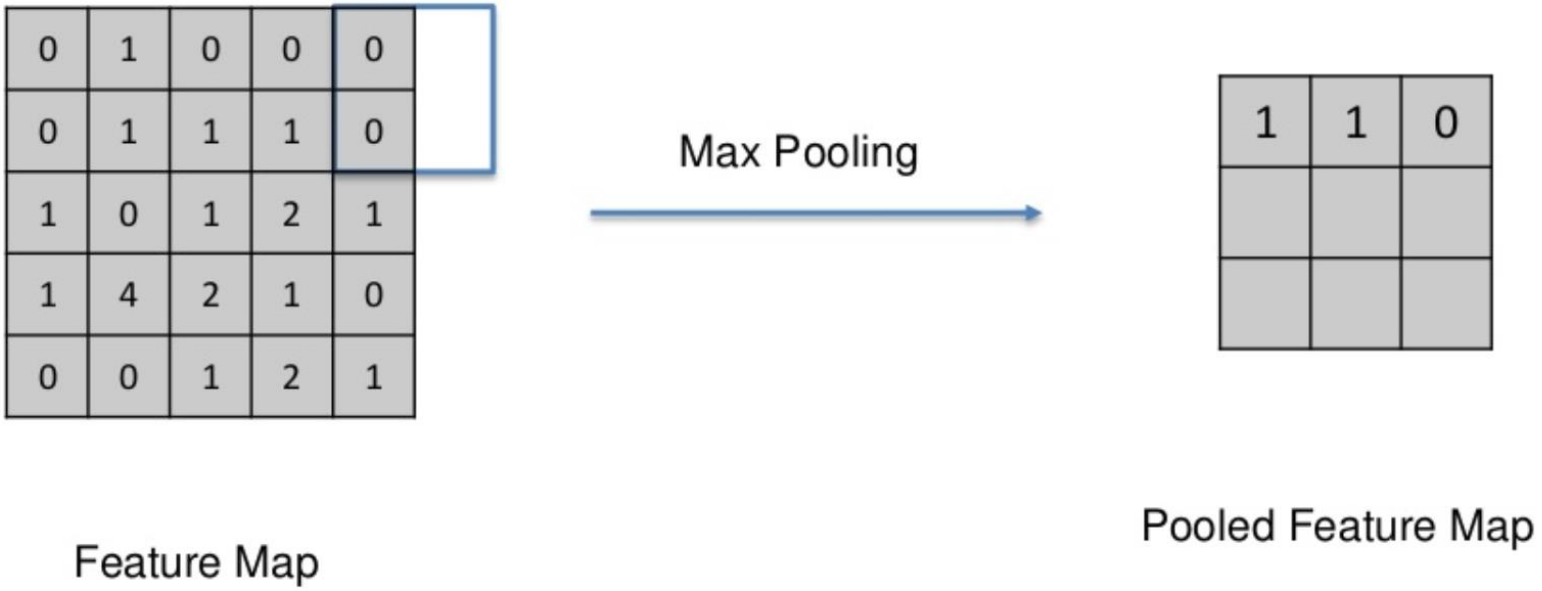


Pooled Feature Map

CNN : Step 2 – Max Pooling



CNN : Step 2 – Max Pooling



CNN : 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

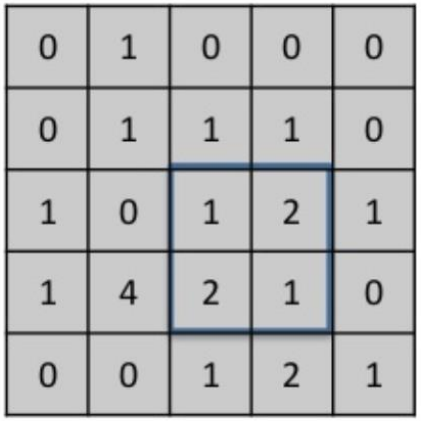
Feature Map

Max Pooling

1	1	0
4		

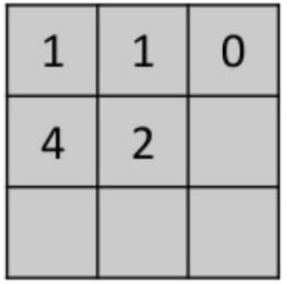
Pooled Feature Map

CNN : Step 2 – Max Pooling



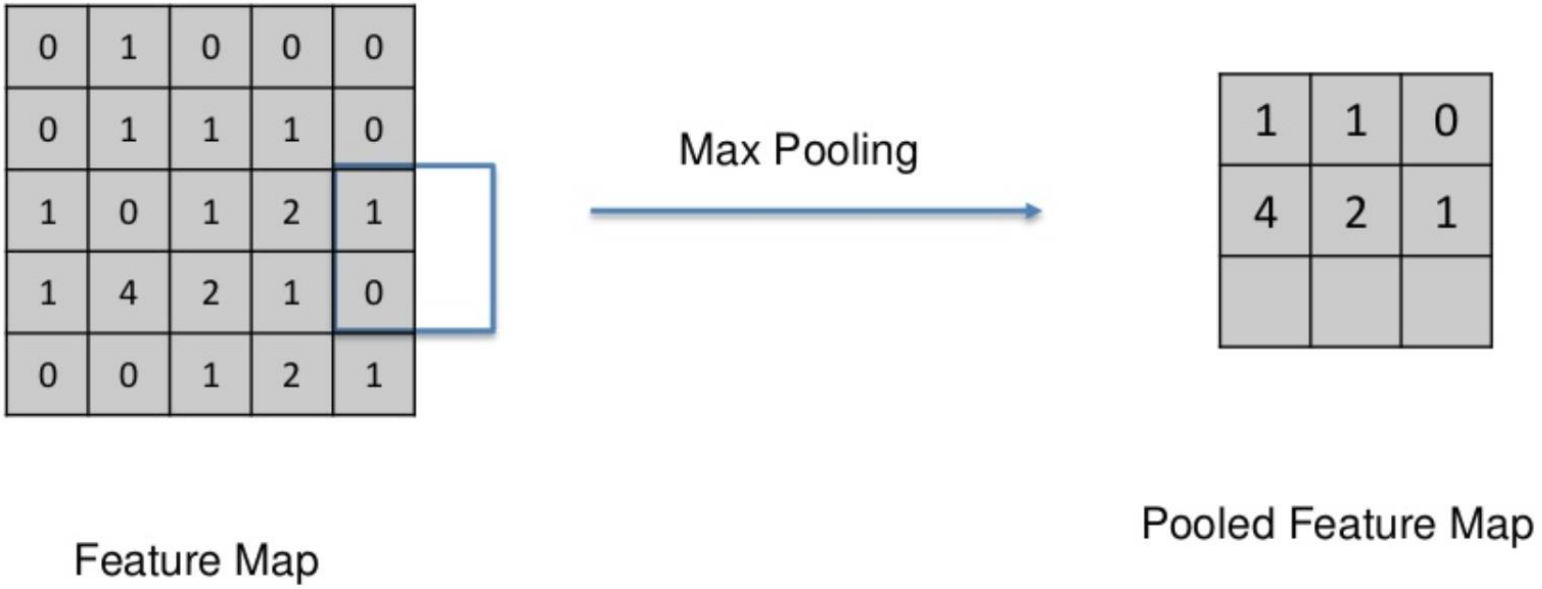
Feature Map

Max Pooling

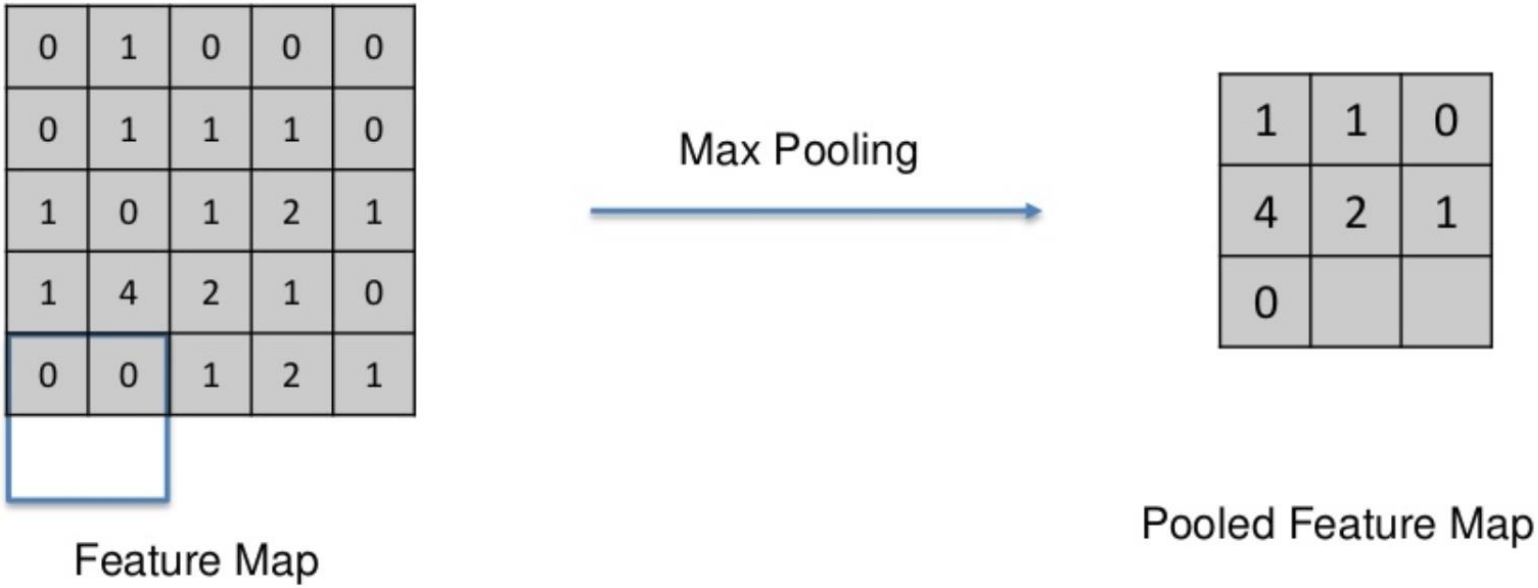


Pooled Feature Map

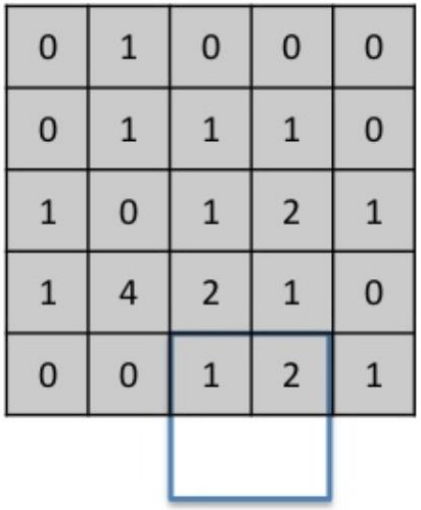
CNN : Step 2 – Max Pooling



CNN : Step 2 – Max Pooling



CNN : Step 2 – Max Pooling



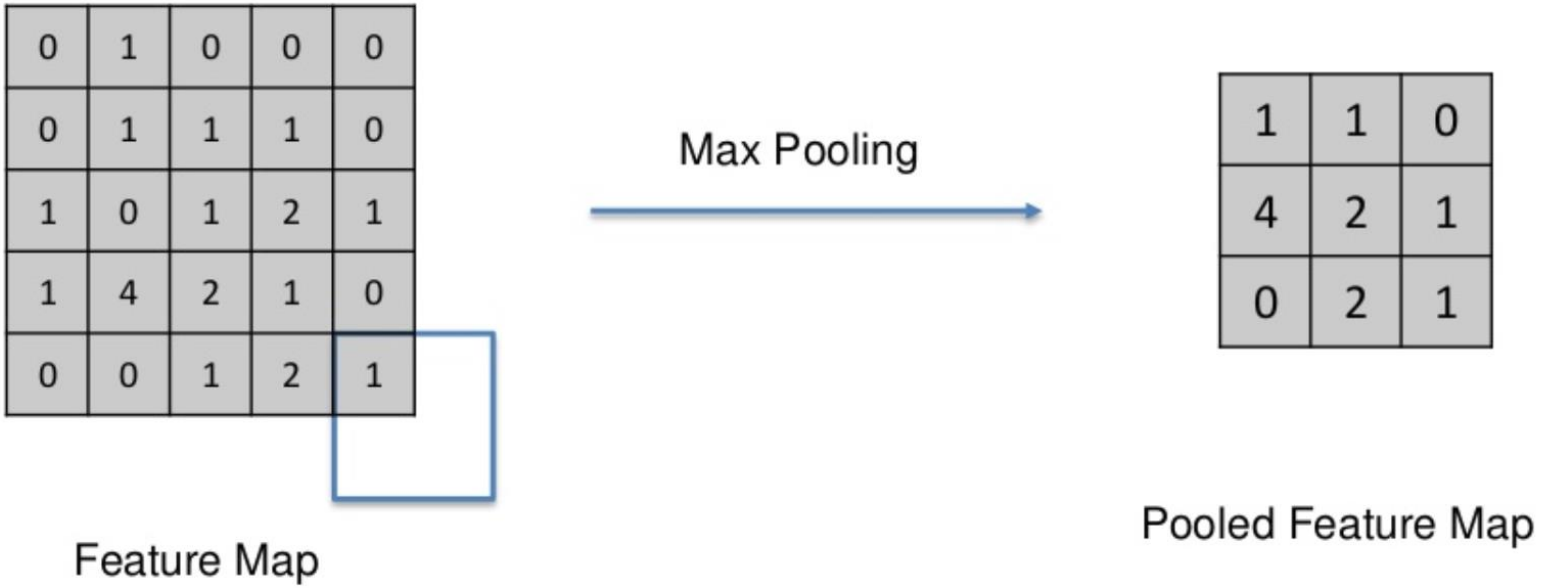
Feature Map

Max Pooling

1	1	0
4	2	1
0	2	

Pooled Feature Map

CNN : Step 2 – Max Pooling



CNN : Step 2 – Max Pooling

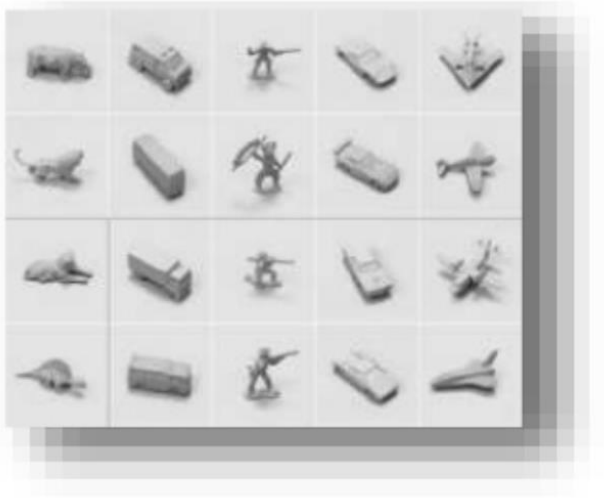
Additional Reading:

Evaluation of Pooling Operations in Convolutional Architectures for Object Recognition

By Dominik Scherer et al. (2010)

Link:

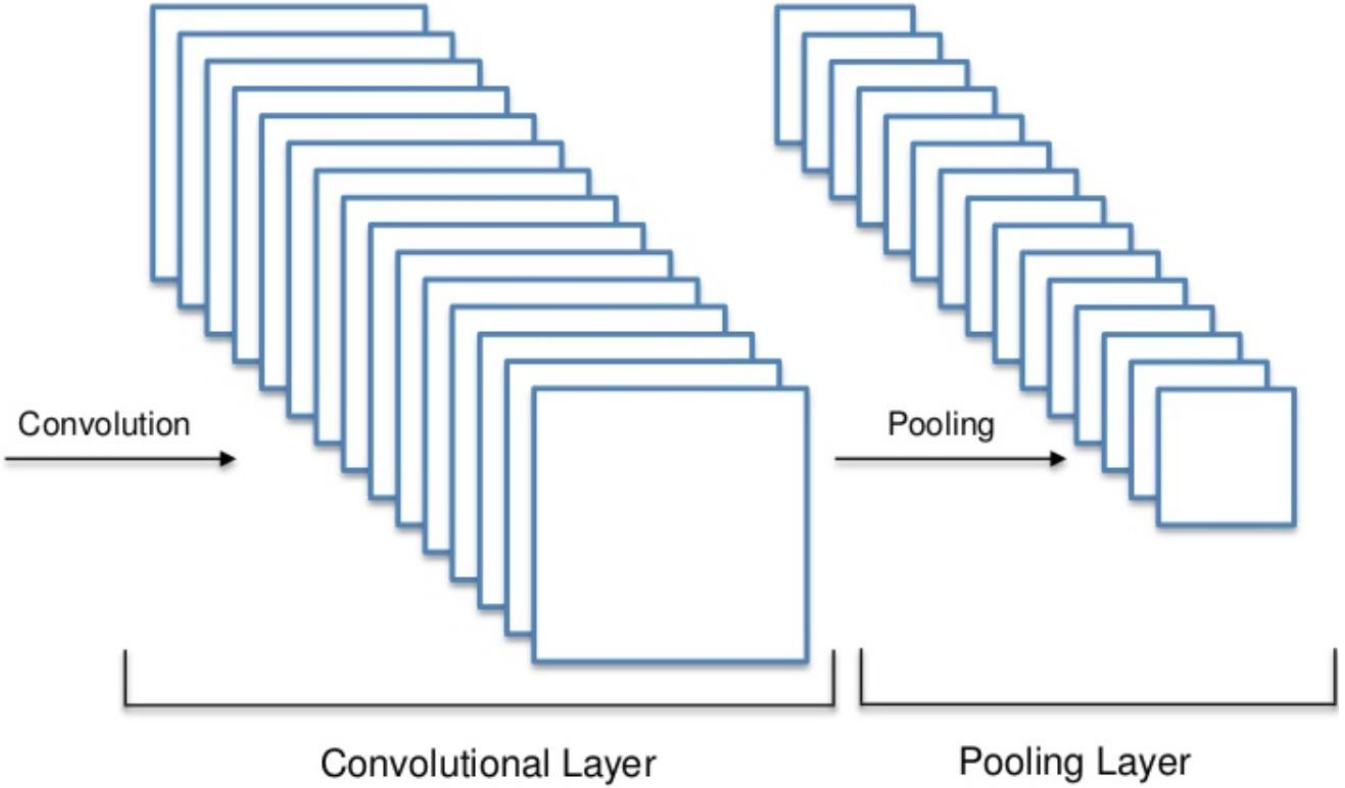
http://ais.uni-bonn.de/papers/icann2010_maxpool.pdf



CNN : 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



CNN : Step 2 – Max Pooling

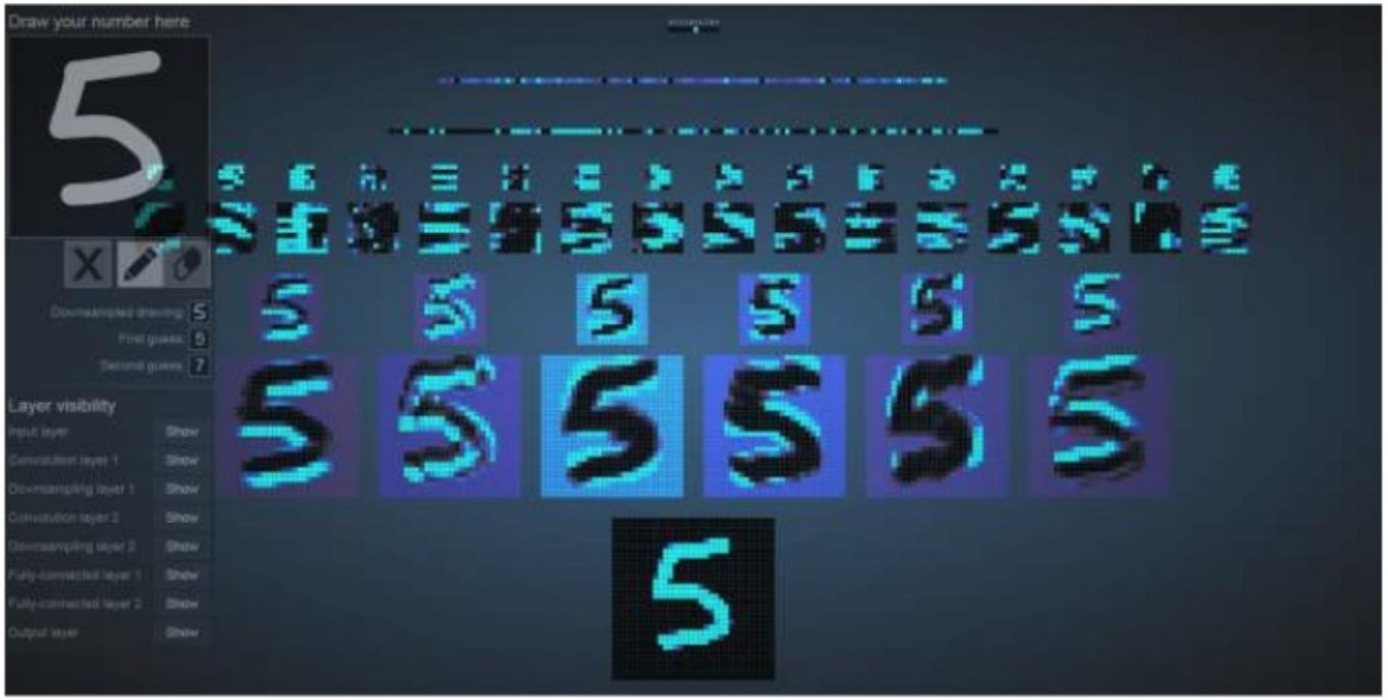


Image Source: scs.ryerson.ca/~aharley/vis/conv/flat.html

Step 3 – Flattening

CNN : Step 3 – Flatterning

1	1	0
4	2	1
0	2	1

Pooled Feature Map

CNN : Step 3 – Flatterning

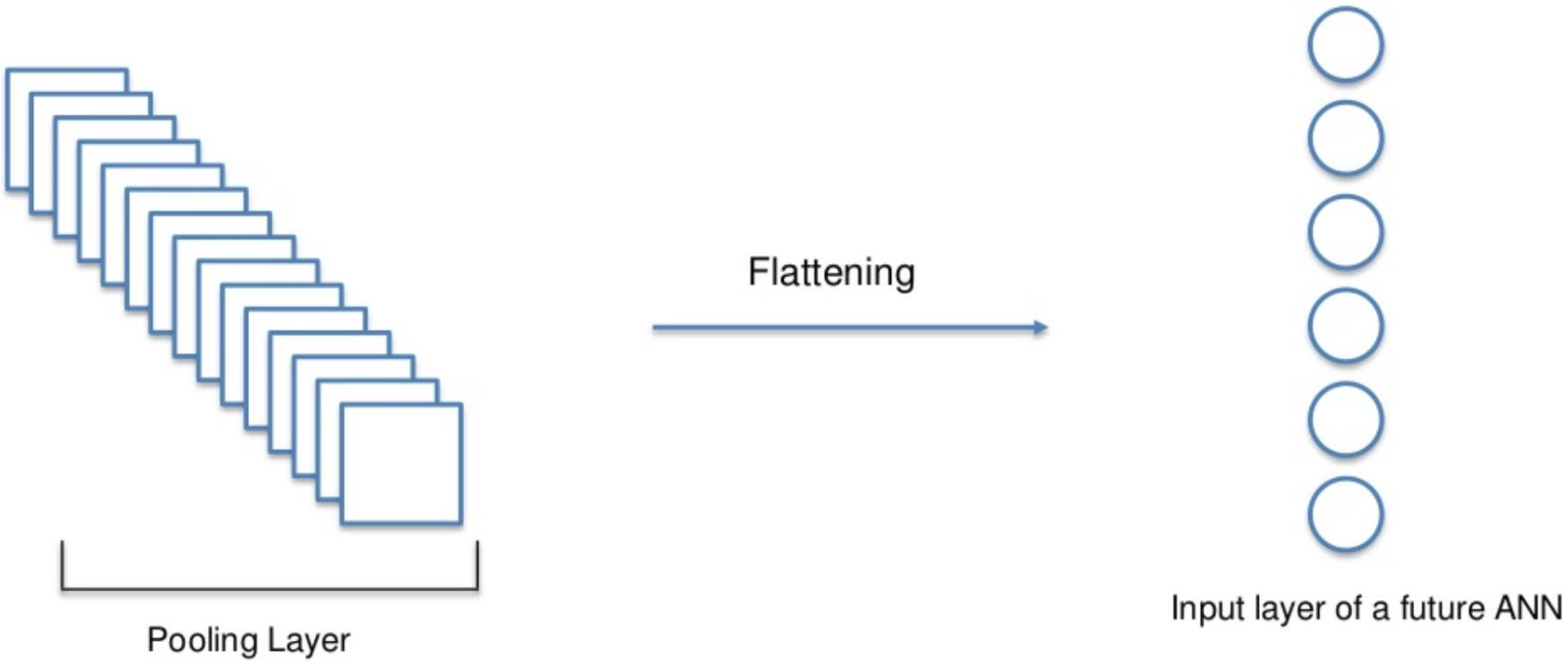
1	1	0
4	2	1
0	2	1

Pooled Feature Map

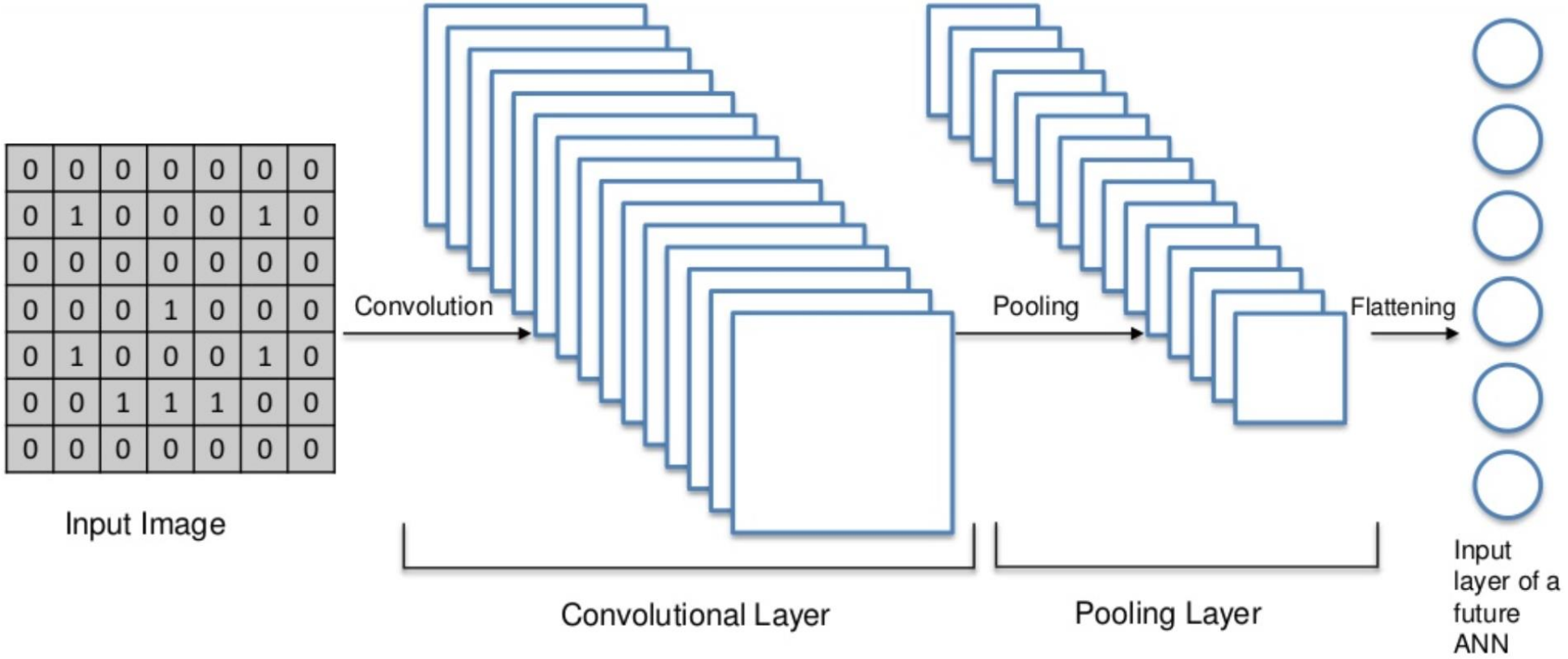
Flattening

1
1
0
4
2
1
0
2
1

CNN : Step 3 – Flatterning

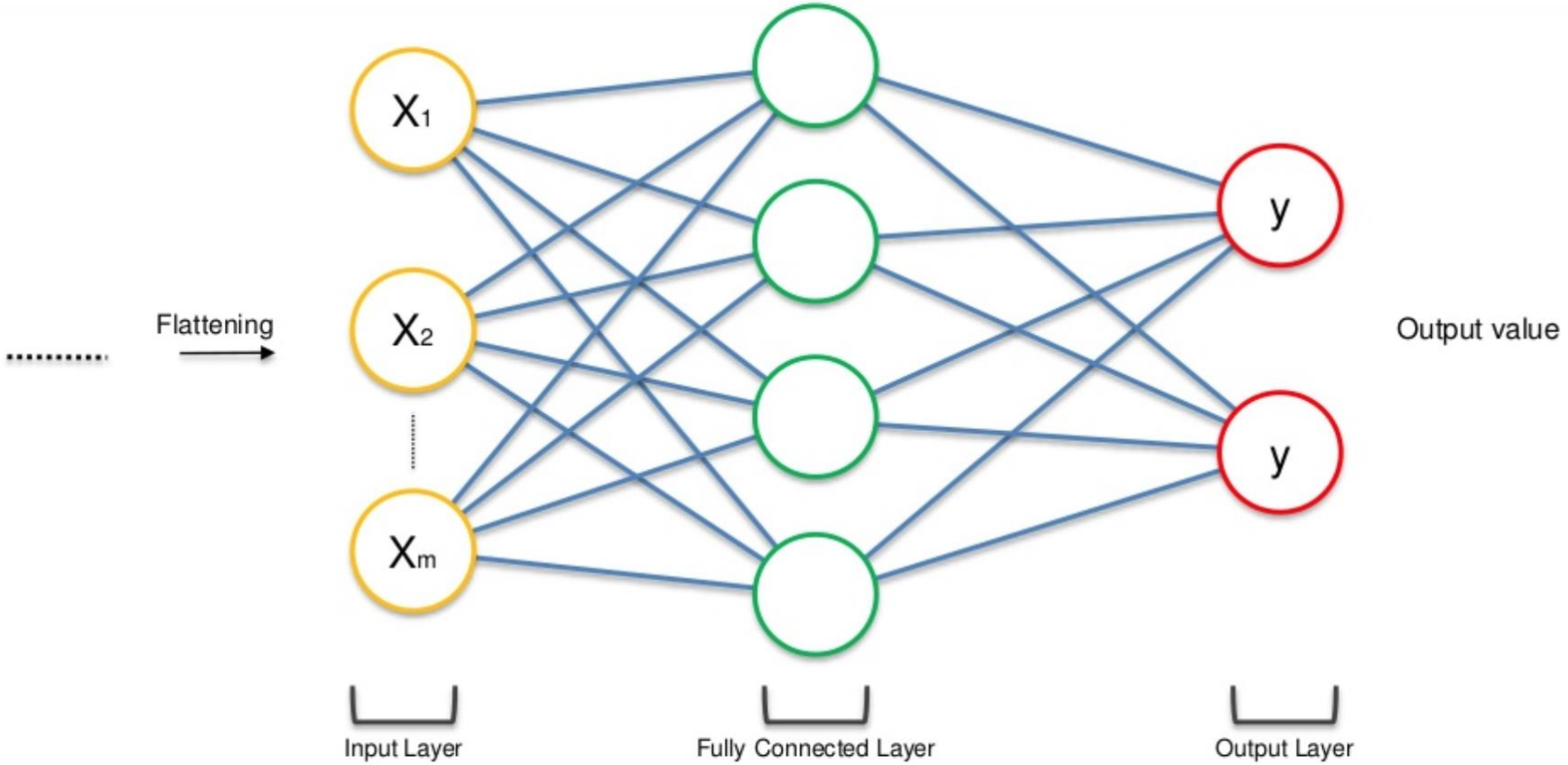


CNN : Step 3 – Flatterning

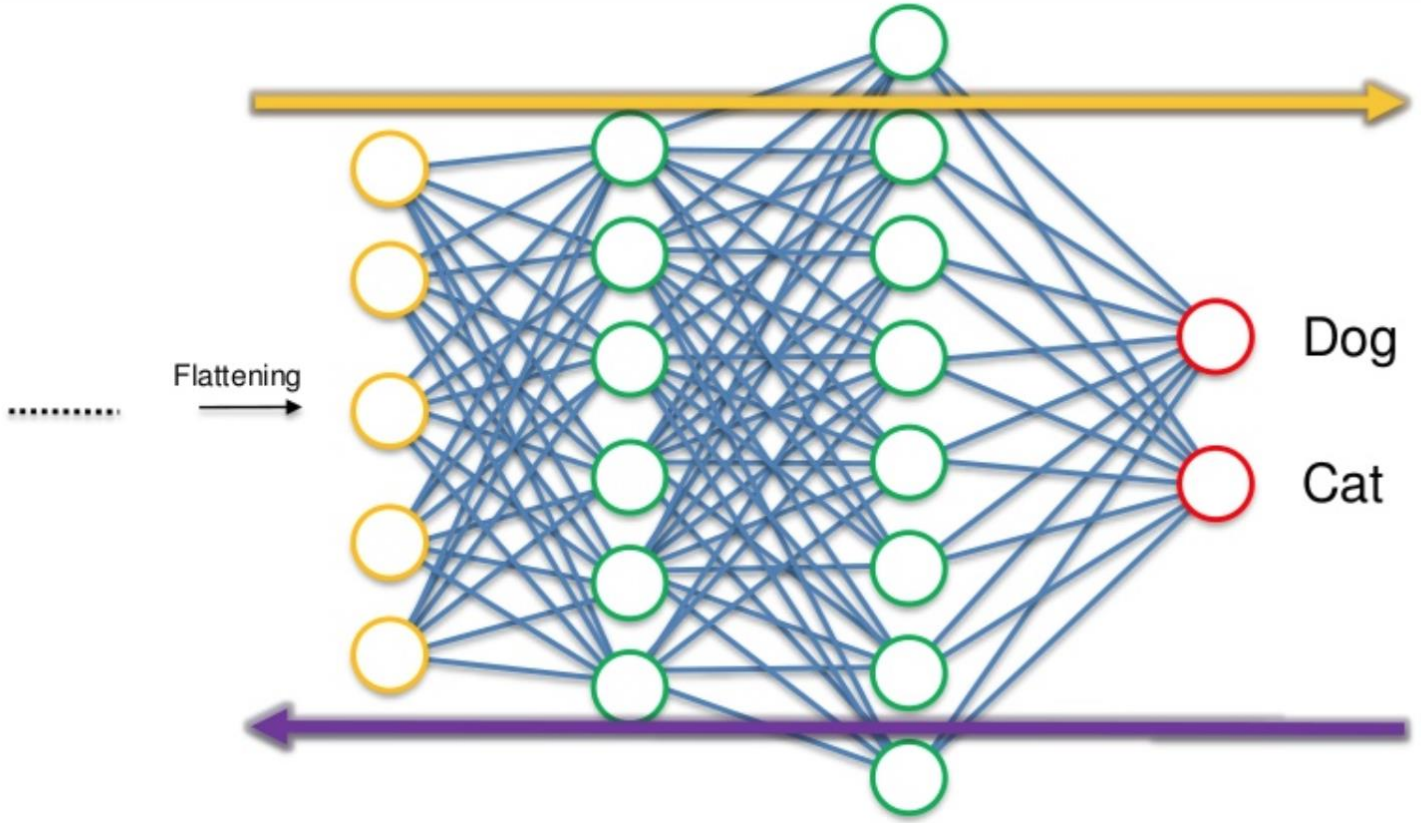


Step 4 – Full Connection

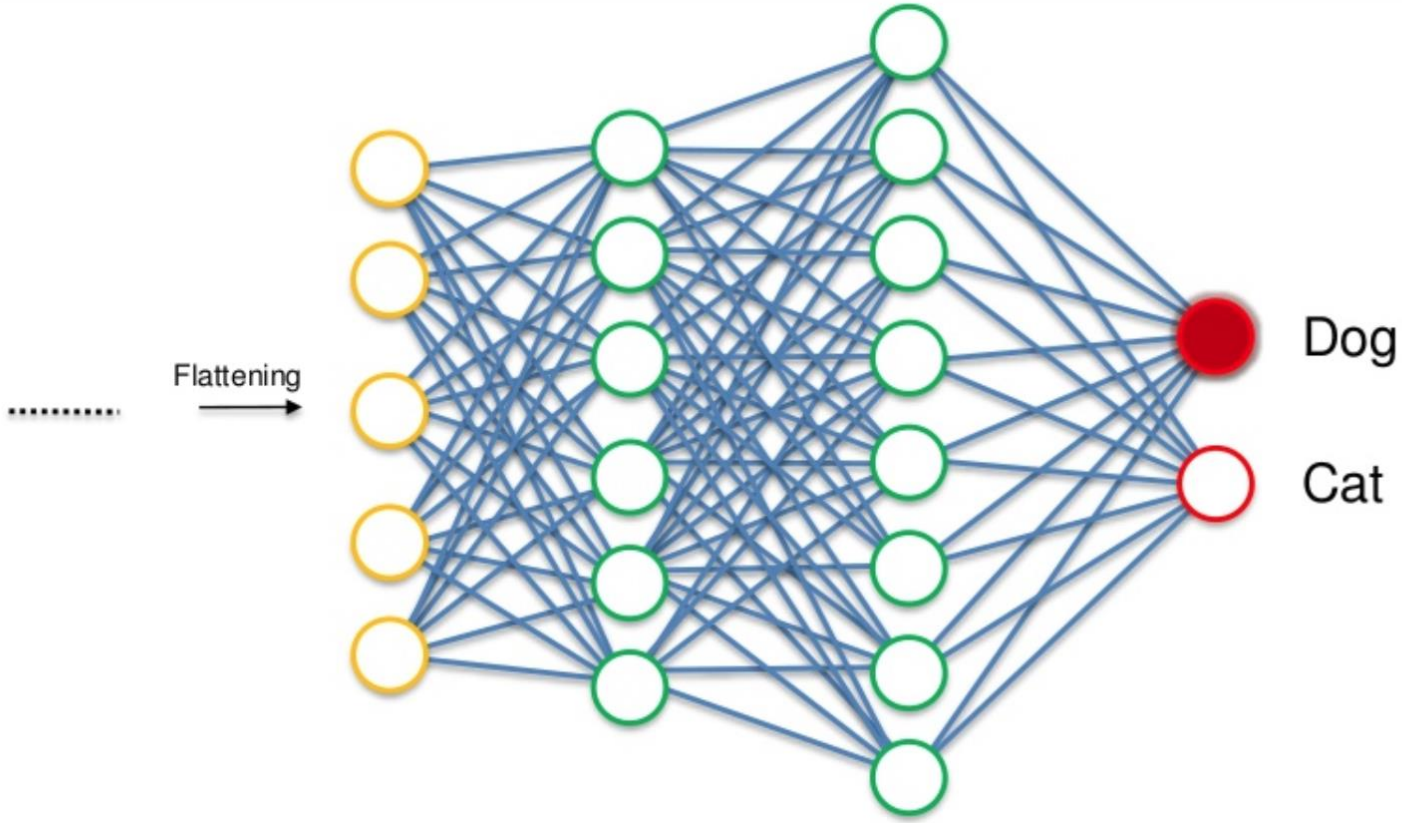
CNN : Step 4 – Full Connection



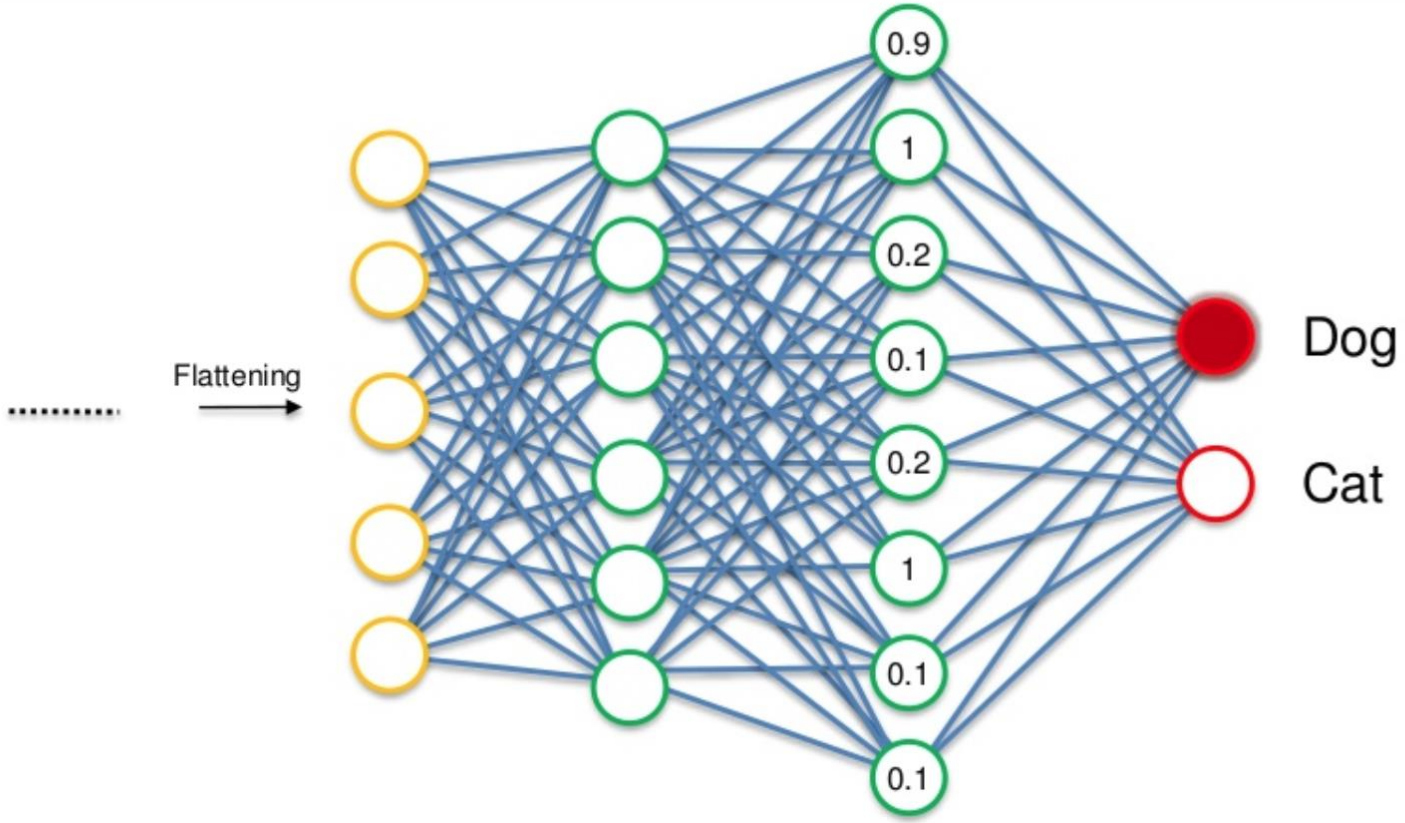
CNN : Step 4 – Full Connection



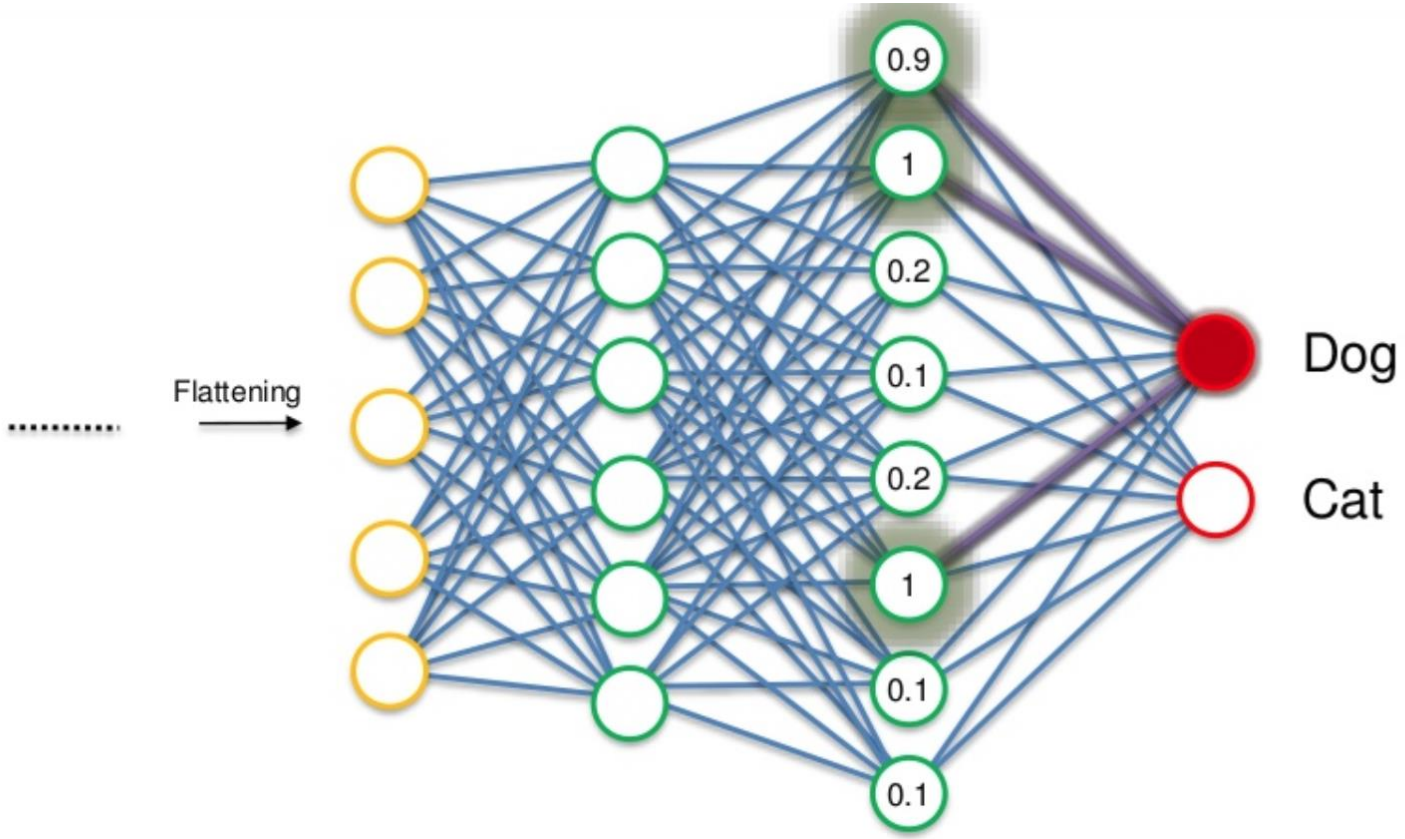
CNN : Step 4 – Full Connection



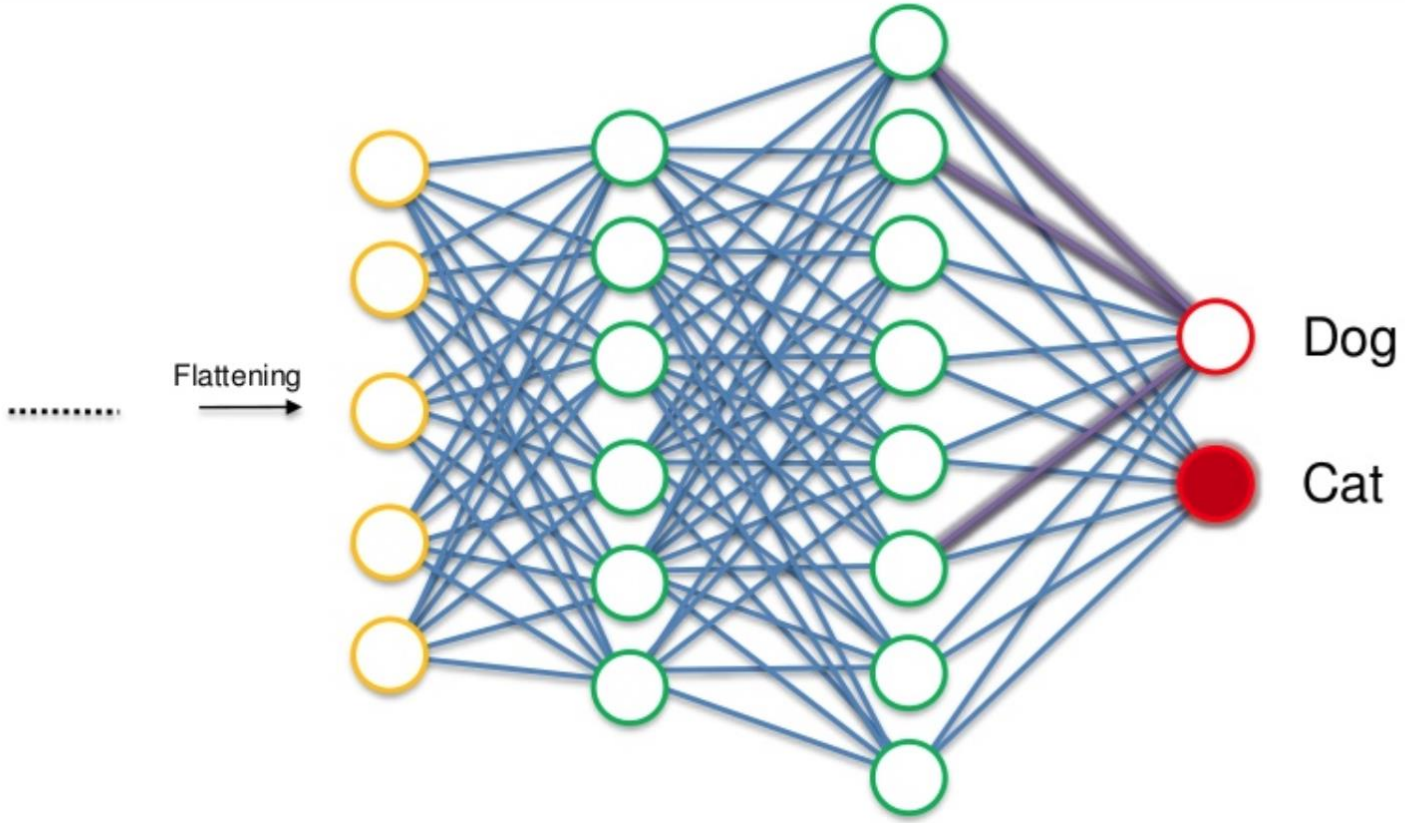
CNN : Step 4 – Full Connection



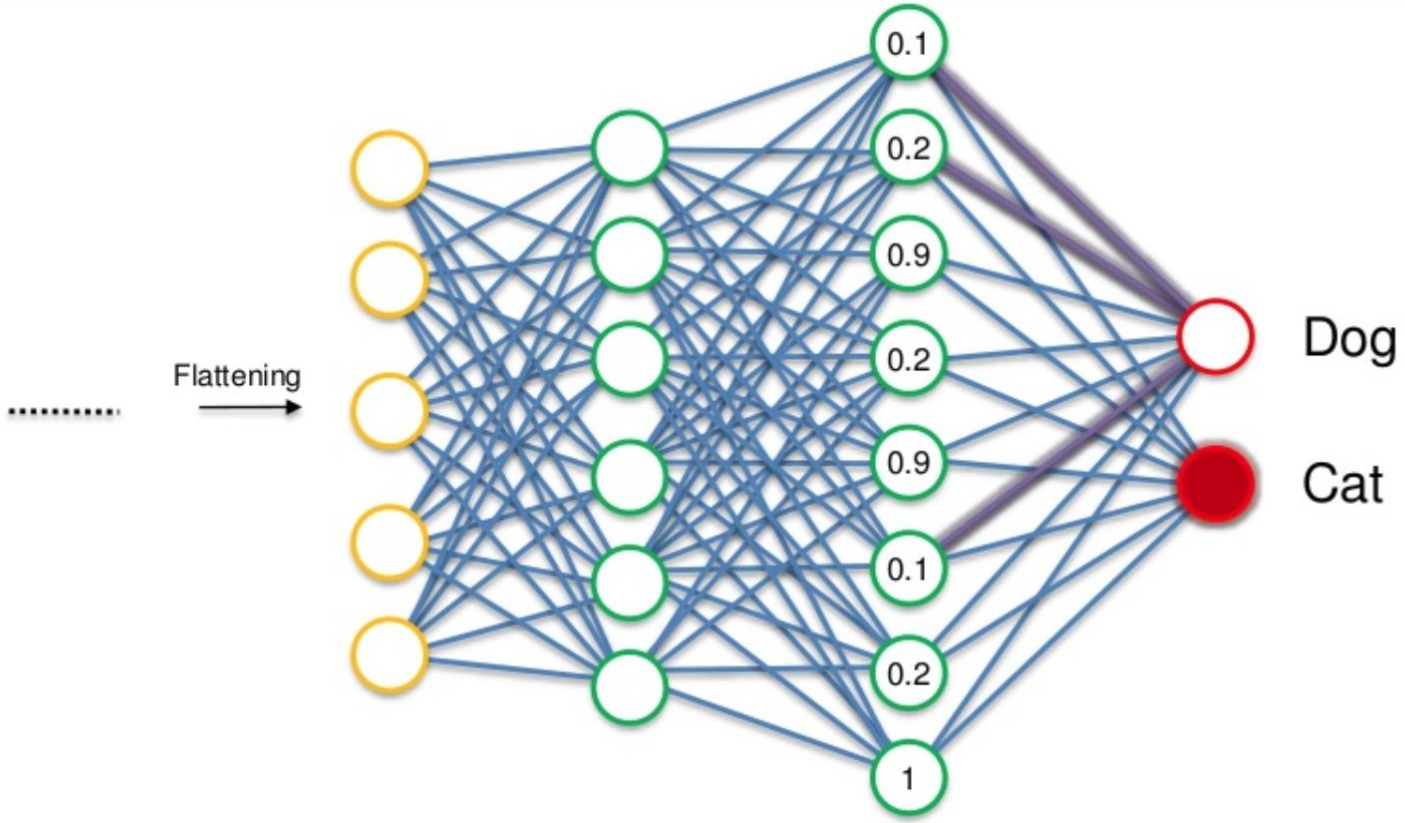
CNN : Step 4 – Full Connection



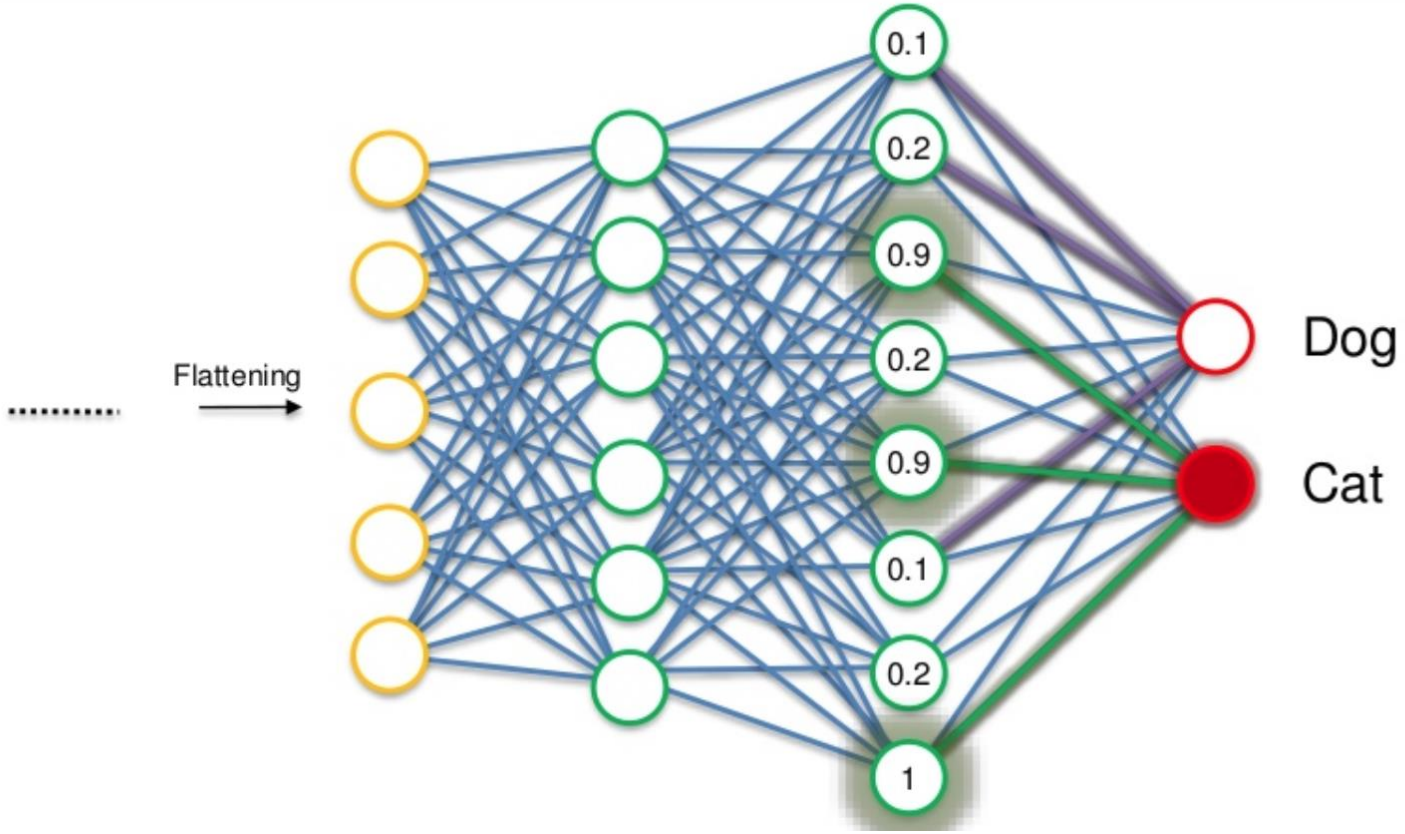
CNN : Step 4 – Full Connection



CNN : Step 4 – Full Connection

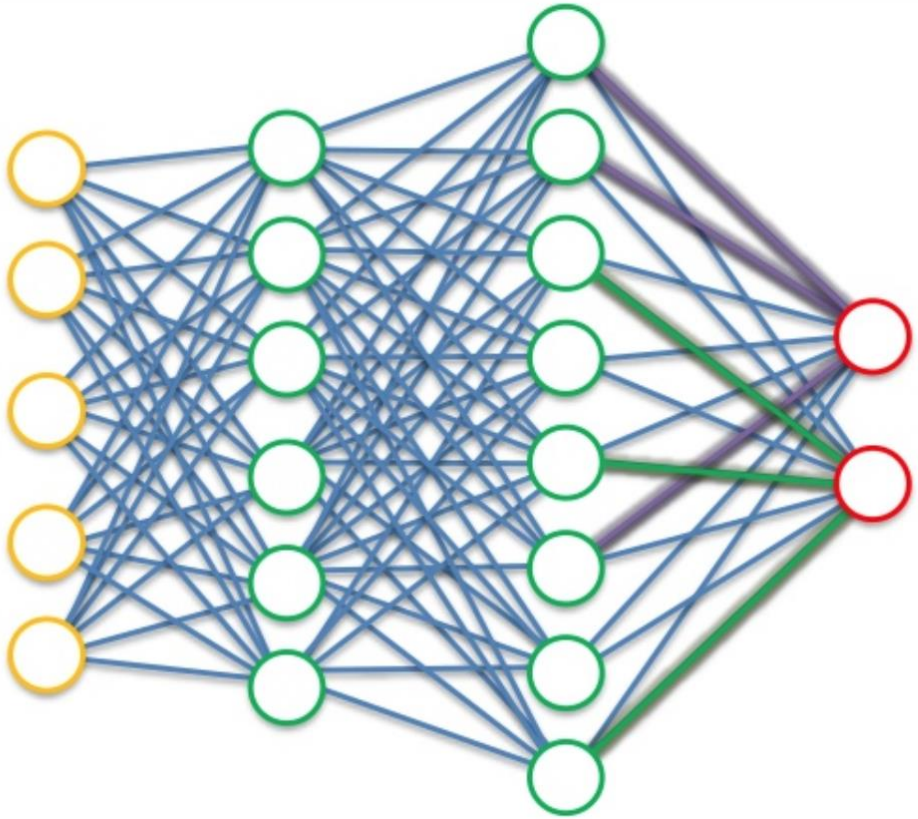


CNN : Step 4 – Full Connection



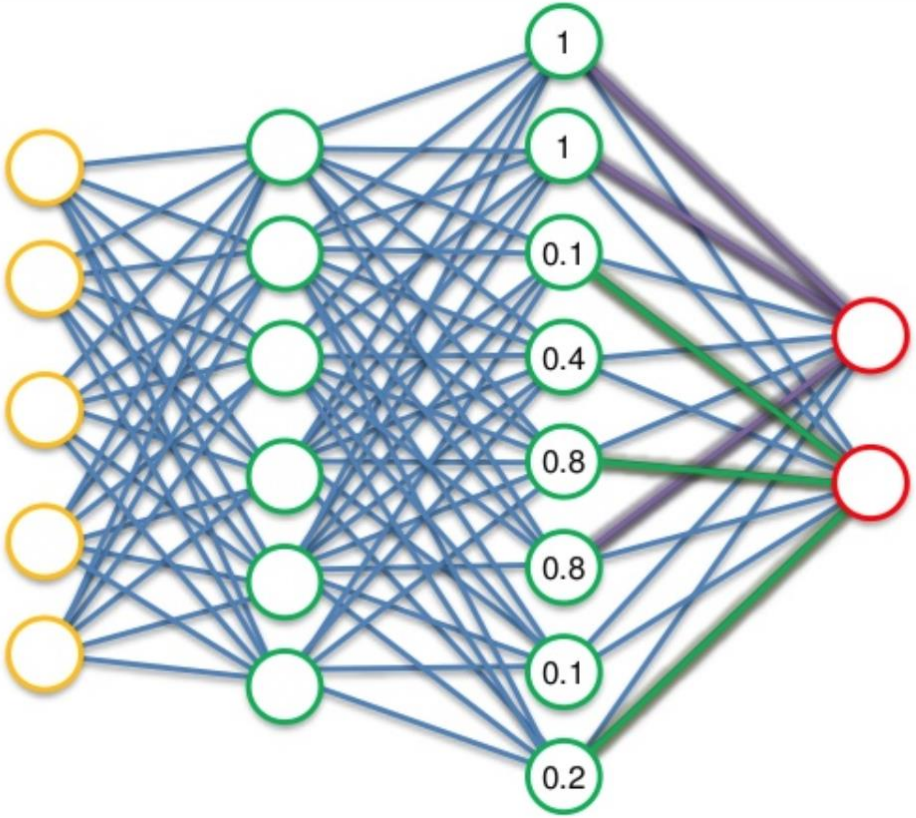
CNN : Step 4 – Full Connection

Flattening



CNN : Step 4 – Full Connection

Flattening

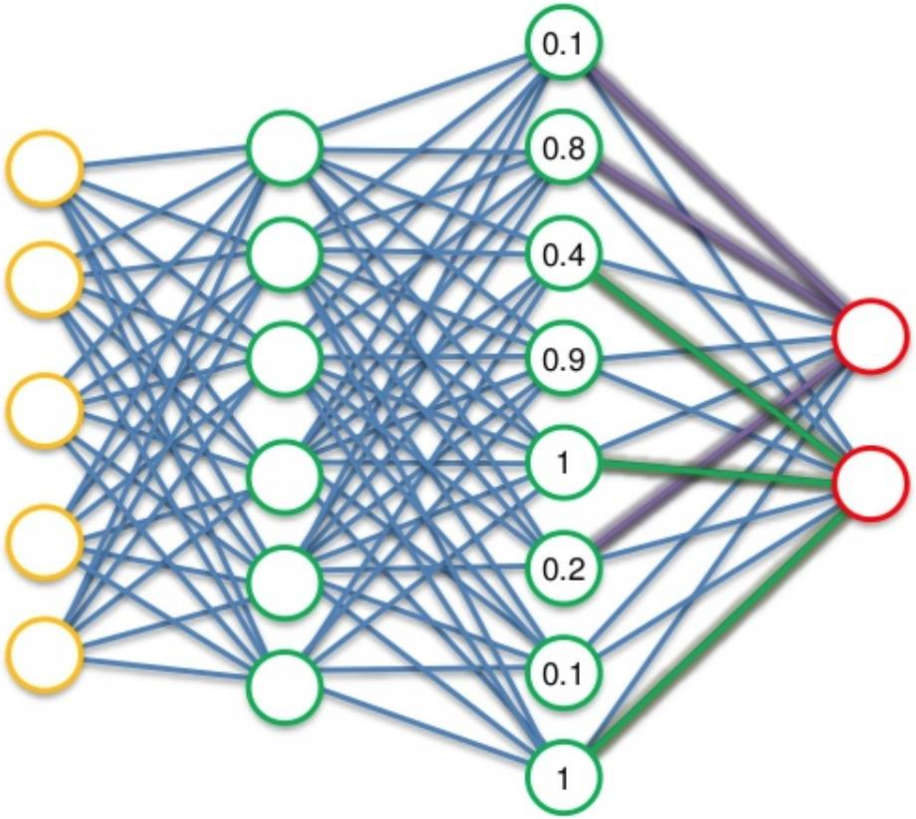


Dog 0.95

Cat 0.05

CNN : Step 4 – Full Connection

Flattening



Dog 0.21

Cat 0.79

CNN : Step 4 – Full Connection

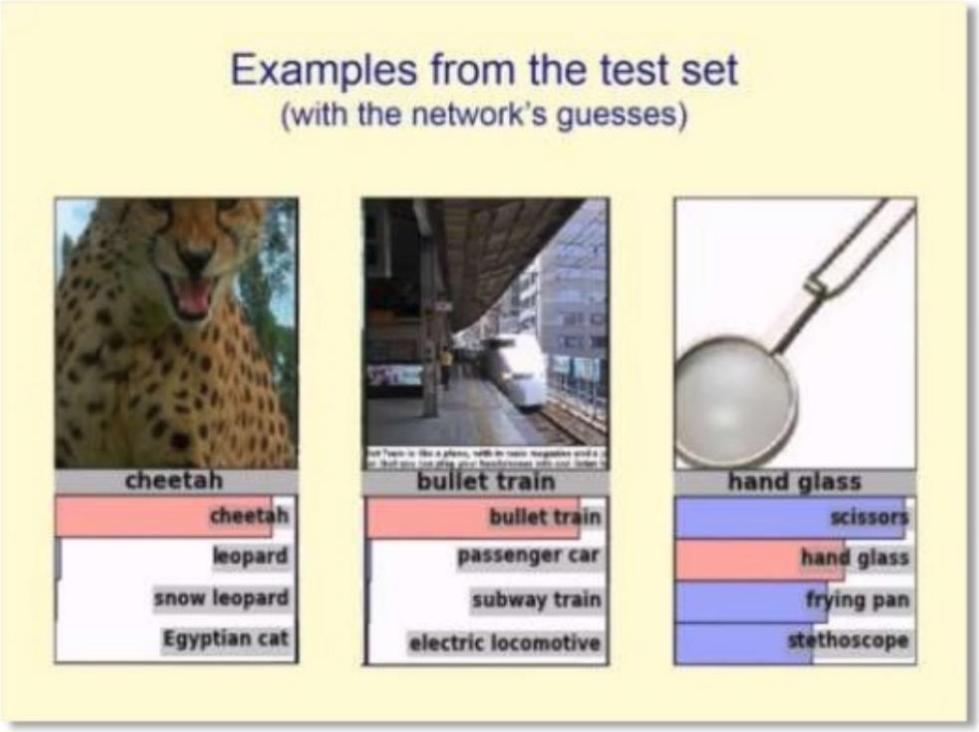
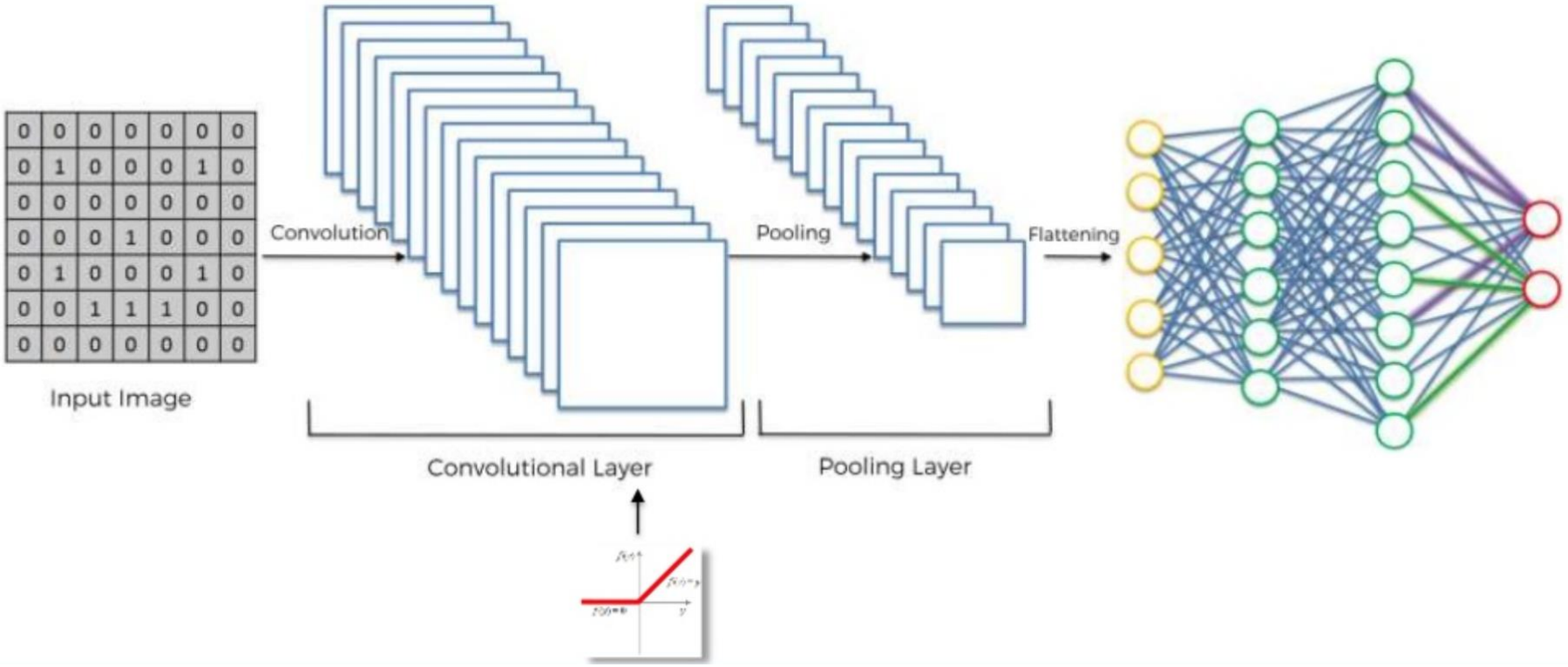


Image Source: a talk by Geoffrey Hinton

Summary

Summary

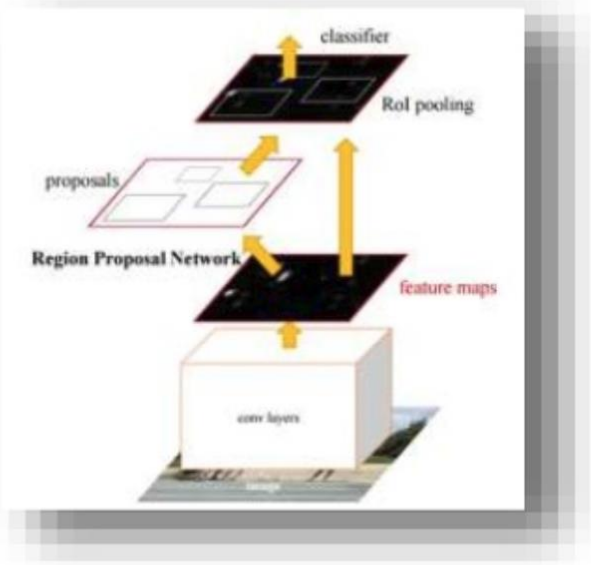

0 0 0 0 0 0 0
0 1 0 0 0 1 0
0 0 0 0 0 0 0
0 0 0 1 0 0 0
0 1 0 0 0 1 0
0 0 1 1 1 0 0
0 0 0 0 0 0 0
Input Image
Convolution
Pooling
Flattening
Convolutional Layer
Pooling Layer

Summary

Additional Reading:

The 9 Deep Learning Papers You Need To Know About (Understanding CNNs Part 3)

Adit Deshpande (2016)



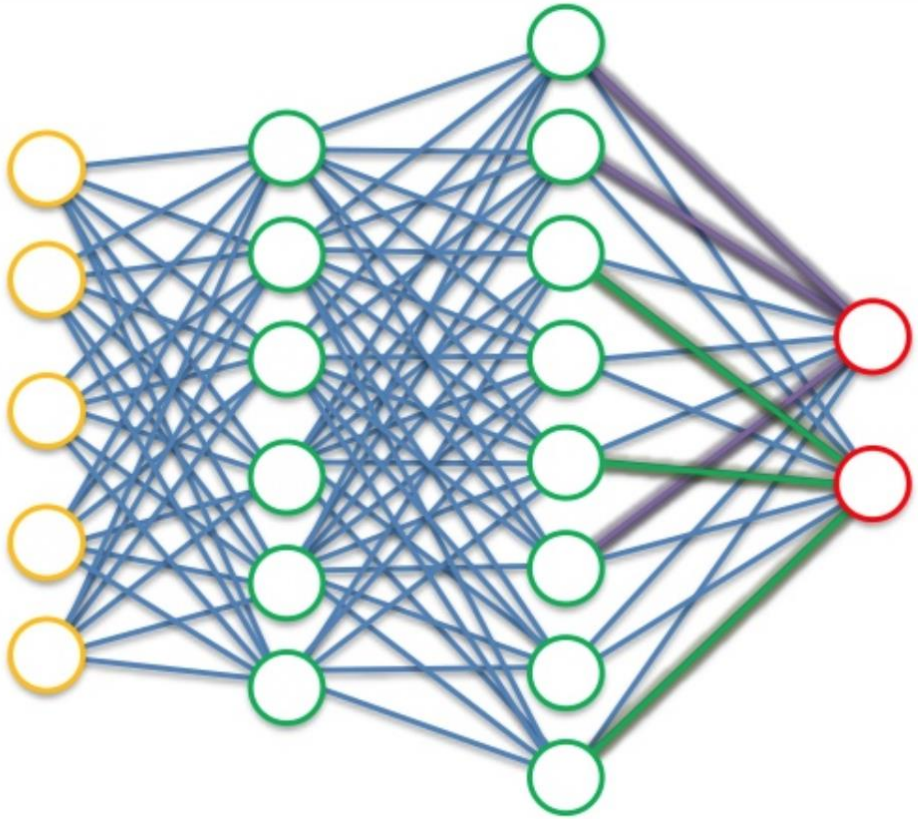
Link:

https://adeshpande3.github.io/adeshpande3.github.io/The-9-Deep-Learning-Papers-You-Need-To-Know-About.html

Softmax & Cross-Entropy

Softmax & Cross-Entropy

Flattening

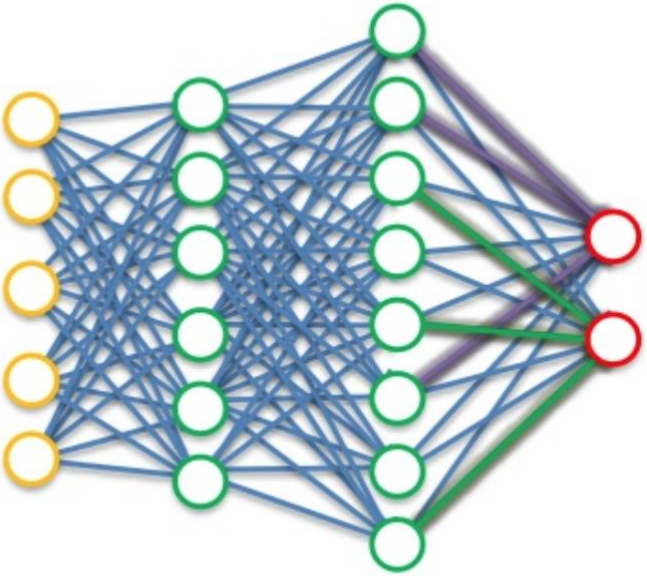


Dog 0.95

Cat 0.05

Softmax & Cross-Entropy

Flattening



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

Dog → z_1 → 0.95

Cat → z_2 → 0.05

Softmax & Cross-Entropy

$$L_i = -\log\left(\frac{e^{f_{y_i}}}{\sum_j e^{f_j}}\right)$$

$$H(p,q) = -\sum_x p(x)\ \log q(x)$$

Softmax & Cross-Entropy

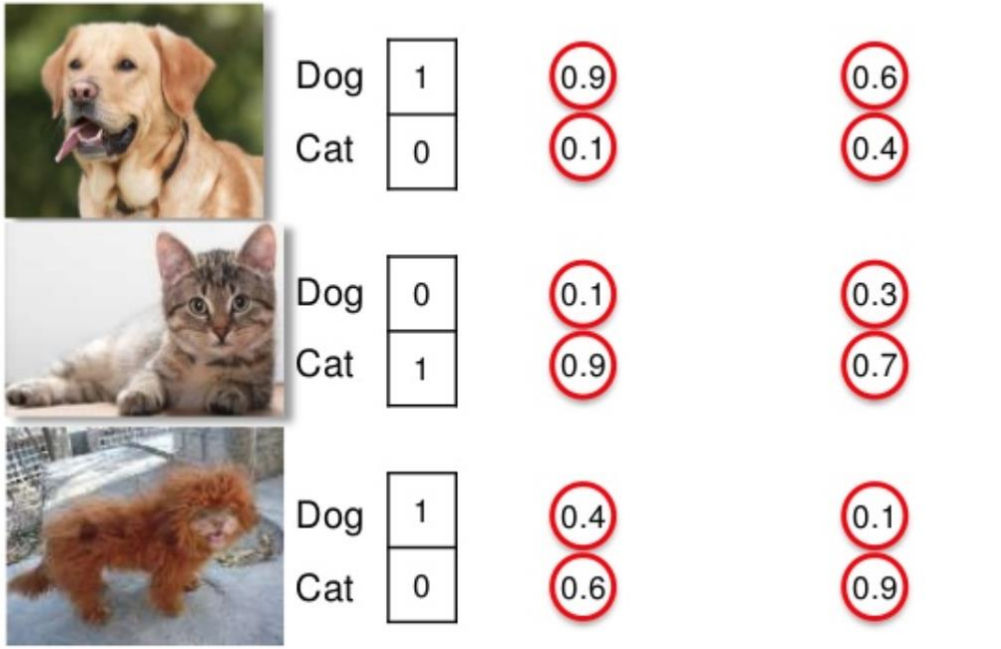
Dog 0.9

Cat 0.1

$$H(p,q) = -\sum_{x} p(x) \log q(x)$$

1
0

Softmax & Cross-Entropy



Softmax & Cross-Entropy

NN1

Row	Dog^	Cat^	Dog	Cat
#1	0.9	0.1	1	0
#2	0.1	0.9	0	1
#3	0.4	0.6	1	0

NN2

Row	Dog^	Cat^	Dog	Cat
#1	0.6	0.4	1	0
#2	0.3	0.7	0	1
#3	0.1	0.9	1	0

Classification Error

1/3 = 0.33 | 1/3 = 0.33

Mean Squared Error

0.25 | 0.71

Cross-Entropy

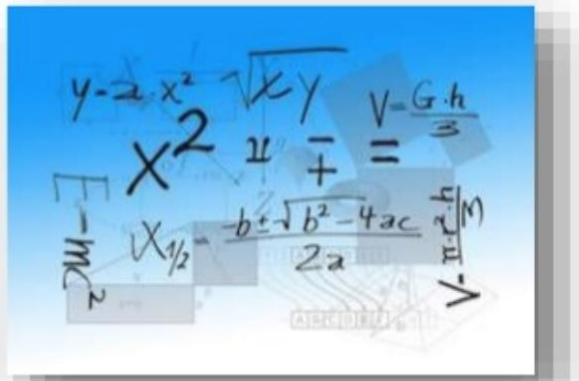
0.38 | 1.06

Softmax & Cross-Entropy

Additional Reading:

A Friendly Introduction to Cross-Entropy Loss

By Rob DiPietro (2016)



Link:

https://rdipietro.github.io/friendly-intro-to-cross-entropy-loss/

Summary

Additional Reading:

How to implement a neural network Intermezzo 2

By Peter Roelants (2016)

$$
\begin{aligned}
\frac{\partial \xi}{\partial z_i} &= -\sum_{j=1}^{C} \frac{\partial t_j log(y_j)}{\partial z_i} = -\sum_{j=1}^{C} t_j \frac{\partial log(y_j)}{\partial z_i} = -\sum_{j=1}^{C} t_j \frac{1}{y_j} \frac{\partial y_j}{\partial z_i} \\
&= -\frac{t_i}{y_i} \frac{\partial y_i}{\partial z_i} - \sum_{j \neq i}^{C} \frac{t_j}{y_j} \frac{\partial y_j}{\partial z_i} = -\frac{t_i}{y_i} y_i (1 - y_i) - \sum_{j \neq i}^{C} \frac{t_j}{y_j} (-y_j y_i) \\
&= -t_i + t_i y_i + \sum_{j \neq i}^{C} t_j y_i = -t_i + \sum_{j=1}^{C} t_j y_i = -t_i + y_i \sum_{j=1}^{C} t_j \\
&= y_i - t_i
\end{aligned}
$$

Link:

http://peterroelants.github.io/posts/neural_network_implementation_intermezzo02/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수고하셨습니다!