

Step 1 - Convolution

Edge Enhance:

$$\begin{matrix} 0 & 0 & 0 \\ -1 & 1 & 0 \\ 0 & 0 & 0 \end{matrix}$$



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

Step 1 - Convolution

Edge Detect:

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$



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

Step 1 - Convolution

Emboss:

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



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

Step 1 - Convolution



*

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



Image Source: eonardoaraujosantos.gitbooks.io

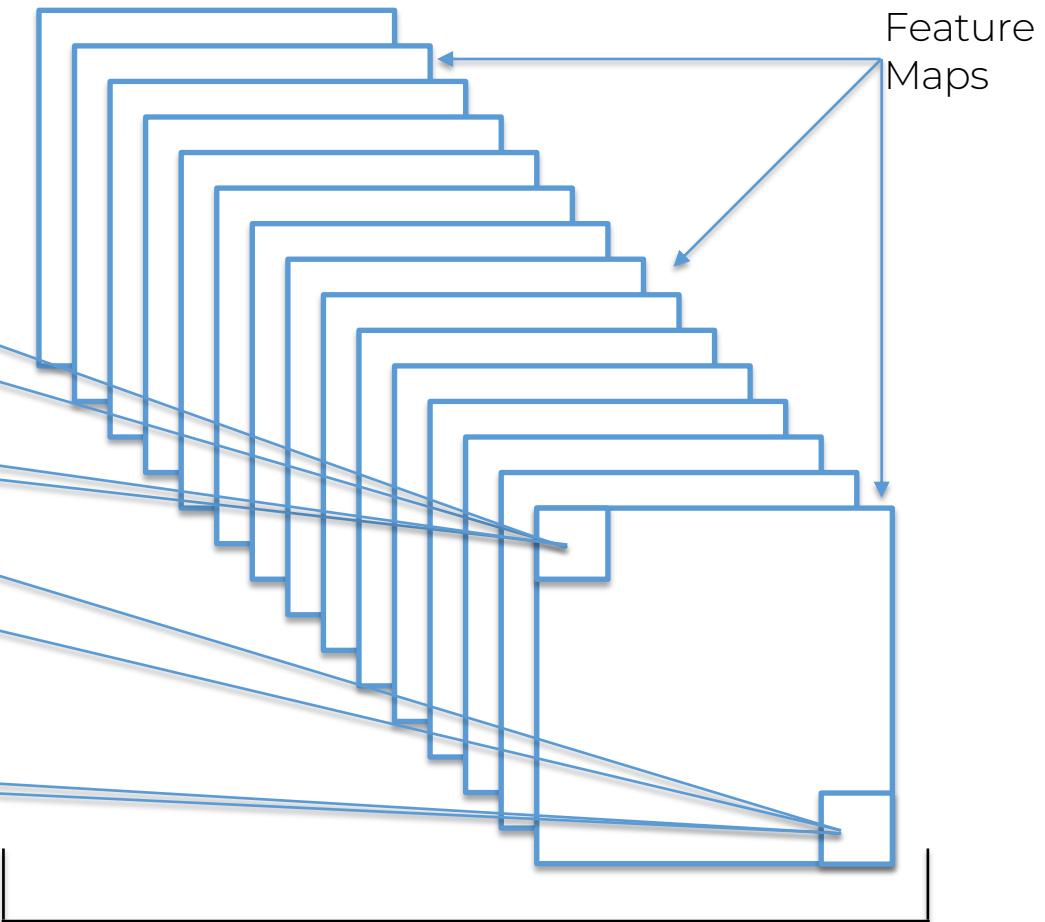
Step 1(B) - ReLU Layer

Step 1(B) – ReLU Layer

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

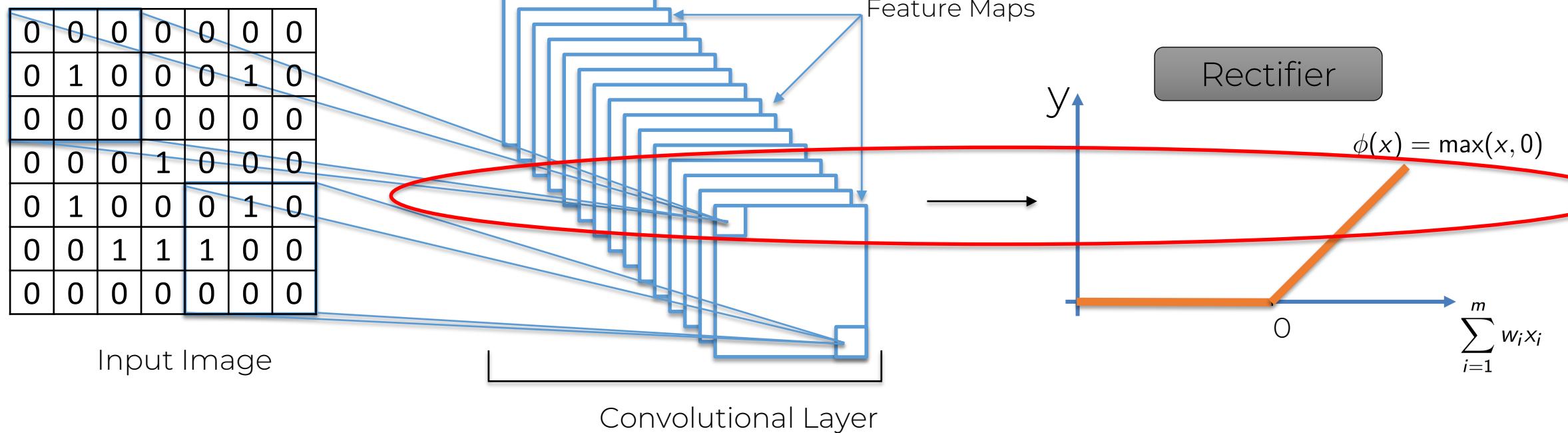
Input Image

We create many feature maps to obtain our first convolution layer



Convolutional
Layer

Step 1(B) – ReLU Layer



Step 1(B) – ReLU Layer



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

Step 1(B) – ReLU Layer



Black = negative; white = positive values

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

Step 1(B) – ReLU Layer



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

Step 1(B) – ReLU Layer

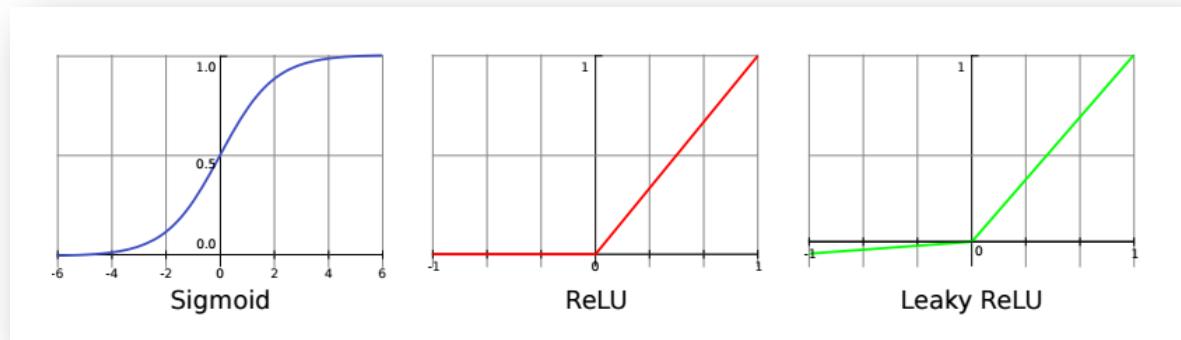
Additional Reading:

*Understanding
Convolutional Neural
Networks with A
Mathematical Model*

By C.-C. Jay Kuo (2016)

Link:

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



Step 1(B) – ReLU Layer

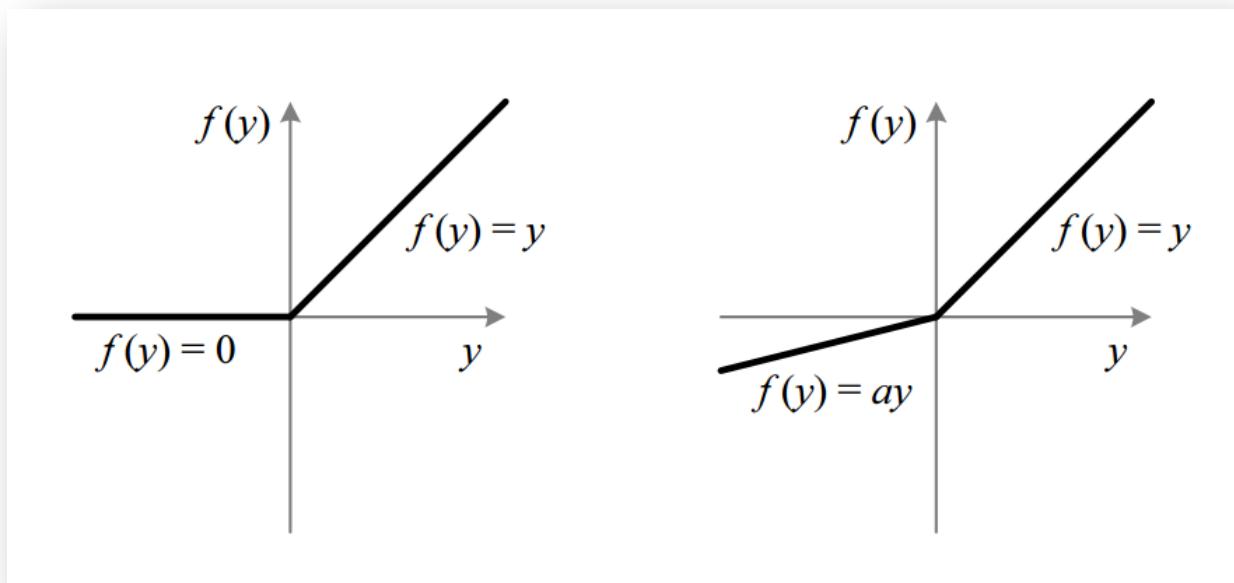
Additional Reading:

*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

Step 2 - Max Pooling



Image Source: Wikipedia

Step 2 - Max Pooling



Image Source: Wikipedia

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

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



Pooled Feature Map

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		

Pooled Feature Map

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	

Pooled Feature Map

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

Pooled Feature Map

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

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	2	

Pooled Feature Map

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

The diagram illustrates the process of Max Pooling. A blue arrow points from the bottom-right cell of the 5x5 Feature Map to the bottom-right cell of the 3x3 Pooled Feature Map. The Feature Map has a stride of 2, indicated by the blue boxes highlighting the receptive fields of the pooled unit at (3,3). The Pooled Feature Map contains the maximum value from each 2x2 pooling window.

1	1	0
4	2	1

Pooled Feature Map

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	2	1
0		

Pooled Feature Map

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	2	1
0	2	

Pooled Feature Map

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	2	1
0	2	1

Pooled Feature Map

Step 2 - Max Pooling

Additional Reading:

Evaluation of Pooling Operations in Convolutional Architectures for Object Recognition

By Dominik Scherer et al. (2010)

Link:

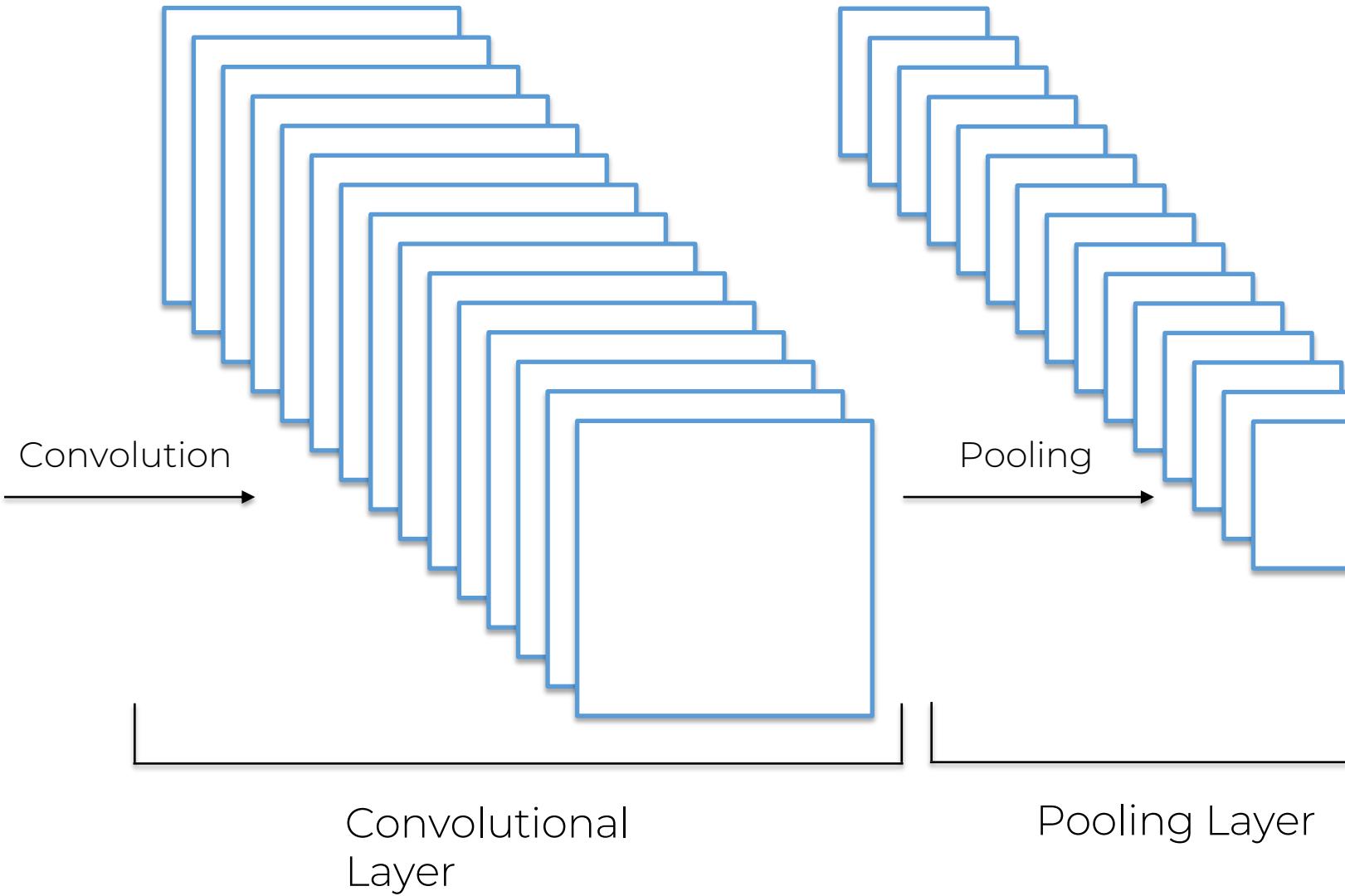
http://ais.uni-bonn.de/papers/icann2010_maxpool.pdf



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



Example

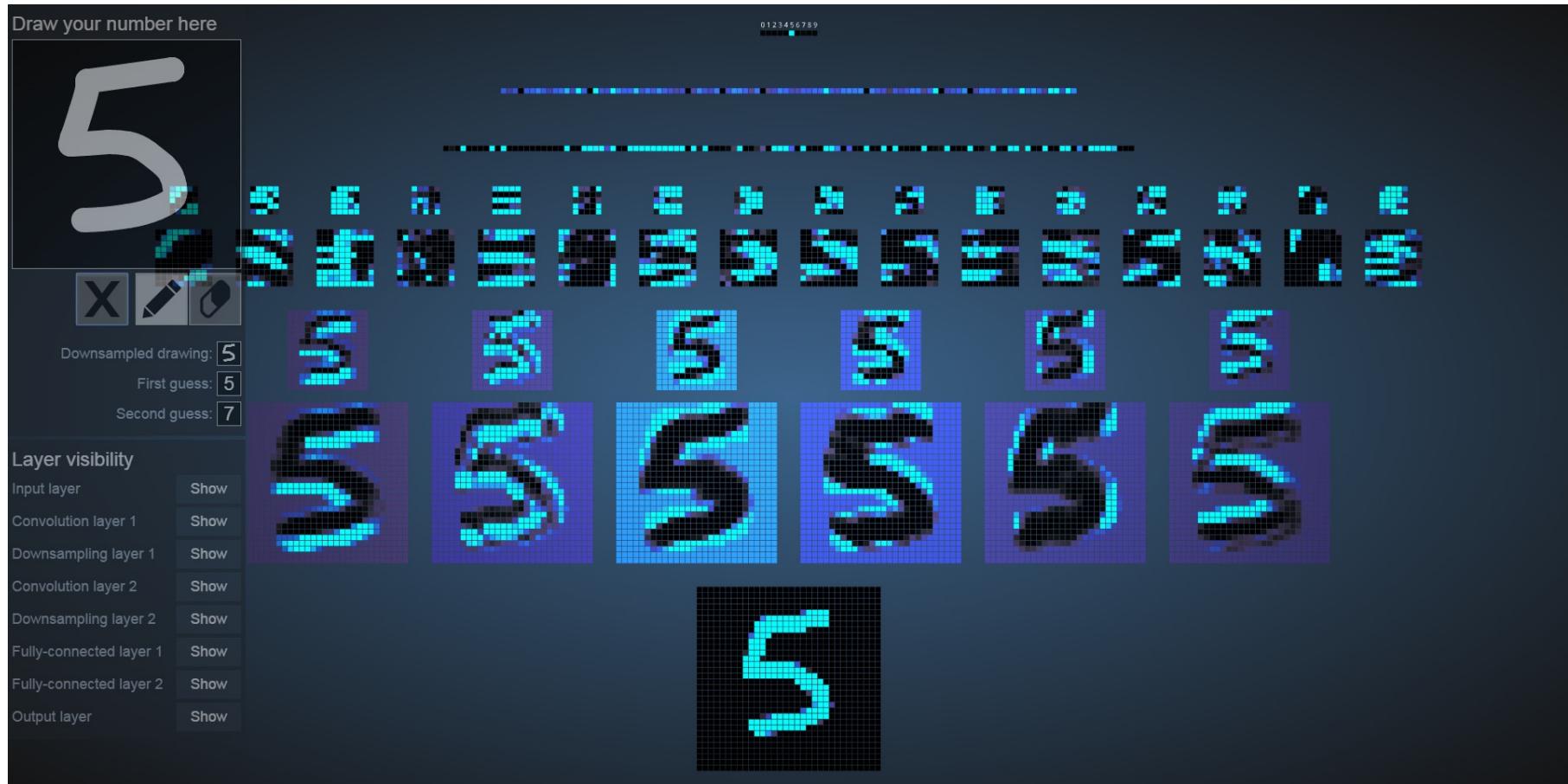


Image Source: scs.ryerson.ca/~aharley/vis/conv/flat.html

Step 3 - Flattening

Step 3 - Flattening

1	1	0
4	2	1
0	2	1

Pooled Feature
Map

Step 3 - Flattening

1	1	0
4	2	1
0	2	1

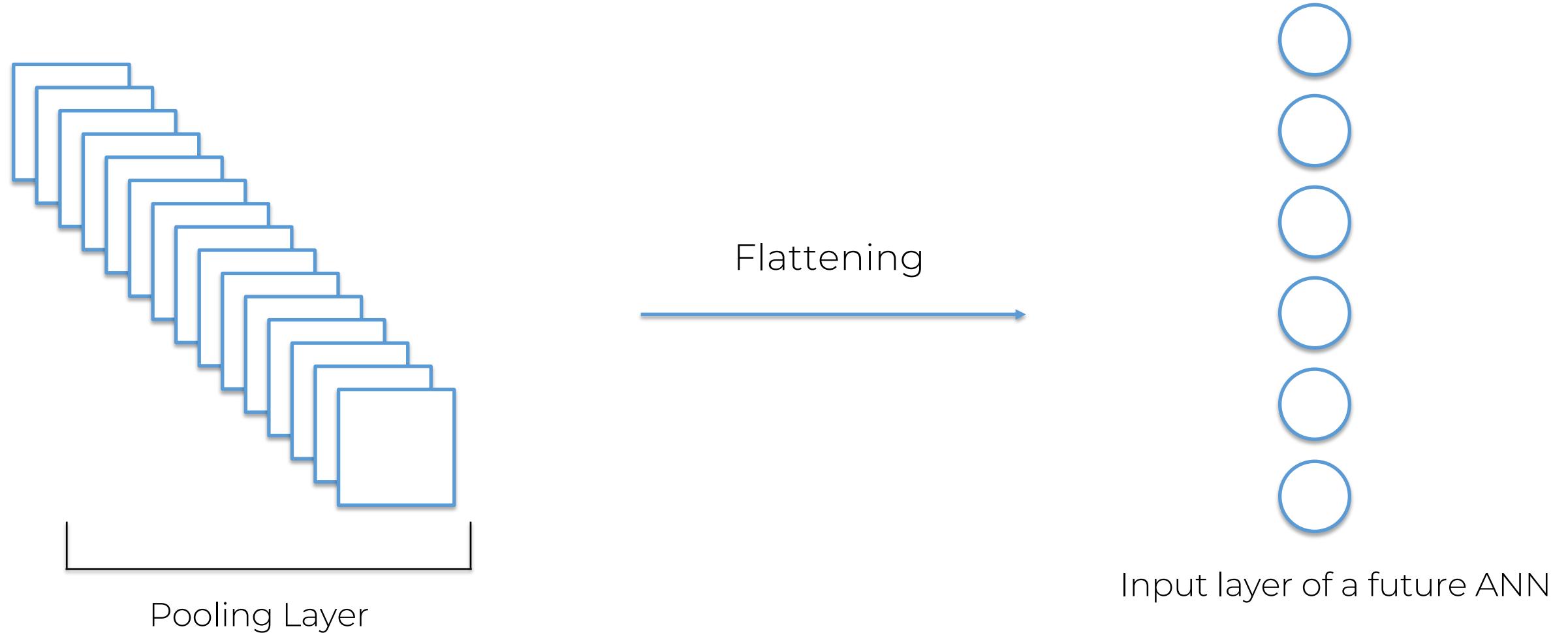
Pooled Feature
Map

Flattening



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

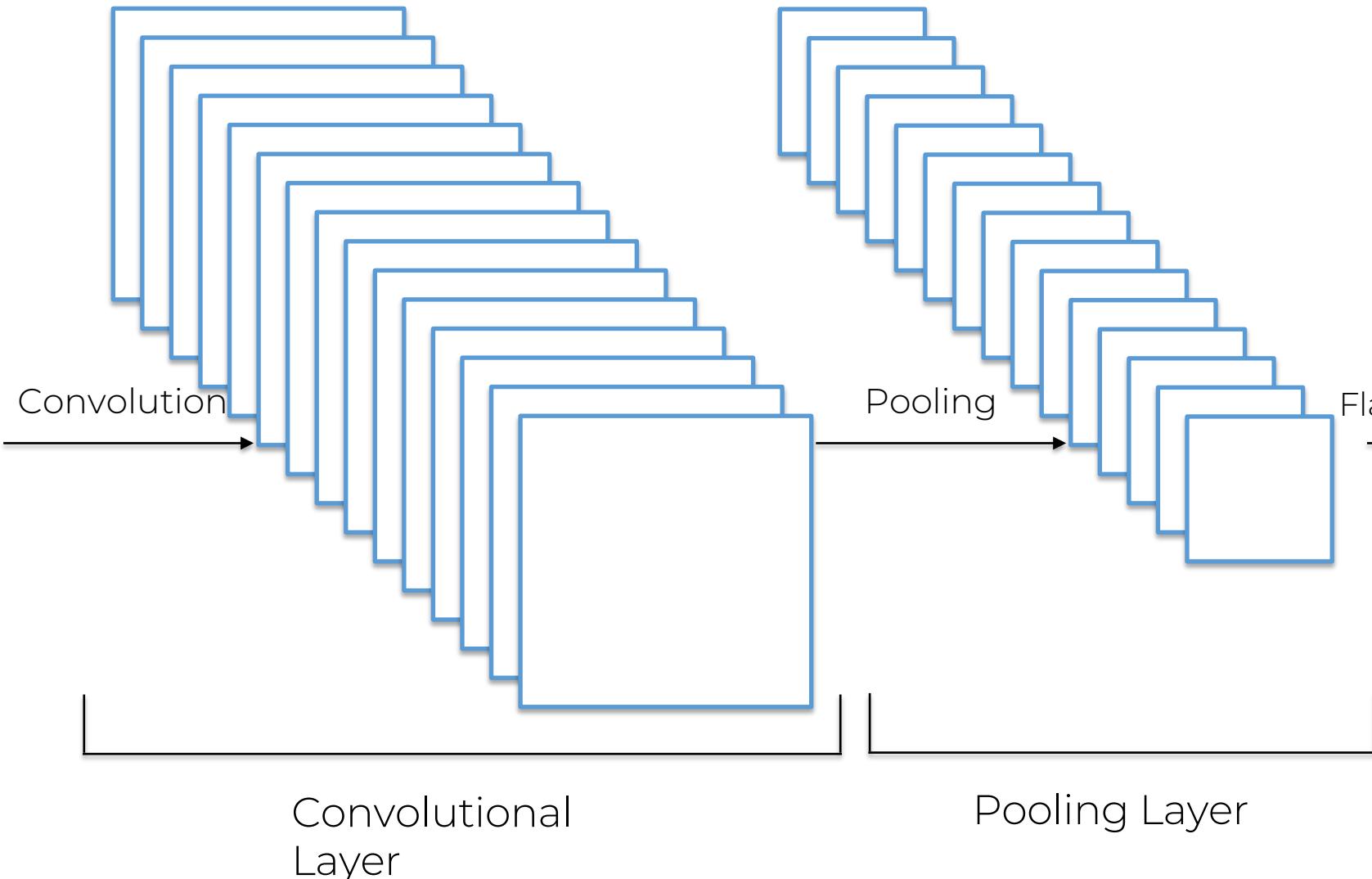
Step 3 - Flattening



Step 3 - Flattening

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

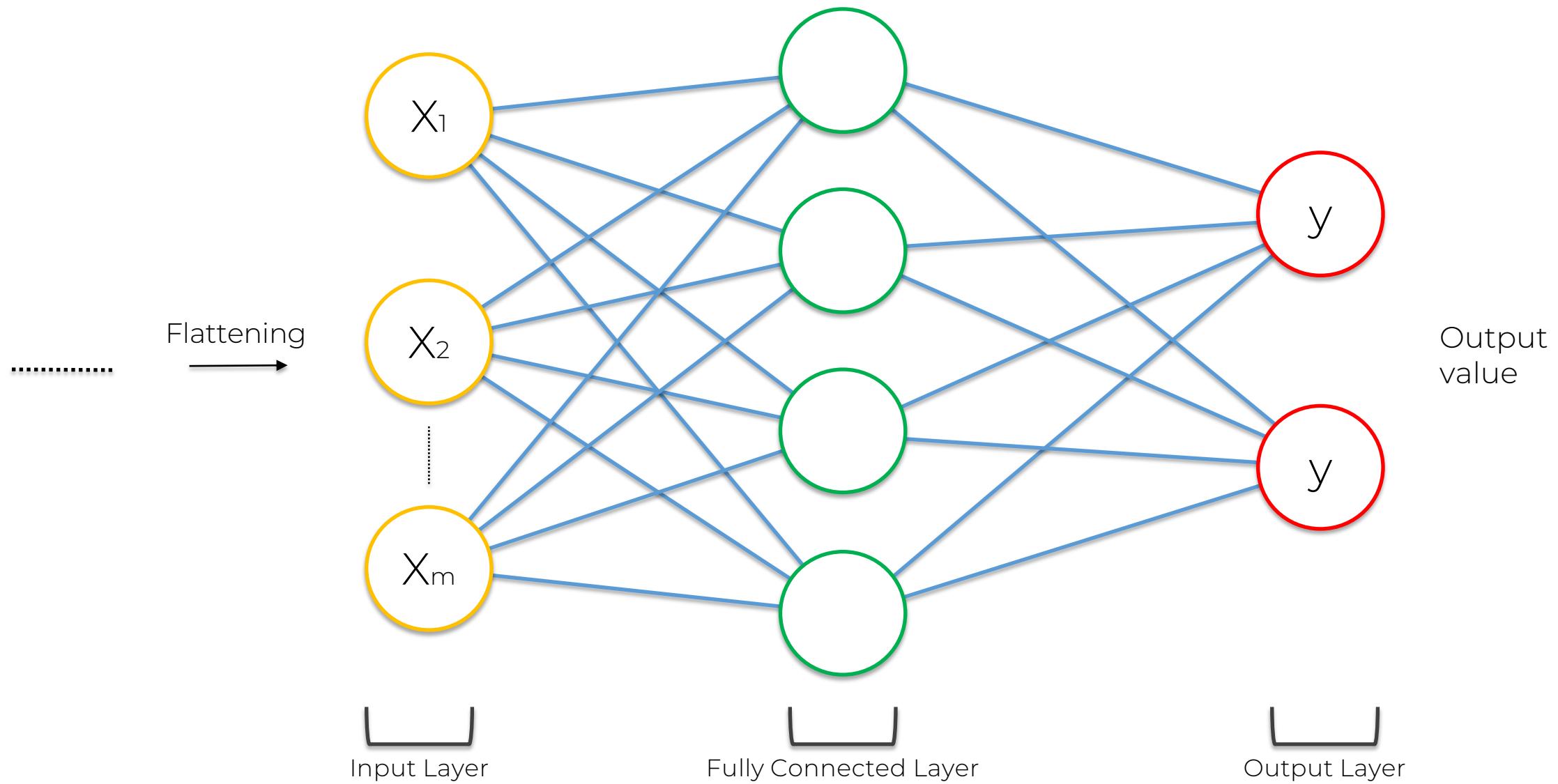
Input Image



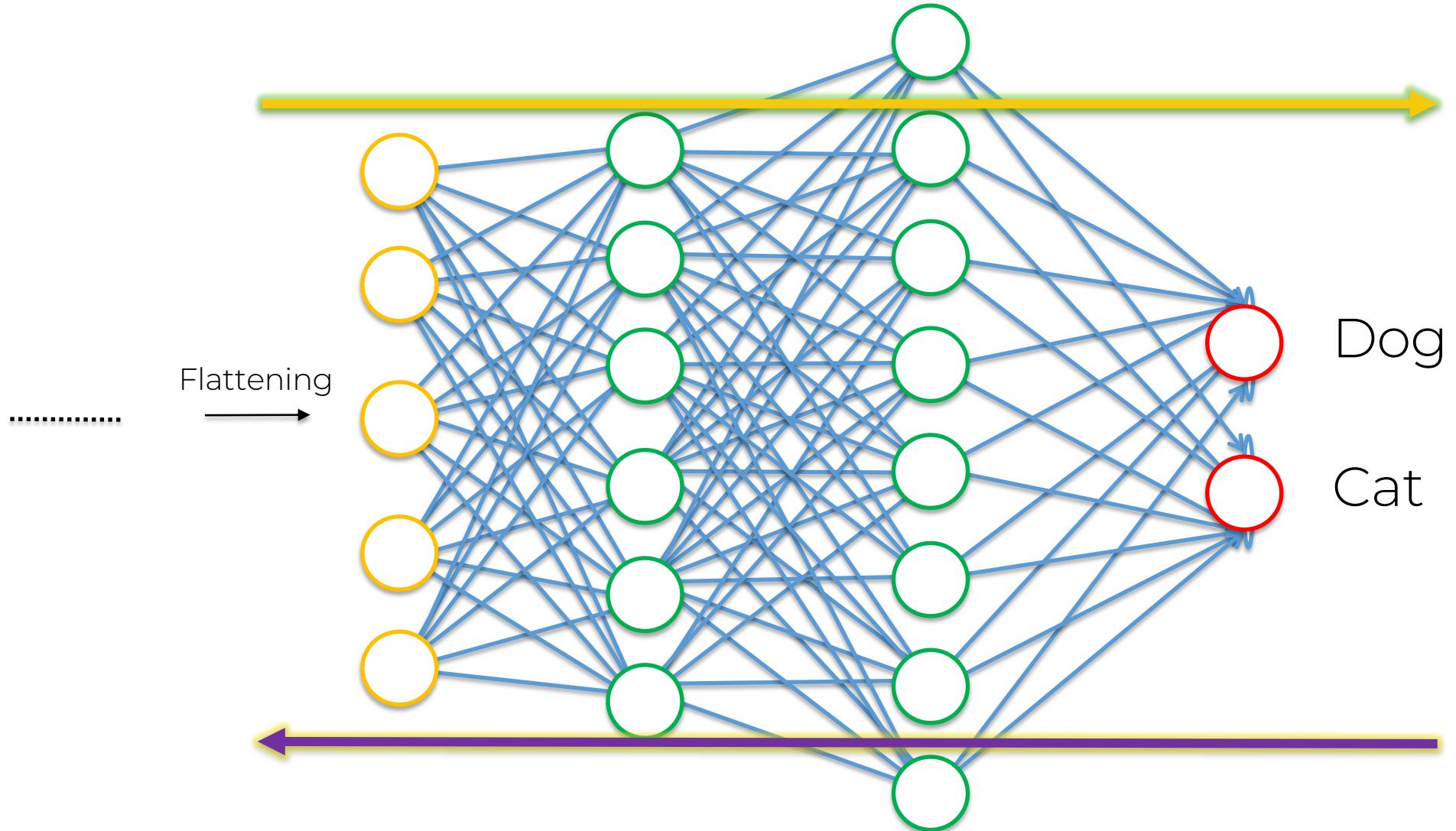
Input layer of a future ANN

Step 4 - Full Connection

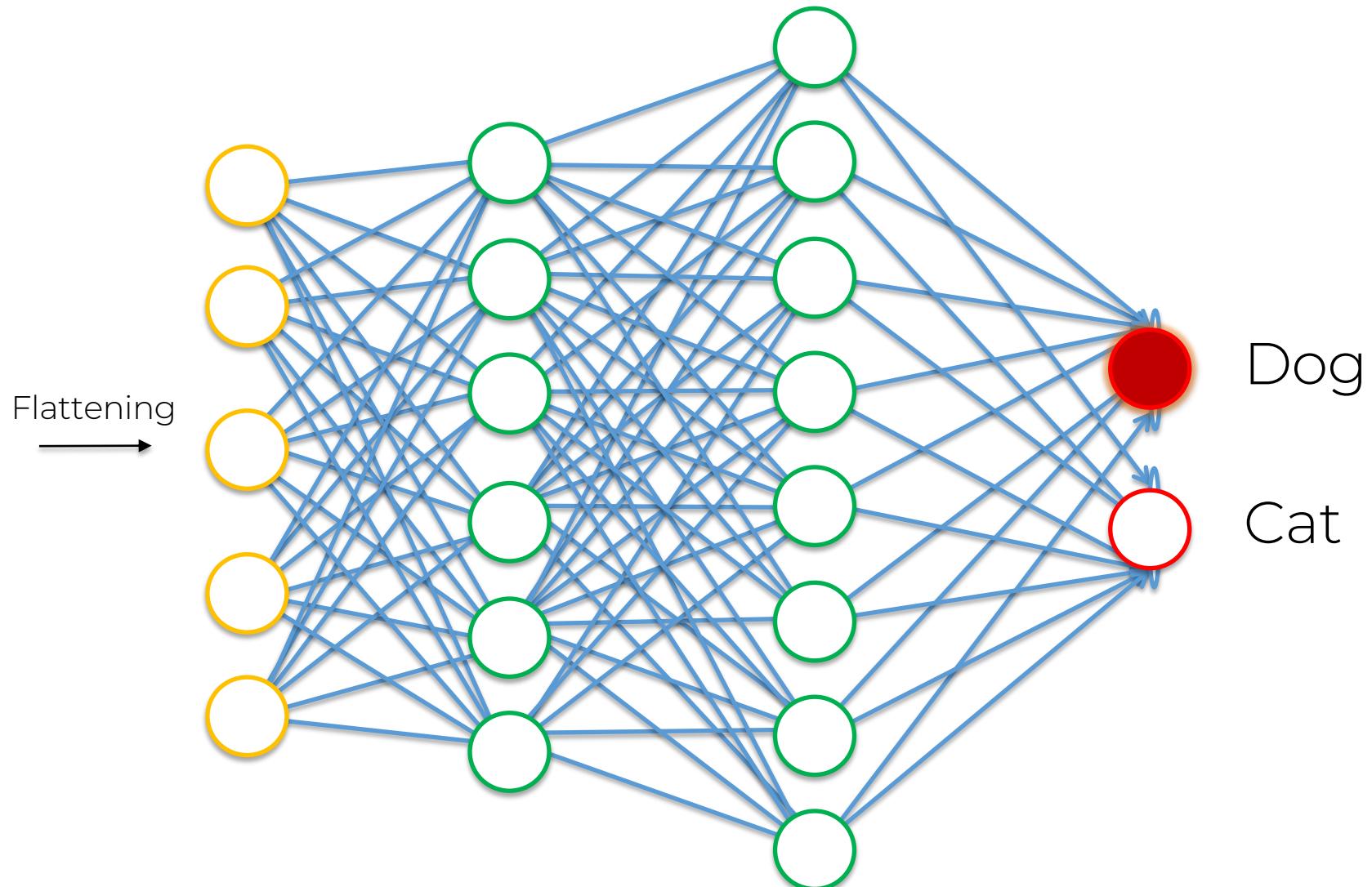
Step 4 - Full Connection



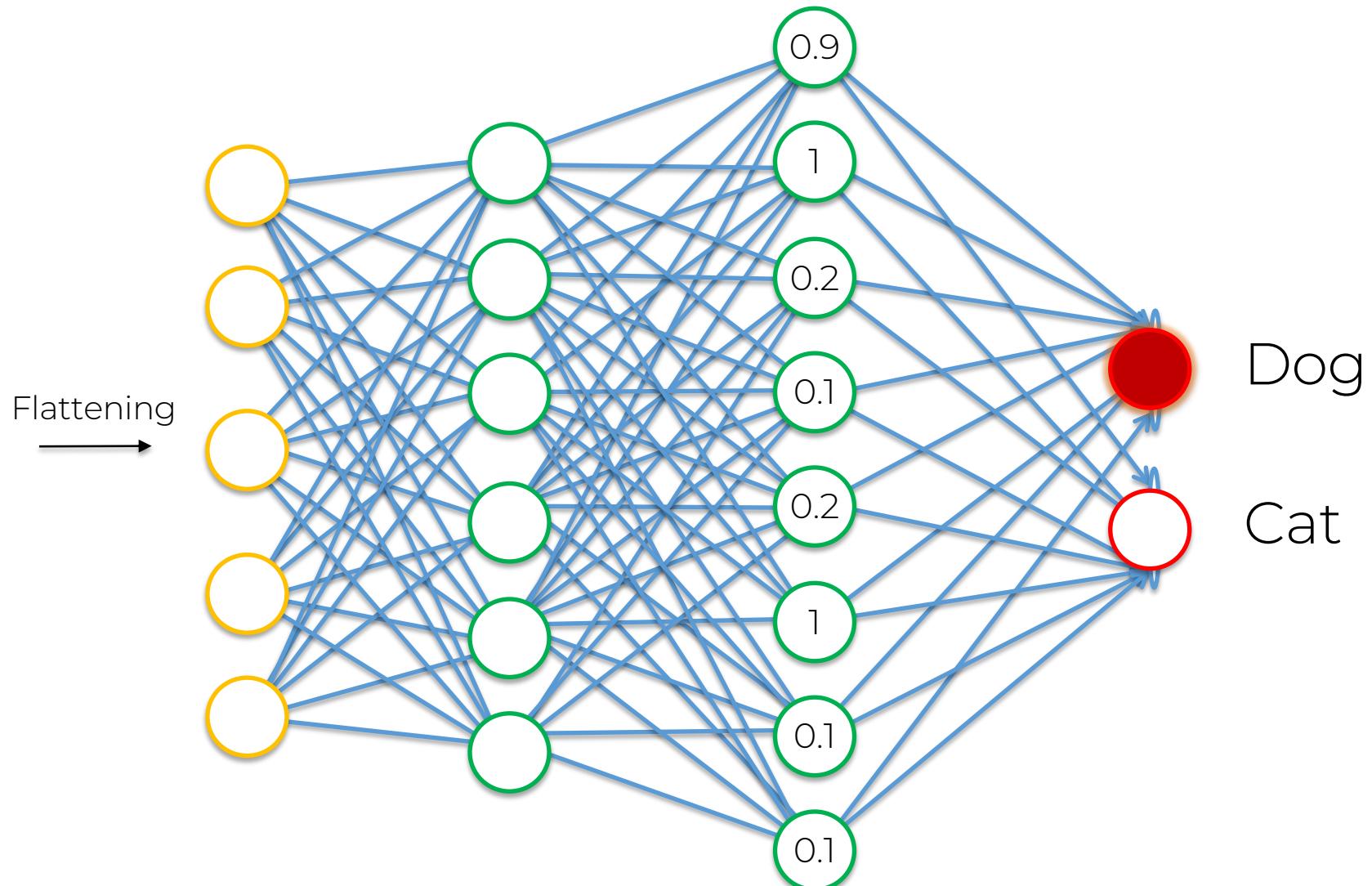
Step 4 - Full Connection



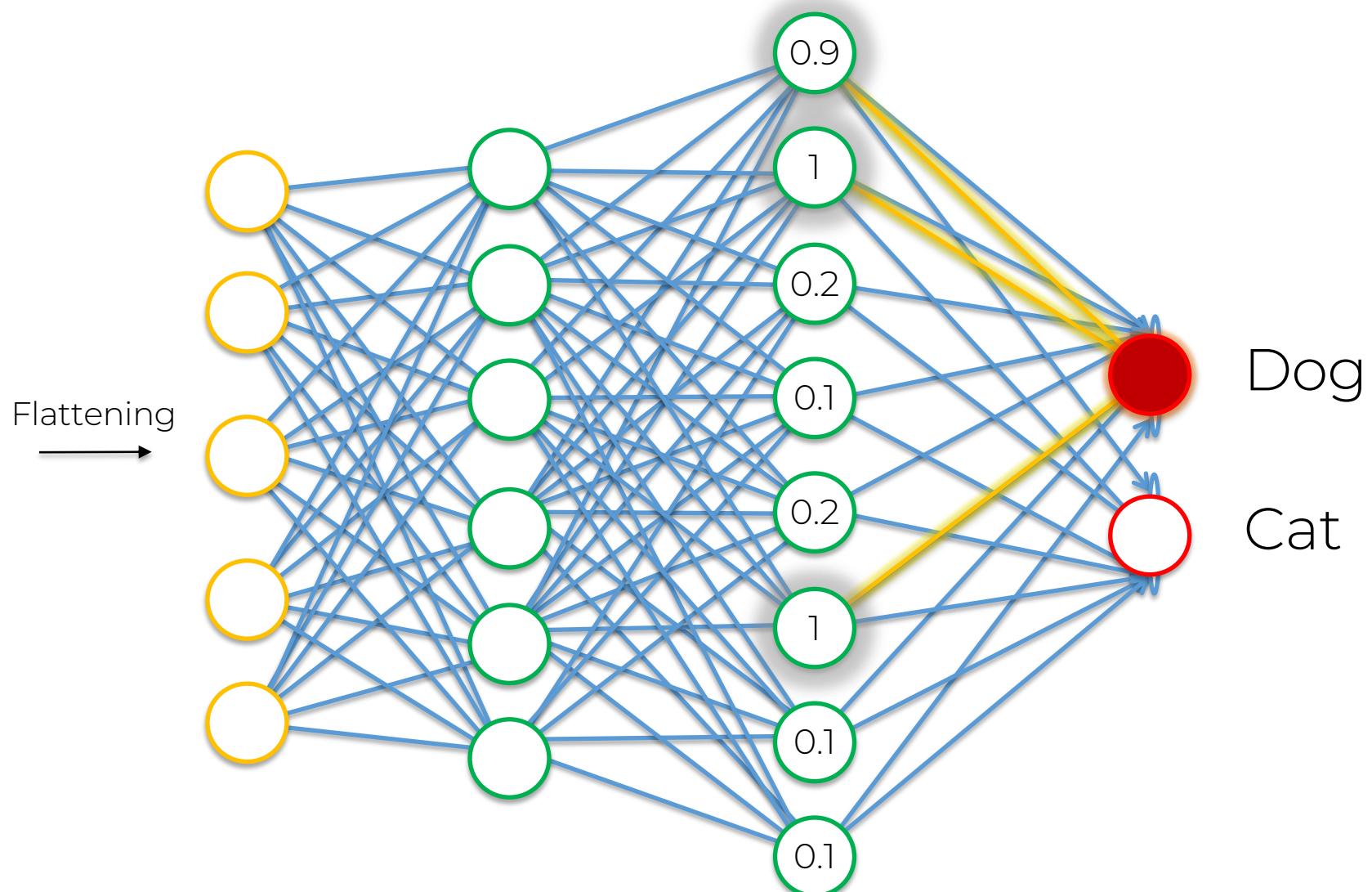
Step 4 - Full Connection



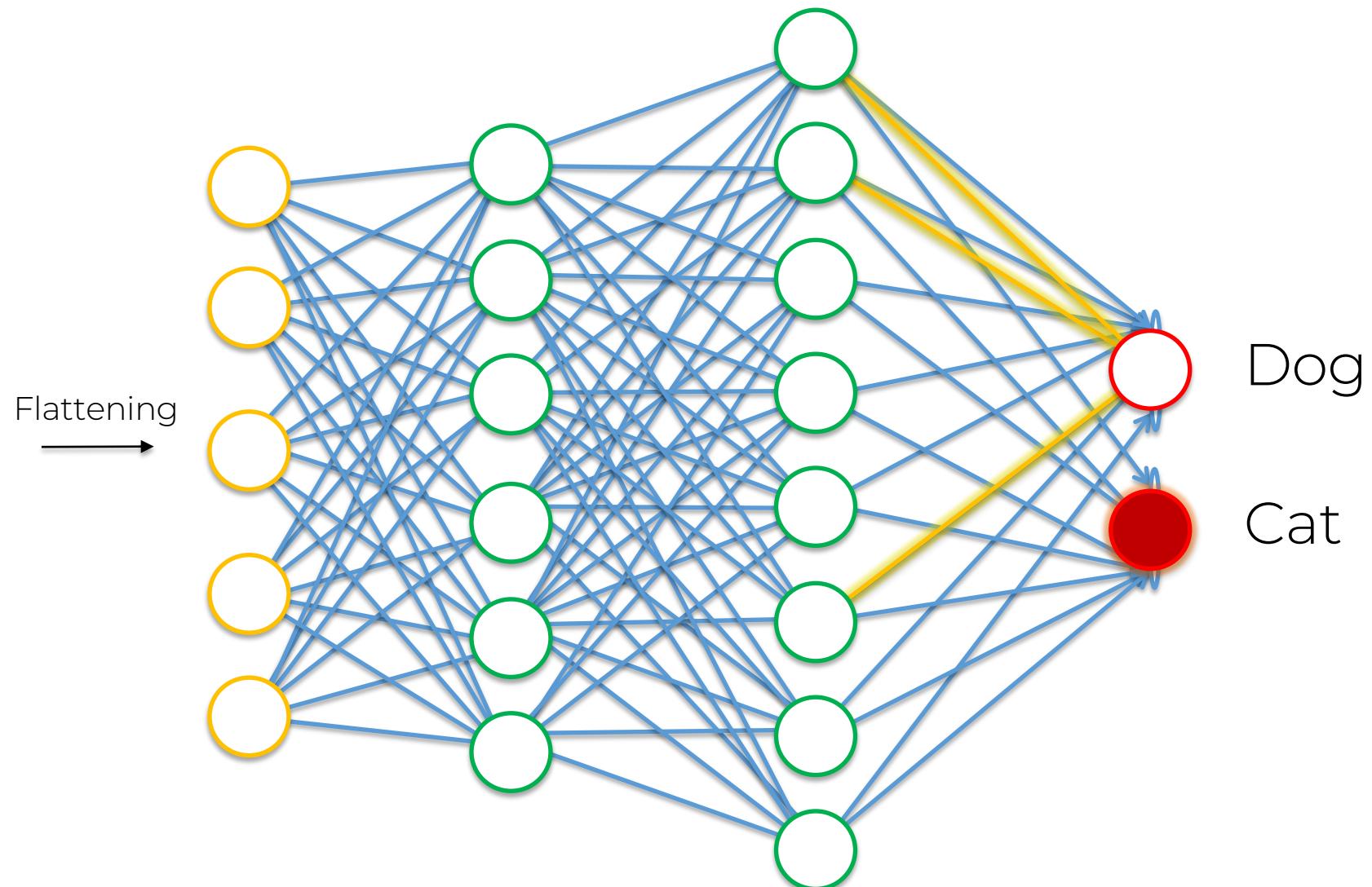
Step 4 - Full Connection



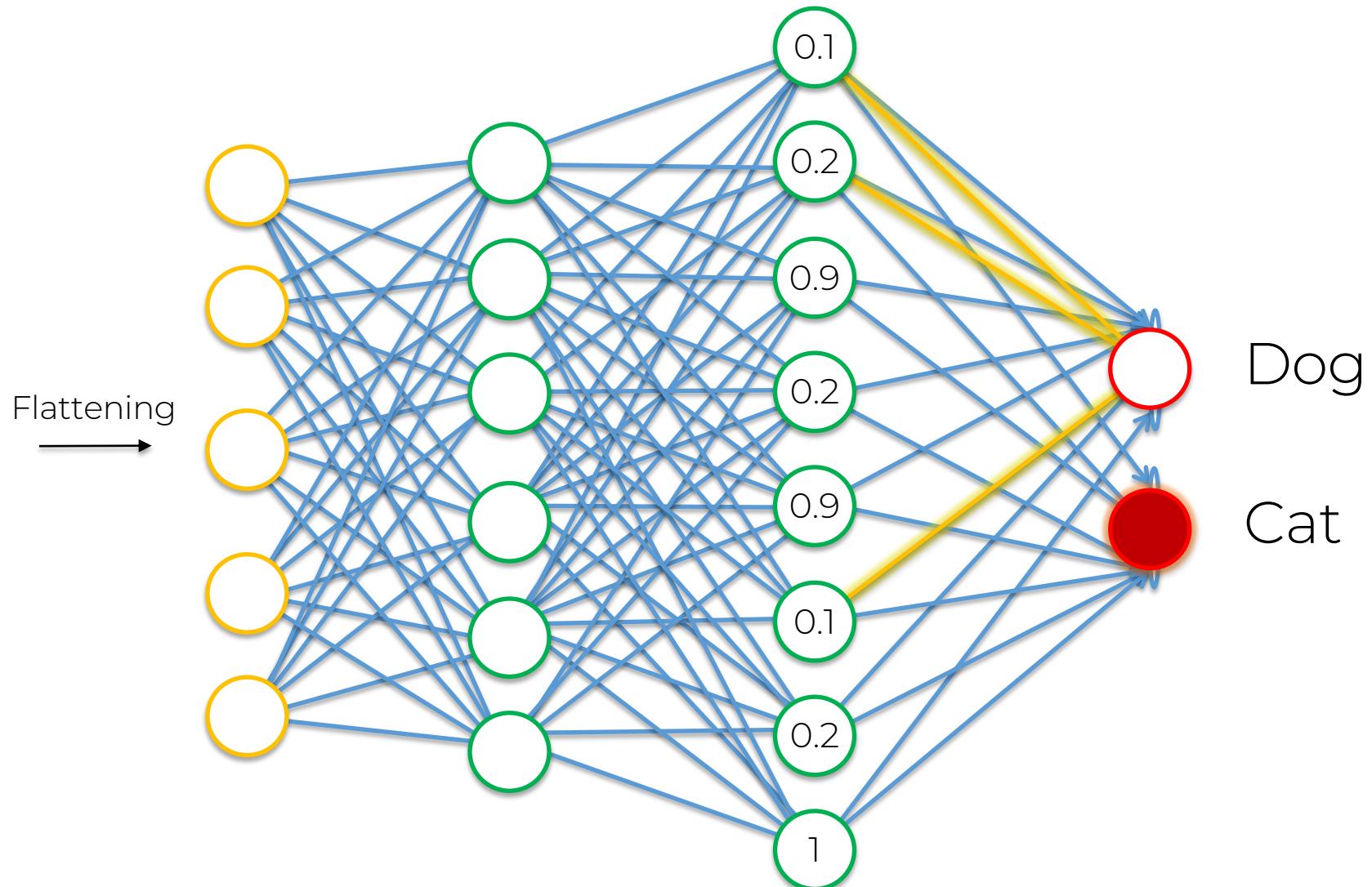
Step 4 - Full Connection



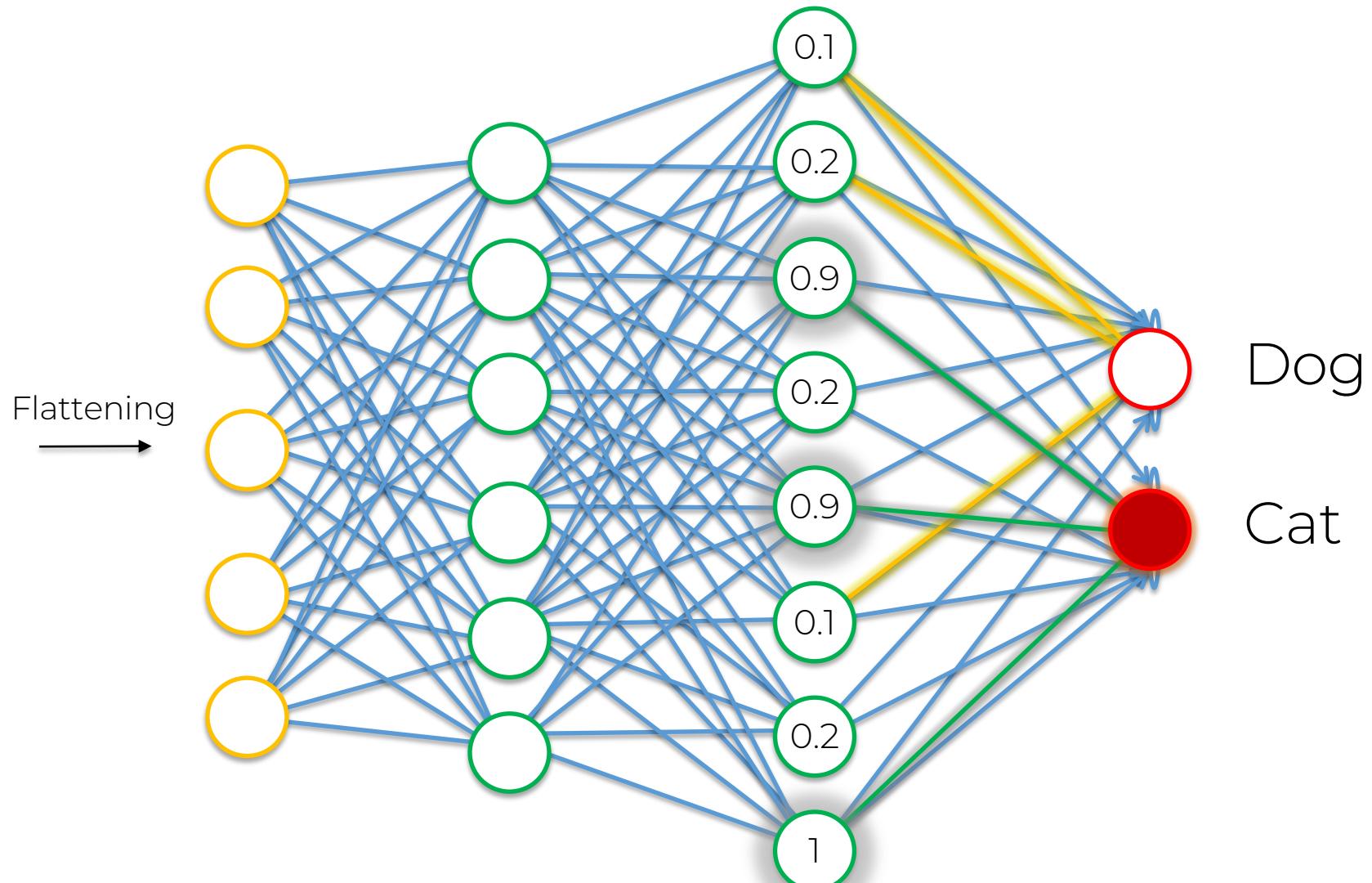
Step 4 - Full Connection



Step 4 - Full Connection



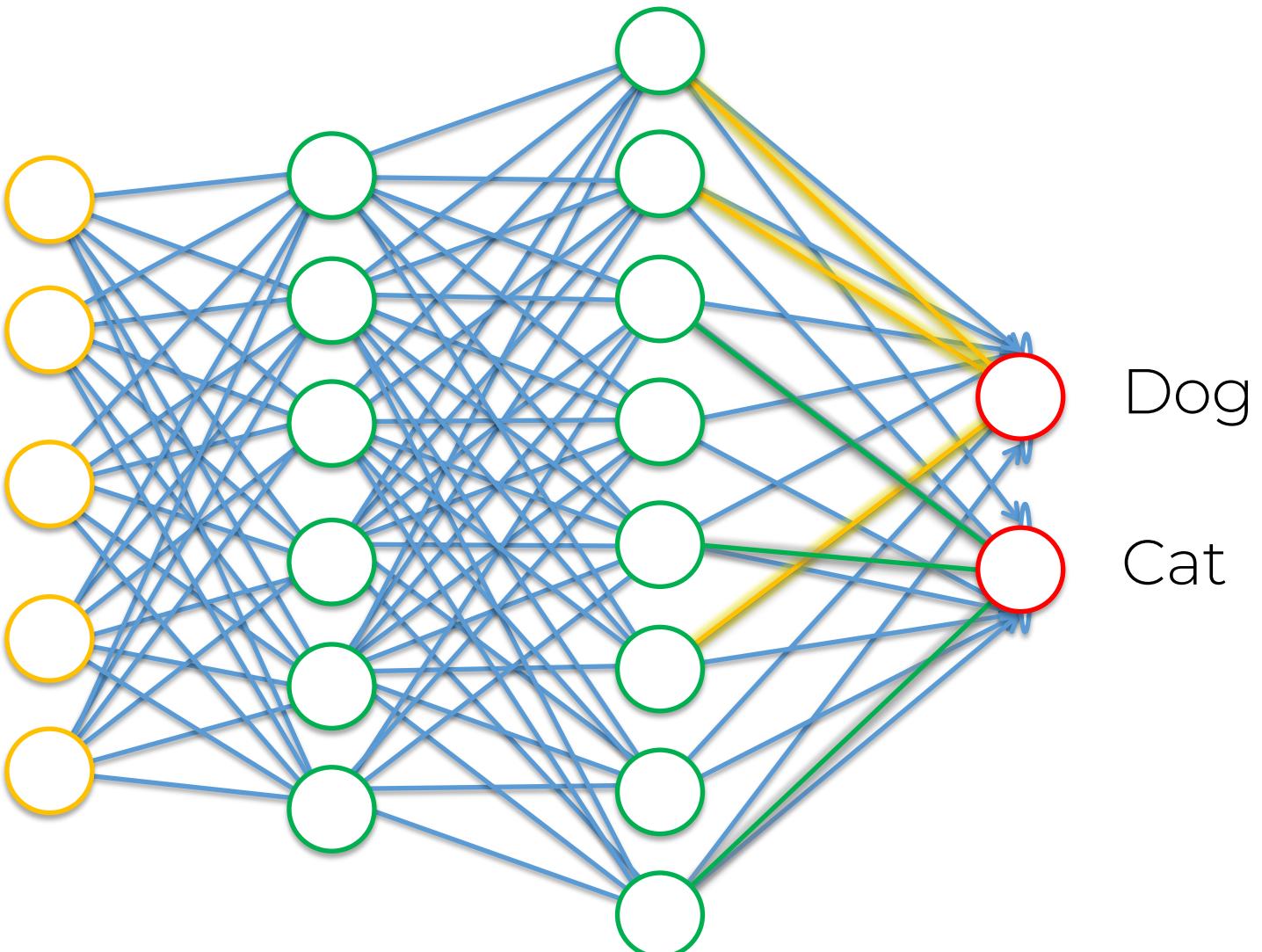
Step 4 - Full Connection



Step 4 - Full Connection



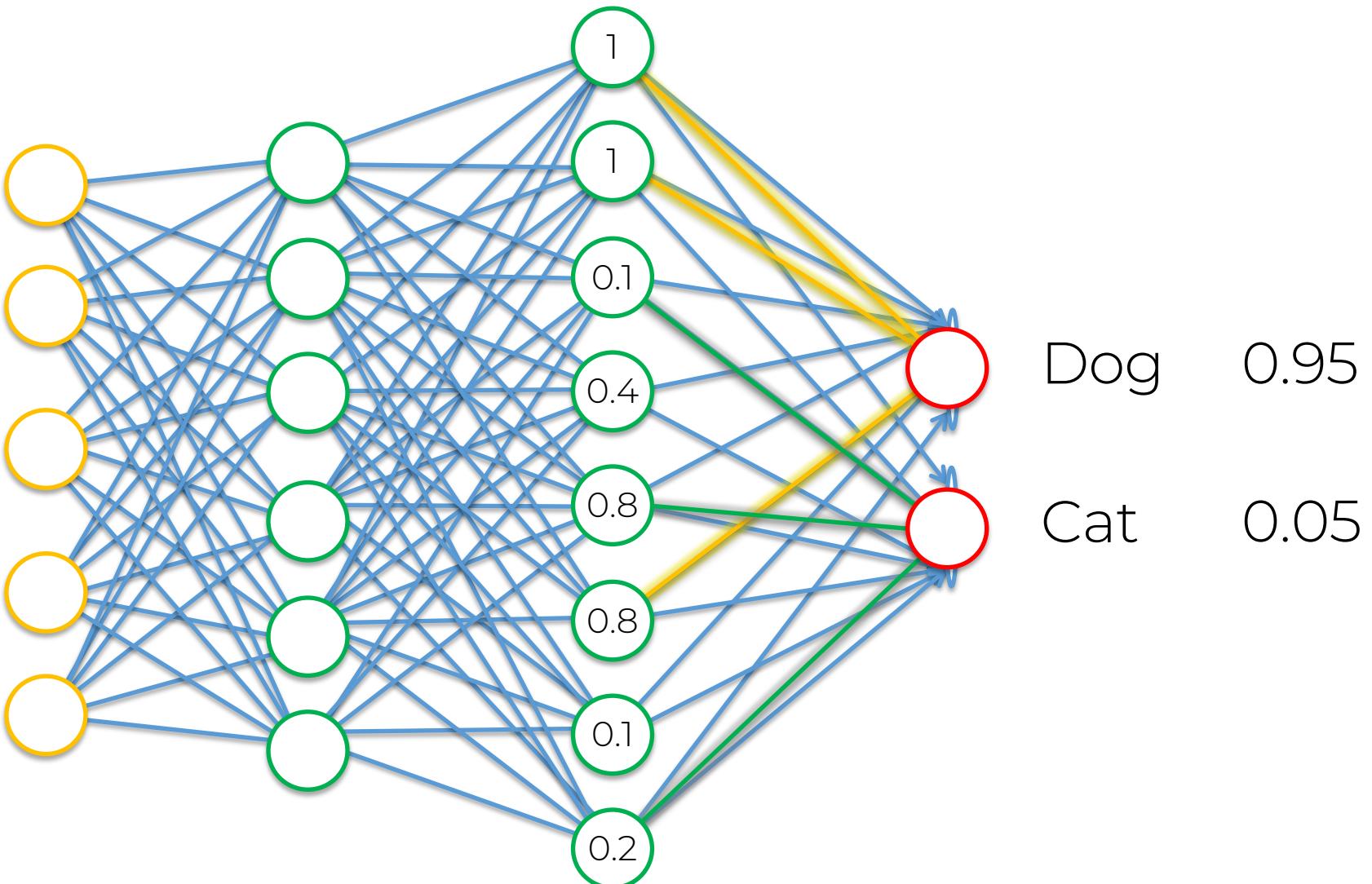
Flattening
→



Step 4 - Full Connection



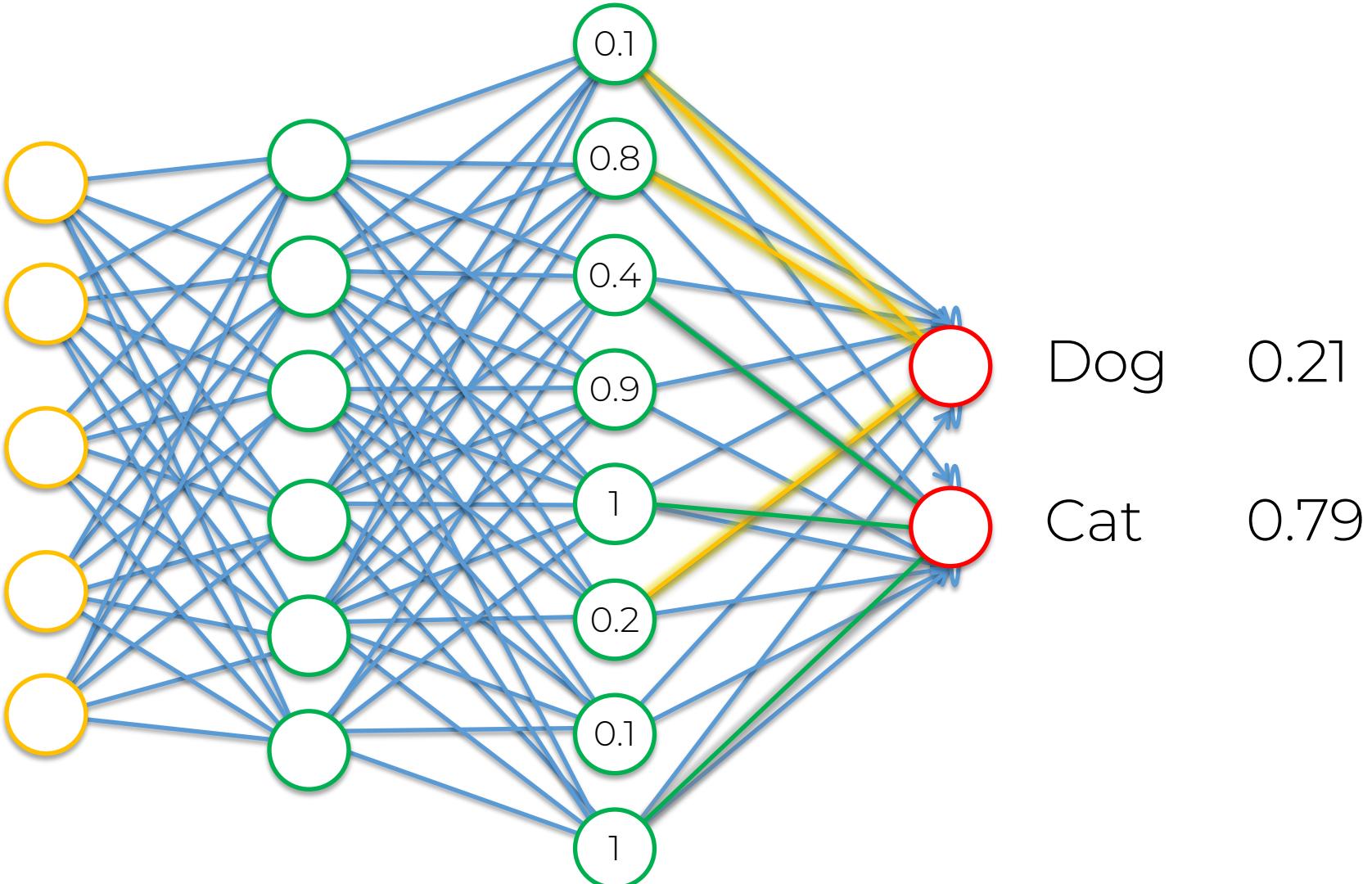
Flattening
→



Step 4 - Full Connection



Flattening
→



Step 4 - Full Connection

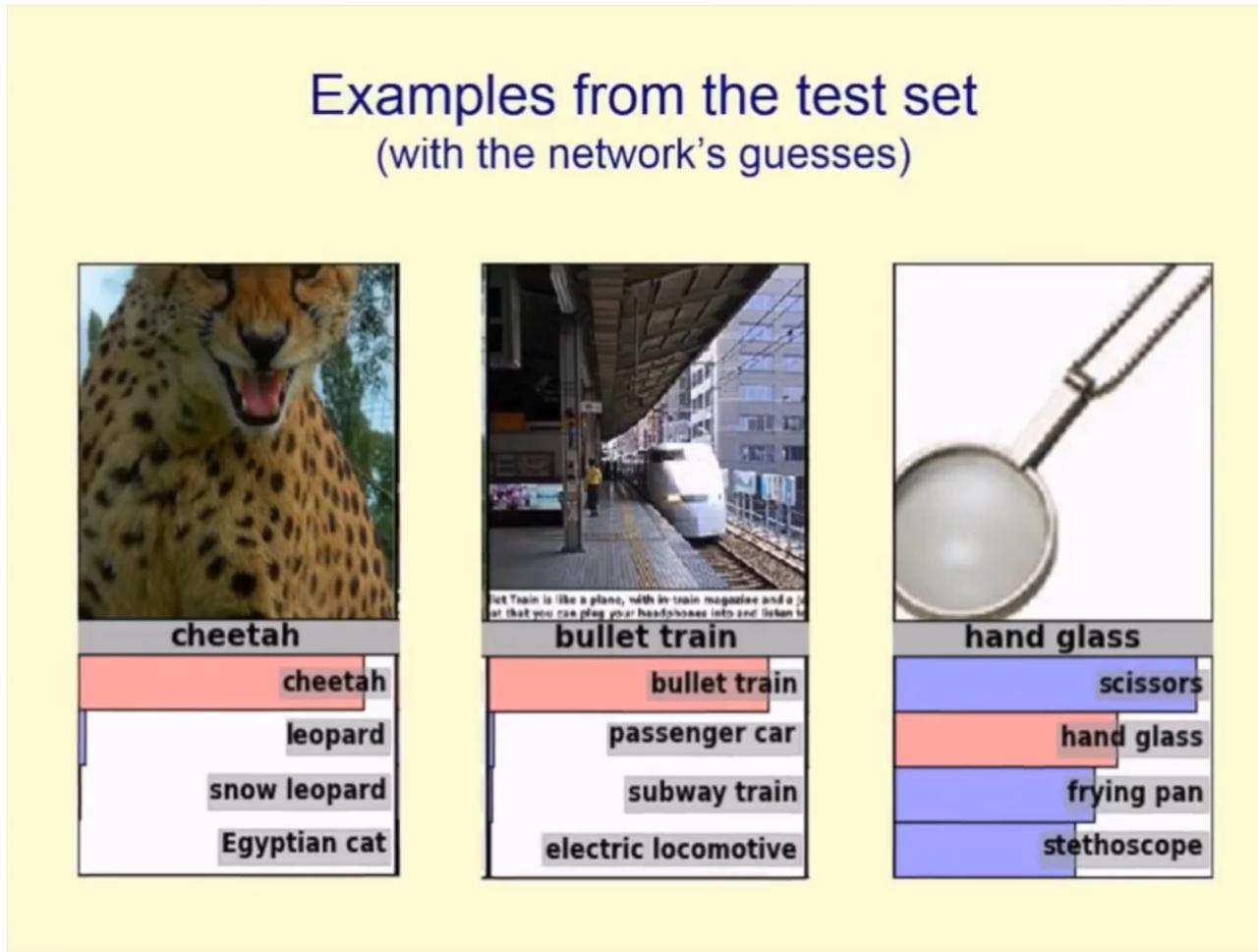
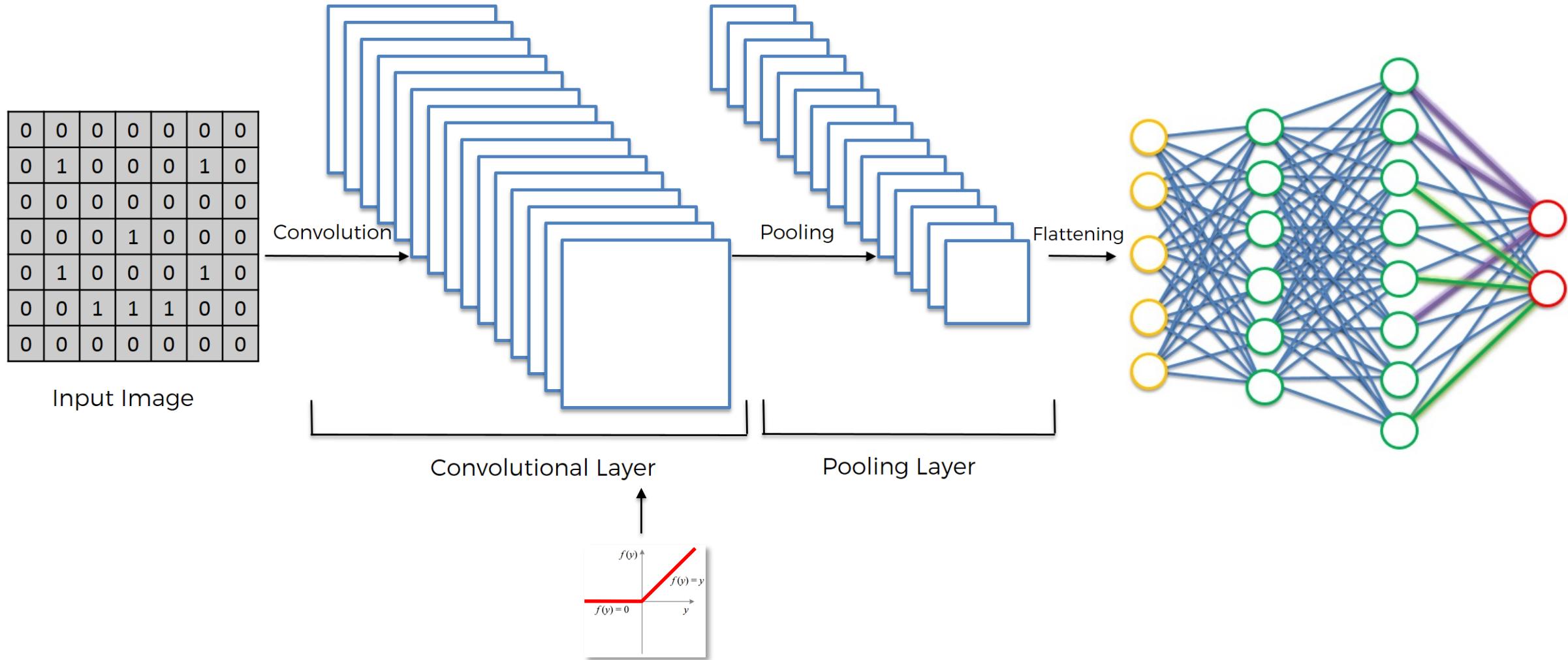


Image Source: a talk by Geoffrey Hinton

Summary

Summary



Summary

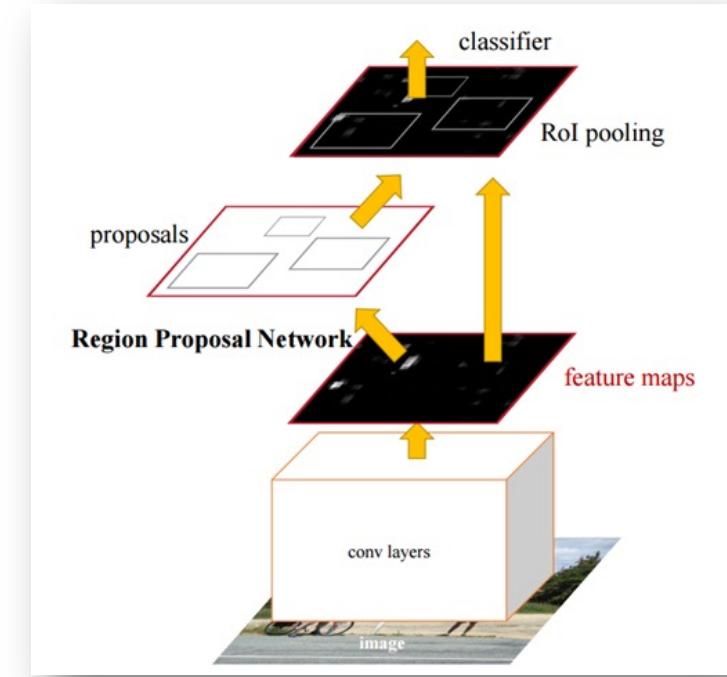
Additional Reading:

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

Adit Deshpande (2016)

Link:

<https://adethpande3.github.io/The-9-Deep-Learning-Papers-You-Need-To-Know-About.html>

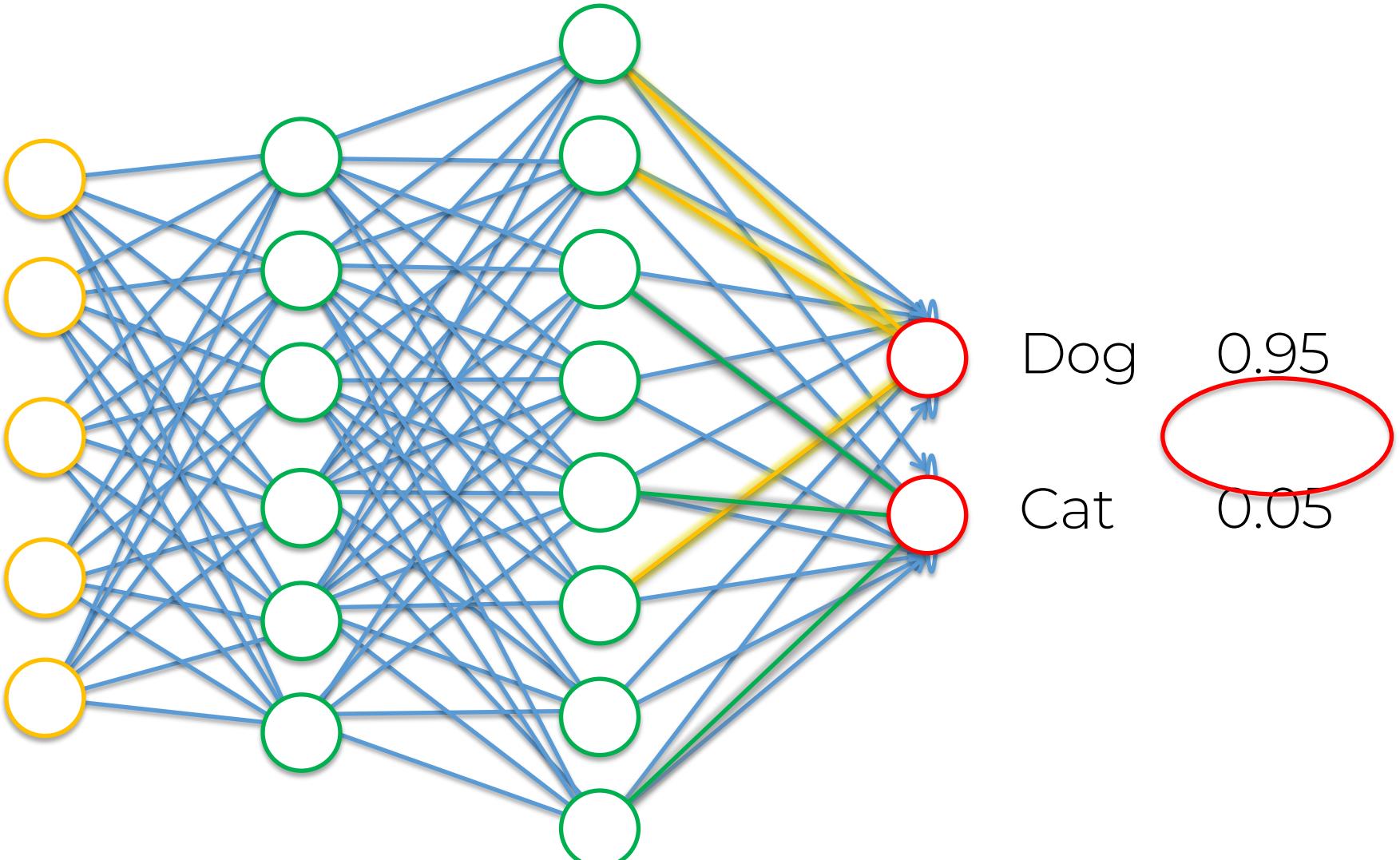


Softmax & Cross-Entropy

Softmax & Cross-Entropy



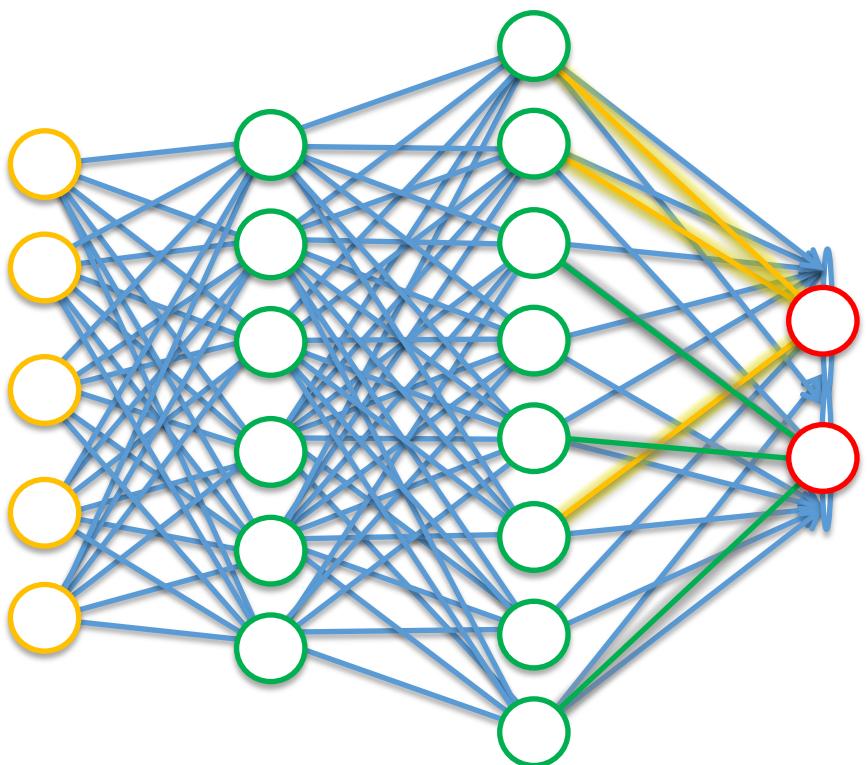
Flattening
→



Softmax & Cross-Entropy



Dog Input



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



Dog $\rightarrow z_1 \rightarrow 0.95$
Cat $\rightarrow z_2 \rightarrow 0.05$

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

Cat

0.9

0.1

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

1
0

Softmax & Cross-Entropy

NN1 NN2



Dog	<table border="1"><tr><td>1</td></tr><tr><td>0</td></tr></table>	1	0
1			
0			
Cat			

0.9
0.1

0.6
0.4



Dog	<table border="1"><tr><td>0</td></tr><tr><td>1</td></tr></table>	0	1
0			
1			
Cat			

0.1
0.9

0.3
0.7



Dog	<table border="1"><tr><td>1</td></tr><tr><td>0</td></tr></table>	1	0
1			
0			
Cat			

0.4
0.6

0.1
0.9

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

Classification Error

0.25

0.38

Mean Squared Error

0.71

1.06

Cross-Entropy

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

0.71

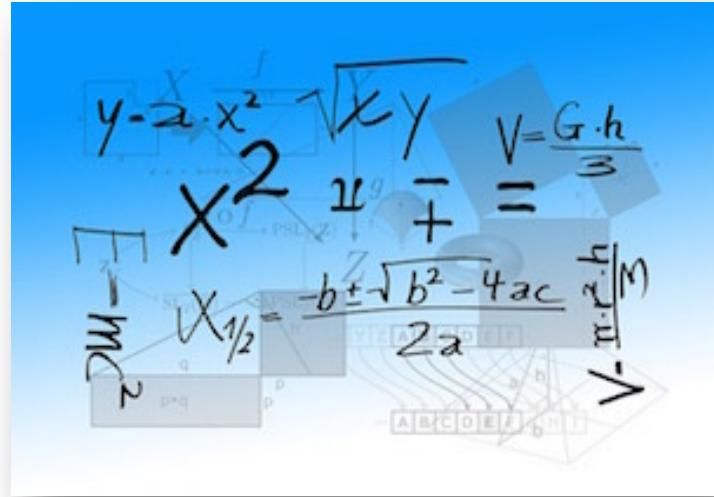
1.06

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/>

Softmax & Cross-Entropy

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/