plain concepts

Introduction to Deep Learning

30.11.2017

Big Data Conference Vilnius

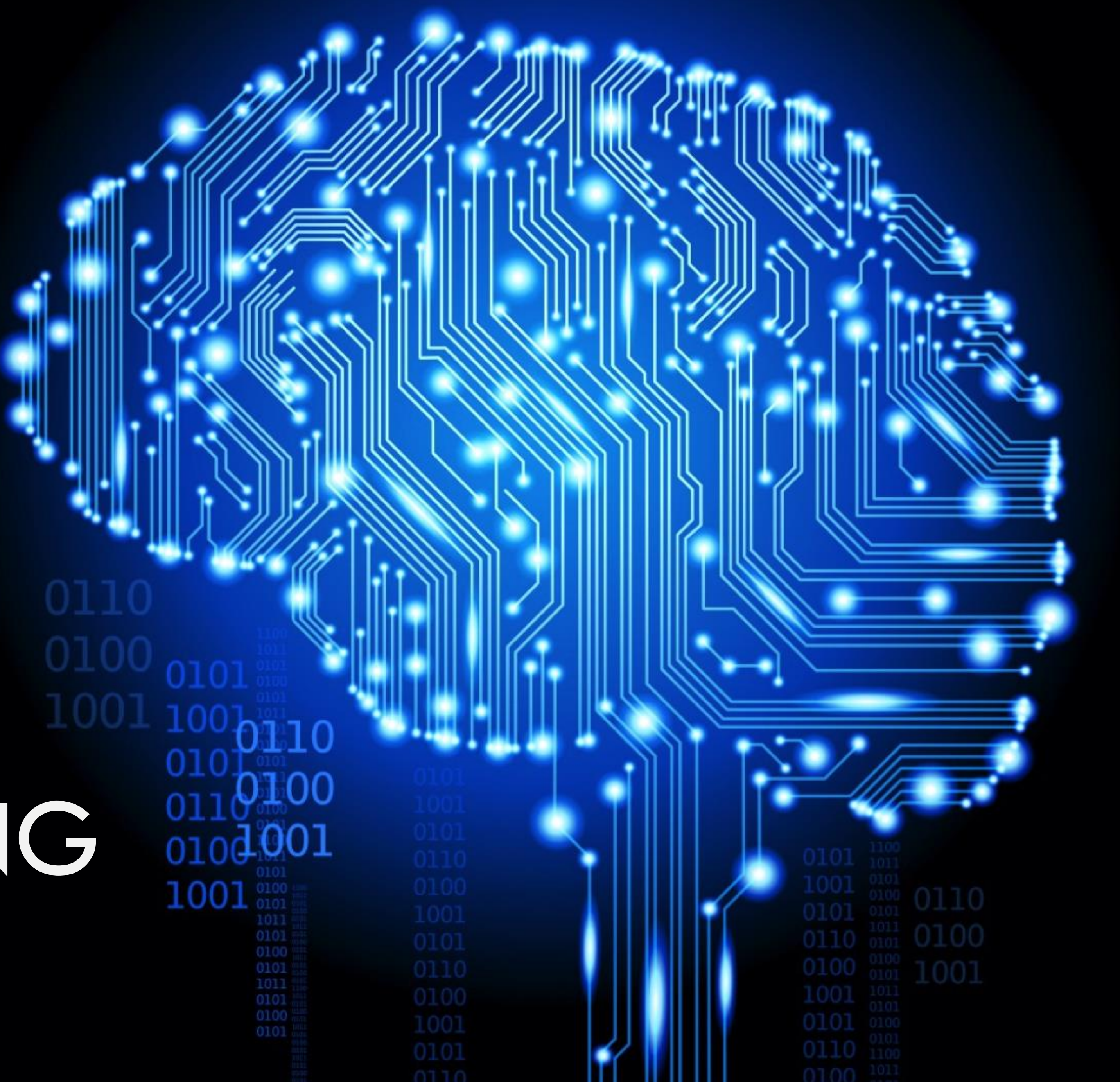
Pablo Doval

Pablo **Doval**

DATA PONTIFEX @ Plain Concepts

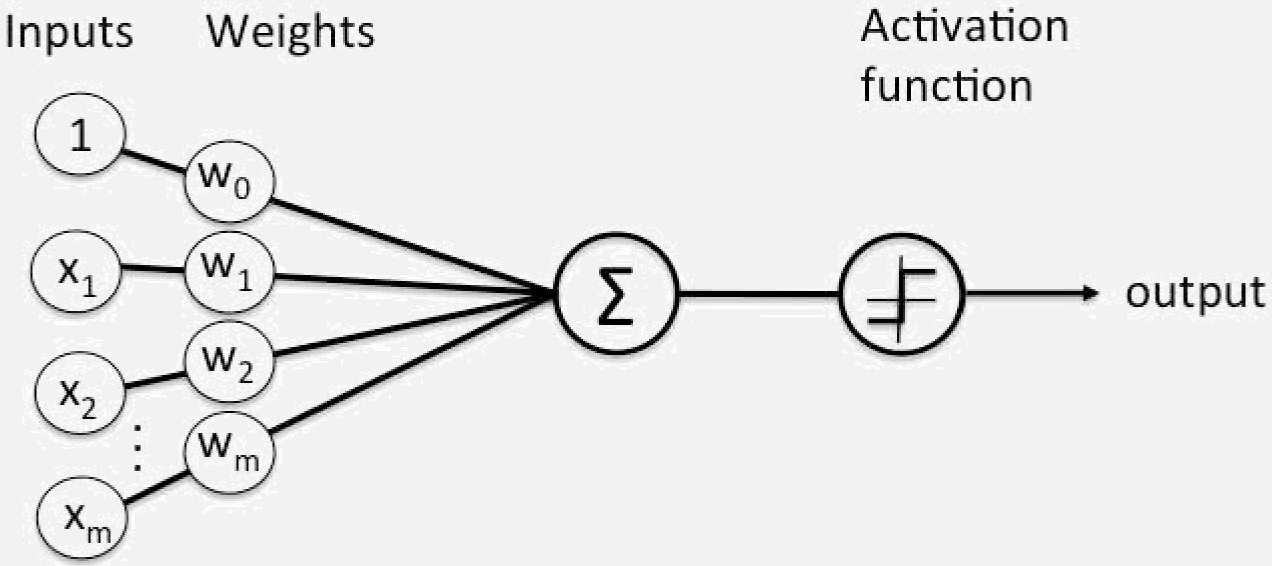
I work with code and data, but don't tell my mom; she thinks I'm a piano player in a whorehouse.

“I’ll create a GUI interface using Visual Basic to see if I can track an IP address”

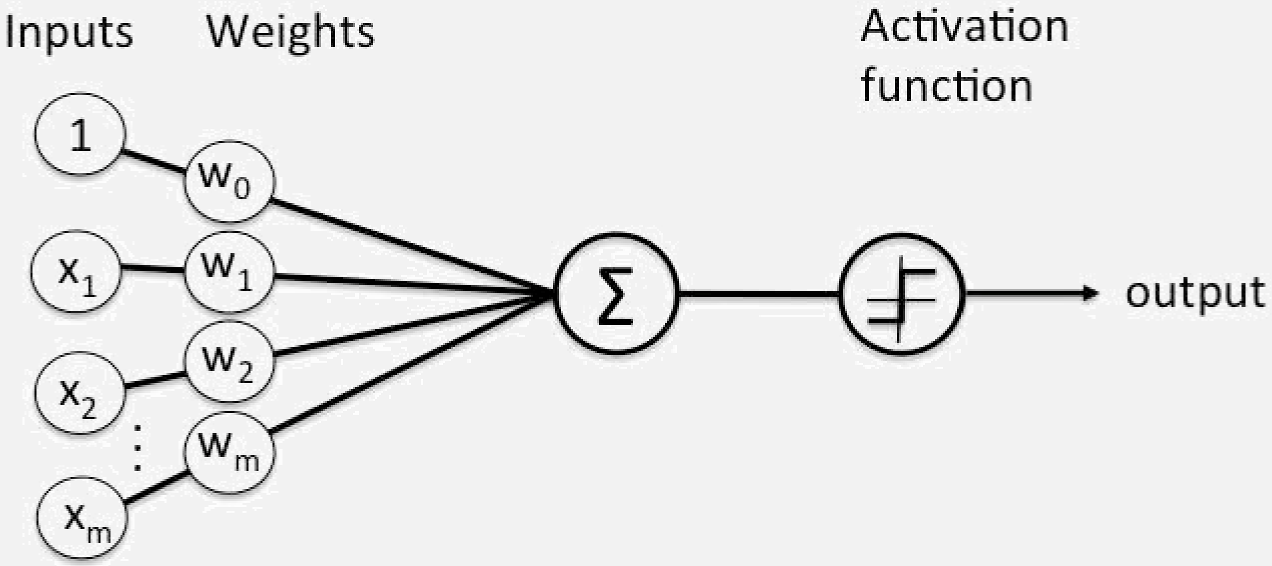


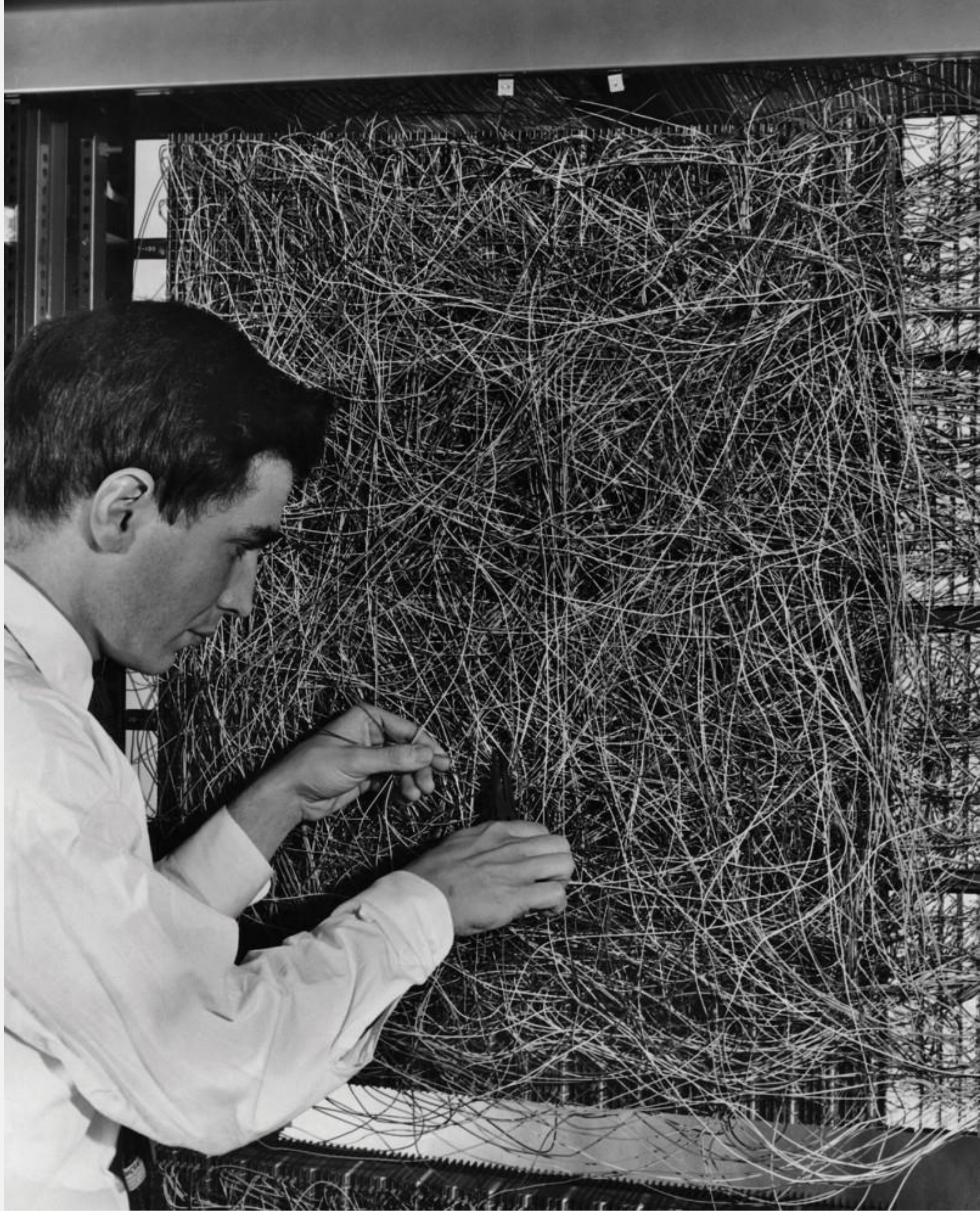
A.I.
MACHINE LEARNING
DEEP LEARNING

PERCEPTRON


Inputs
Weights
Activation function
1
x_1
x_2
x_m
w_0
w_1
w_2
w_m
Σ
output

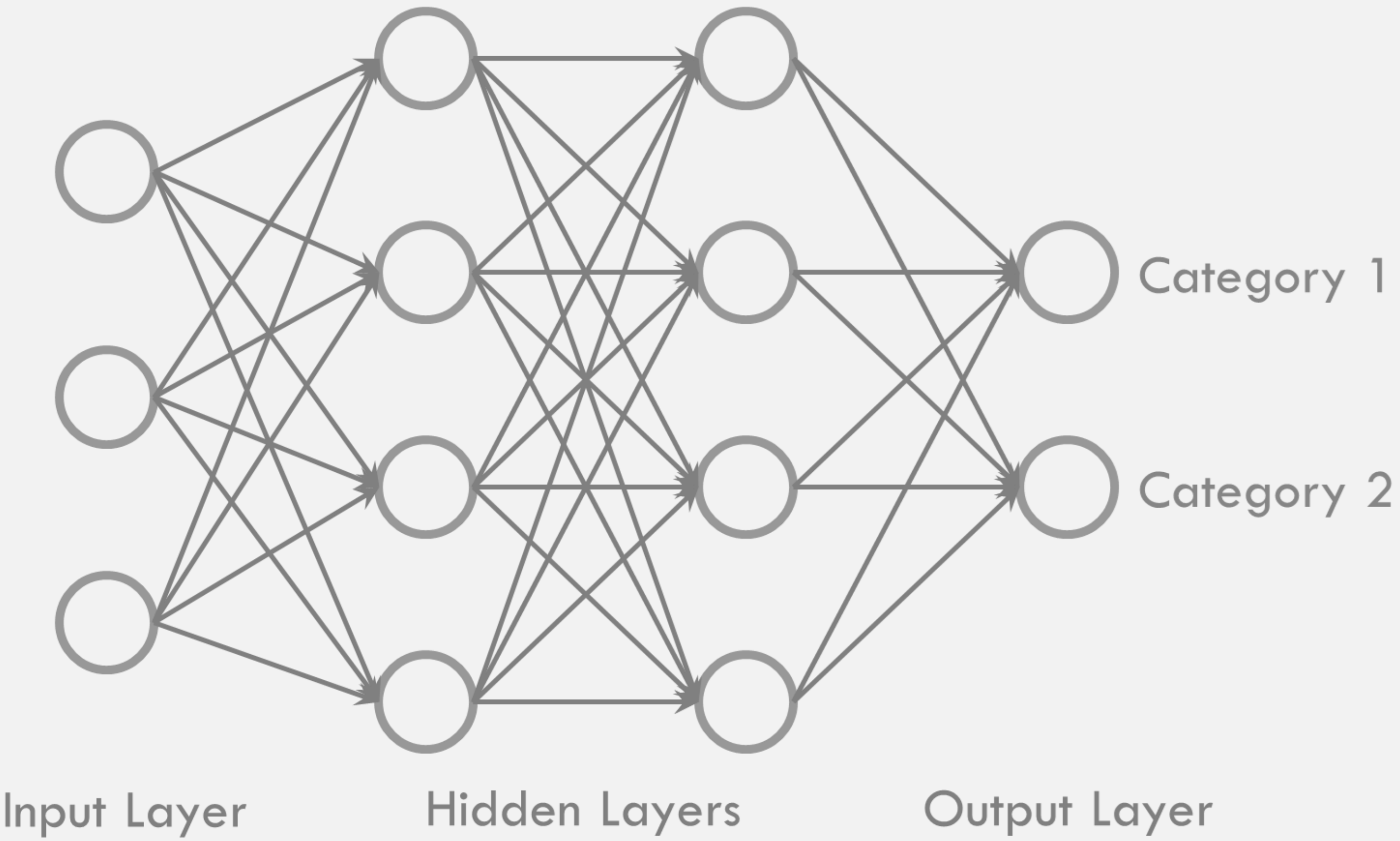
PERCEPTRON


Inputs
Weights
Activation function
1
w_0
x_1
w_1
x_2
w_2
x_m
w_m
Σ
output

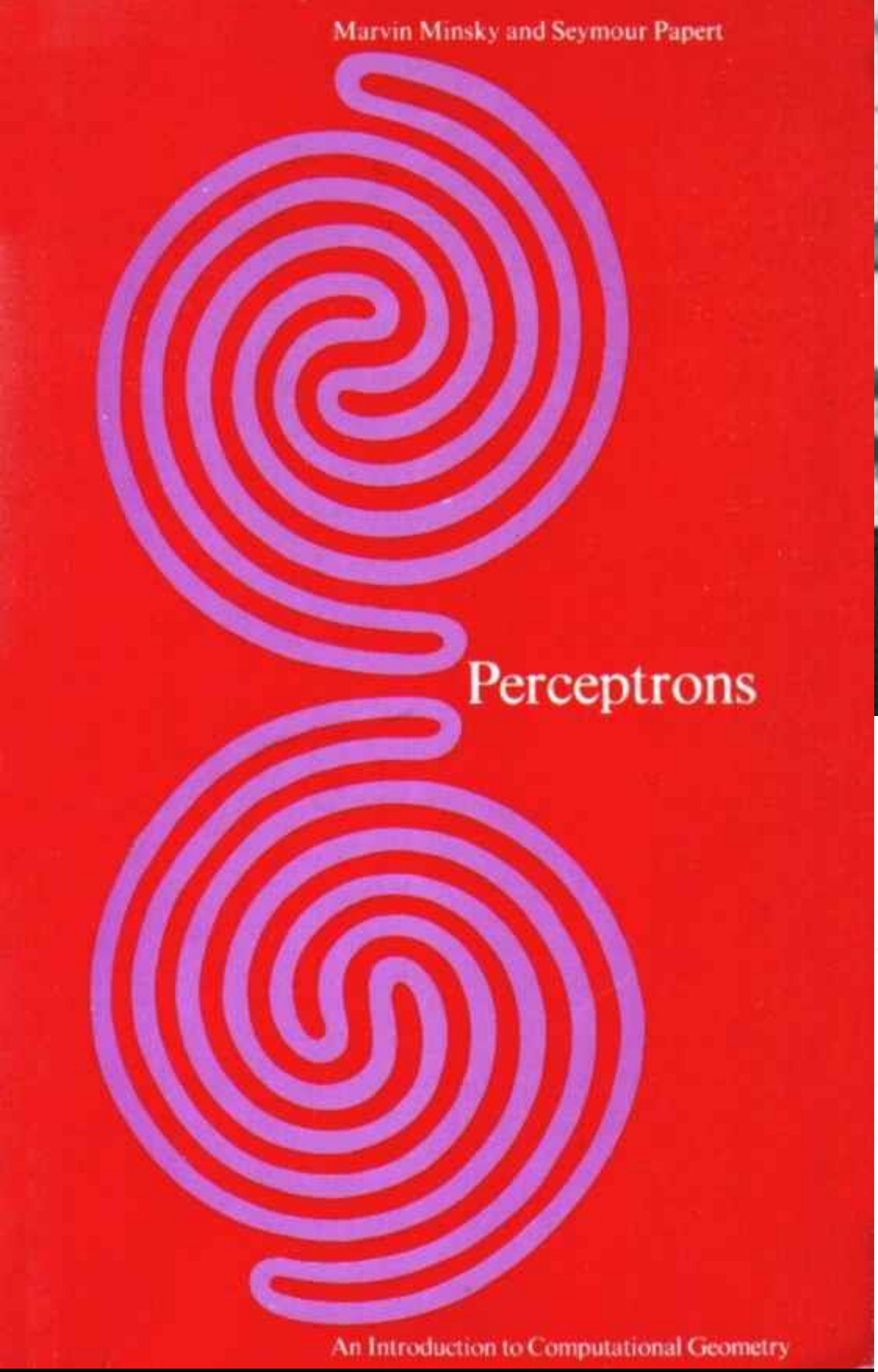


ARTIFICIAL INTELLIGENCE

MULTILAYER PERCEPTRON



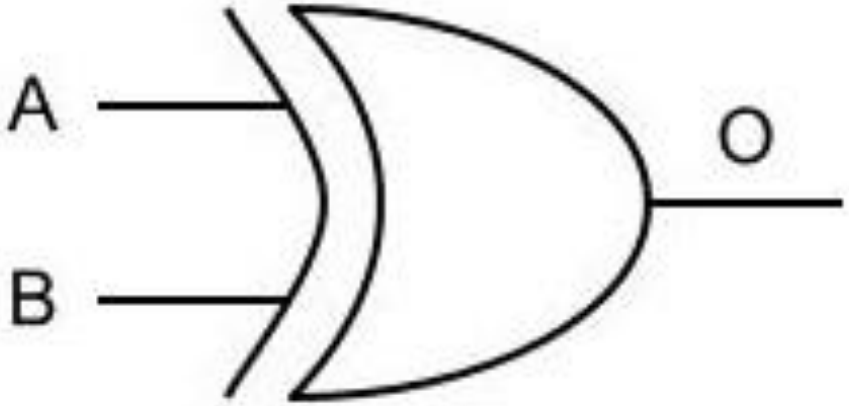
Winter Is Coming



Marvin Minsky and Seymour Papert

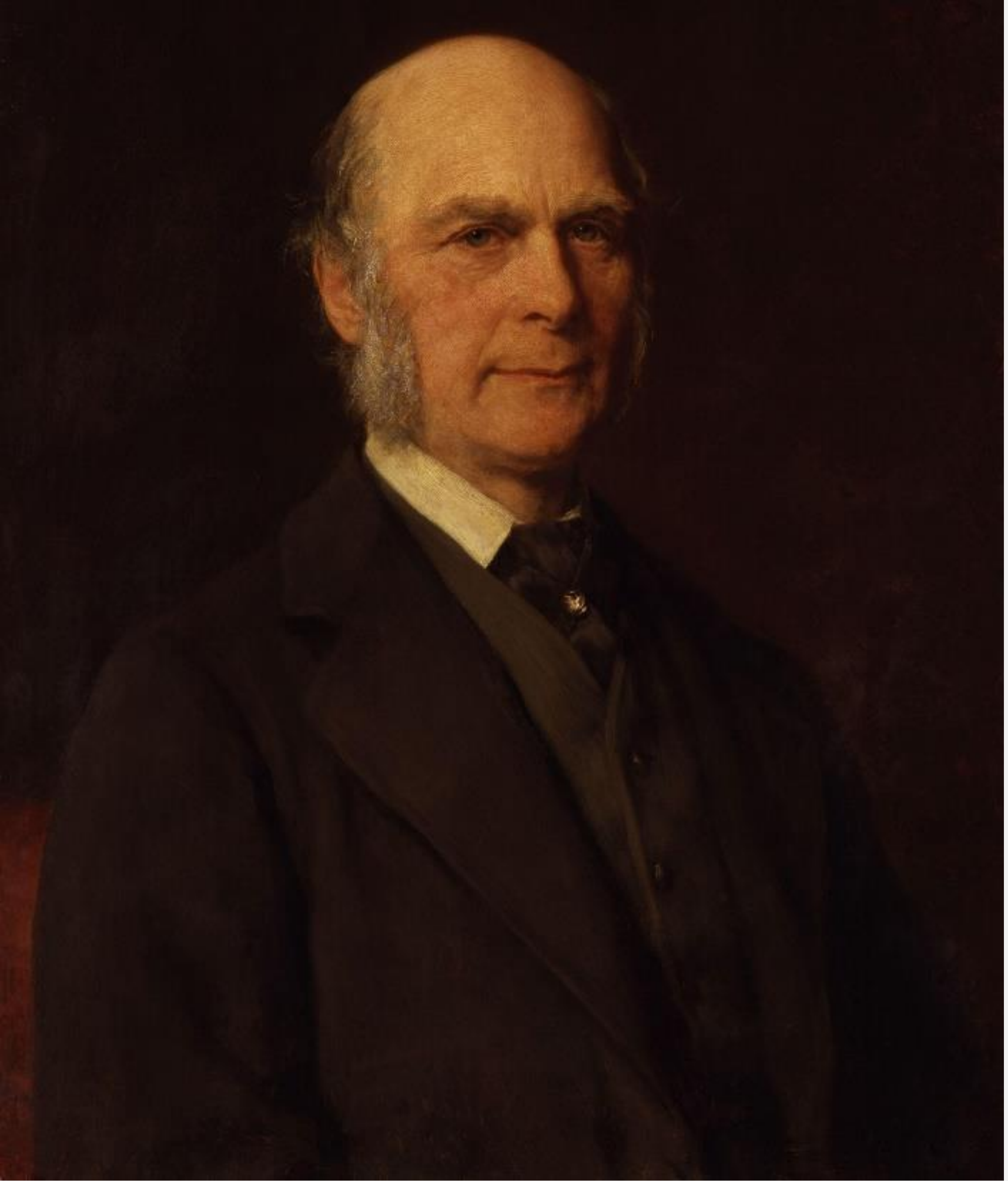
Perceptrons

An Introduction to Computational Geometry

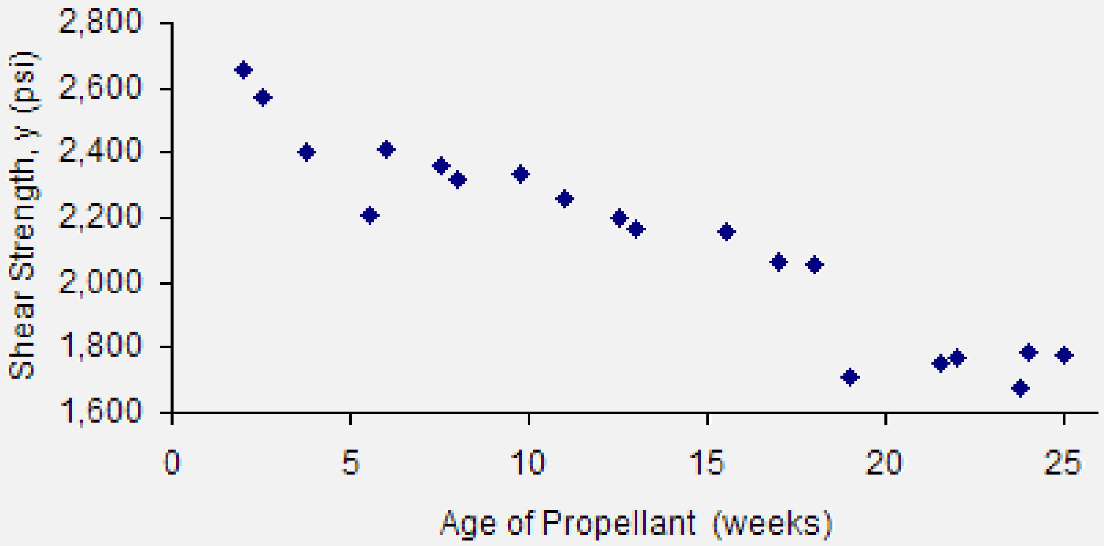


A	B	O
0	0	0
0	1	1
1	0	1
1	1	0

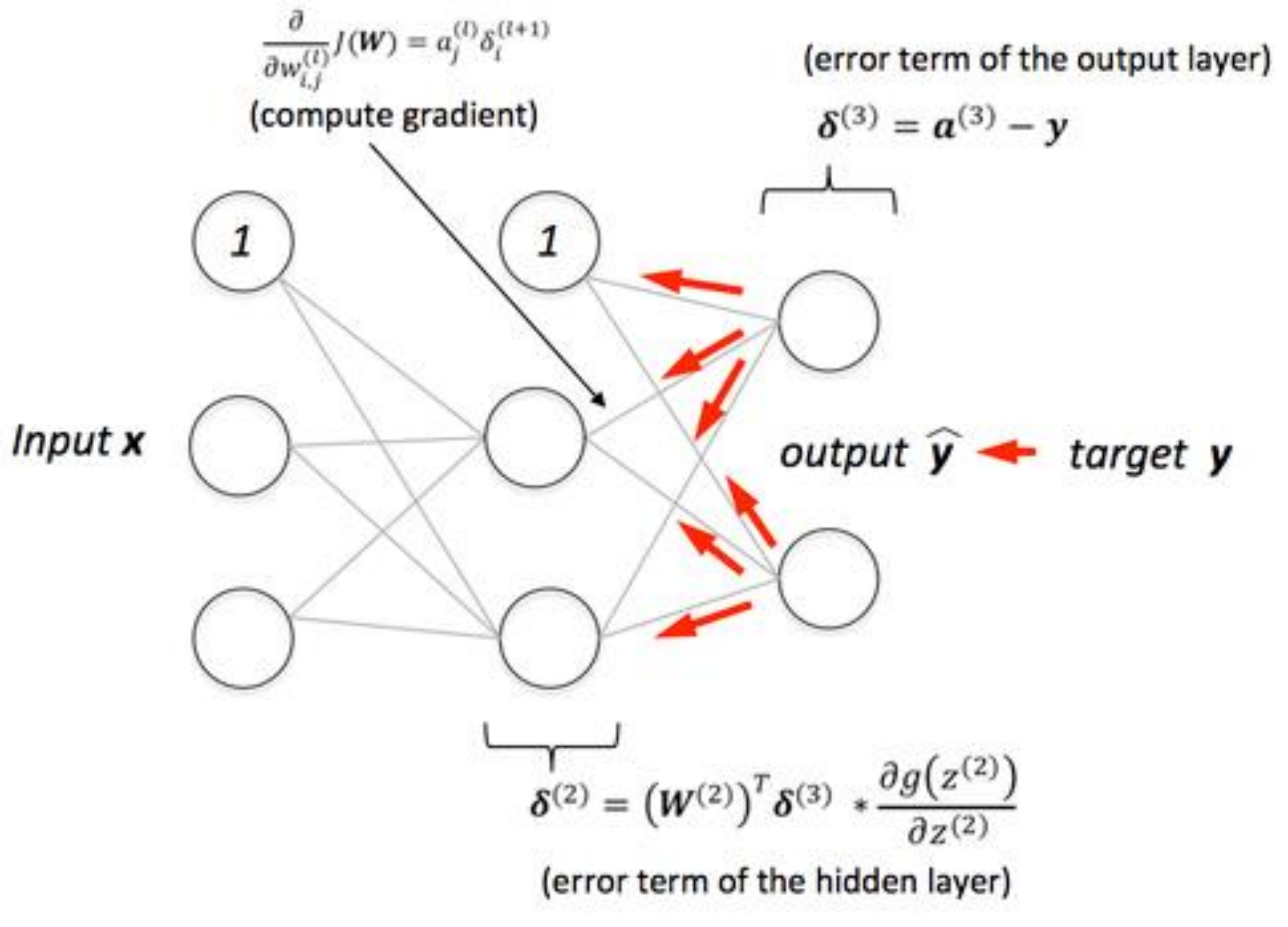
EXPERT SYSTEMS?



MACHINE LEARNING

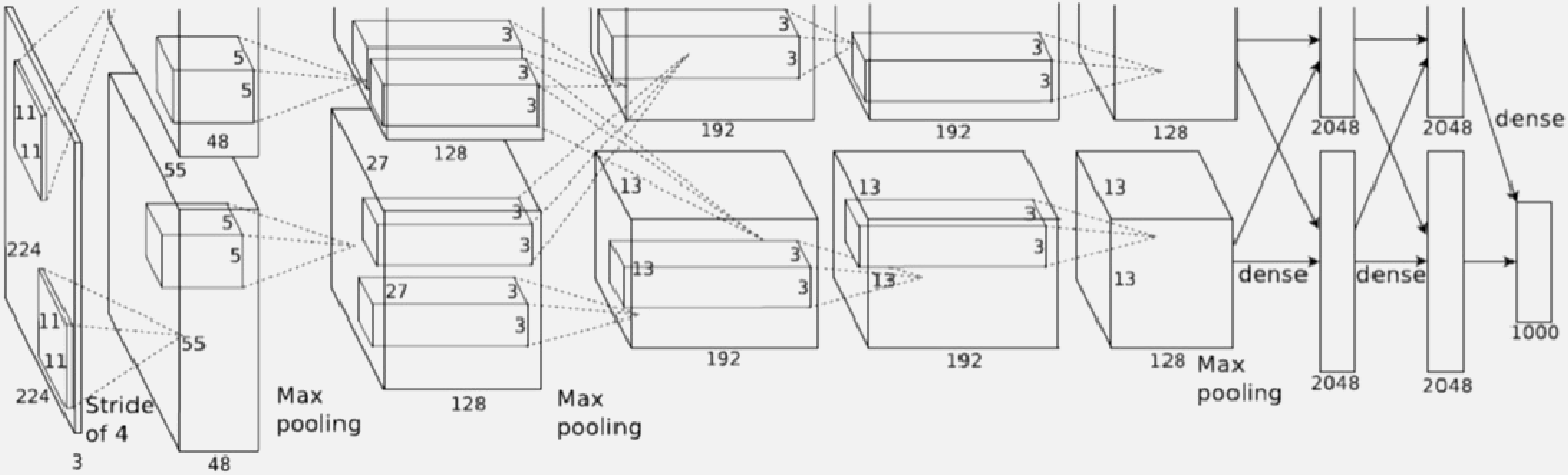


BACKPROPAGATION

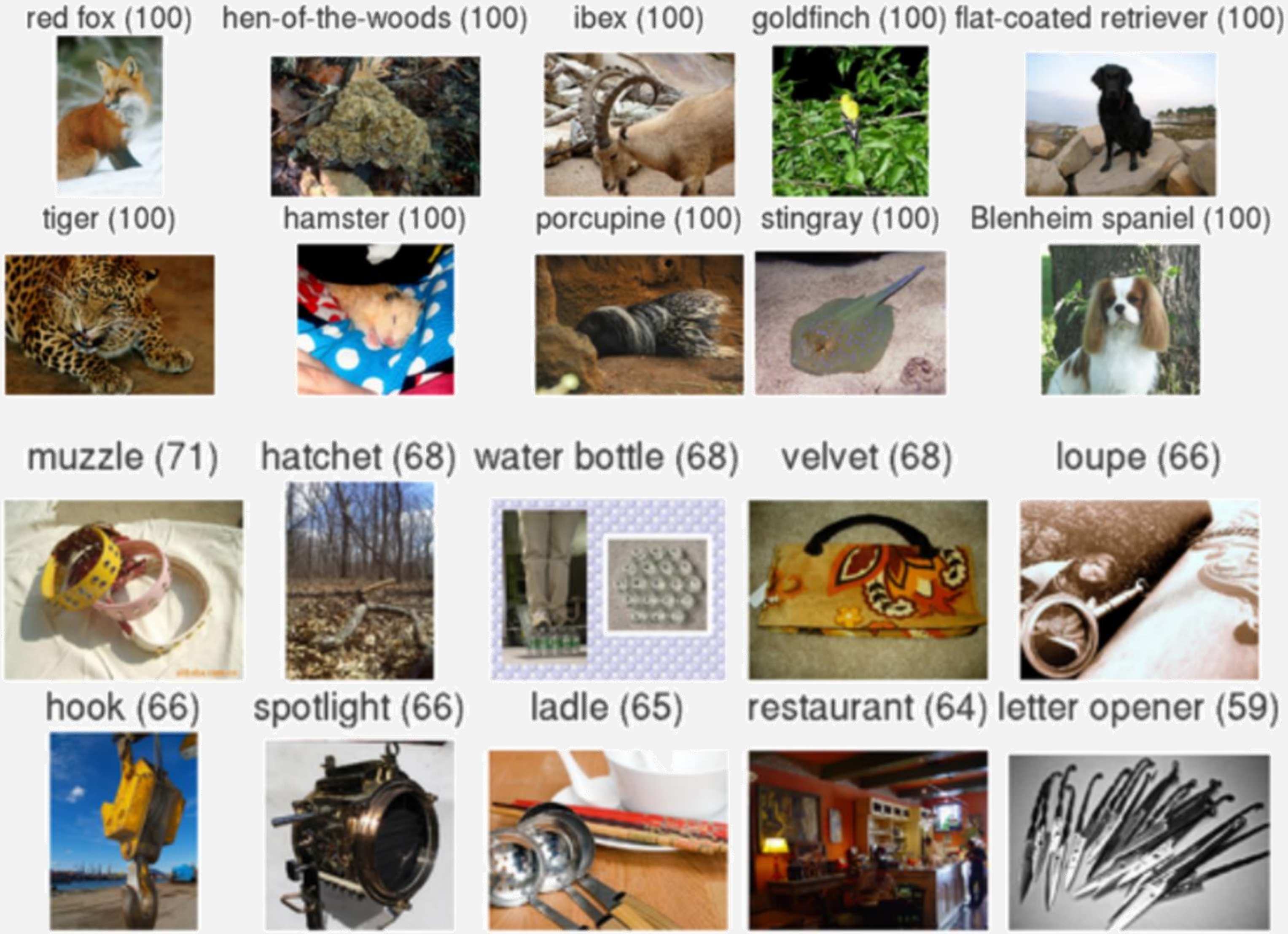


DEEP LEARNING

A Machine Learning technique



IMAGENET CHALLENGE



Karen Zack (@teenybiscuit)

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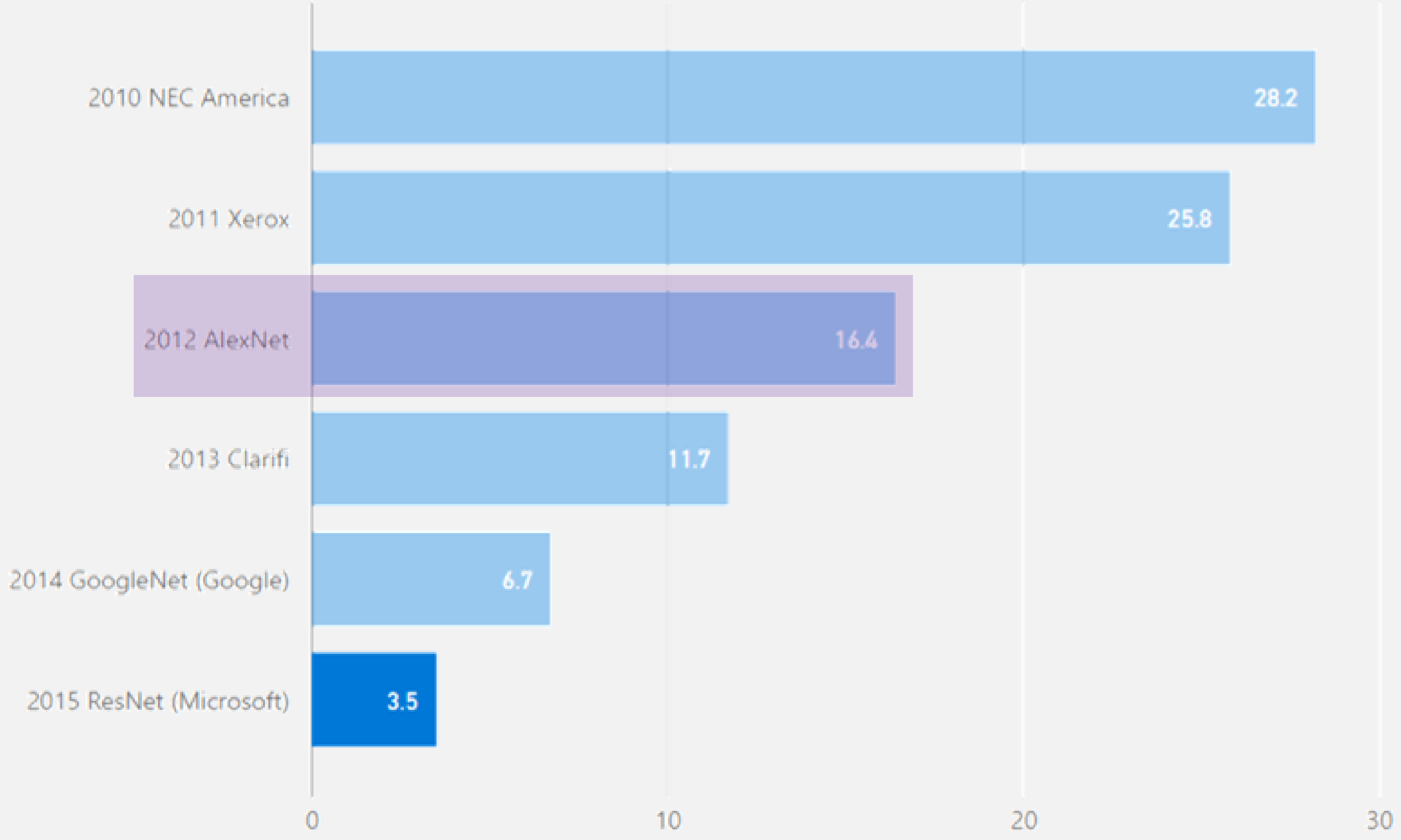
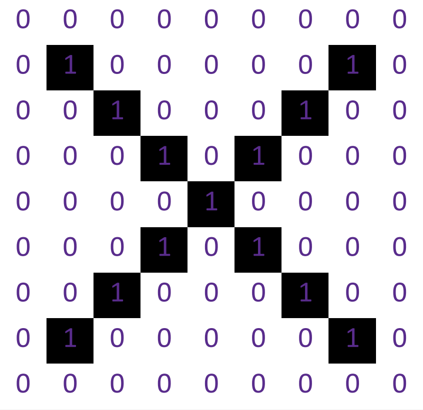
IMAGENET CHALLENGE



FILTERING



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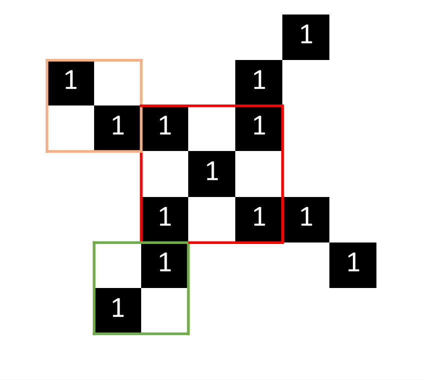
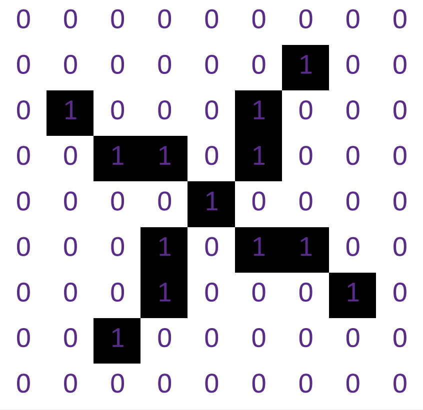


						1		
	1				1			
		1	1		1			
				1				
			1		1	1		
			1				1	
		1						



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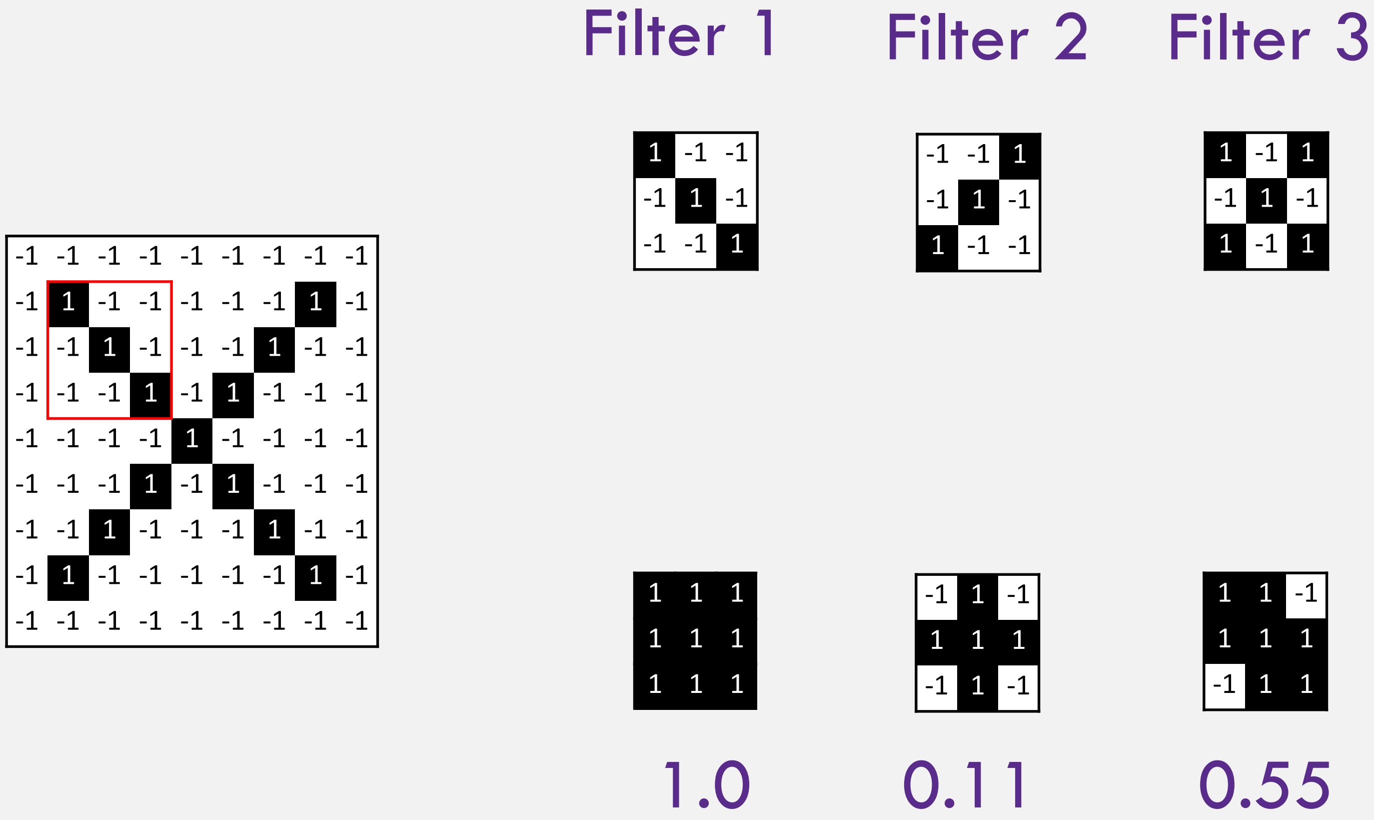
0	0	0	0	1	0	0	0	0
0	0	0	1	0	1	1	0	0
0	0	0	1	0	0	0	1	0
0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0

FILTERING

…looking for common characteristics



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

Filter 1

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

1	1	1
1	1	1
1	1	1

1.0

Filter 2

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

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

0.11

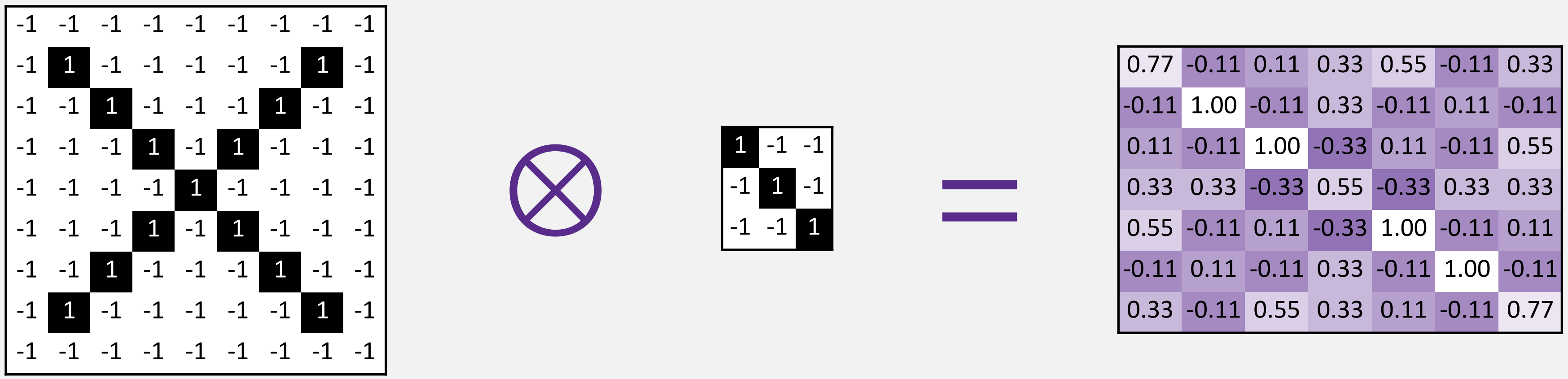
Filter 3

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

1	1	-1
1	1	1
-1	1	1

0.55

CONVOLUTION



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-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	-1	1

=

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

CONVOLUTION

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

⊗

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

=

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

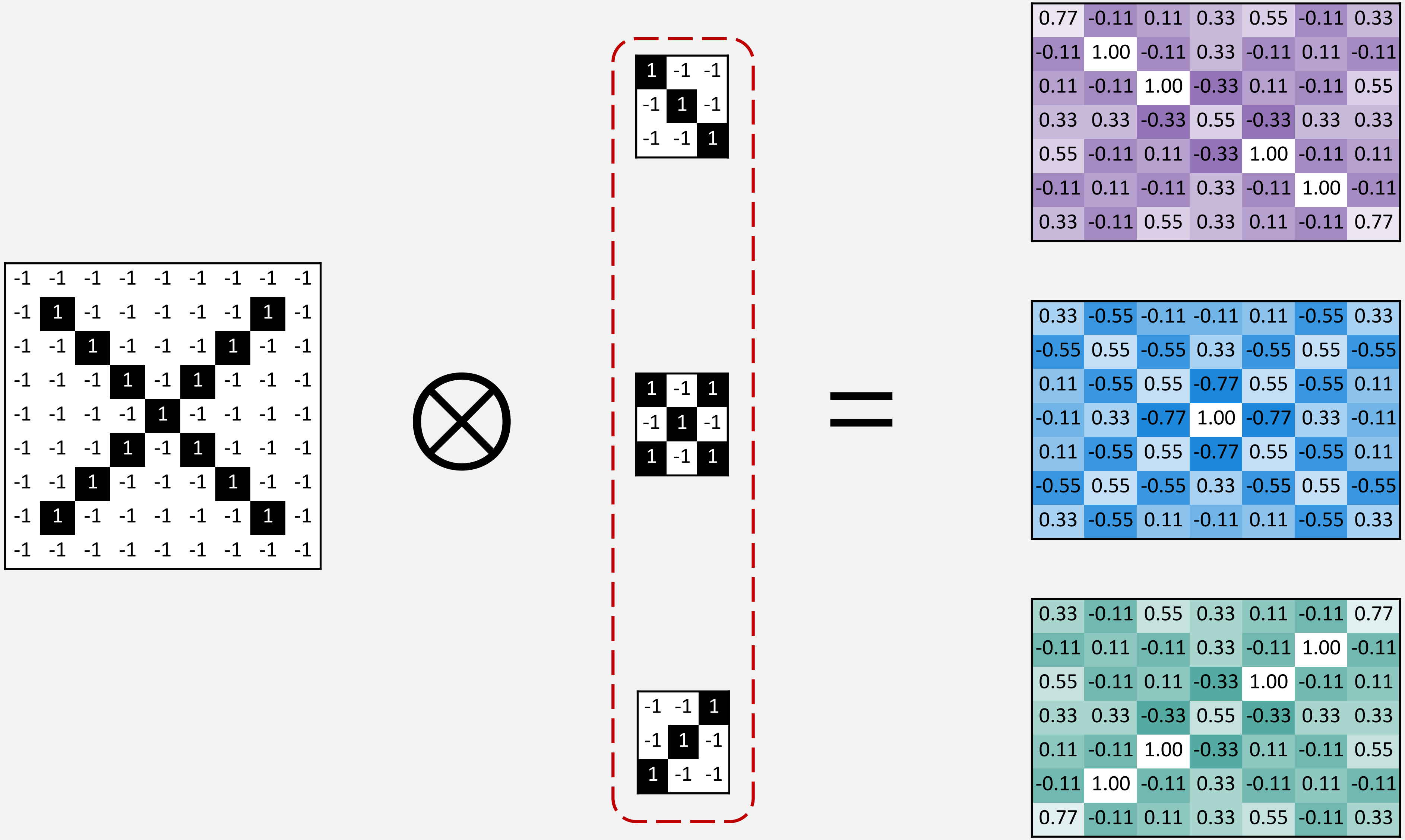
-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

⊗

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

=

0.33	-0.11	0.55	0.33	0.11	-0.11	0.77
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.77	-0.11	0.11	0.33	0.55	-0.11	0.33



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-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	-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

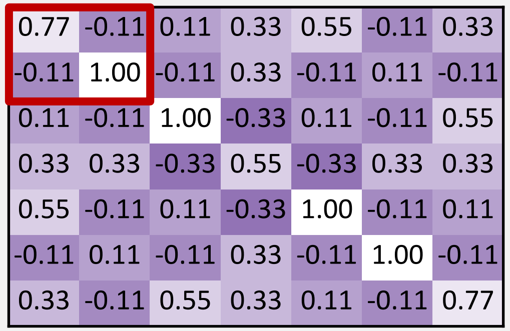
=

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

0.33	-0.55	-0.11	-0.11	0.11	-0.55	0.33
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.11	0.33	-0.77	1.00	-0.77	0.33	-0.11
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33

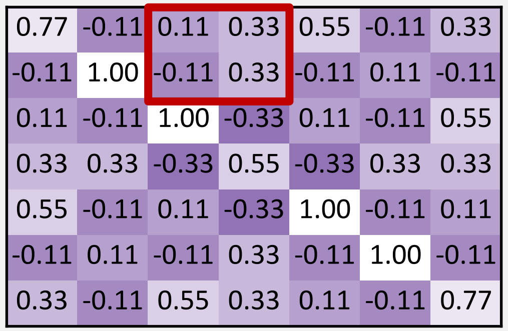
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.77	-0.11	0.11	0.33	0.55	-0.11	0.33

POOLING



0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

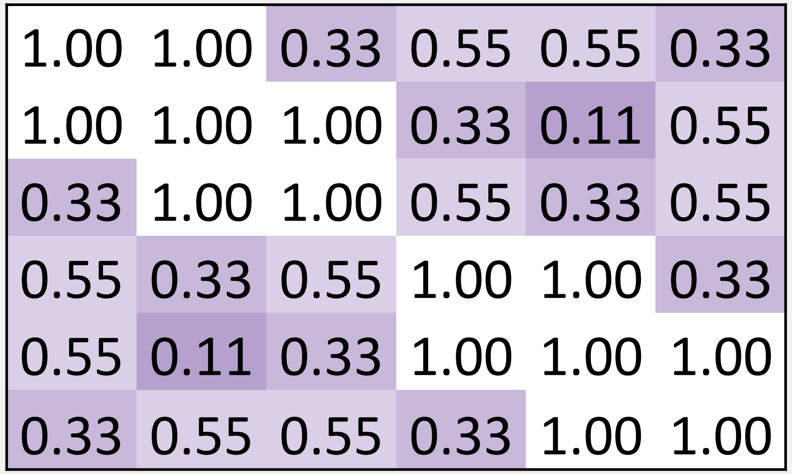
POOLING



0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

MAX POOLING – STRIDE 1

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77



1.00	1.00	0.33	0.55	0.55	0.33
1.00	1.00	1.00	0.33	0.11	0.55
0.33	1.00	1.00	0.55	0.33	0.55
0.55	0.33	0.55	1.00	1.00	0.33
0.55	0.11	0.33	1.00	1.00	1.00
0.33	0.55	0.55	0.33	1.00	1.00

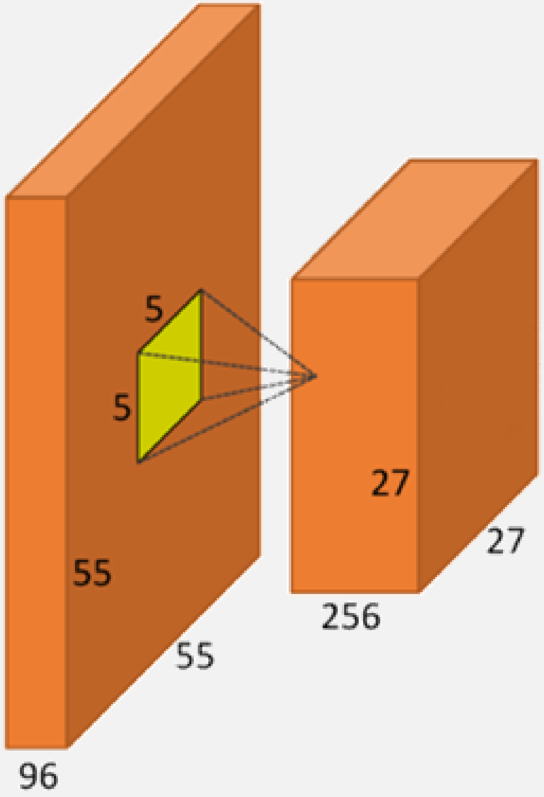
AVERAGE POOLING – STRIDE 2

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

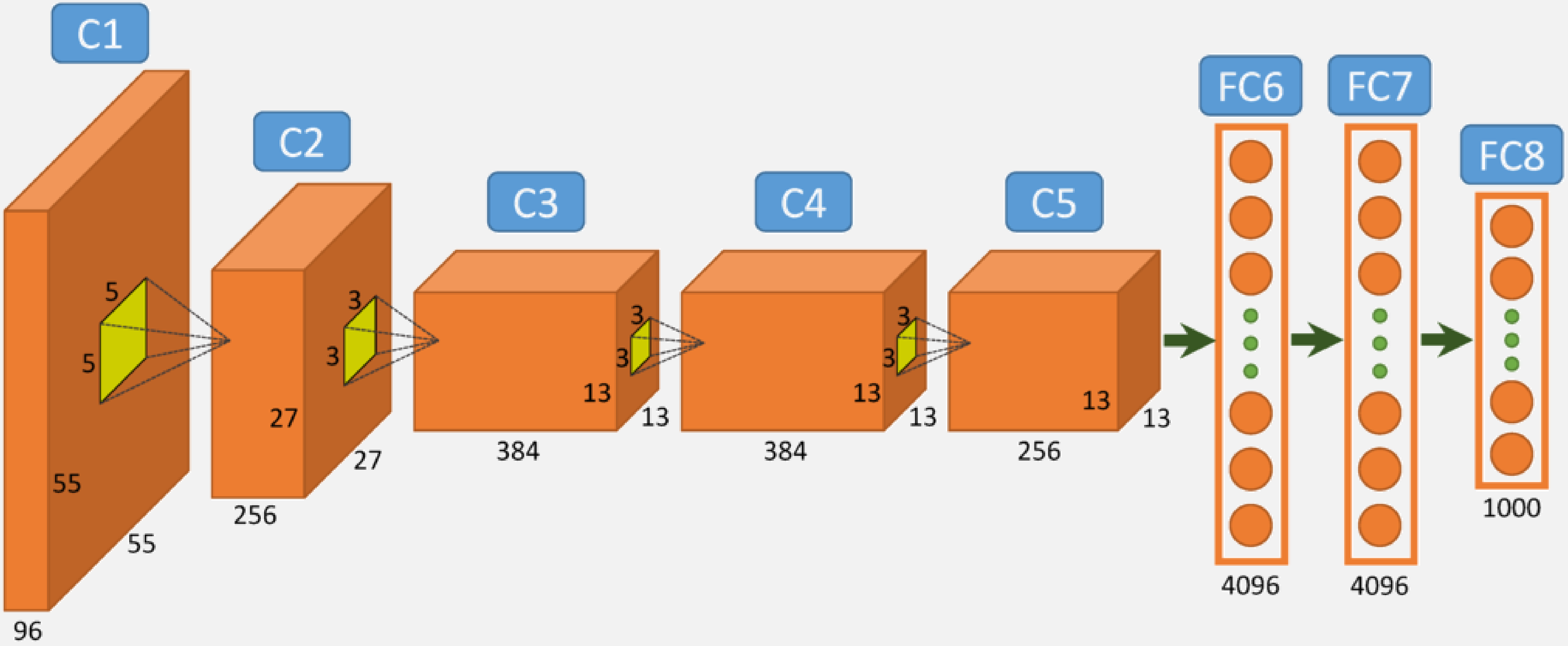
1.00	0.33	0.55	0.33
0.33	1.00	0.33	0.55
0.55	0.33	1.00	0.11
0.33	0.55	0.11	0.77

WHY POOLING?

ACTIVATION FUNCTIONS?



ALEXNET


C1
C2
C3
C4
C5
FC6
FC7
FC8
5
5
55
55
96
3
3
27
27
256
3
3
13
13
384
3
3
13
13
384
13
13
256
4096
4096
1000

WHAT IS MISSING?

Filter 1

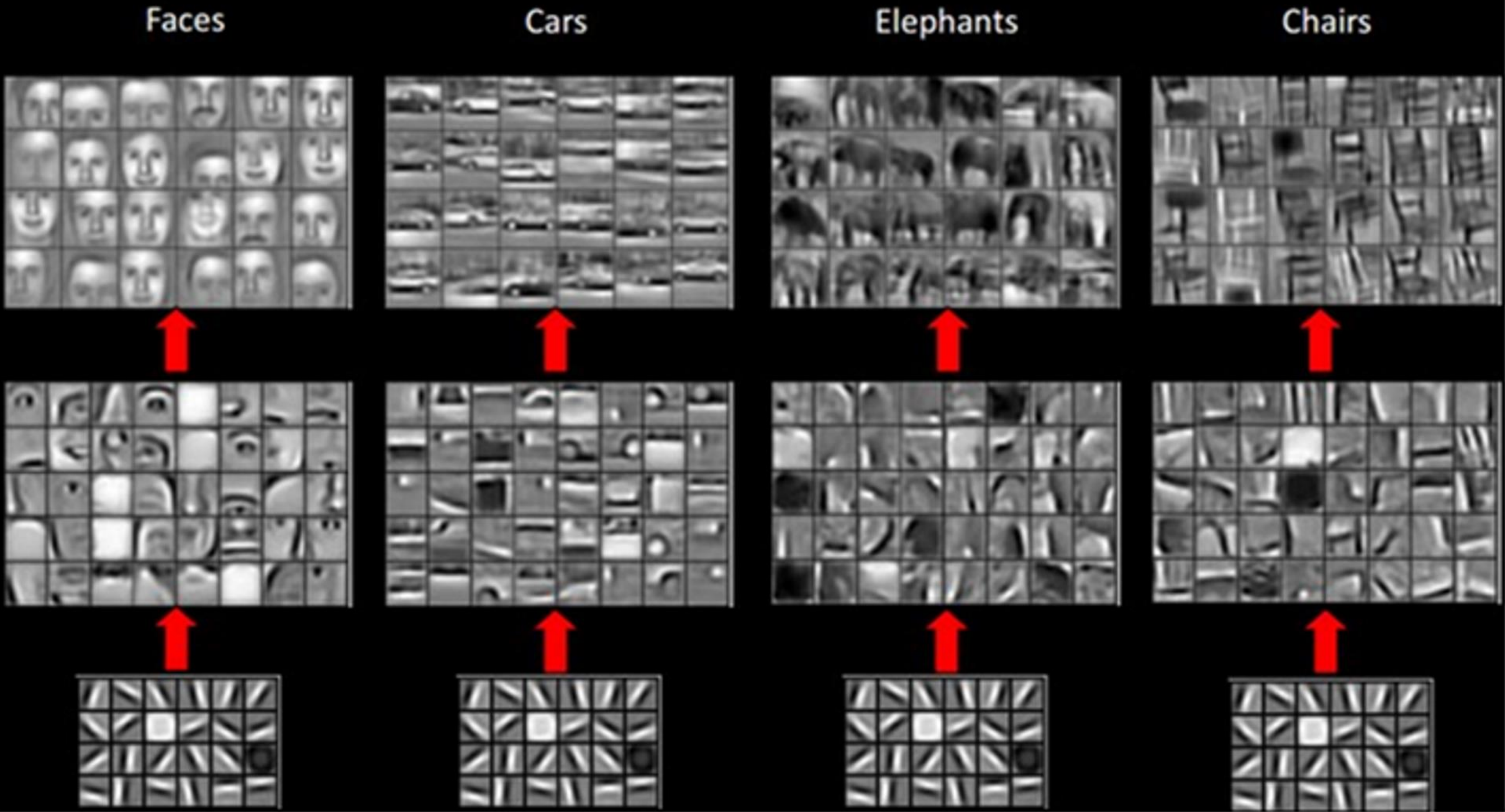
1	-1	-1
-1	1	-1
-1	-1	1

Filter 2

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

Filter 3

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



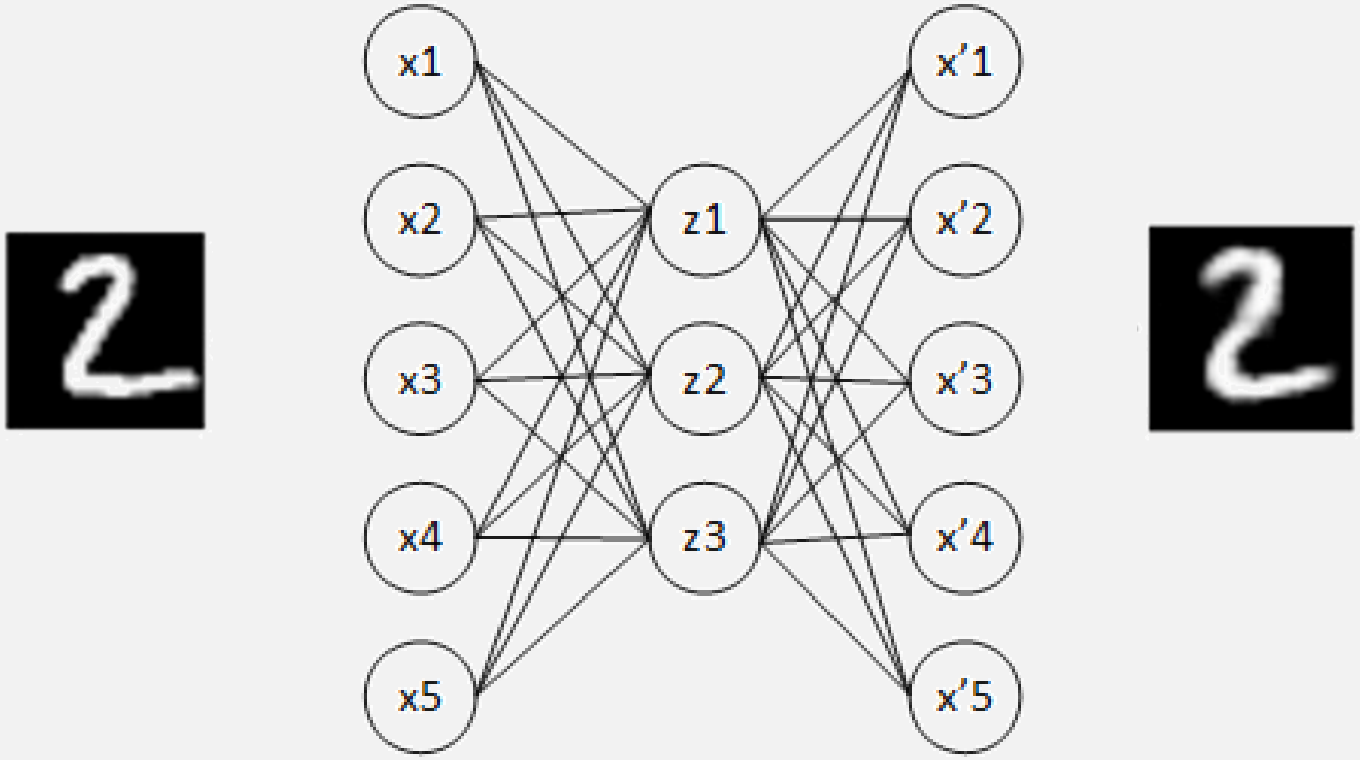
Faces

Cars

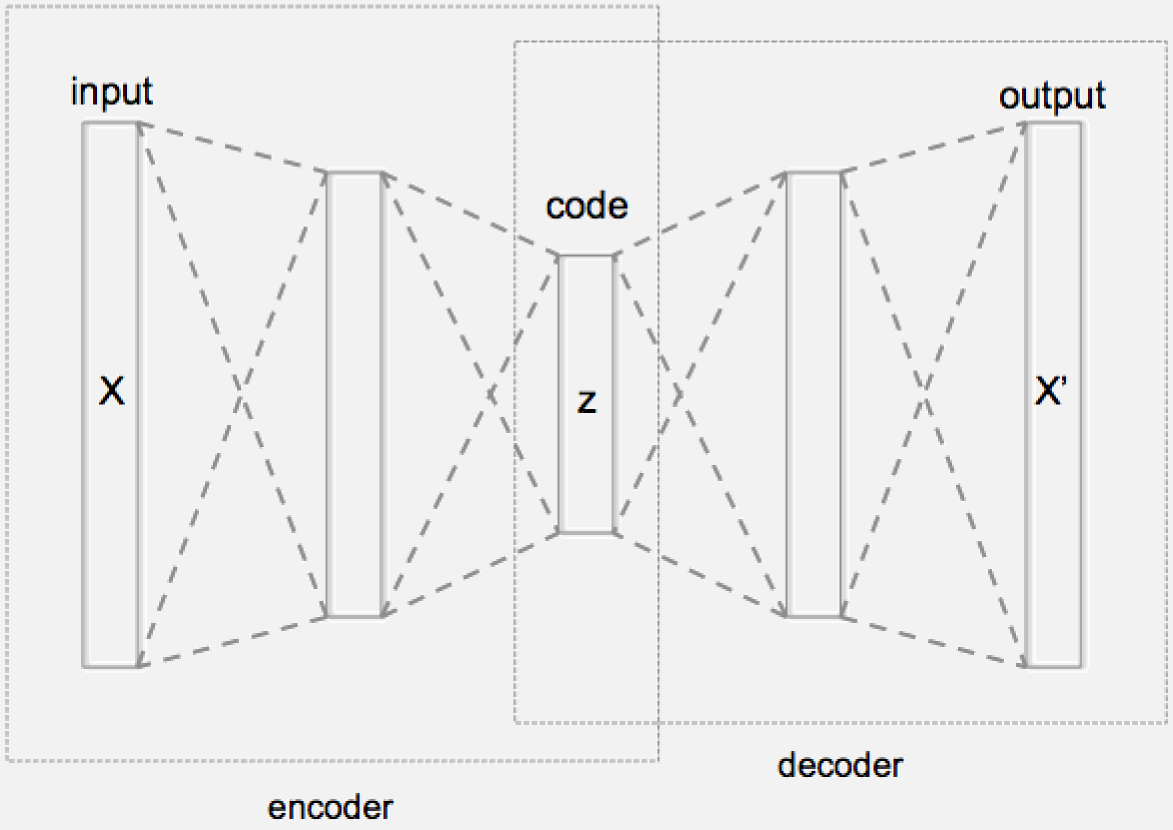
Elephants

Chairs

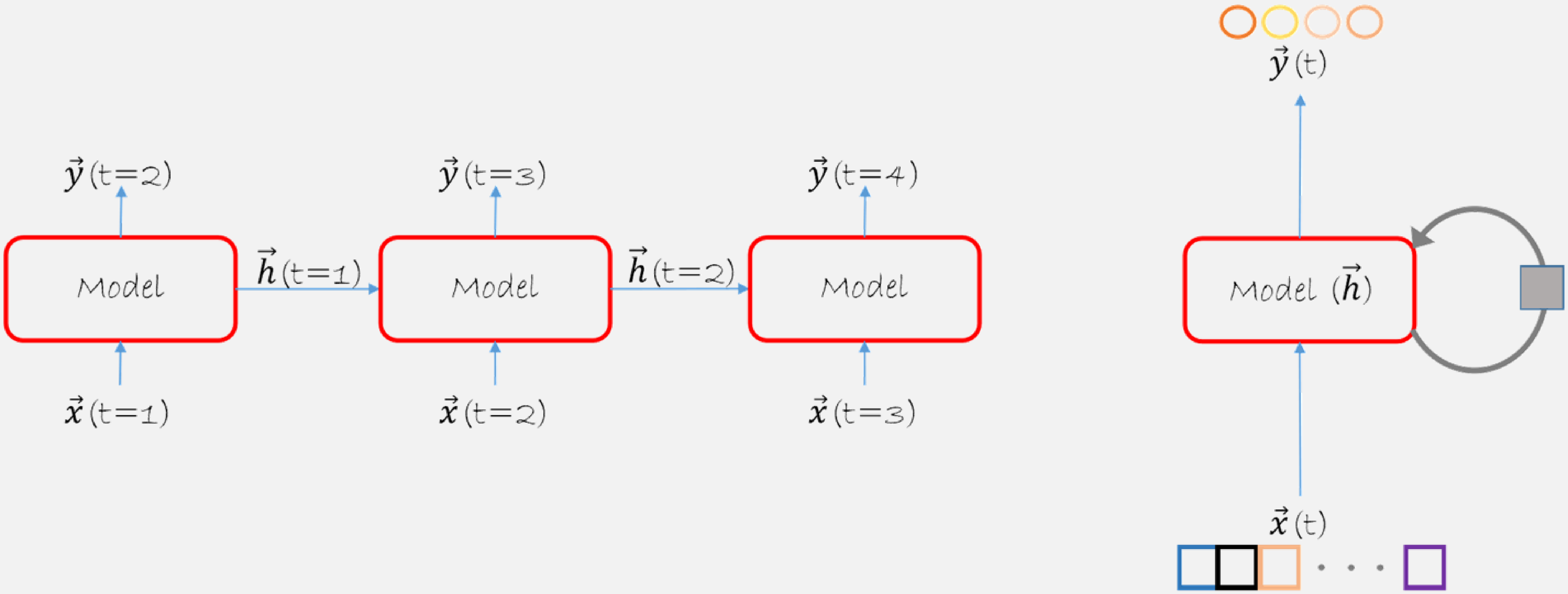
BASIC AUTOENCODER



BASIC AUTOENCODER



RNN & LONG SHORT TERM MEMORY



Automated Mammogram BIRADS Classifier

AUTOENCODER, FASTRCNN

Evaluate the new opportunities offered to the breast cancer diagnosis by the latest advances in Deep Learning (deep neural models), extracting location, BIRADS classification and degree of confidence of each abnormality found in the mammography supplied as an input.

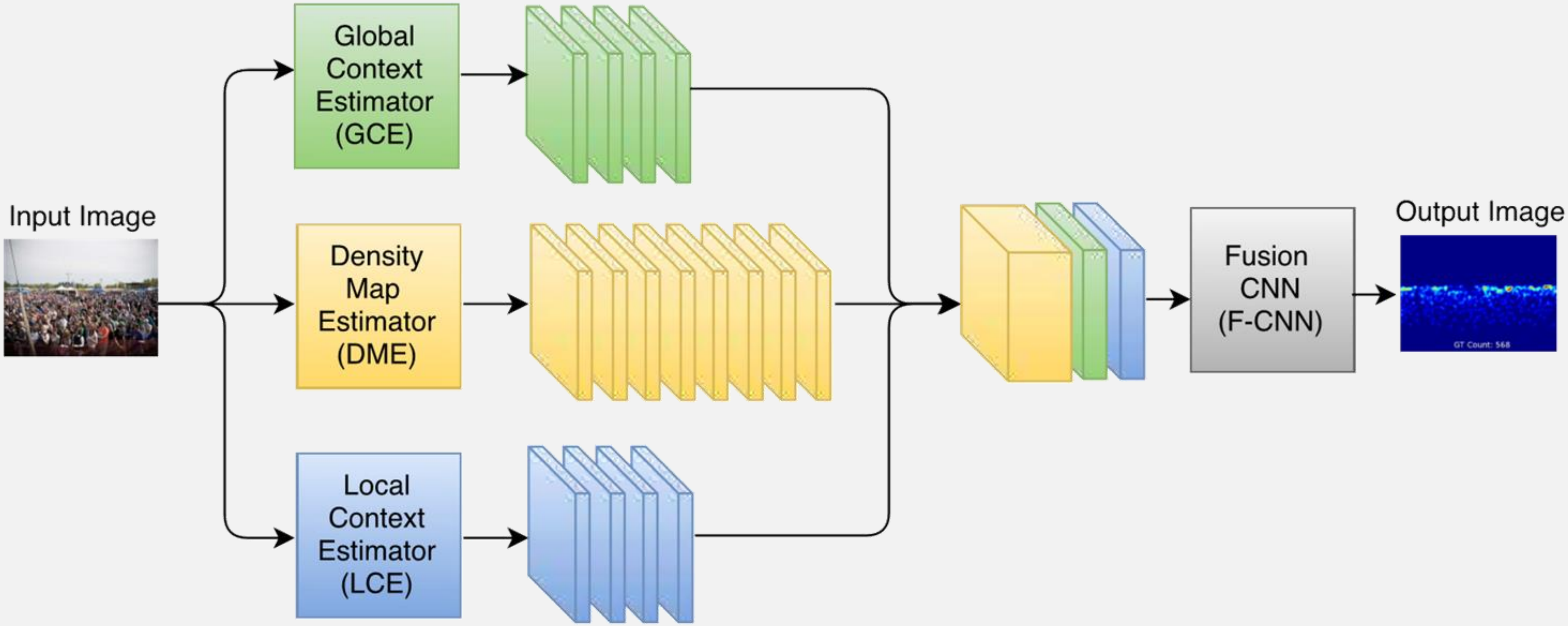

Bonpoint
إنجلز
angels
SOLD
45
80

Counting people in a crowd

CONTEXTUAL PYRAMID CNN (CP-CNN)

A new method named Contextual Pyramid CNN (CP-CNN) is proposed here to generate density maps and influx estimations, by explicitely incorporating global and local context information. Composed of four modules: Global Context Estimator (GCE), Local Context Estimator (LCE), Density Map Estimator (DME) and a Fusion-CNN (F-CNN) convolutional network.

Vishwanath A. Sindagi, Vishal M. Patel; The IEEE International Conference on Computer Vision (ICCV), 2017, pp. 1861-1870



Input Image

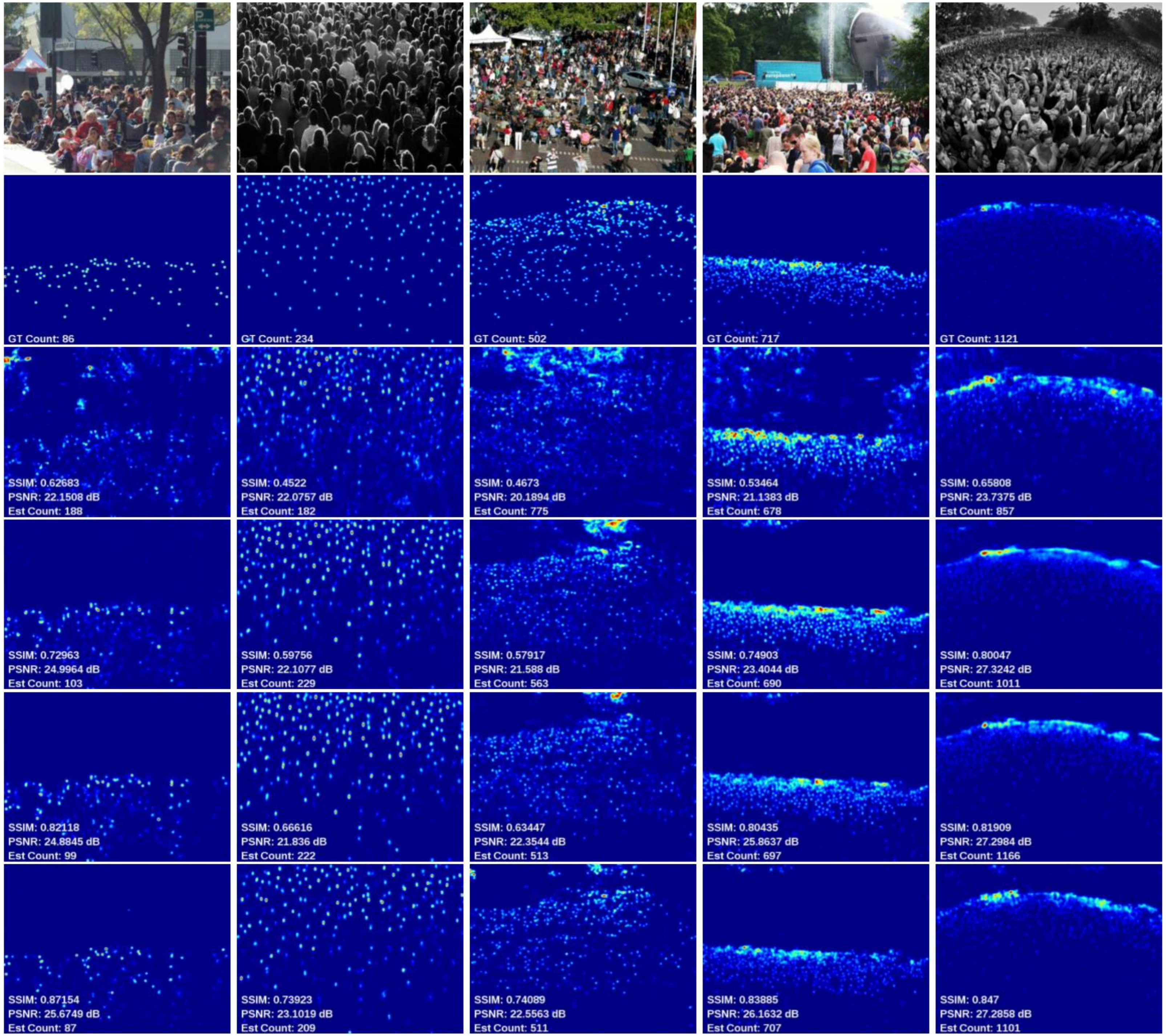
Global Context Estimator (GCE)

Density Map Estimator (DME)

Local Context Estimator (LCE)

Fusion CNN (F-CNN)

Output Image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GT Count: 502
GT Count: 717
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Est Count: 188
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PSNR: 22.0757 dB
Est Count: 182
SSIM: 0.4673
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Est Count: 775
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SSIM: 0.59756
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Est Count: 229
SSIM: 0.57917
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Est Count: 563
SSIM: 0.74903
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Est Count: 87
SSIM: 0.73923
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Est Count: 209
SSIM: 0.74089
PSNR: 22.5563 dB
Est Count: 511
SSIM: 0.83885
PSNR: 26.1632 dB
Est Count: 707
SSIM: 0.847
PSNR: 27.2858 dB
Est Count: 1101

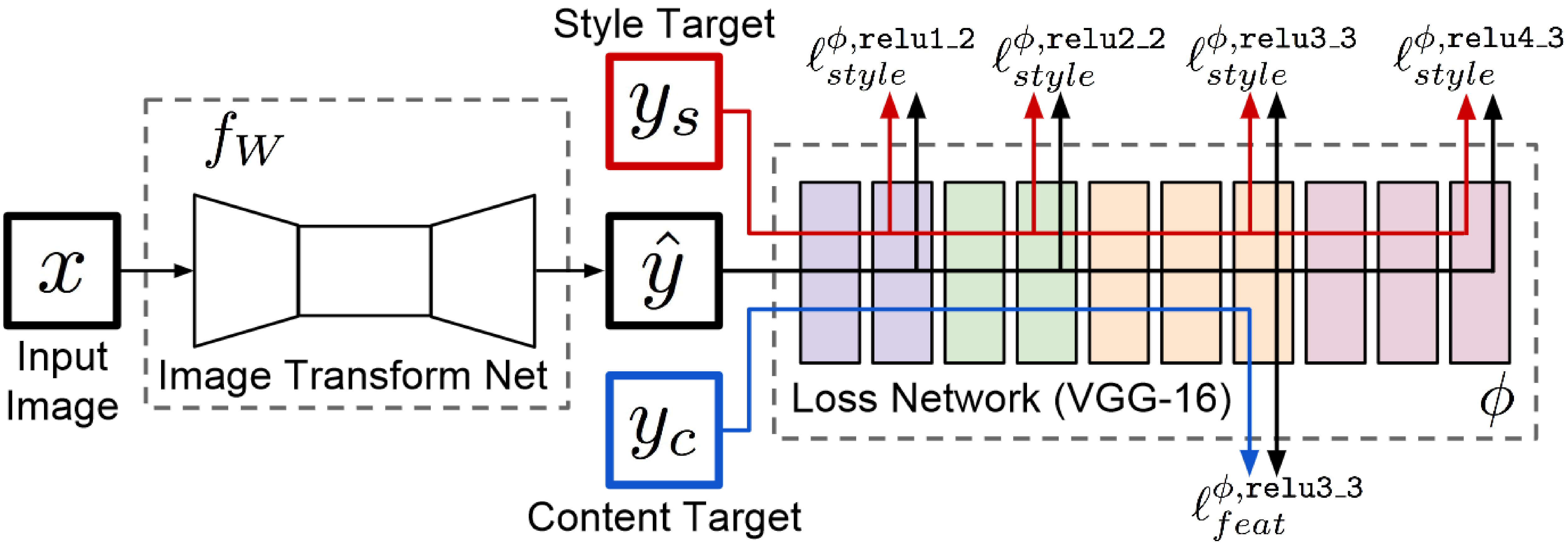
Transferring style across images

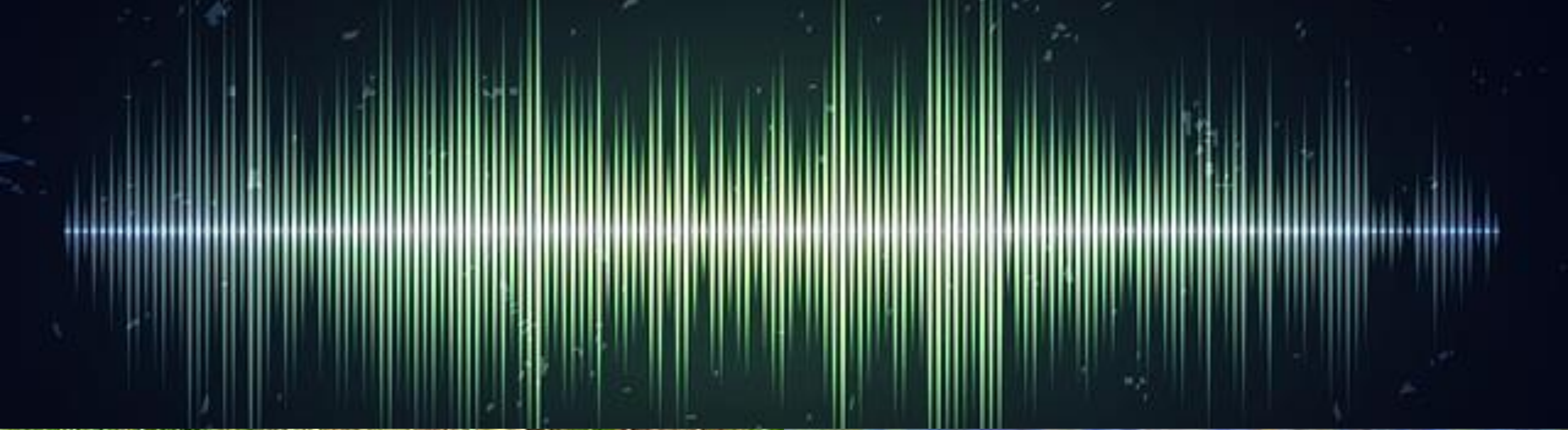
CONVOLUTIONAL NEURAL NETWORKS

By using a perceptual loss functions based on high-level features extracted from pretrained networks, networks for image transformation tasks can be trained, and by fine tuning the loss function different features can be kept for the source image and the style image.

Justin Johnson, Alexandre Alahi, Li Fei-Fei; Perceptual Losses for Real-Time Style Transfer and Super-Resolution, 2016

HOW DOES THIS WORK?





Using GANs to drive design decisions

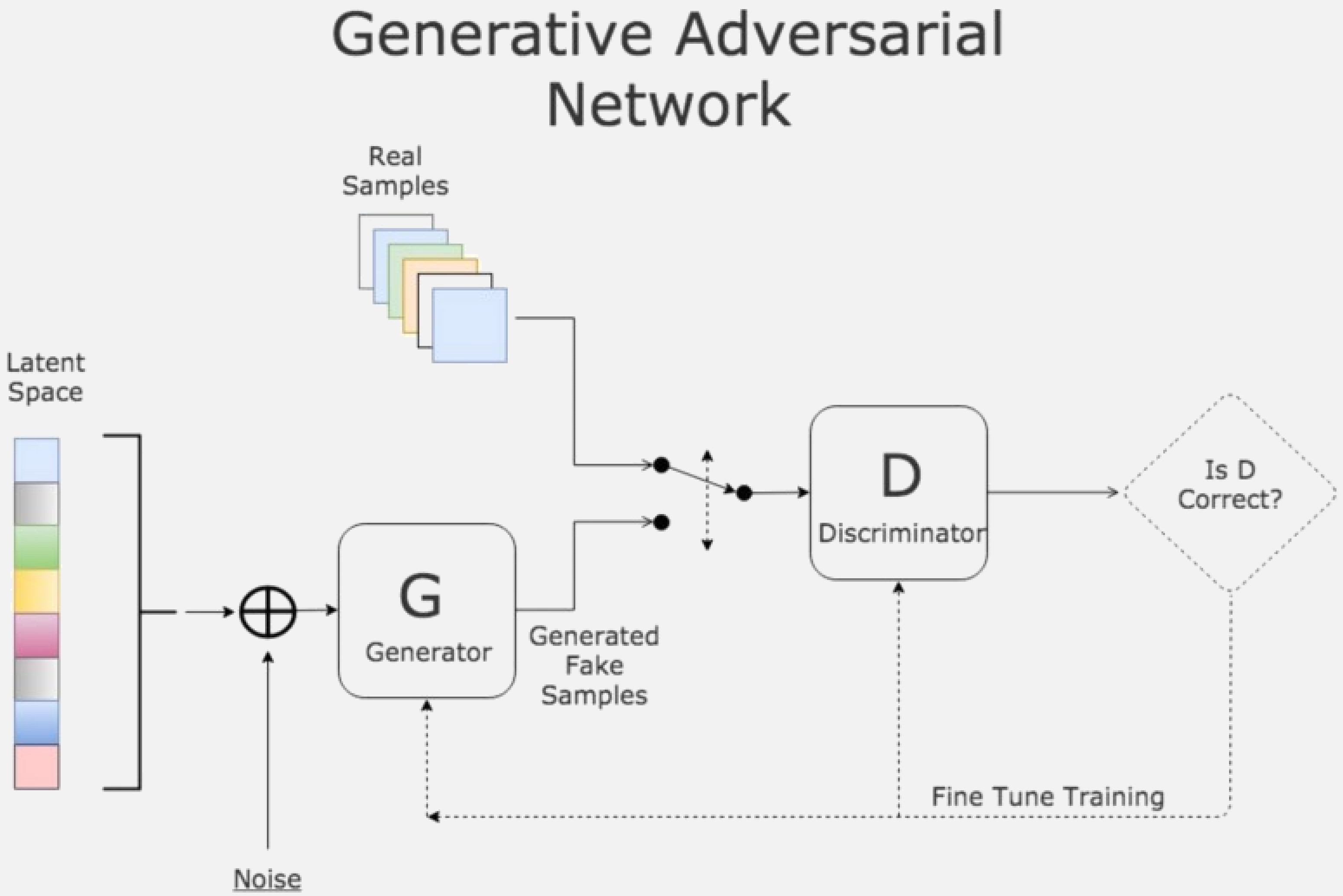
GENERATIVE ADVERSARIAL NETWORKS

By taking advantage of Generational Adversarial Networks, synthetic images based on the training data can be generated. Including an external array of features, the generated images can be tailored to a specific set of requirements.

Jaime Deverall, Jiwoo Lee, Miguel Ayala; Using Generative Adversarial Networks to Design Shoes

Text description	This bird is blue with white and has a very short beak	This bird has wings that are brown and has a yellow belly	A white bird with a black crown and yellow beak	This bird is white, black, and brown in color, with a brown beak	The bird has small beak, with reddish brown crown and gray belly	This is a small, black bird with a white breast and white on the wingbars.	This bird is white black and yellow in color, with a short black beak

HOW DOES THIS WORK?




TELIO


ZM 0000
NS 0000
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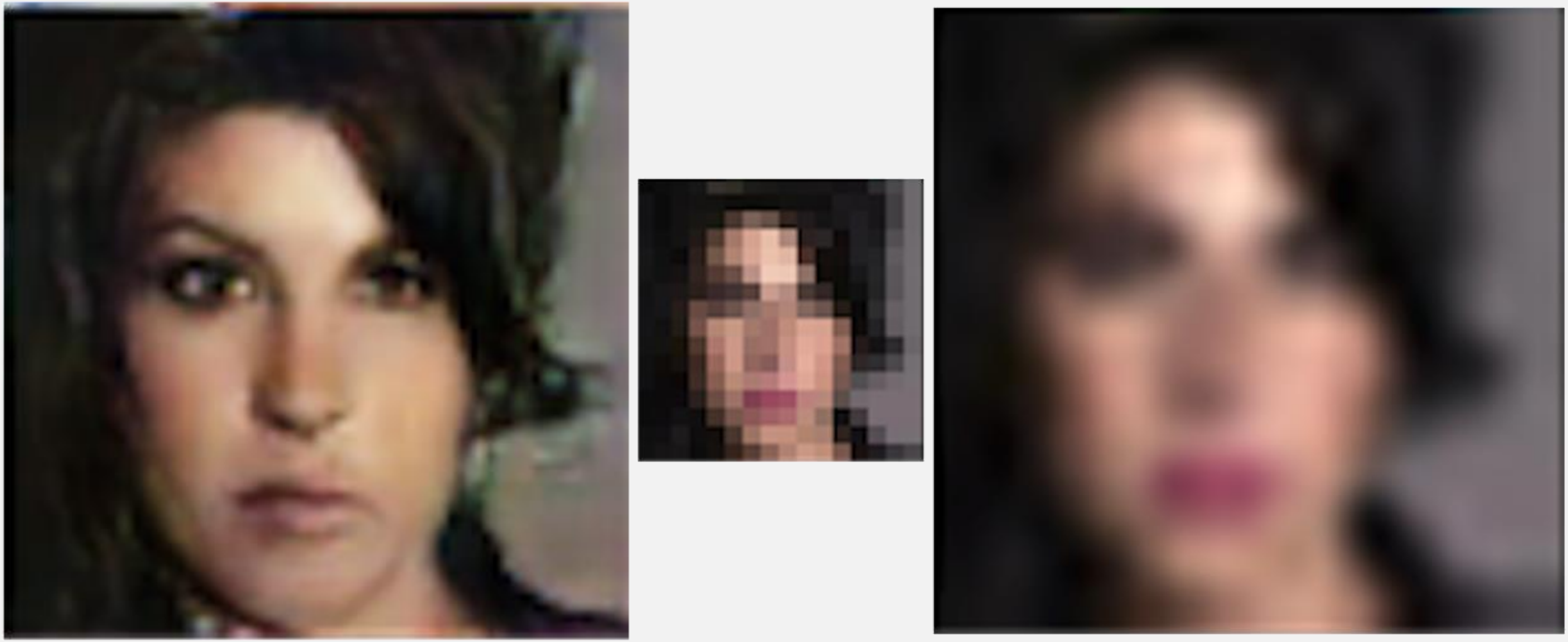
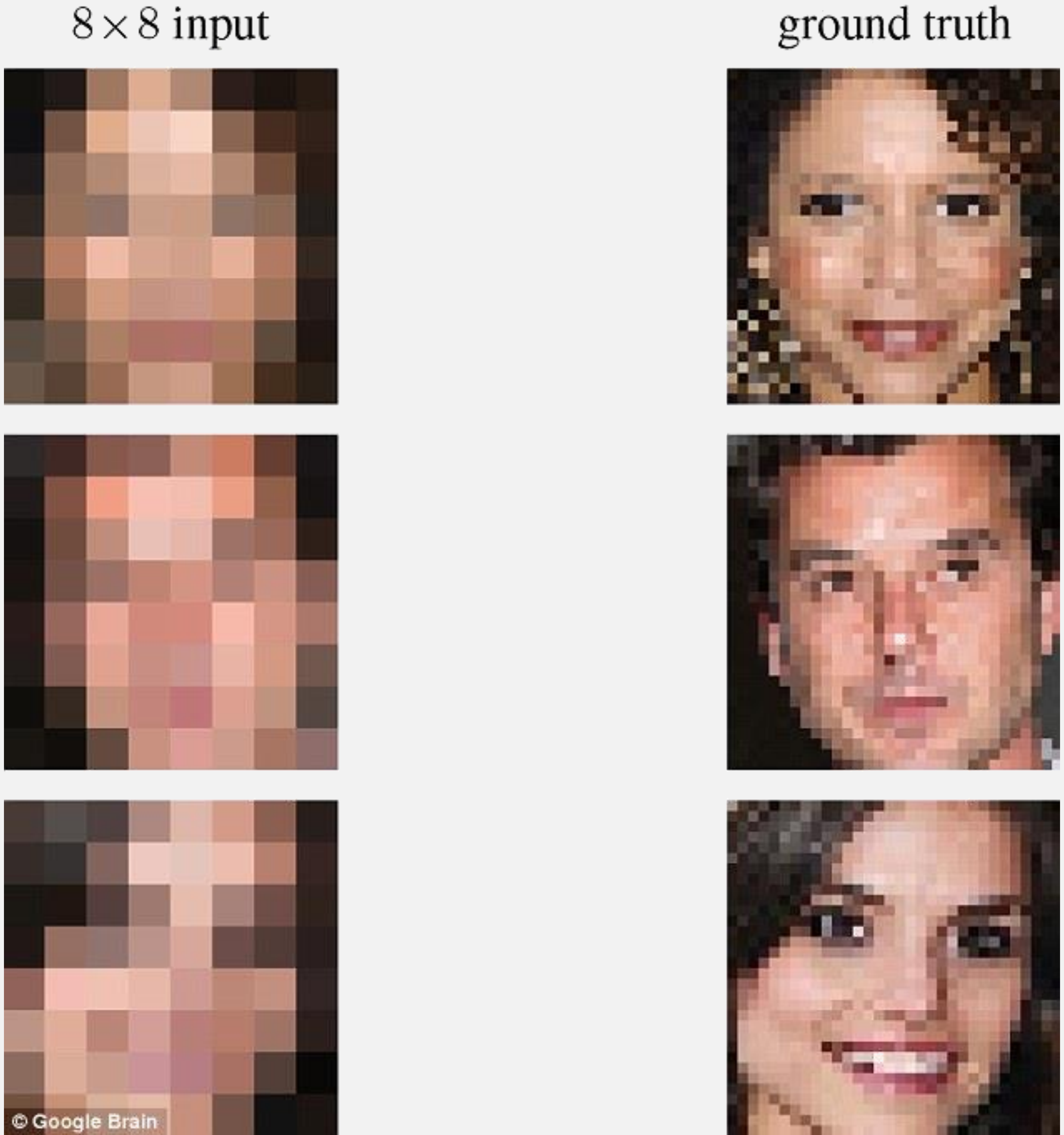
Helping solve gruesome crimes

SR-GAN AND SRRESNET, PIXELCNN

By using Generative Adversarial Networks, we are going to be able to upscale a pixelated image, and help the security enforcement team of our favourite TV show find the actual face of the criminal!

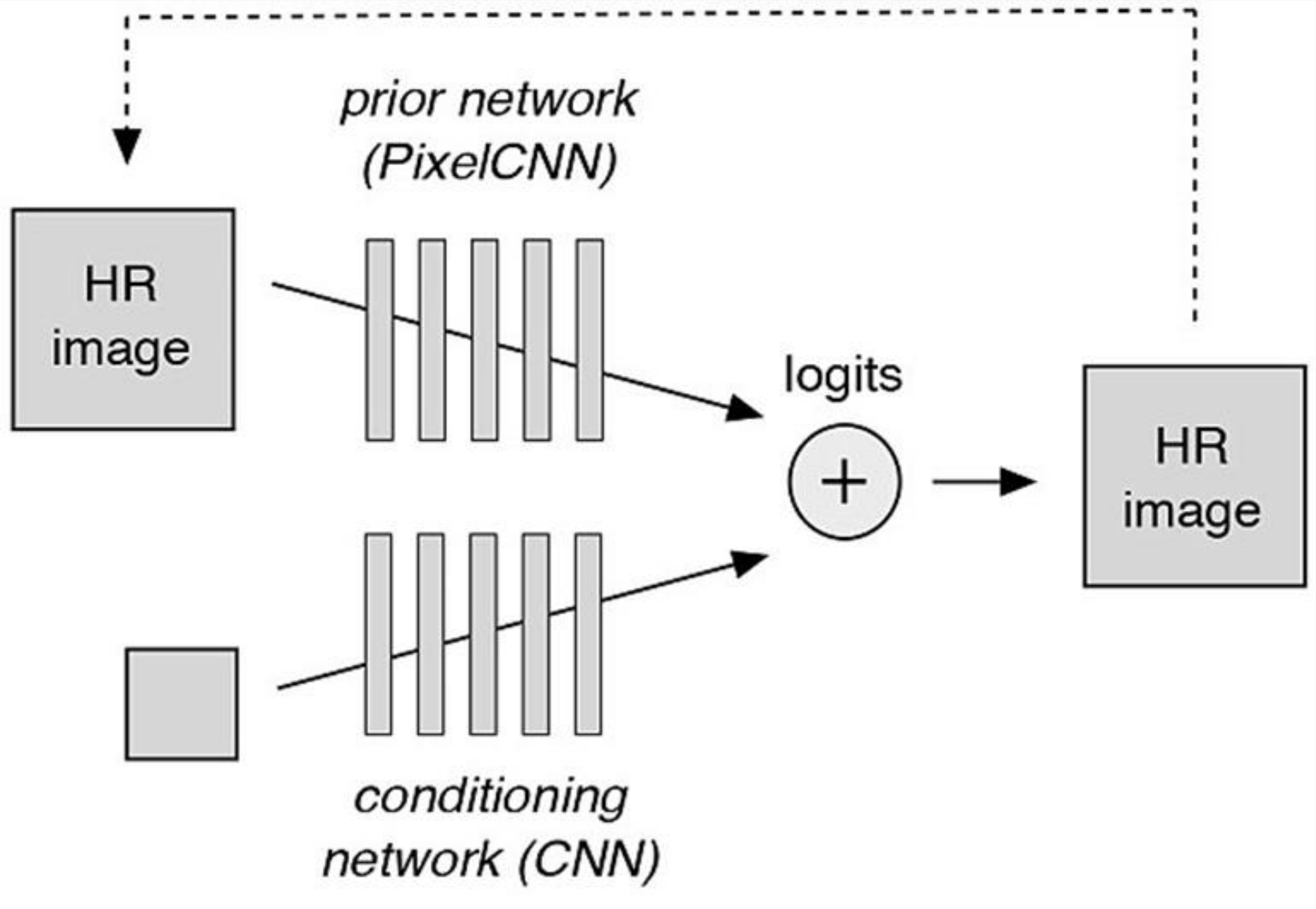
Ledig, Theis, et al.; Photo-RealisticSingleImageSuper-ResolutionUsingaGenerativeAdversarial Network, 2017



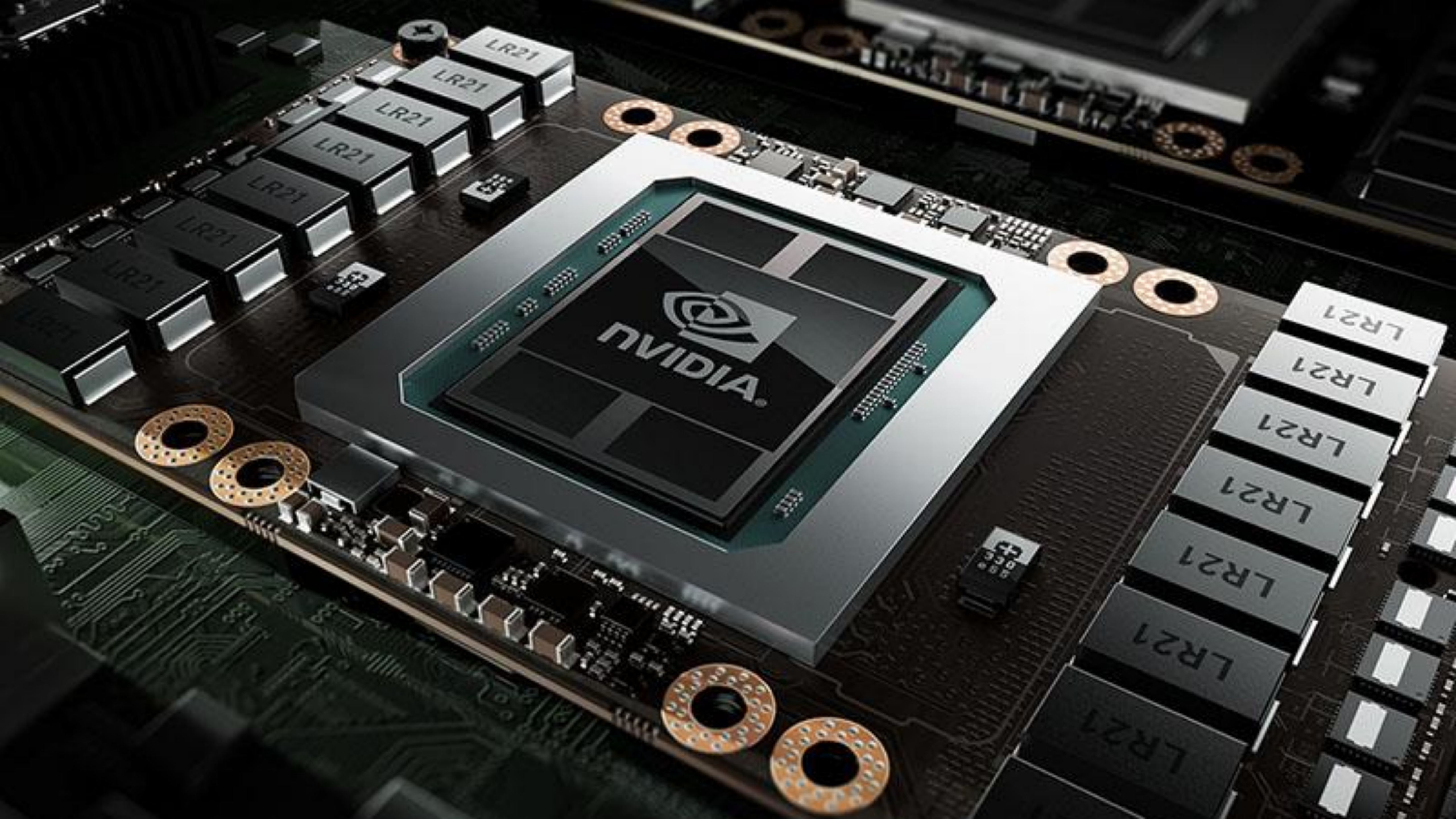


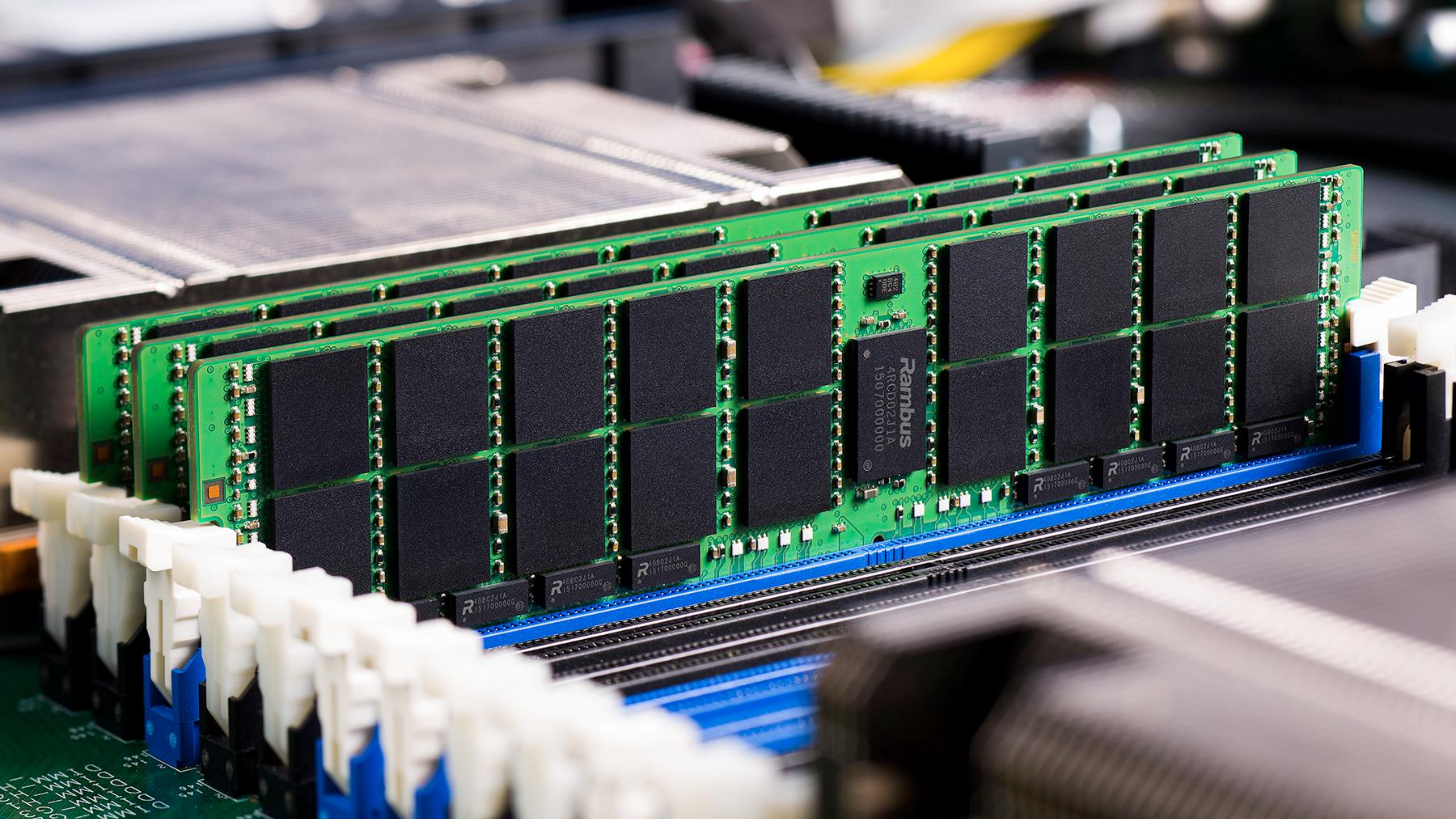
© Google Brain

HOW DOES THIS WORK?




100
SHUT UP AND TAKE MY MONEY


NVIDIA
LR21


Rambus
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4DB02J1A
1517000000

Caffe

Chainer

DL4J
Deeplearning4j

K
KERAS

Microsoft
CNTK

MatConvNet

MINERVA

mxnet

Purine

TensorFlow

theano

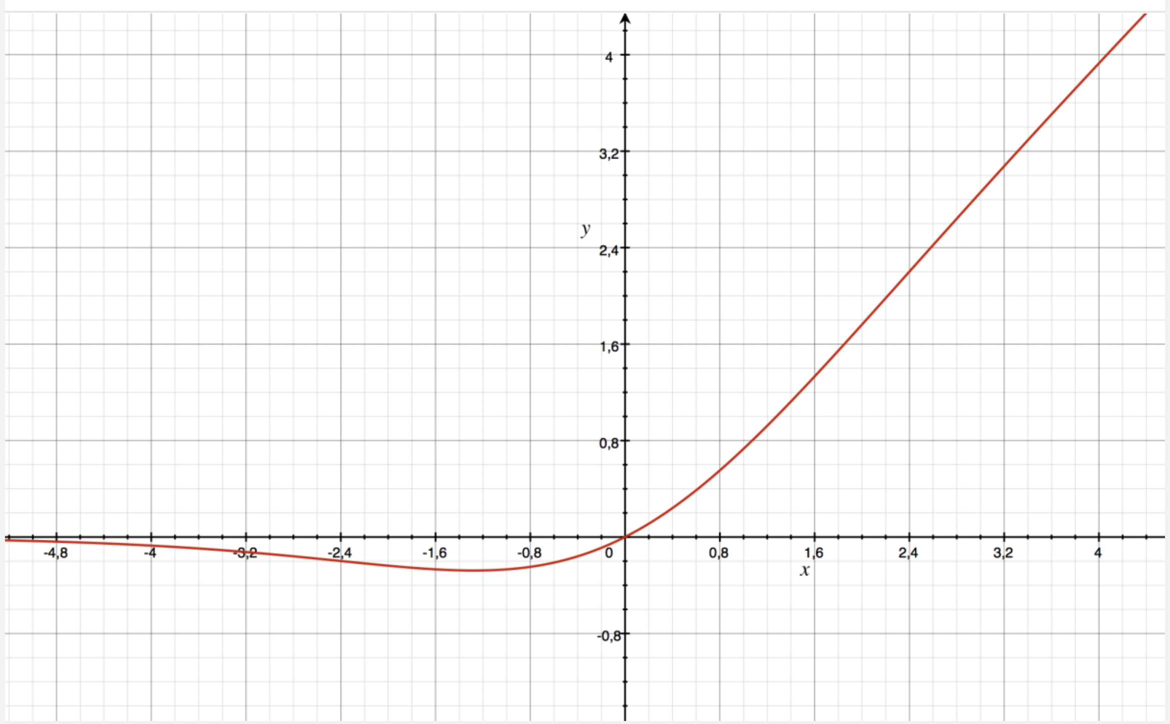
torch

ONNX

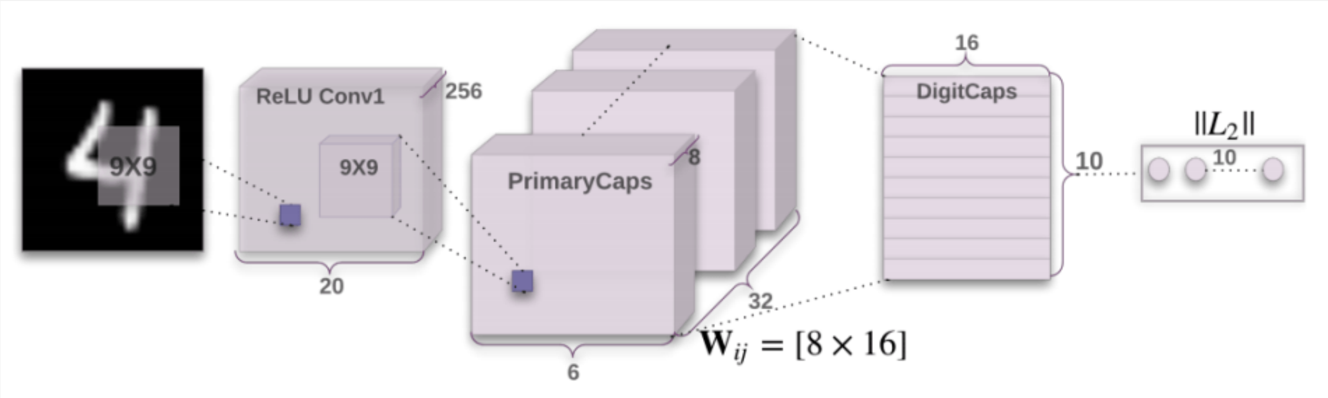
OPEN NEURAL NETWORK EXCHANGE FORMAT

The new open ecosystem for interchangeable AI models

MOVING FAST!



MOVING FAST!


9X9
ReLU Conv1
256
9X9
20
PrimaryCaps
8
32
6
$\mathbf{W}_{ij} = [8 \times 16]$
16
DigitCaps
10
$\|L_2\|$
10

plain concepts

¡THANKS!

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