15 DECEMBER 2018

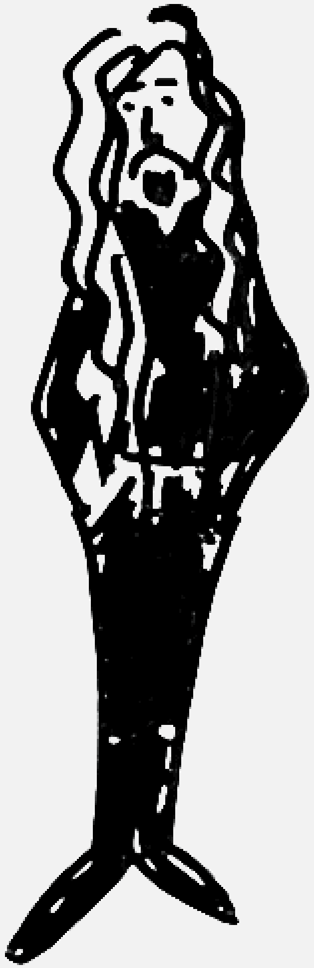
GLOBAL AI BOOTCAMP

NEW INTELLIGENT WORLDS

LONDON 2018

Past and Future of Deep Learning

Pablo Doval
Data Pontifex @Plain Concepts



Pablo Doval

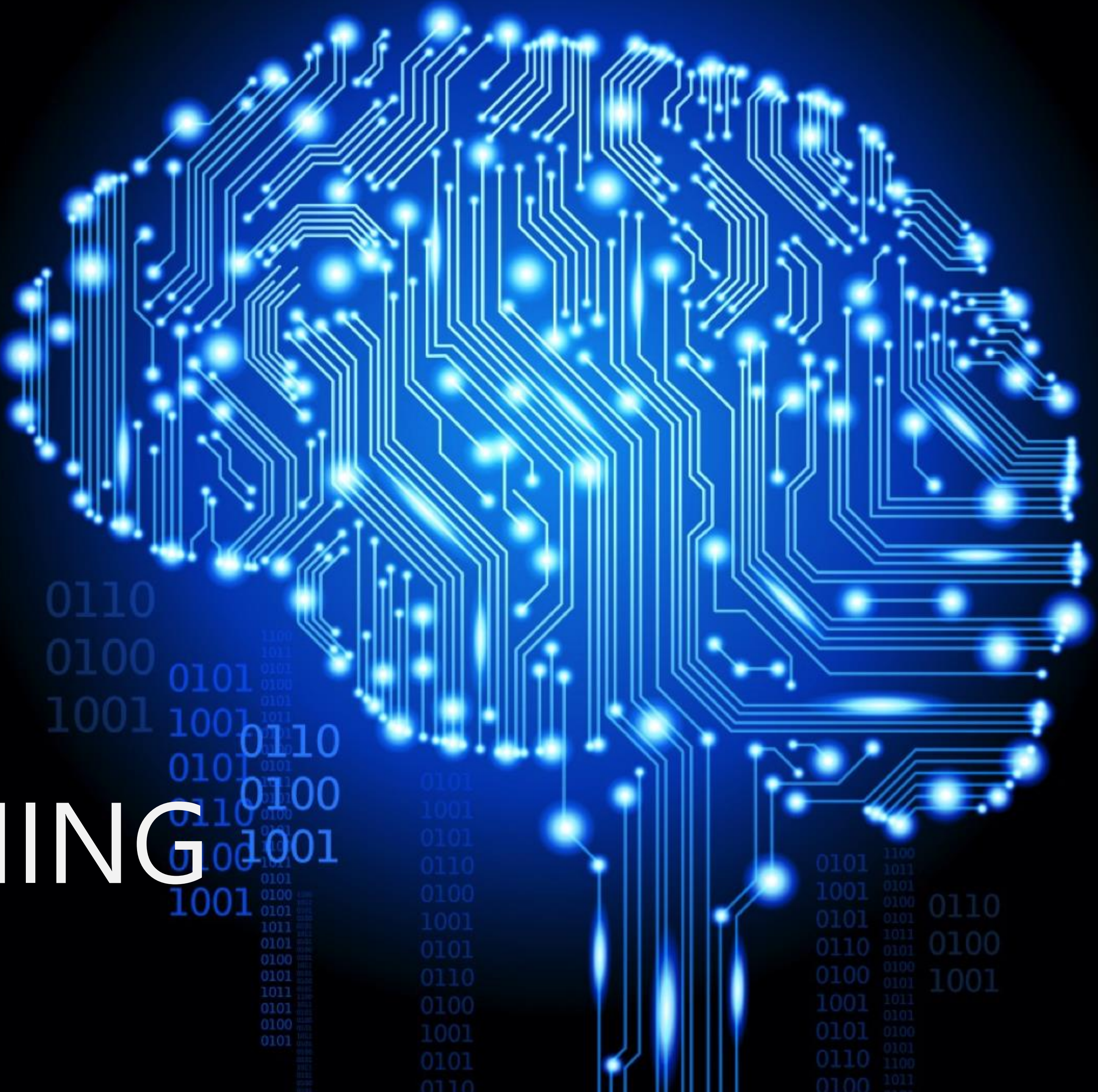
DATA PONTIFEX @Plain Concepts

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

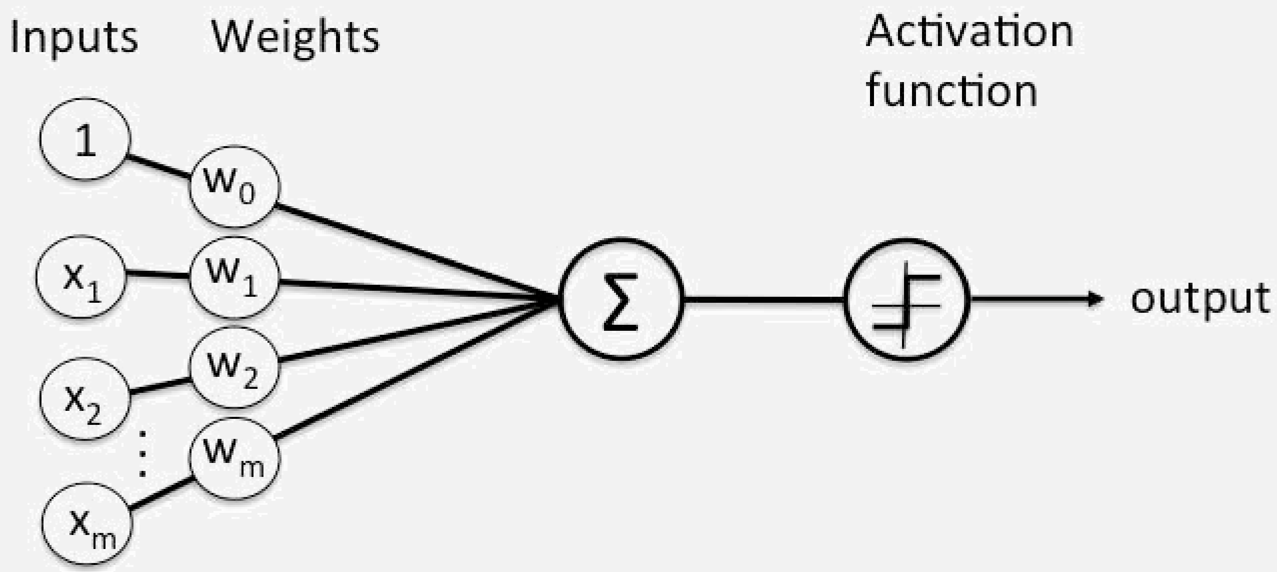
@PabloDoval


ews Blog

A.I.
MACHINE LEARNING
DEEP LEARNING

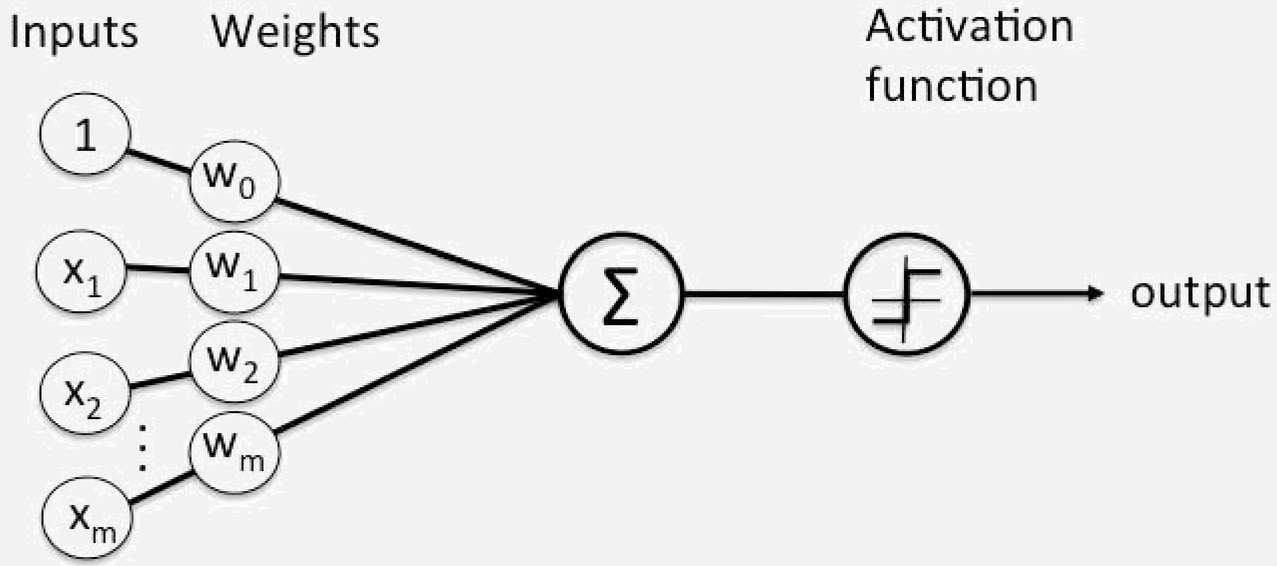


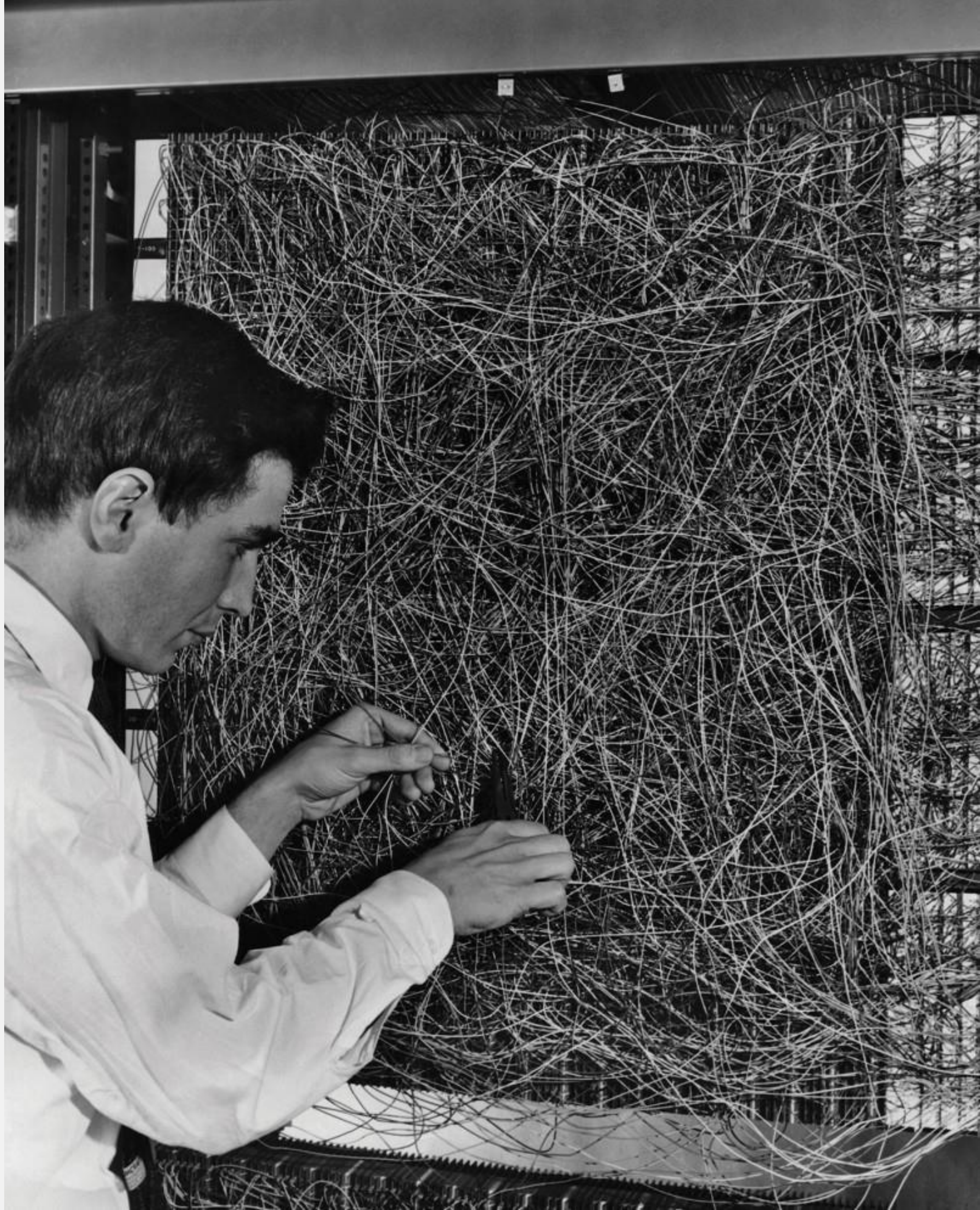
PERCEPTRON



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

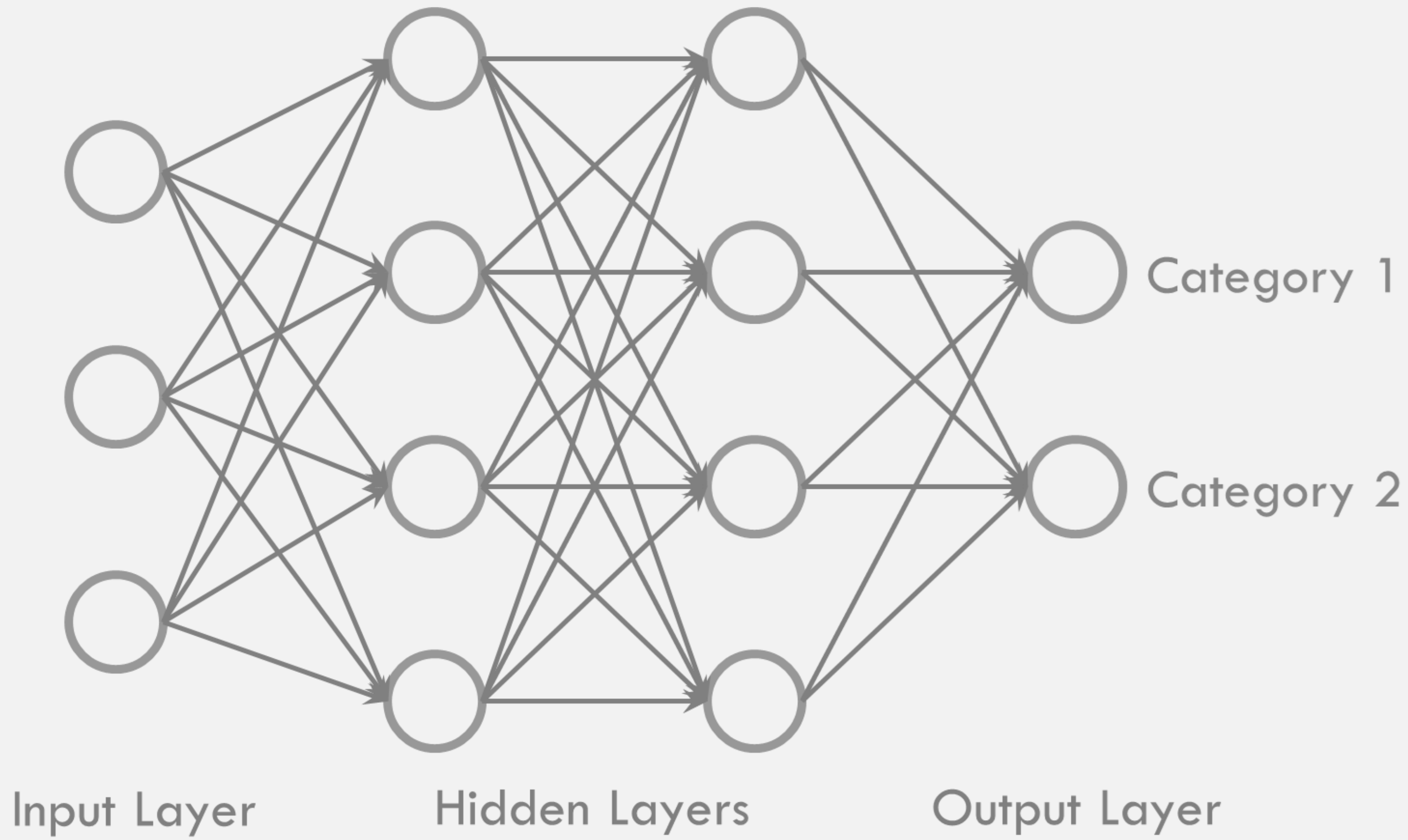
PERCEPTRON


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

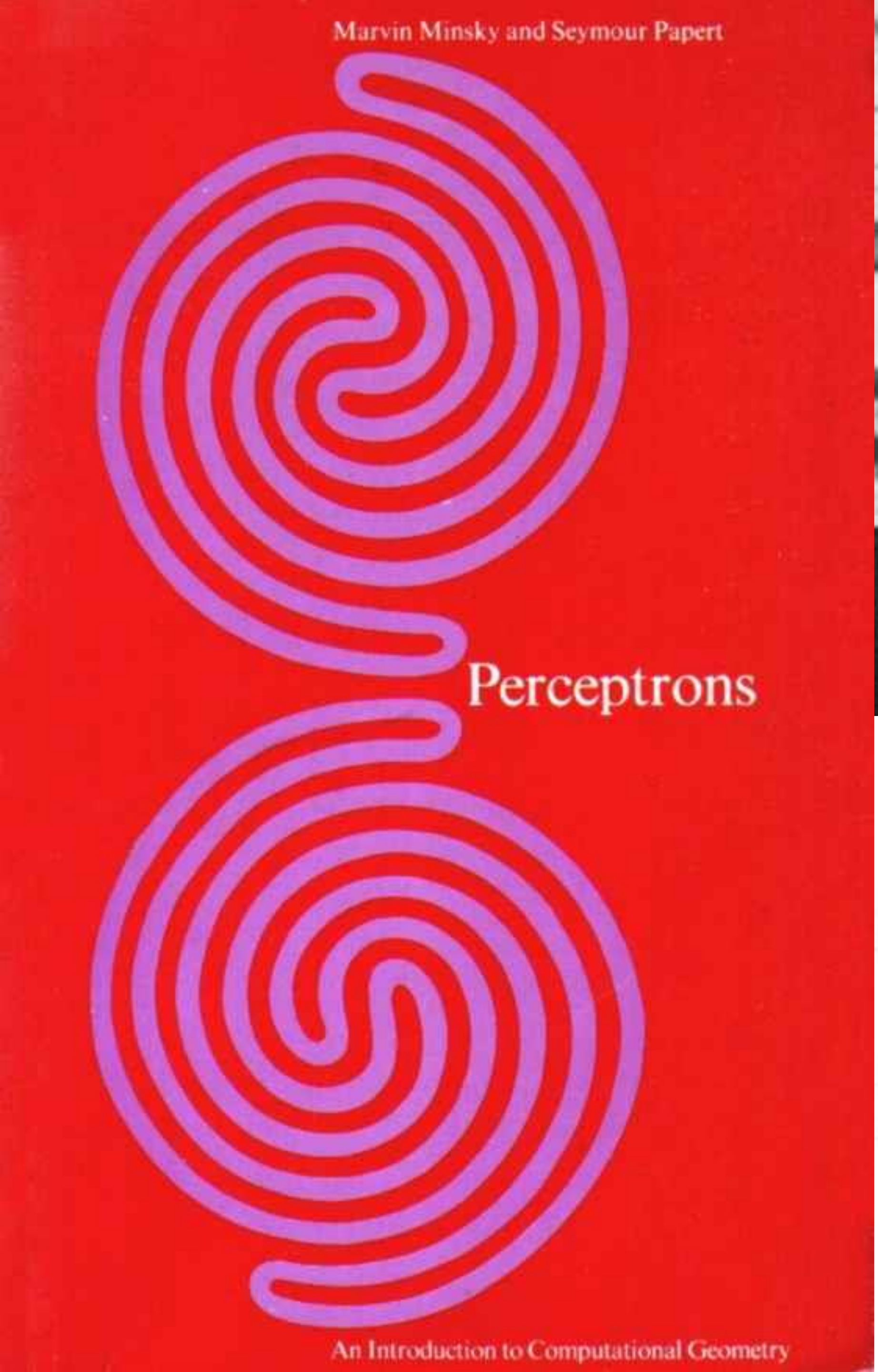


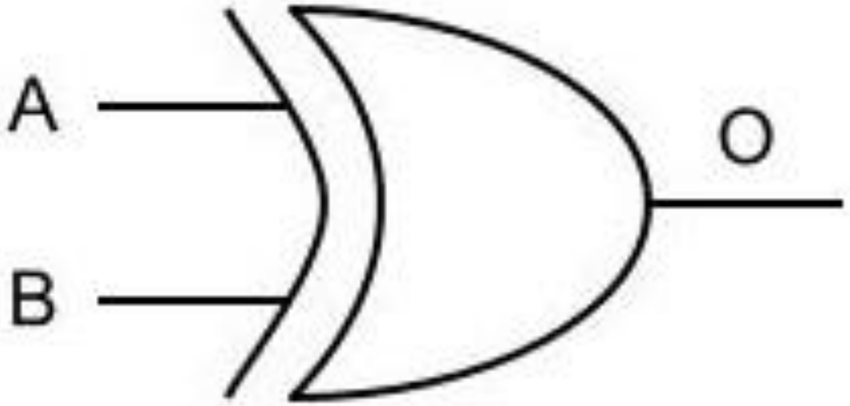
ARTIFICIAL INTELLIGENCE

MULTILAYER PERCEPTRON



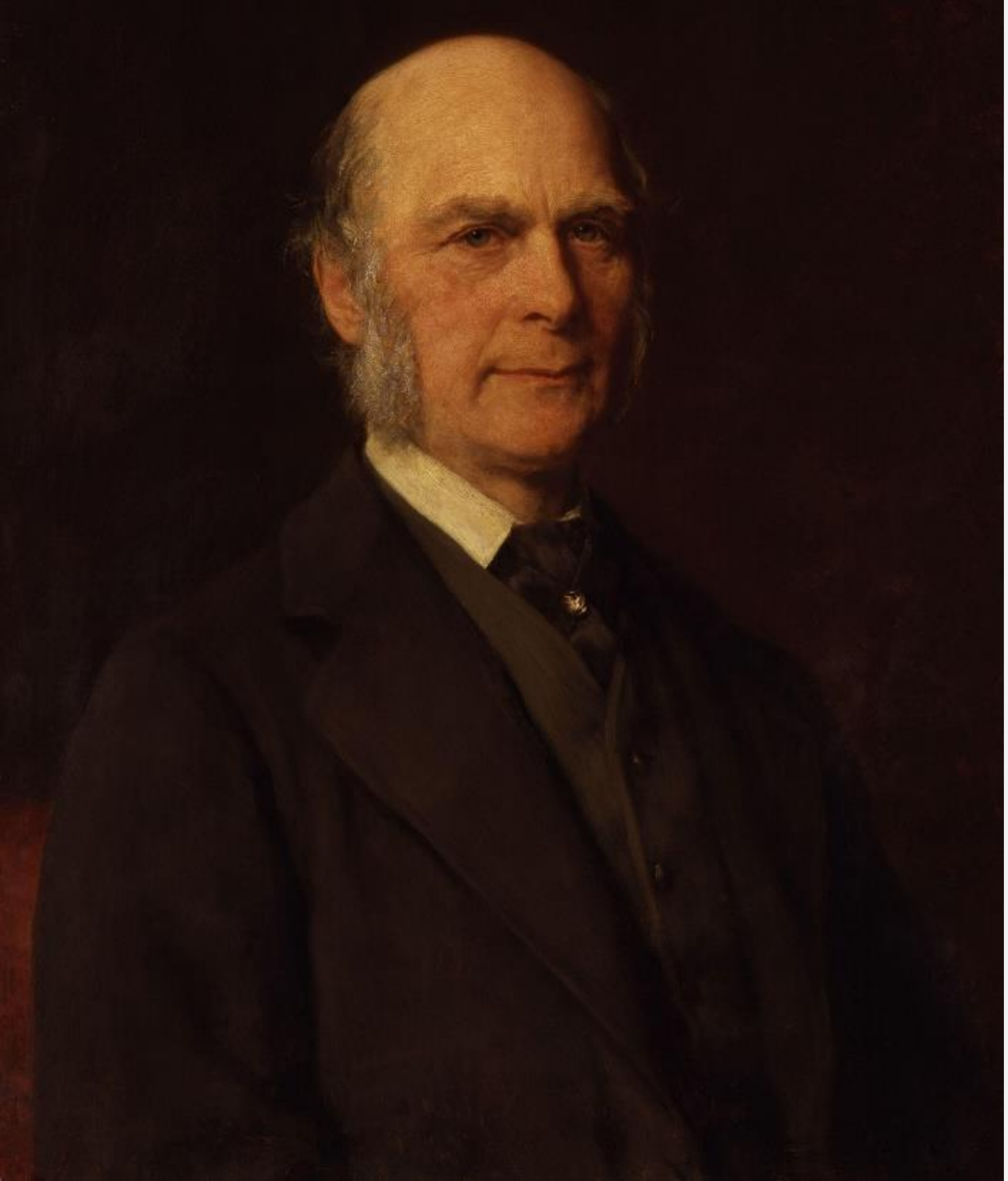
Winter is Coming



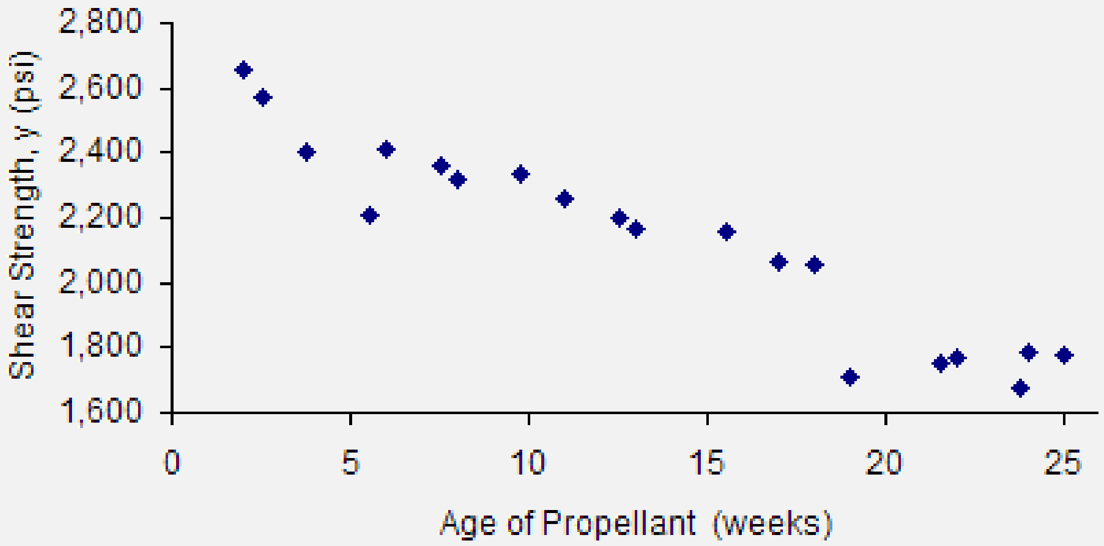


A	B	O
0	0	0
0	1	1
1	0	1
1	1	0

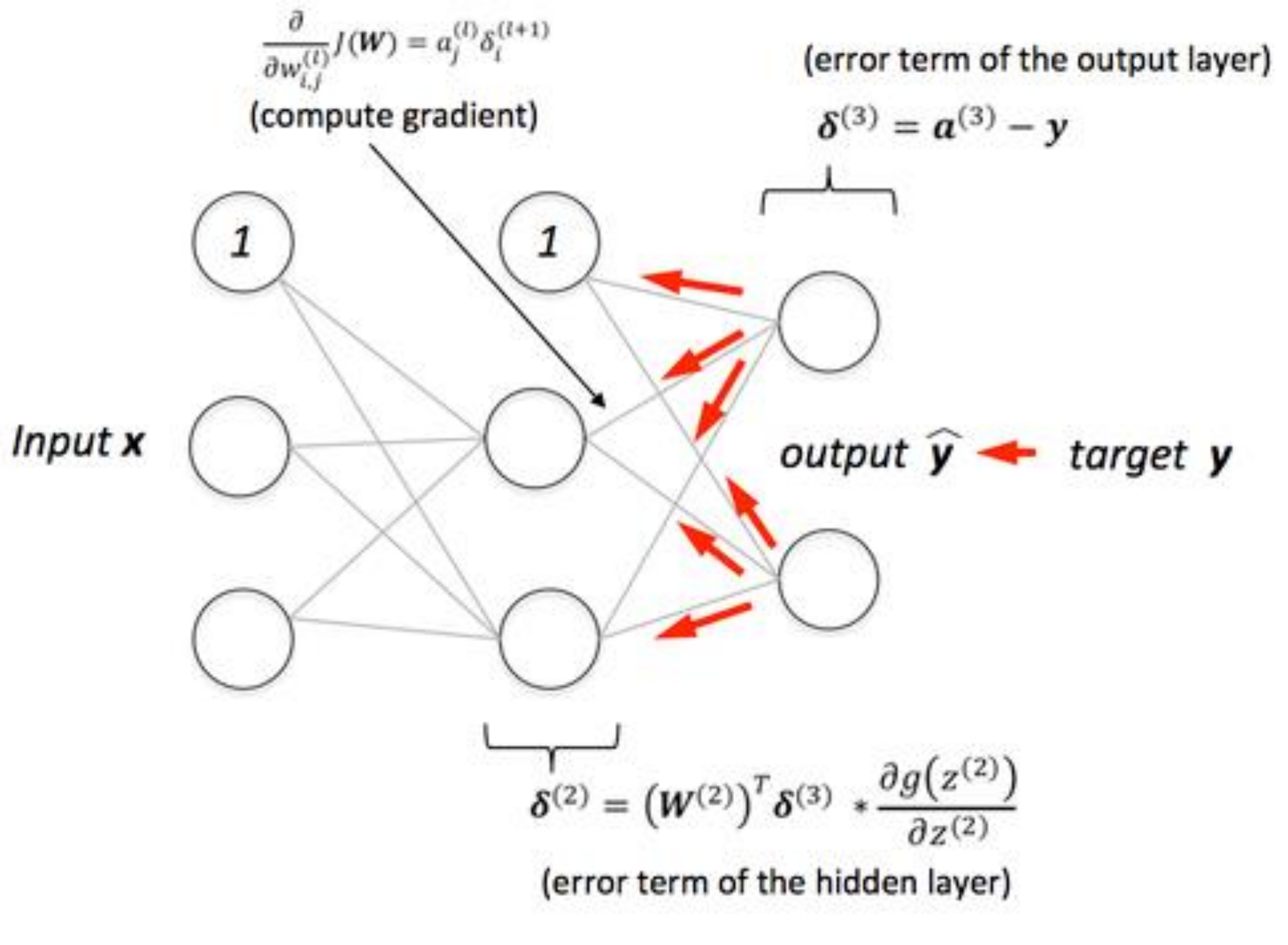
EXPERT SYSTEMS?



MACHINE LEARNING



BACKPROPAGATION



DEEP LEARNING

A Machine Learning technique

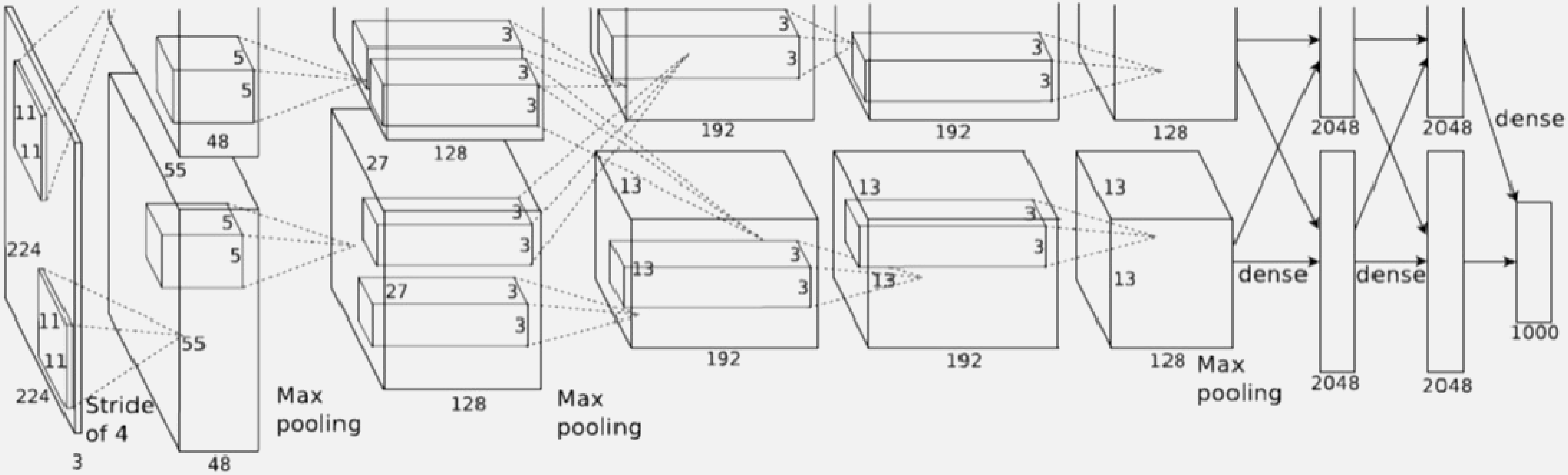
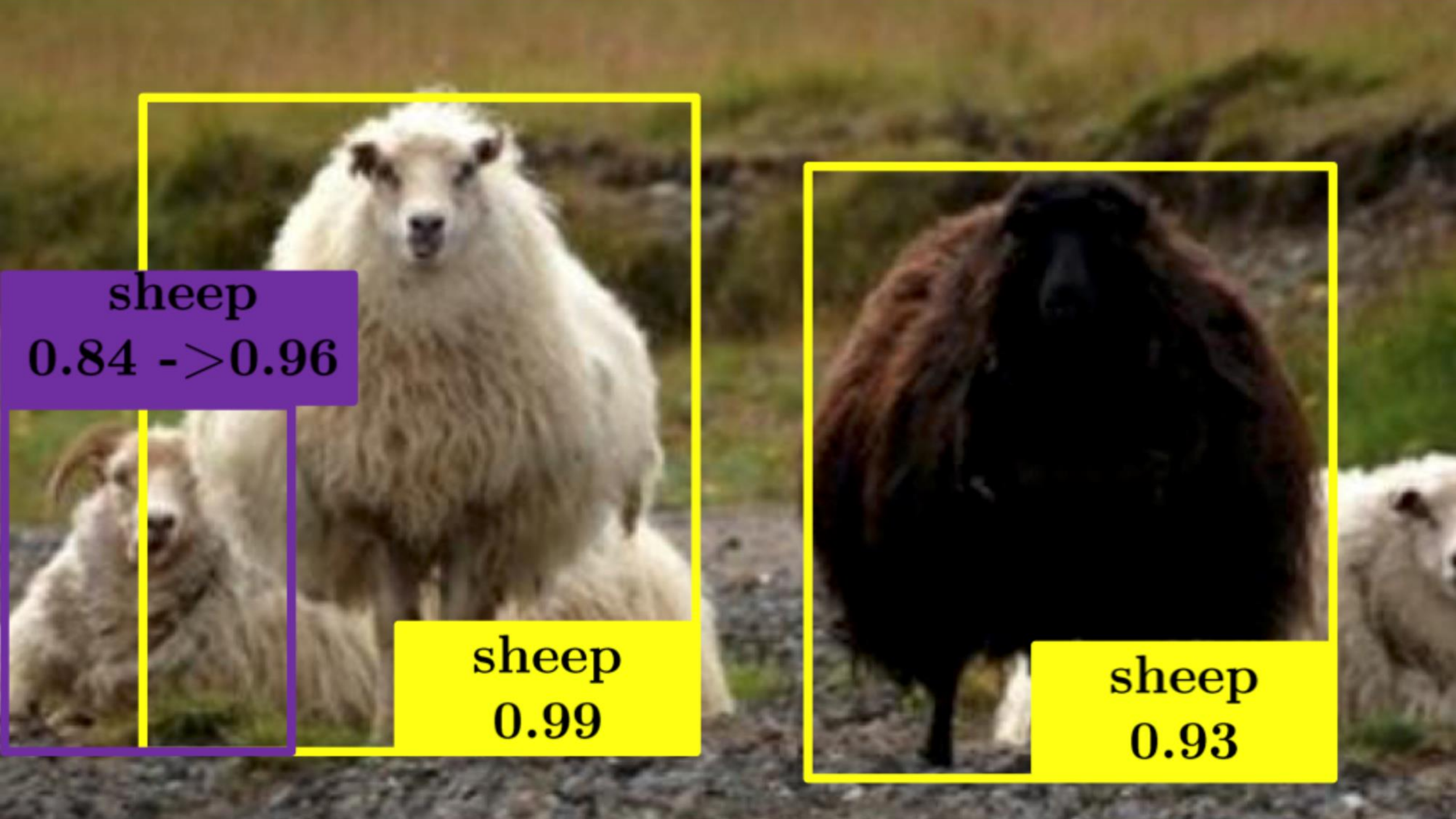


Image
- Image Classification
- Object Detection
- Synthetical Generation of Images

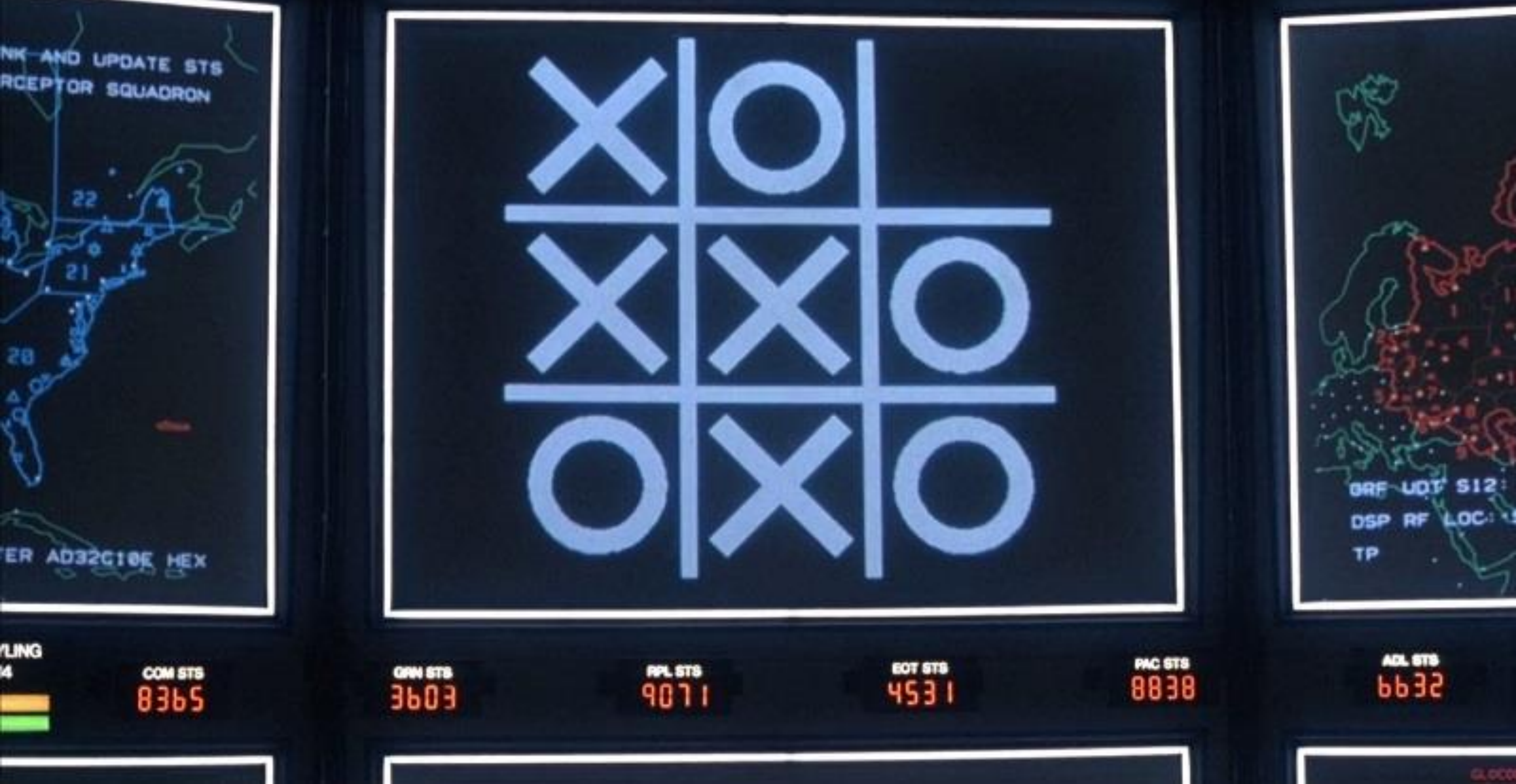
Sound
- Fraud Detection
- Defect Enhancement
- Style Transfer

Text
- Information Retrieval
- Knowledge Extraction
- Sentiment Analysis
- Style Transefer

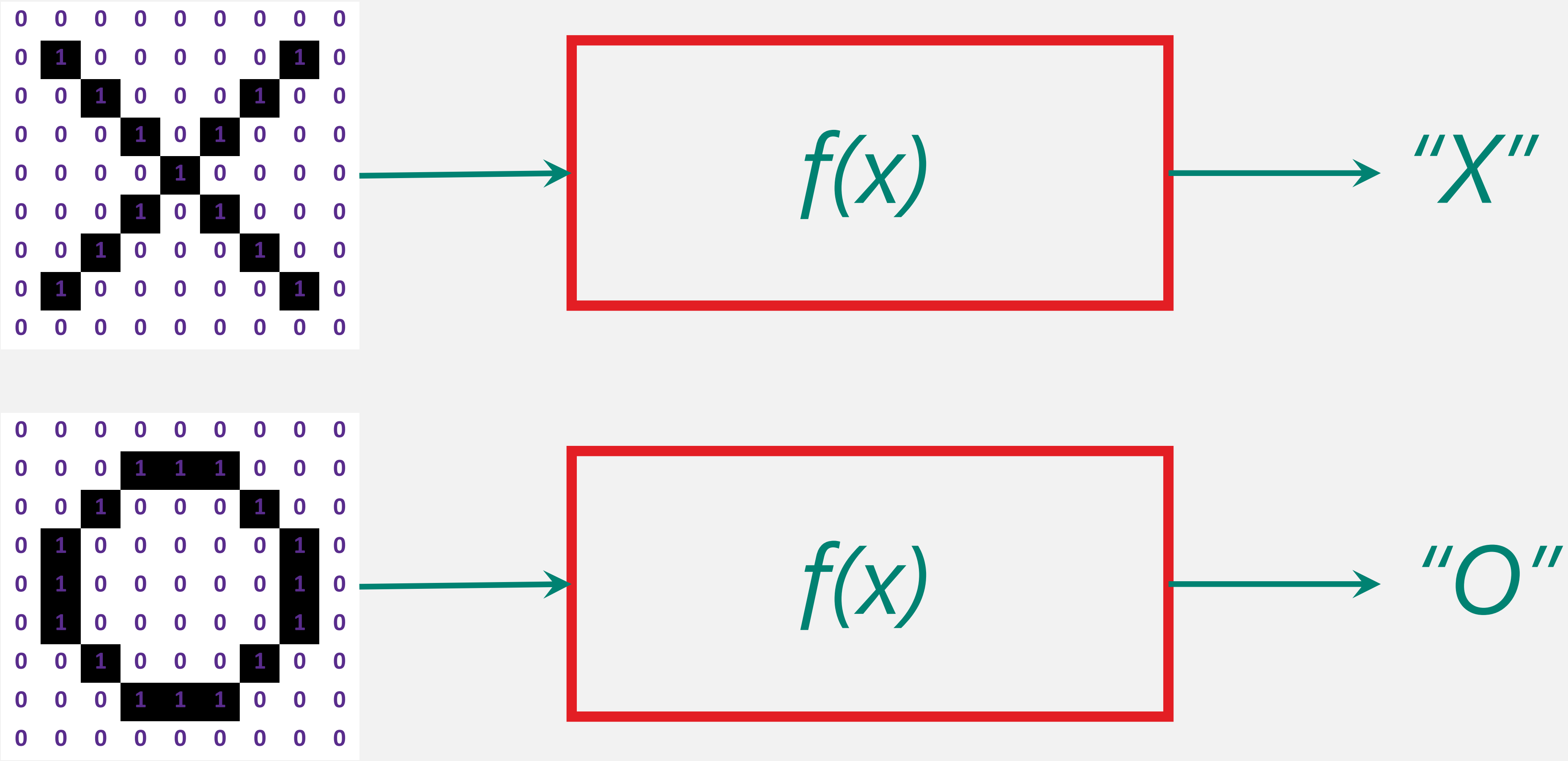
Signal Analysis
- Time Series Analysis


sheep
0.84 ->0.96
sheep
0.99
sheep
0.93

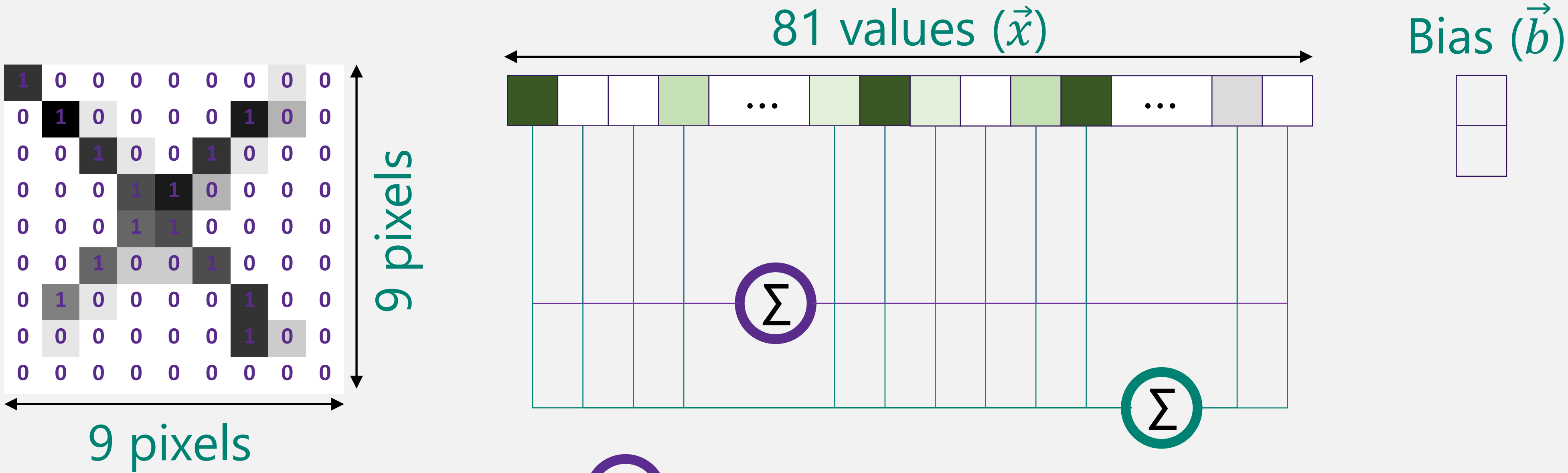
SHALL WE PLAY A LITTLE GAME?



A SIMPLE EXAMPLE



A SIMPLE EXAMPLE



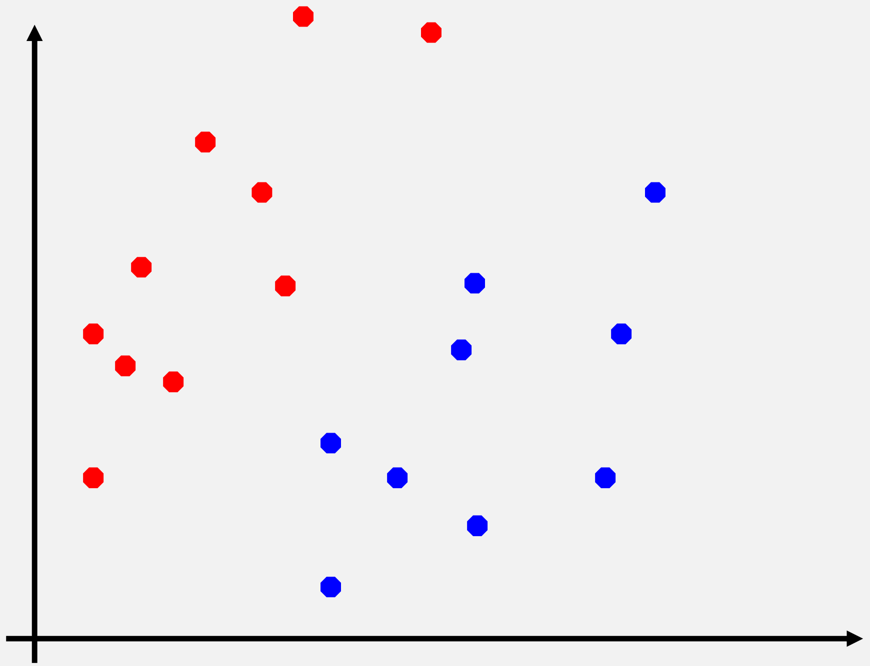
Σ *Sum (weights x pixels)* = $\overrightarrow{w_x} \cdot \vec{x}$

Σ *Sum (weights x pixels)* = $\overrightarrow{w_O} \cdot \vec{x}$

$$z = \vec{w} \cdot \vec{x} + b$$

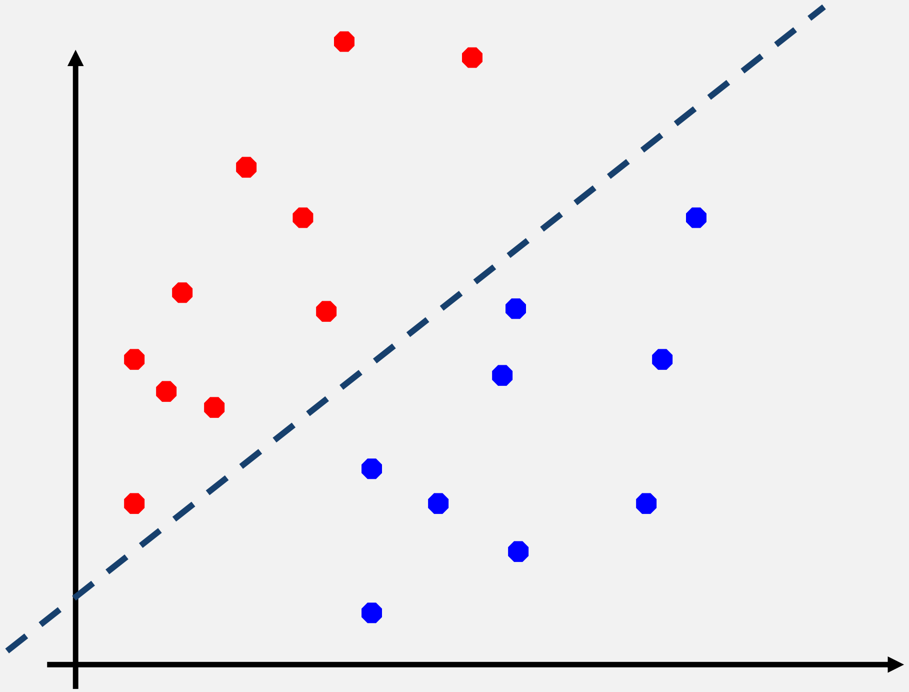
NOW THAT YOU MENTION IT…

$$z = w \cdot \vec{x} + b$$



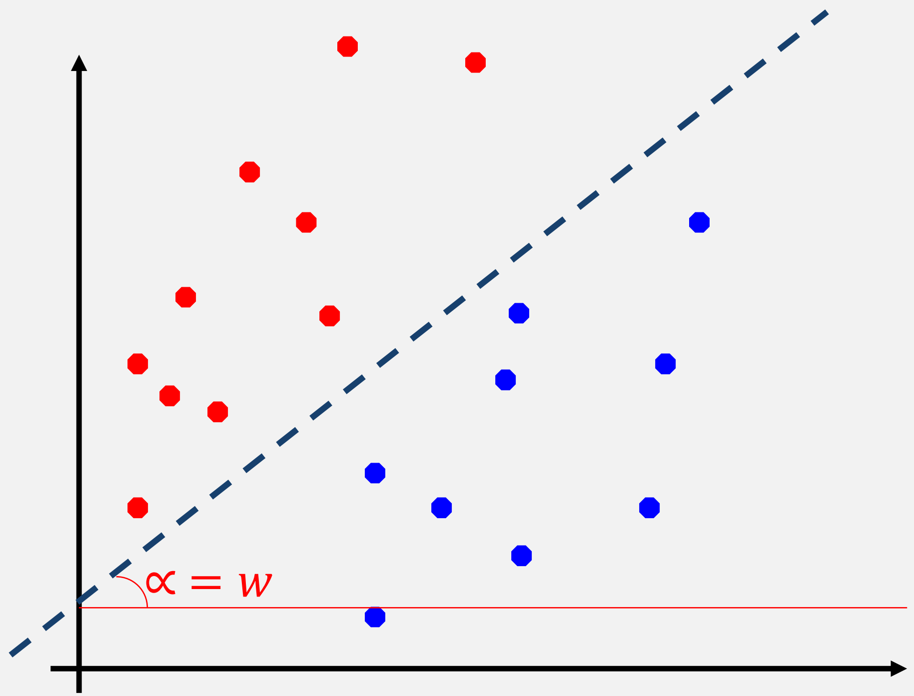
NOW THAT YOU MENTION IT...

$$z = w \cdot \vec{x} + b$$



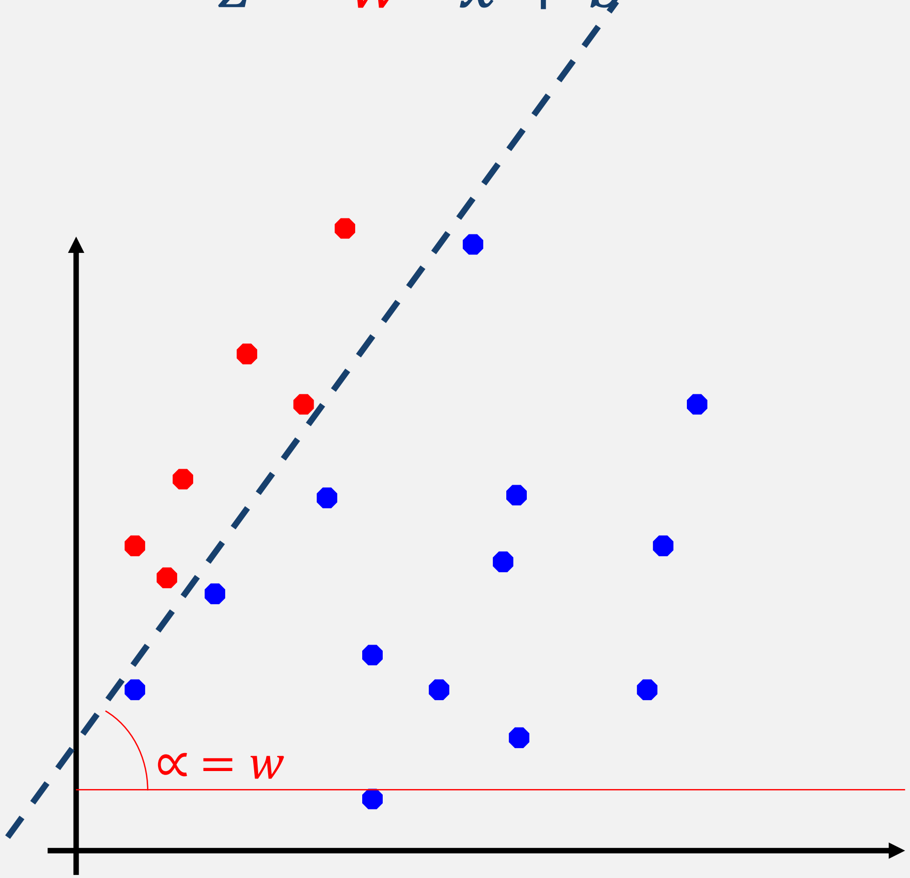
NOW THAT YOU MENTION IT…

$$z = w \cdot \vec{x} + b$$



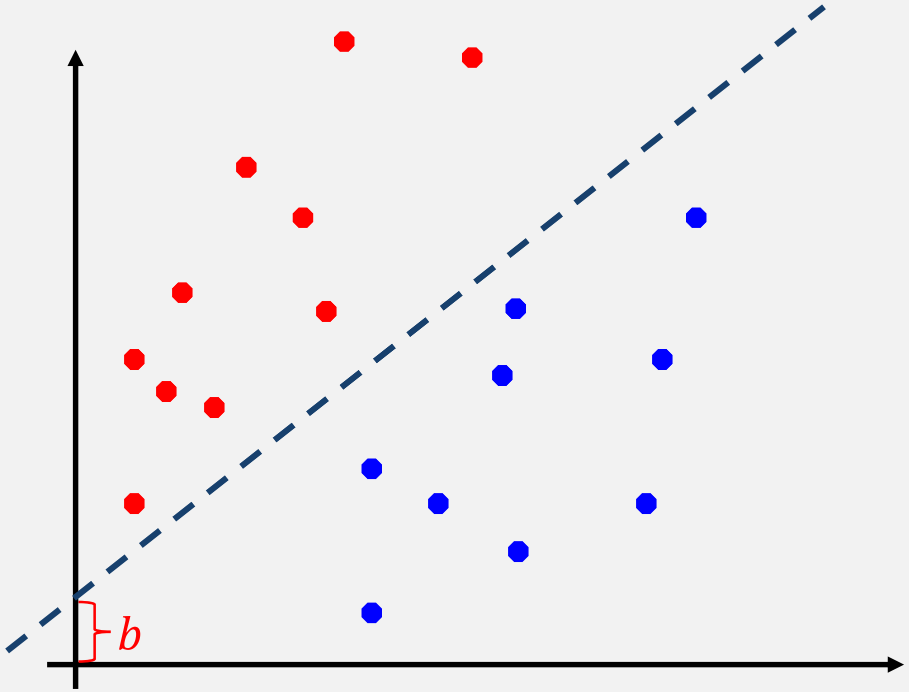
NOW THAT YOU MENTION IT...

$$z = w \cdot \vec{x} + b$$



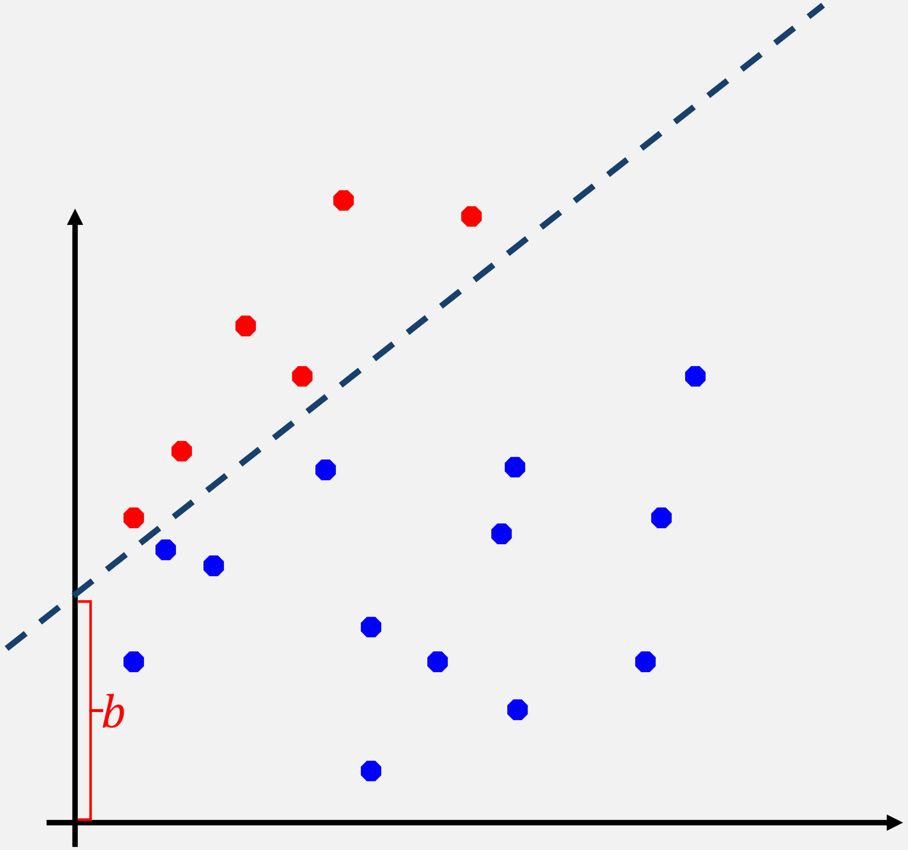
NOW THAT YOU MENTION IT…

$$z = \vec{w} \cdot \vec{x} + b$$

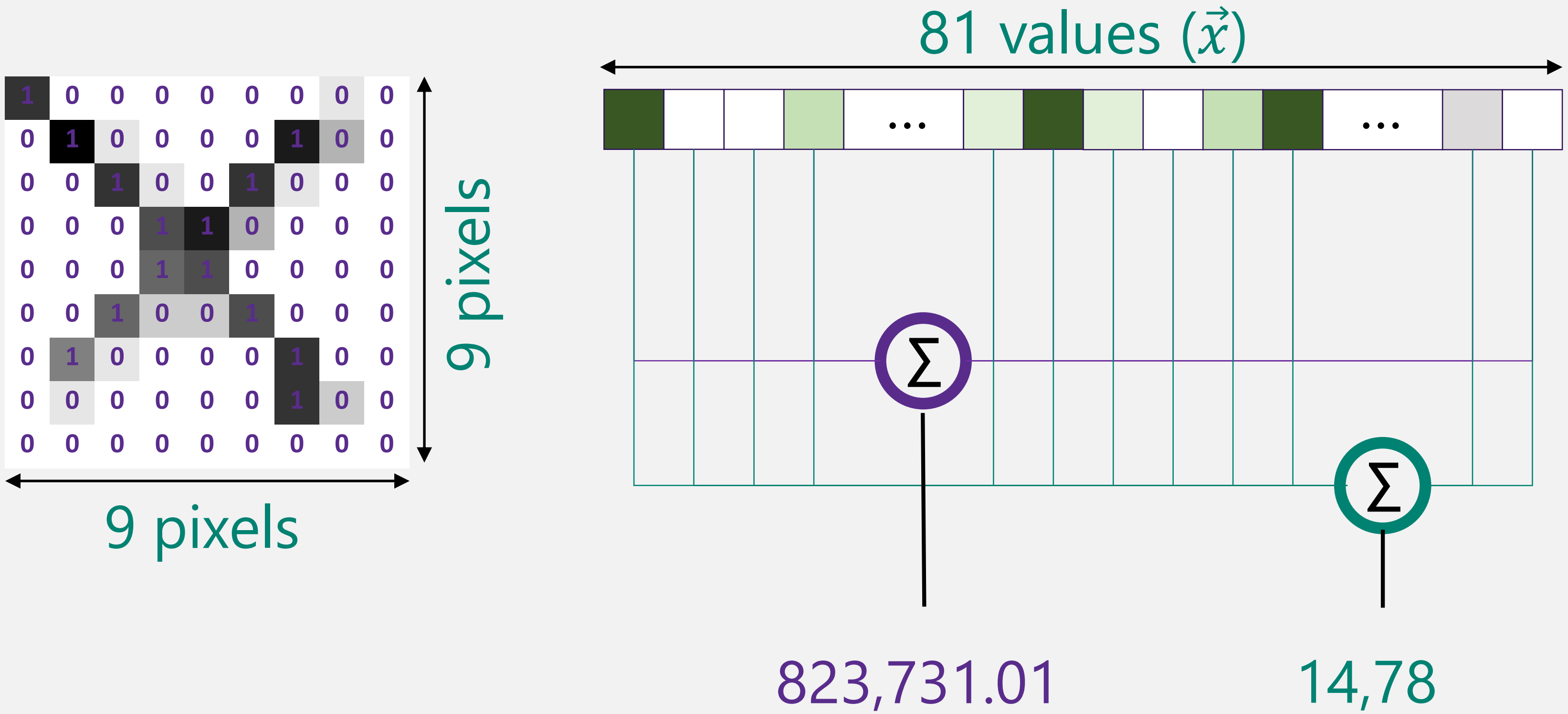


NOW THAT YOU MENTION IT...

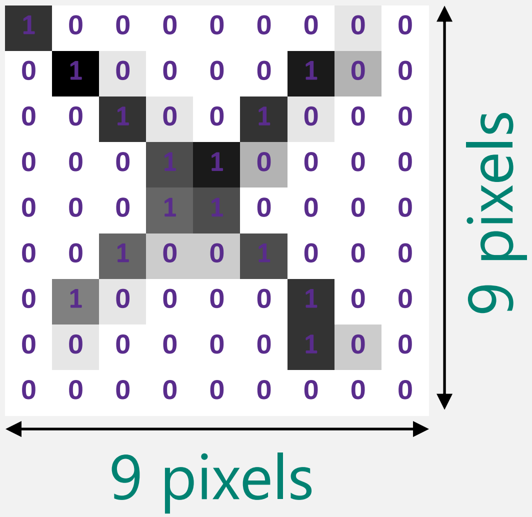
$$z = \overrightarrow{w} \cdot \vec{x} + b$$

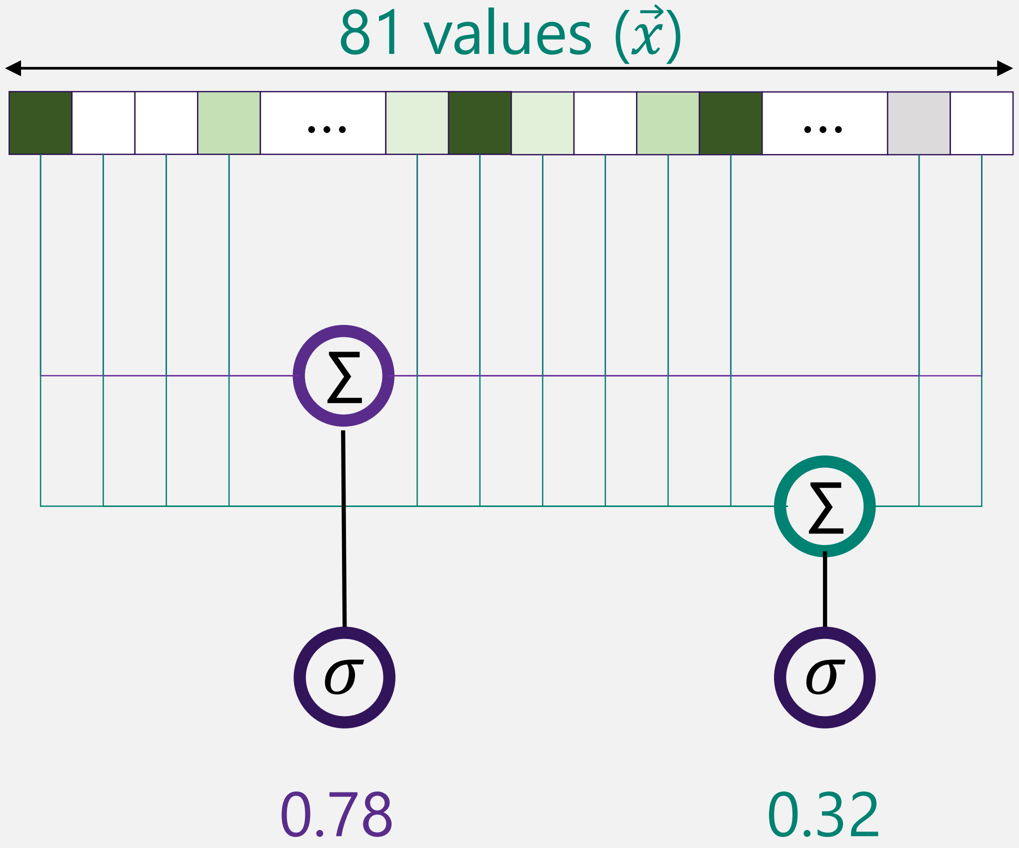


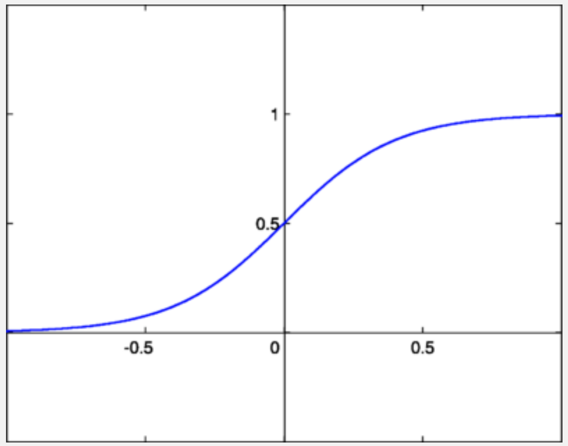
SIGMOID



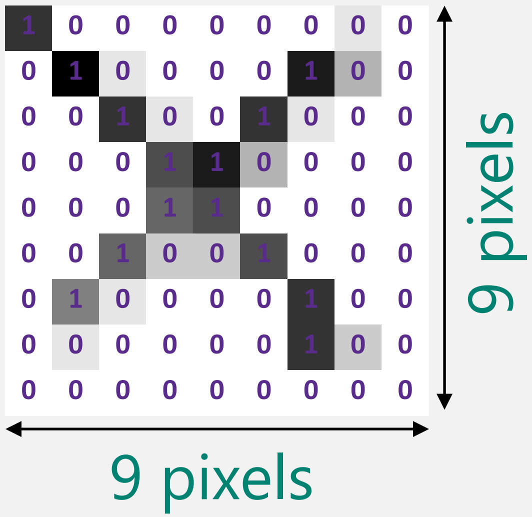
SIGMOID

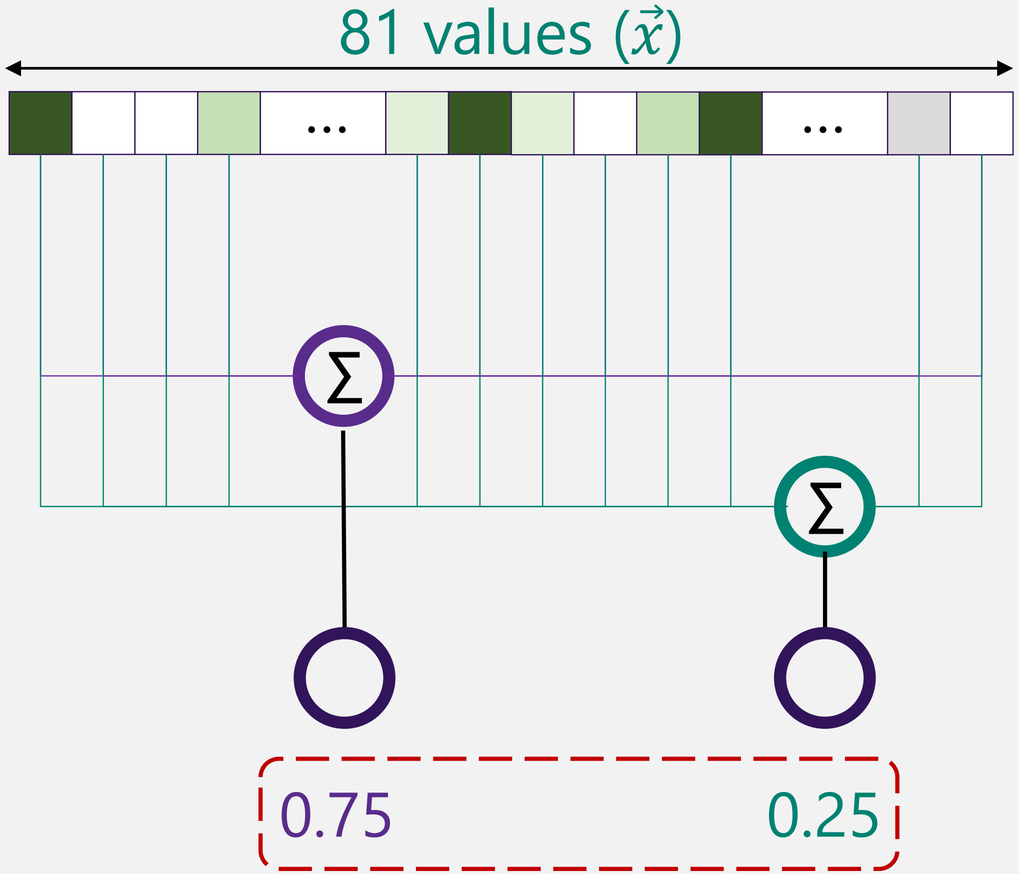

1 0 0 0 0 0 0 0 0
0 1 0 0 0 0 1 0 0
0 0 1 0 0 1 0 0 0
0 0 0 1 1 0 0 0 0
0 0 0 1 1 0 0 0 0
0 0 1 0 0 1 0 0 0
0 1 0 0 0 0 1 0 0
0 0 0 0 0 0 1 0 0
0 0 0 0 0 0 0 0 0
9 pixels
9 pixels


81 values ($\vec{x}$)
...
...
Σ
Σ
σ
σ
0.78
0.32


1
0.5
-0.5
0
0.5

SOFTMAX

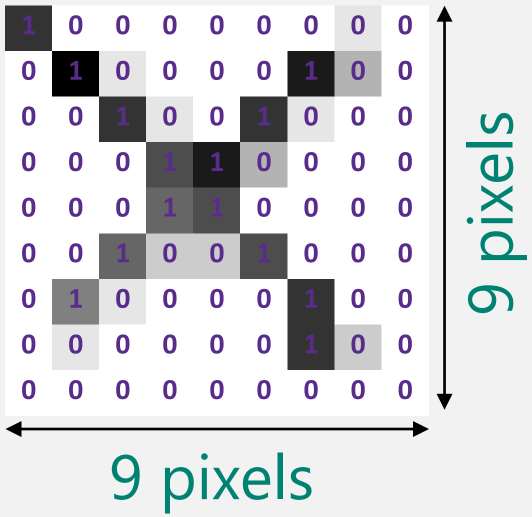




$$s_{(y_i)} = \frac{e^{y_i}}{\sum_j e^{y_i}}$$

These are actual probabilities

LOSS FUNCTION

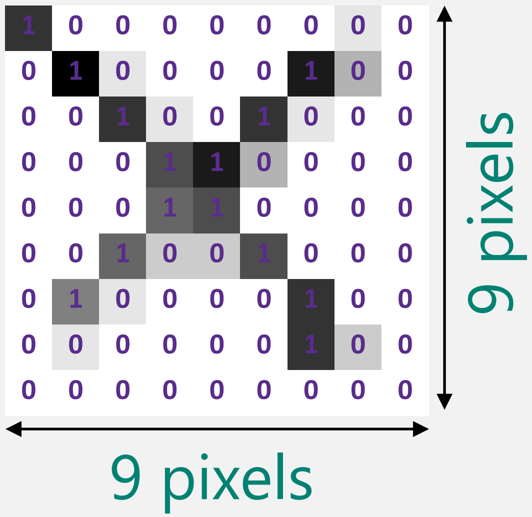


One-hot encoding

1 0

0.75 0.25

LOSS FUNCTION

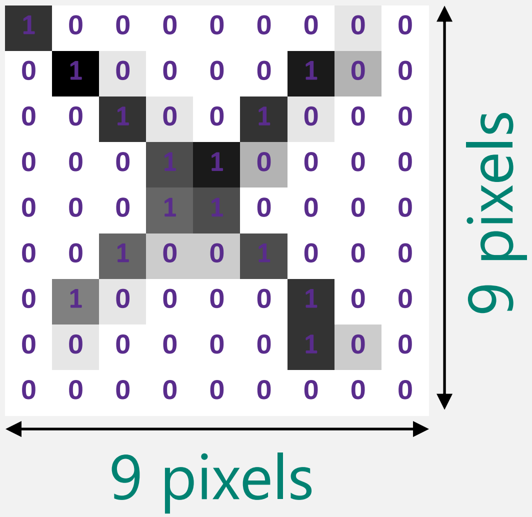


1	0

$$\text{error} = \left(y_j - p_j\right)$$

0.75	0.25

LOSS FUNCTION

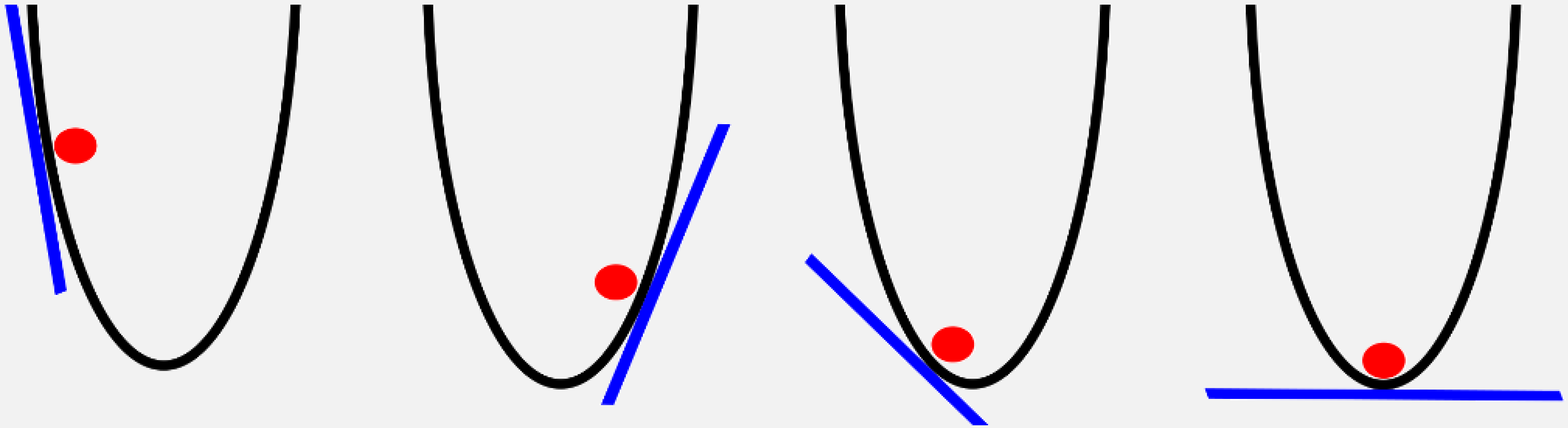


1 0

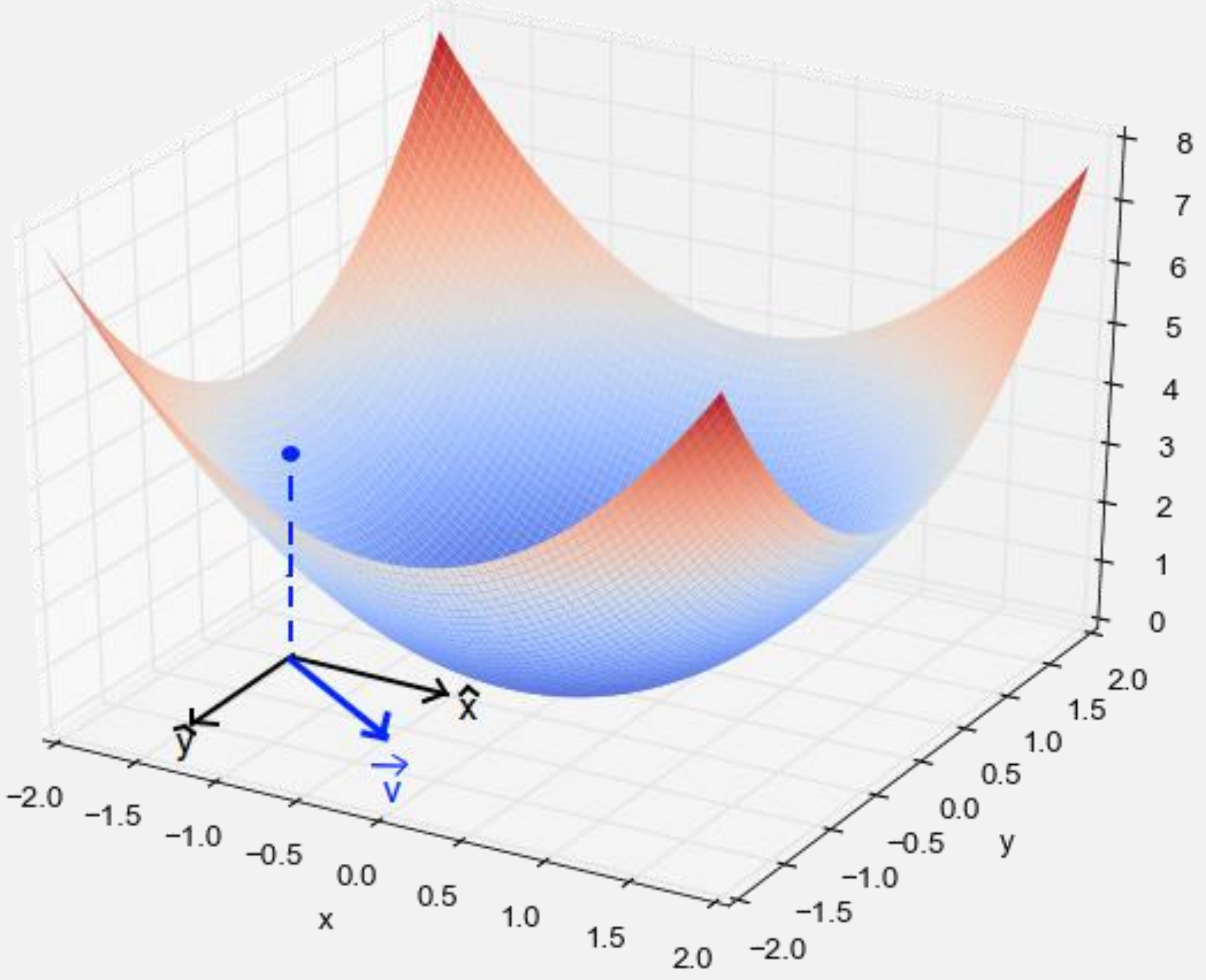
$$\text{loss} = \frac{1}{n}\sum_{i=1}^{n}\left(y_j - p_j\right)^2$$

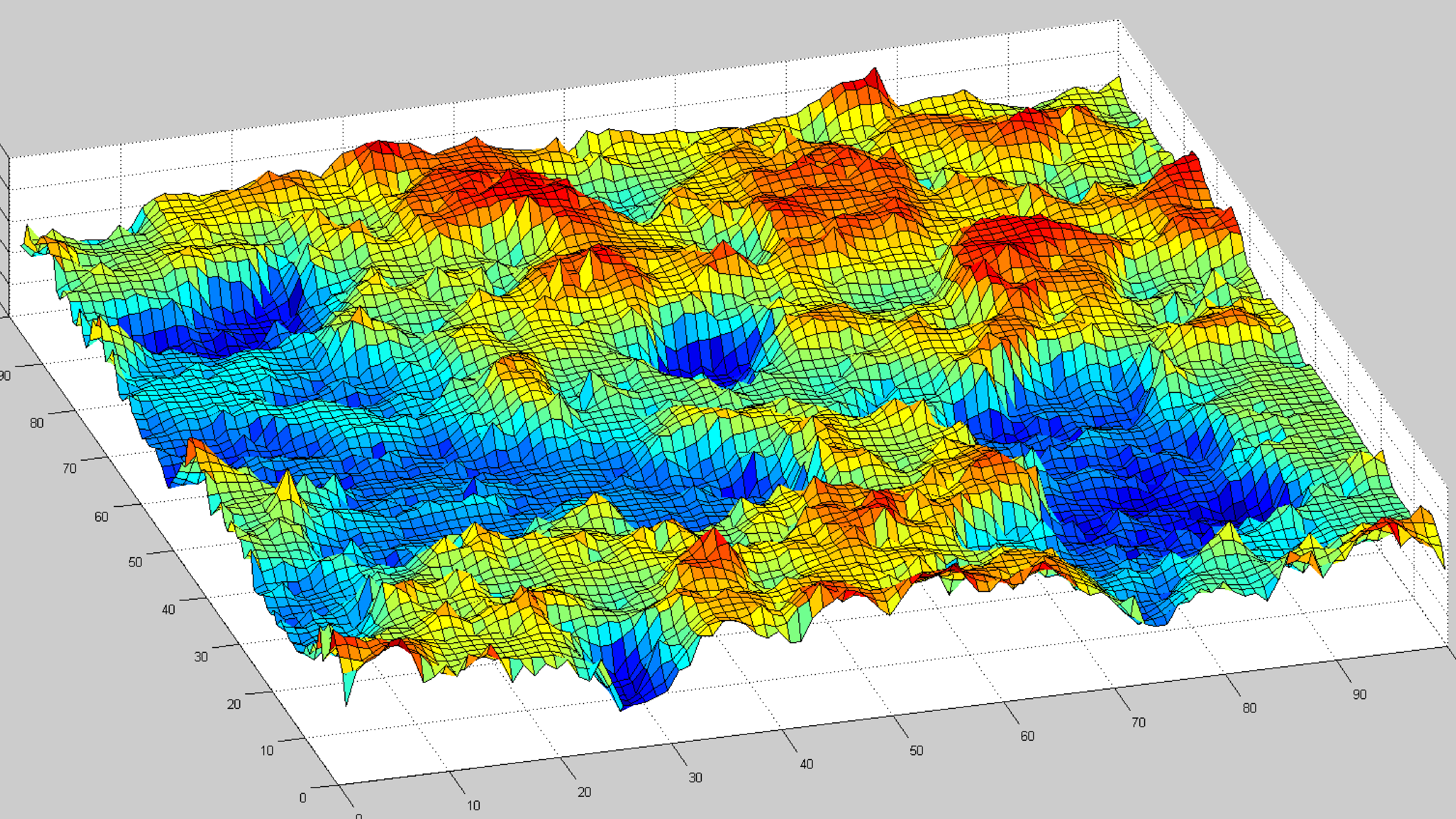
0.75 0.25

GRADIENT DESCENT



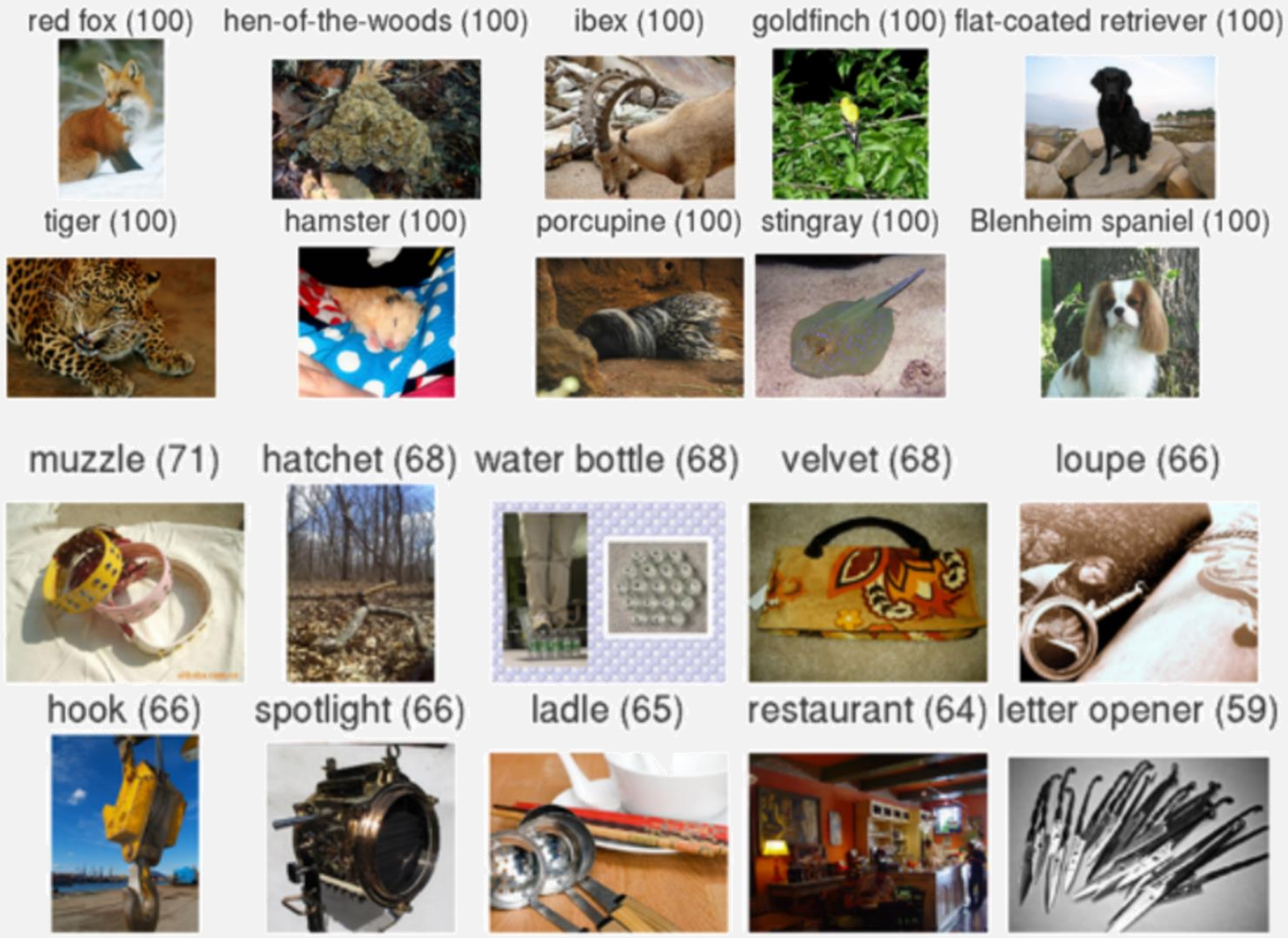
GRADIENT DESCENT



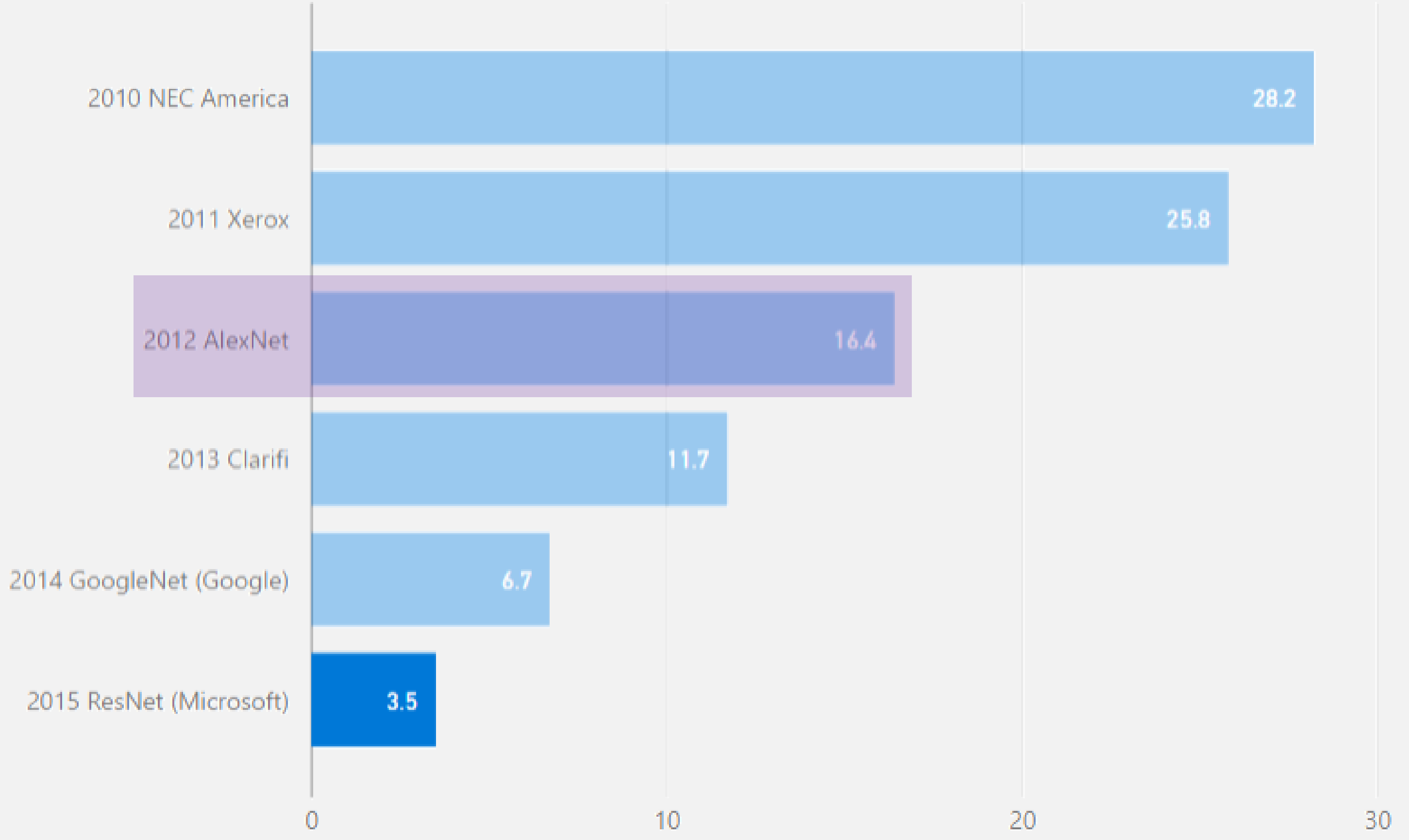


90
80
70
60
50
40
30
20
10
0
0
10
20
30
40
50
60
70
80
90

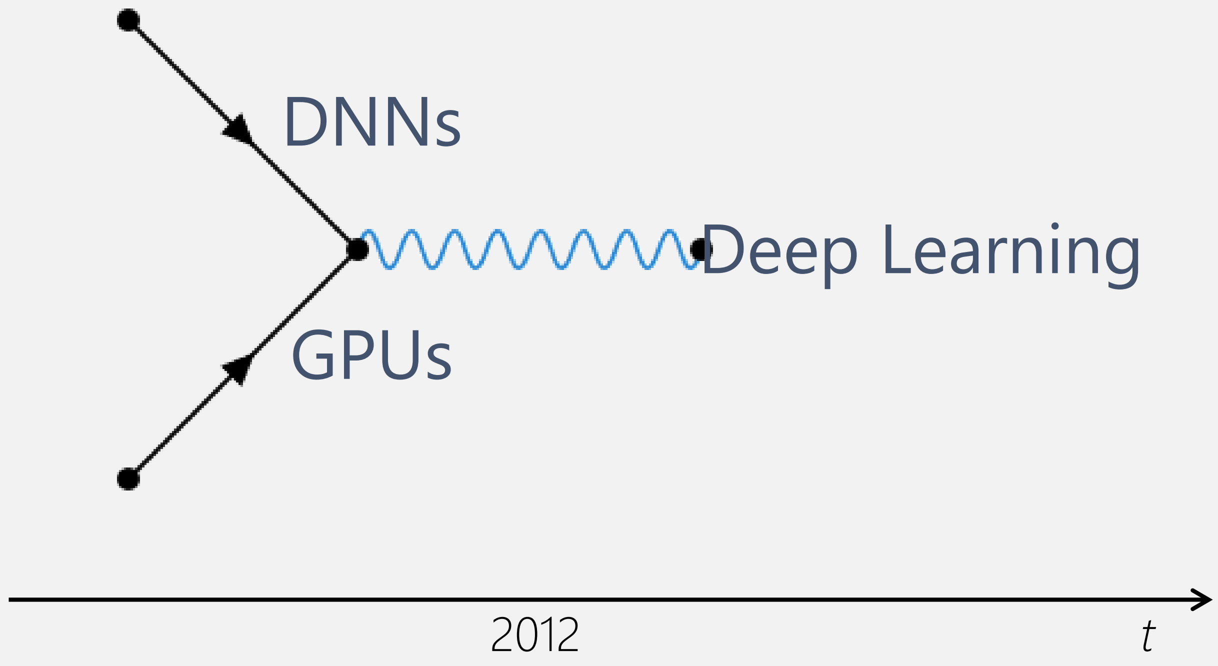
IMAGENET CHALLENGE



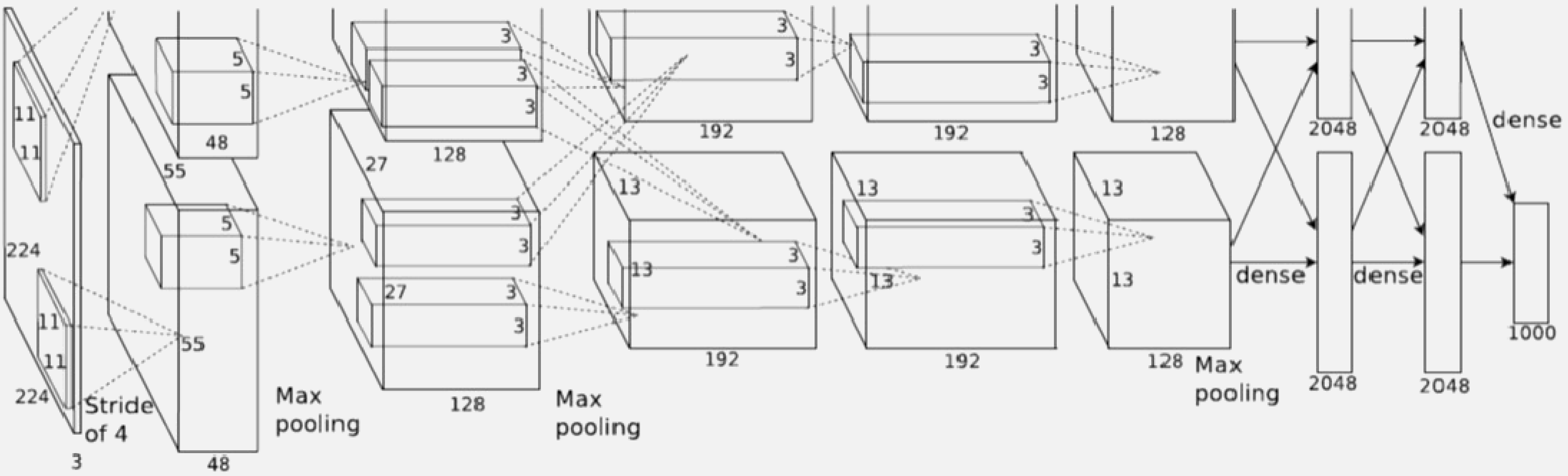
IMAGENET CHALLENGE (CLASSIFICATION)



WHAT HAPPENED IN 2012?



REMEMBER THIS THING?



FILTERING

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

						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
0	0	1	1	0	1	0	0	0
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

-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

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

$$
\begin{bmatrix}
-1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \\
-1 & 1 & -1 & -1 & -1 & -1 & -1 & 1 & -1 \\
-1 & -1 & 1 & -1 & -1 & -1 & 1 & -1 & -1 \\
-1 & -1 & -1 & 1 & -1 & 1 & -1 & -1 & -1 \\
-1 & -1 & -1 & -1 & 1 & -1 & -1 & -1 & -1 \\
-1 & -1 & -1 & 1 & -1 & 1 & -1 & -1 & -1 \\
-1 & -1 & 1 & -1 & -1 & -1 & 1 & -1 & -1 \\
-1 & 1 & -1 & -1 & -1 & -1 & -1 & 1 & -1 \\
-1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1
\end{bmatrix}
\otimes
\begin{bmatrix}
1 & -1 & -1 \\
-1 & 1 & -1 \\
-1 & -1 & 1
\end{bmatrix}
=
\begin{bmatrix}
0.77 & -0.11 & 0.11 & 0.33 & 0.55 & -0.11 & 0.33 \\
-0.11 & 1.00 & -0.11 & 0.33 & -0.11 & 0.11 & -0.11 \\
0.11 & -0.11 & 1.00 & -0.33 & 0.11 & -0.11 & 0.55 \\
0.33 & 0.33 & -0.33 & 0.55 & -0.33 & 0.33 & 0.33 \\
0.55 & -0.11 & 0.11 & -0.33 & 1.00 & -0.11 & 0.11 \\
-0.11 & 0.11 & -0.11 & 0.33 & -0.11 & 1.00 & -0.11 \\
0.33 & -0.11 & 0.55 & 0.33 & 0.11 & -0.11 & 0.77
\end{bmatrix}
$$

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

$\otimes$

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

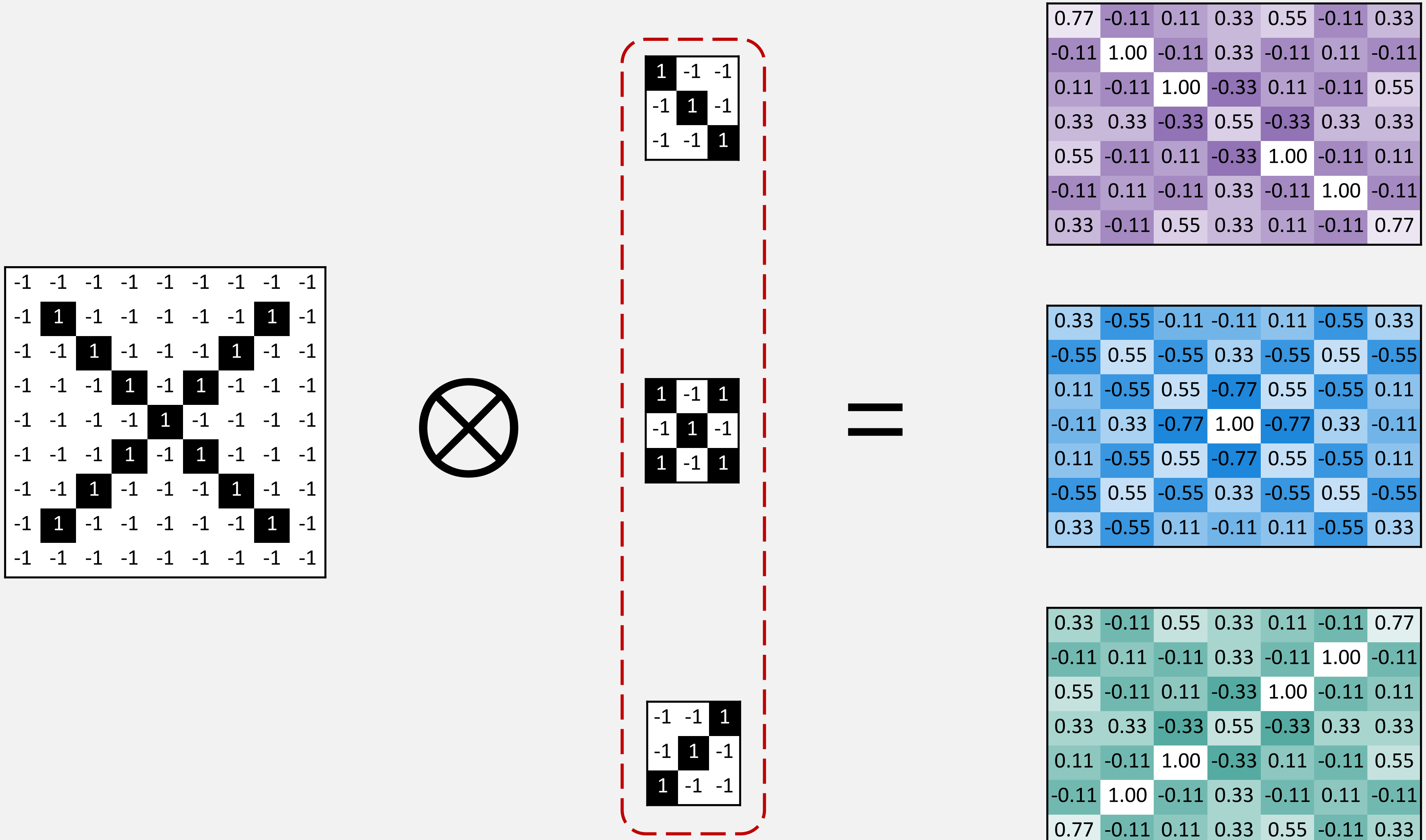
-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

$\otimes$

-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


-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
-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

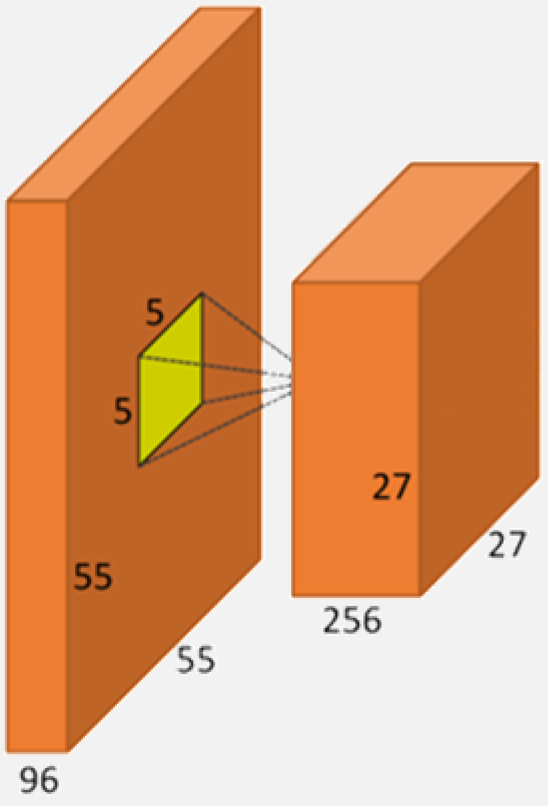
AVERAGE POOLING – STRIDE 2

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?



WHAT IS MISSING?

Filter 1

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

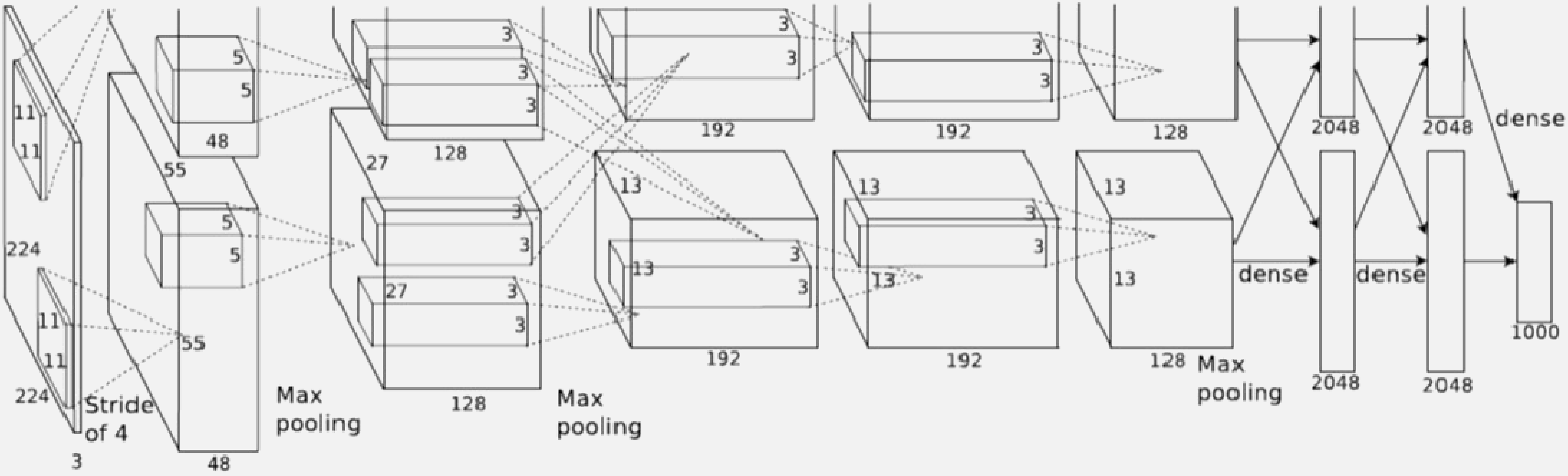
Filter 2

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

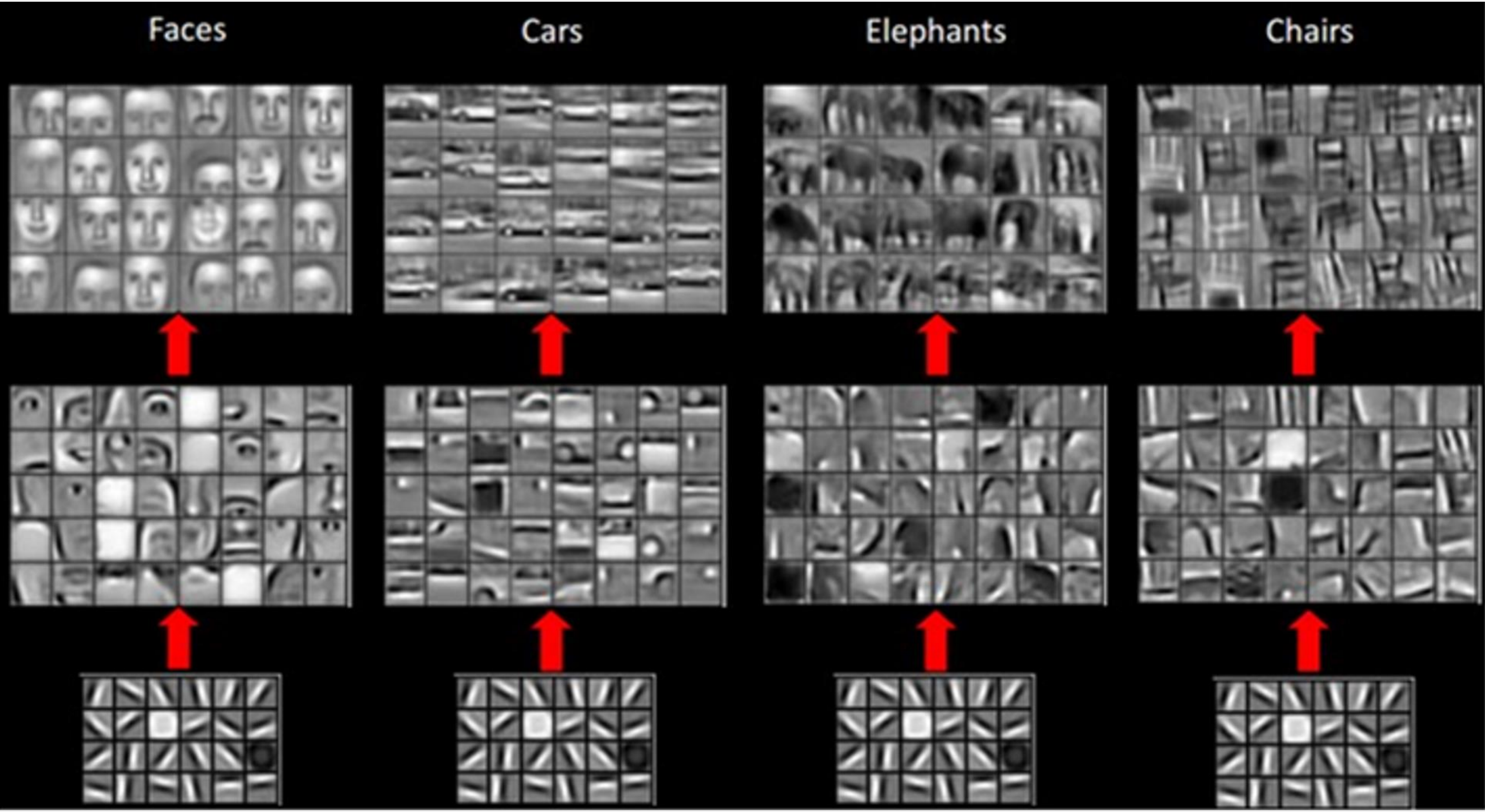
Filter 3

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

AlexNet

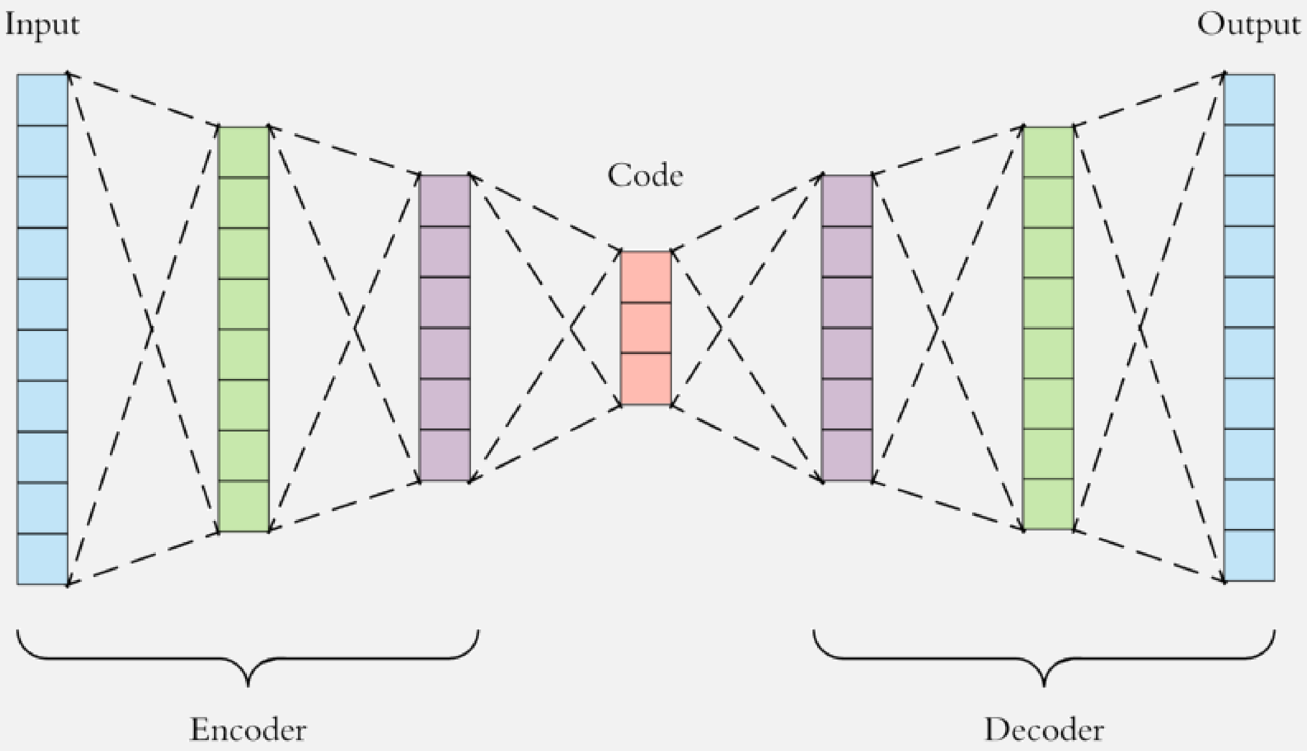


224
224
3
11
11
11
11
Stride
of 4
55
55
48
48
5
5
5
5
Max
pooling
27
27
128
128
3
3
3
3
3
3
3
Max
pooling
13
13
192
192
3
3
3
3
13
13
192
192
3
3
3
3
13
13
128
128
Max
pooling
dense
2048
2048
dense
2048
2048
dense
1000

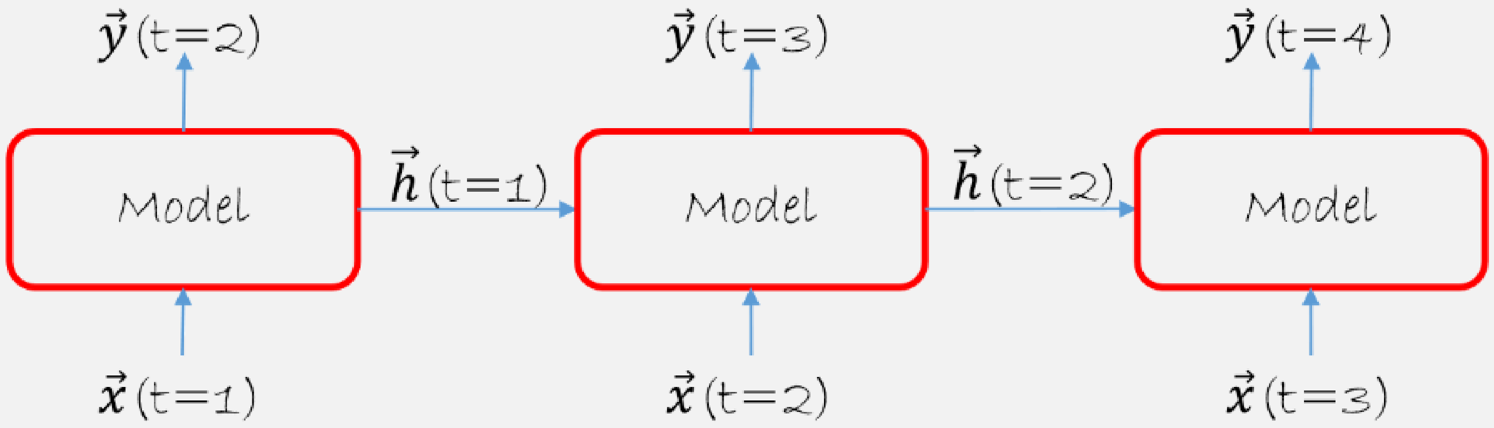

Faces
Cars
Elephants
Chairs

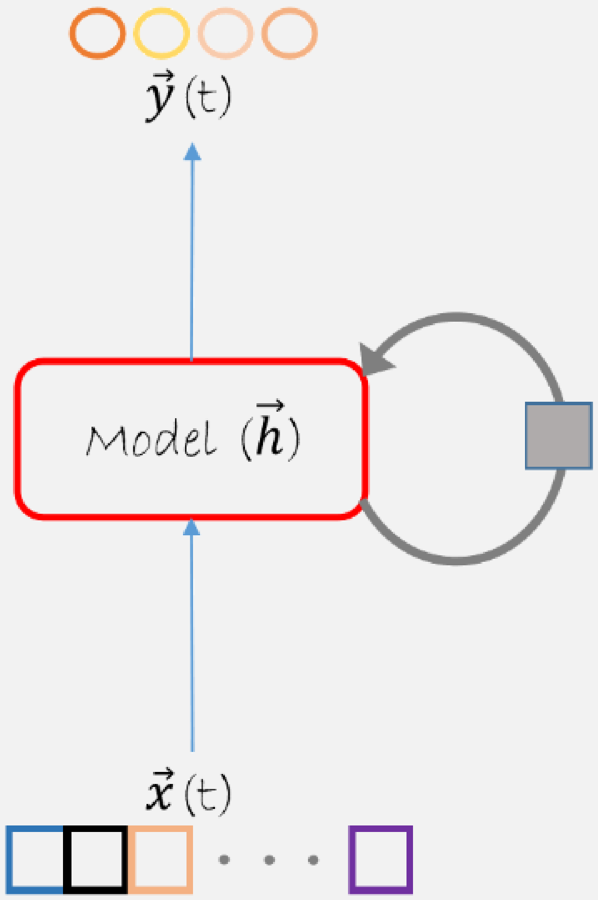
BASIC AUTOENCODER

$$\hat{x} = h_{W,b} \approx x$$



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.

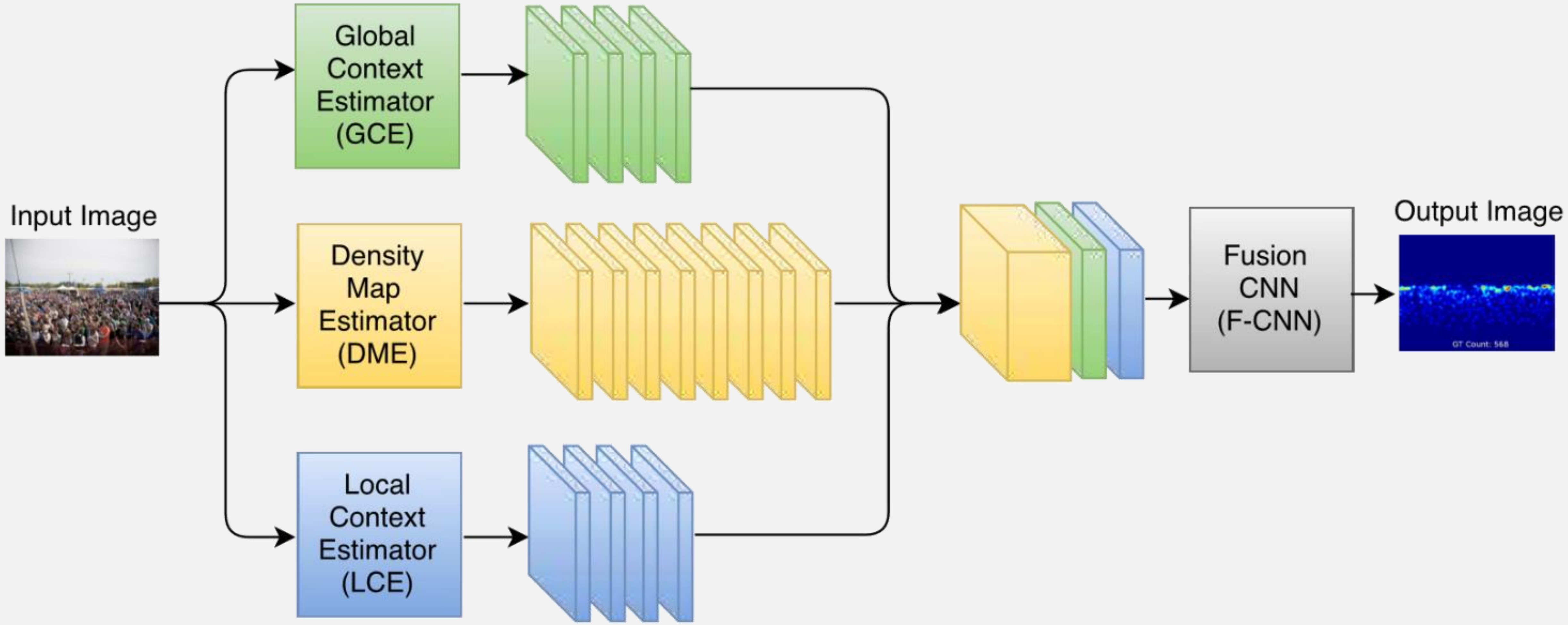

angels
SOLD

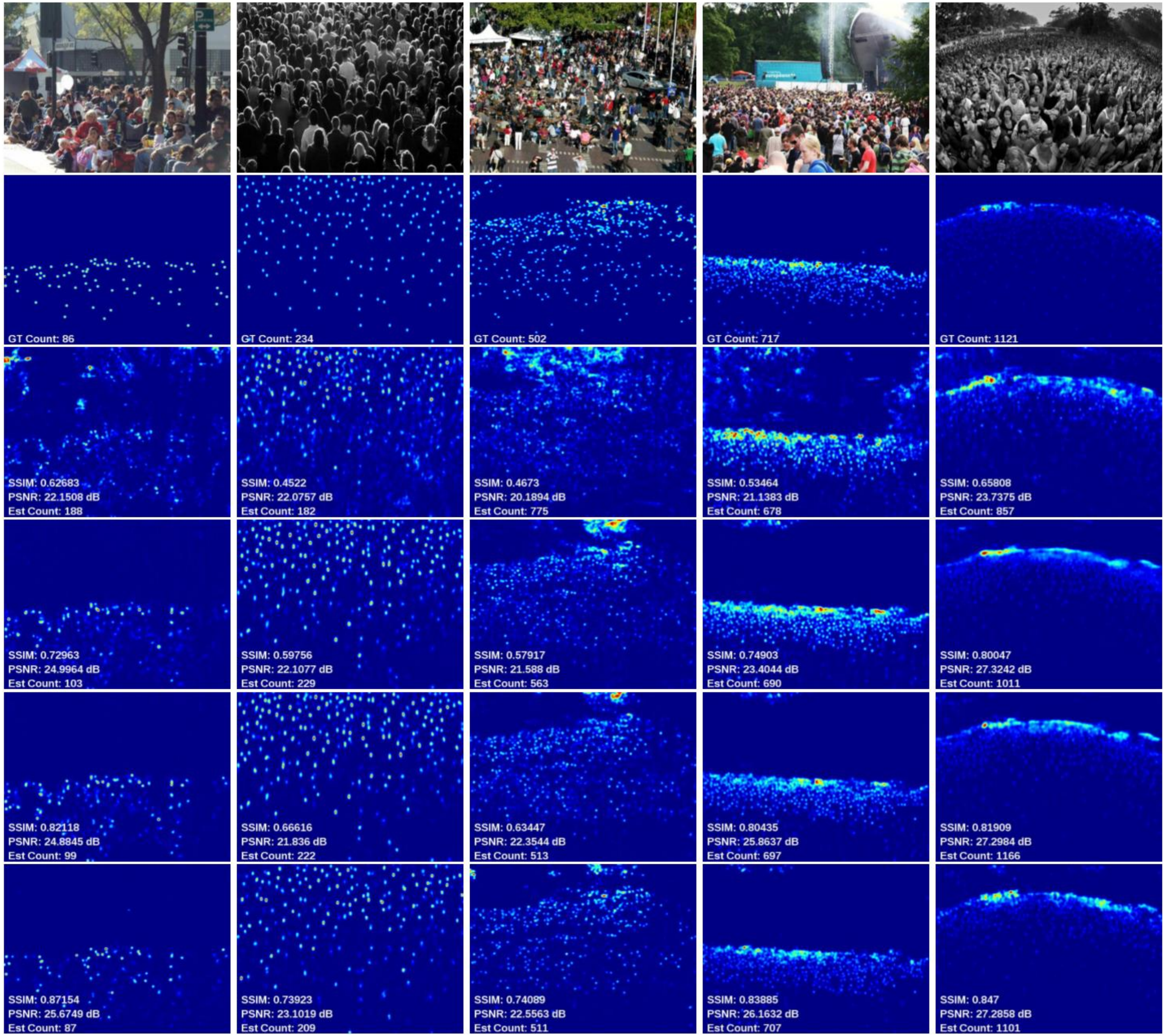
Counting people in a crowd

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


GT Count: 86
GT Count: 234
GT Count: 502
GT Count: 717
GT Count: 1121
SSIM: 0.62683
PSNR: 22.1508 dB
Est Count: 188
SSIM: 0.4522
PSNR: 22.0757 dB
Est Count: 182
SSIM: 0.4673
PSNR: 20.1894 dB
Est Count: 775
SSIM: 0.53464
PSNR: 21.1383 dB
Est Count: 678
SSIM: 0.65808
PSNR: 23.7375 dB
Est Count: 857
SSIM: 0.72963
PSNR: 24.9964 dB
Est Count: 103
SSIM: 0.59756
PSNR: 22.1077 dB
Est Count: 229
SSIM: 0.57917
PSNR: 21.588 dB
Est Count: 563
SSIM: 0.74903
PSNR: 23.4044 dB
Est Count: 690
SSIM: 0.80047
PSNR: 27.3242 dB
Est Count: 1011
SSIM: 0.82118
PSNR: 24.8845 dB
Est Count: 99
SSIM: 0.66616
PSNR: 21.836 dB
Est Count: 222
SSIM: 0.63447
PSNR: 22.3544 dB
Est Count: 513
SSIM: 0.80435
PSNR: 25.8637 dB
Est Count: 697
SSIM: 0.81909
PSNR: 27.2984 dB
Est Count: 1166
SSIM: 0.87154
PSNR: 25.6749 dB
Est Count: 87
SSIM: 0.73923
PSNR: 23.1019 dB
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

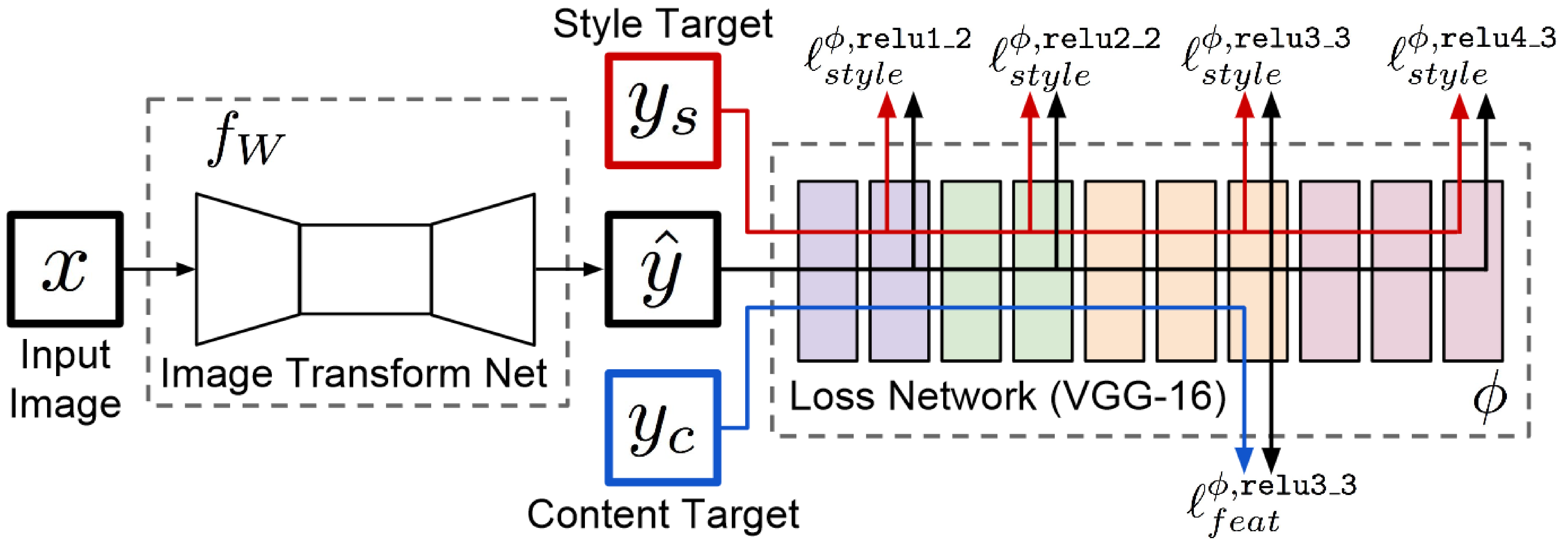
Transferring style across images

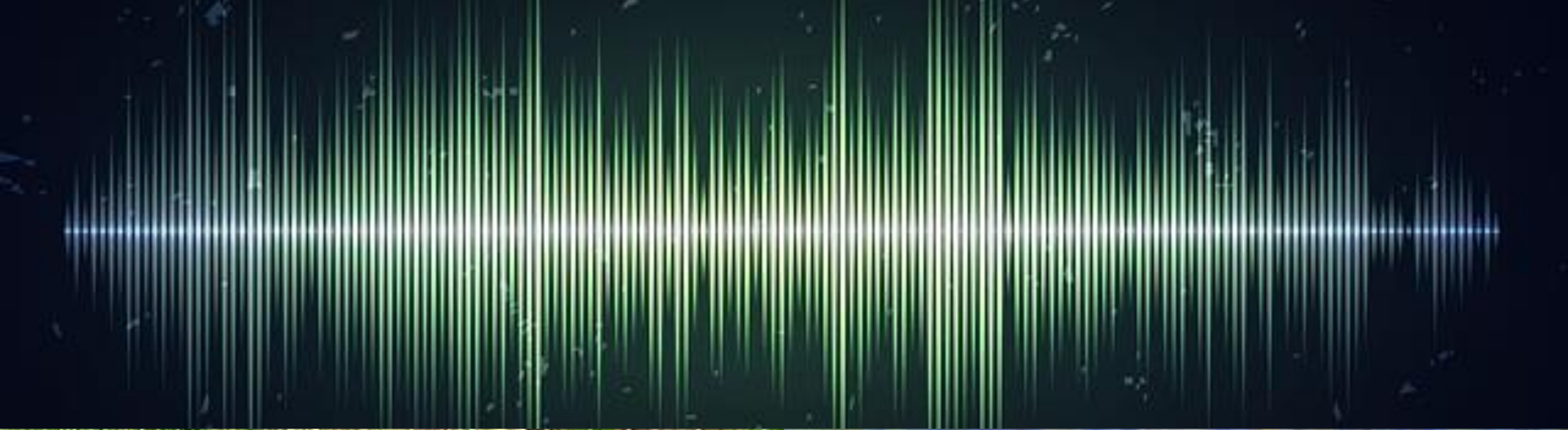
CONVOLUTIONAL NEURAL NETWORKS

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

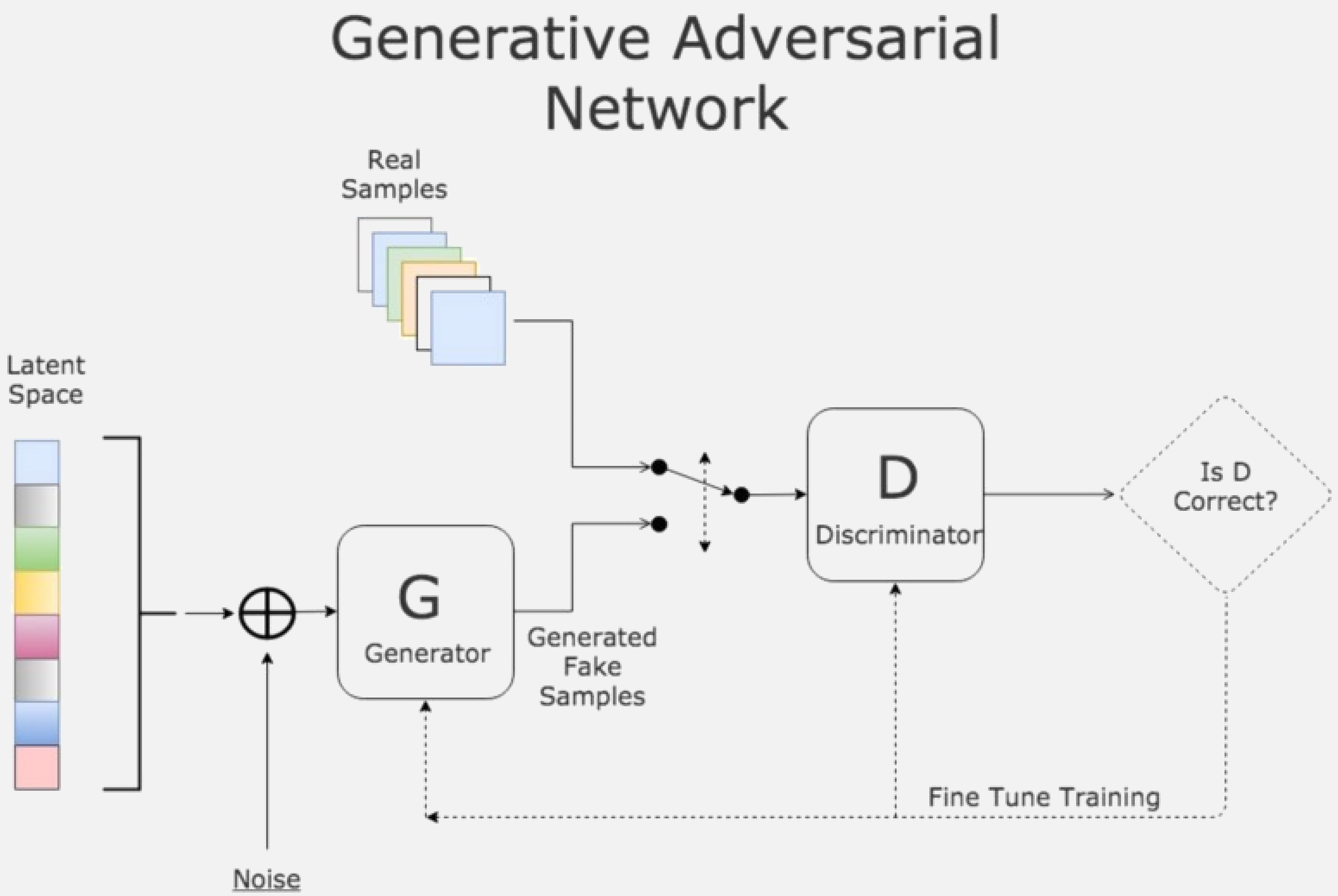

Text description
This bird is blue with white and has a very short beak
This bird has wings that are brown and has a yellow belly
A white bird with a black crown and yellow beak
This bird is white, black, and brown in color, with a brown beak
The bird has small beak, with reddish brown crown and gray 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
Stage-I images
Stage-II images

Create your novel image now!

Enter the description of a **bird**, example: “This bird has wings that are blue and has a red belly”.

I want a blue bird with yellow belly and short beak	**Create!**

HOW DOES THIS WORK?




TELIO

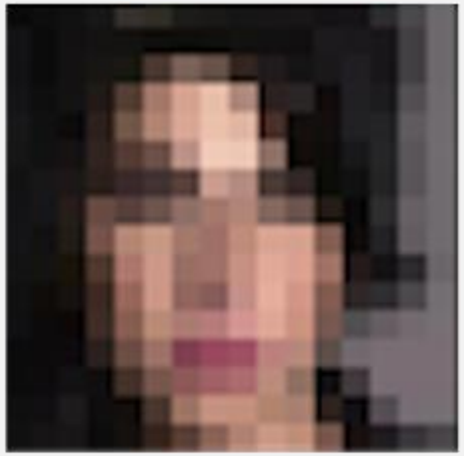
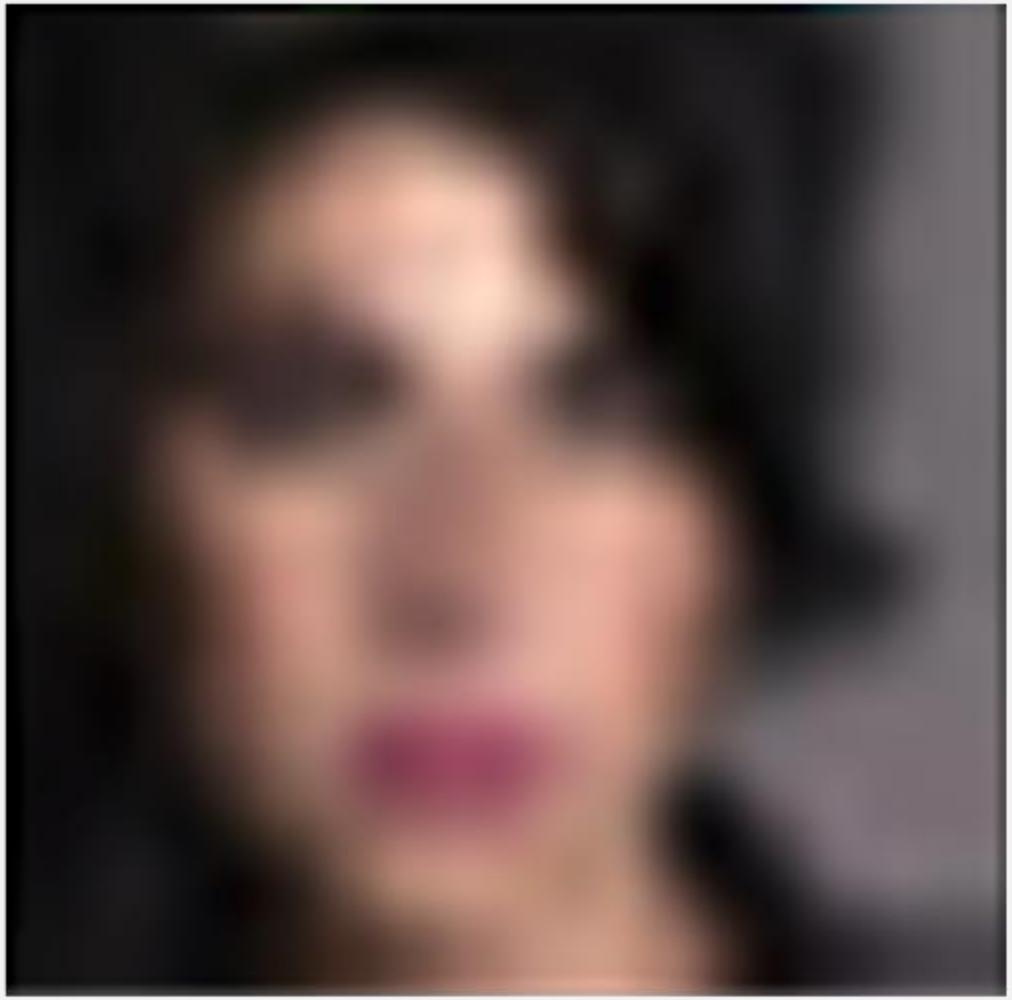

ZM 0000

Helping solve gruesome crimes

SR-GAN AND SRRESNET, PIXELCNN

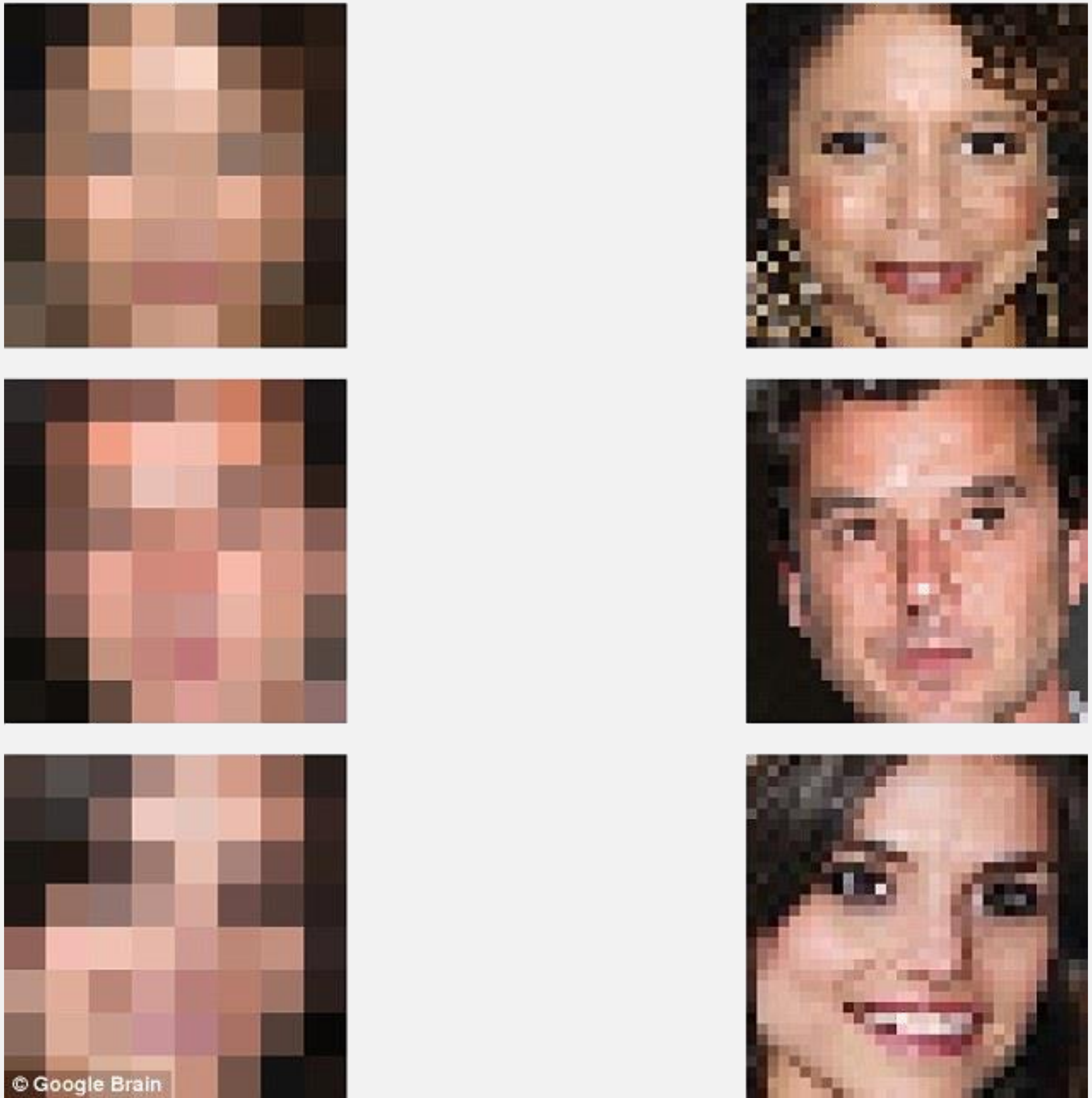
By using Generative Adversarial Networks, we are going to be able to upscale a pixelated image, and help the security enforcement team of our favourite TV show find the actual face of the criminal!

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

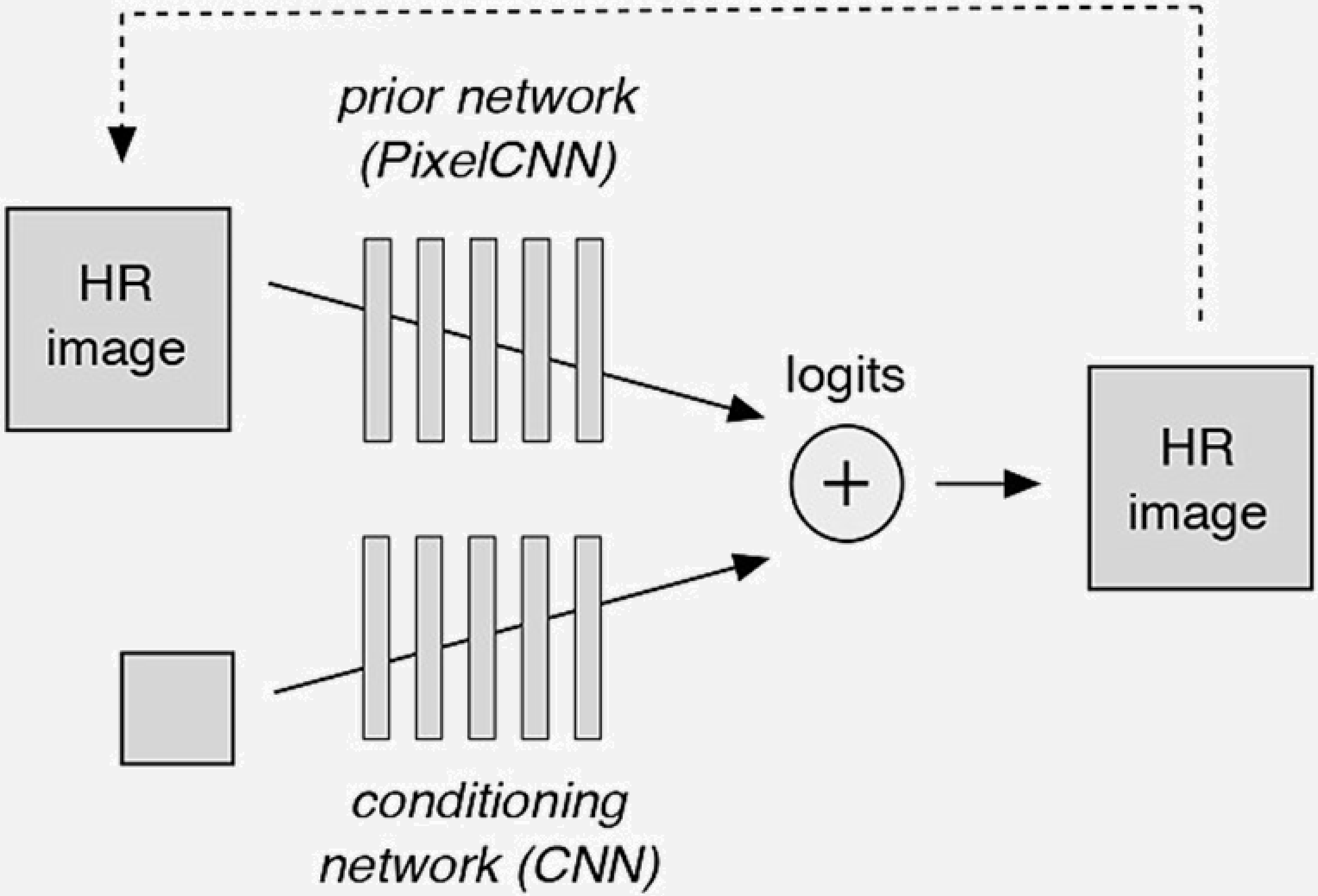




8×8 input

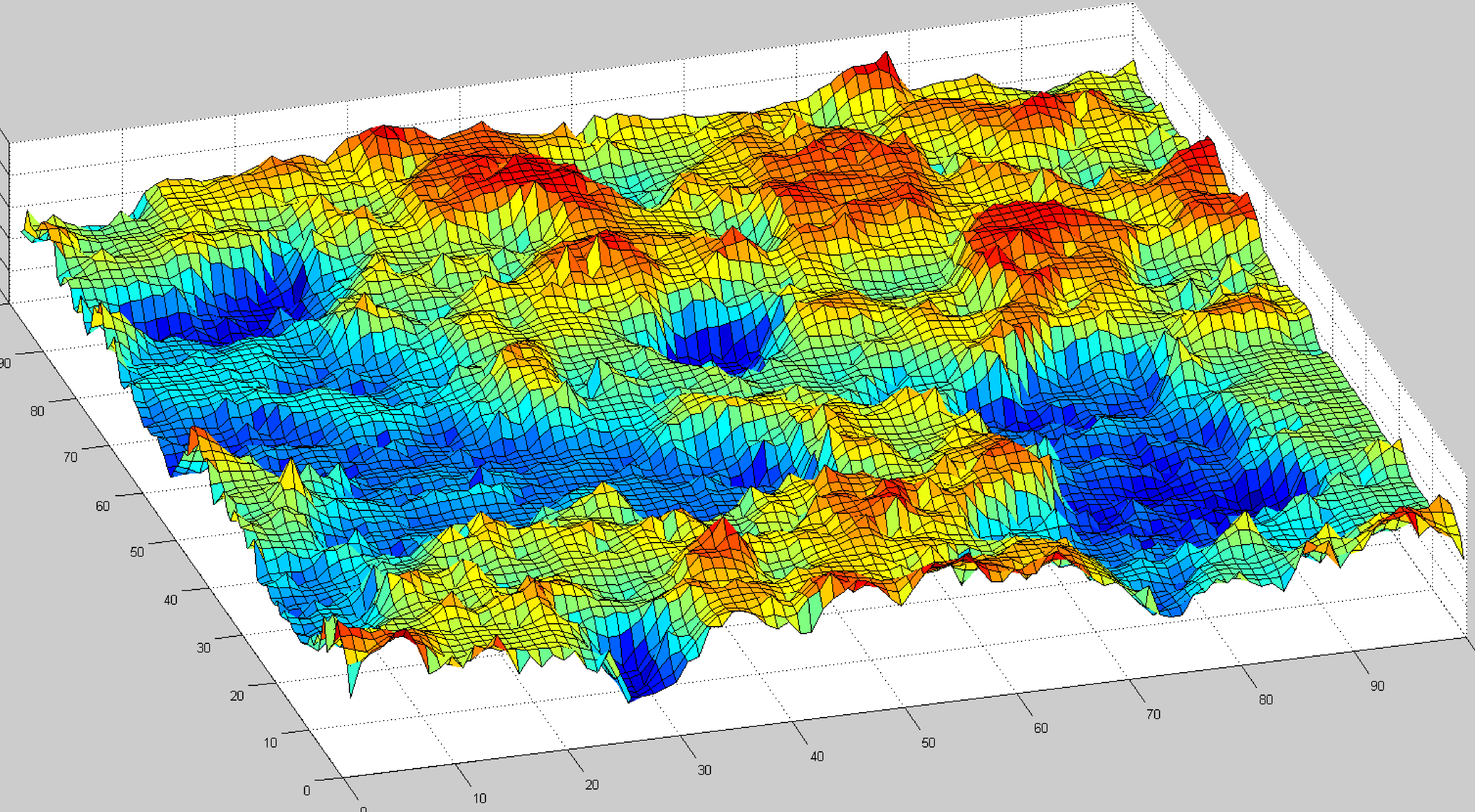
ground truth

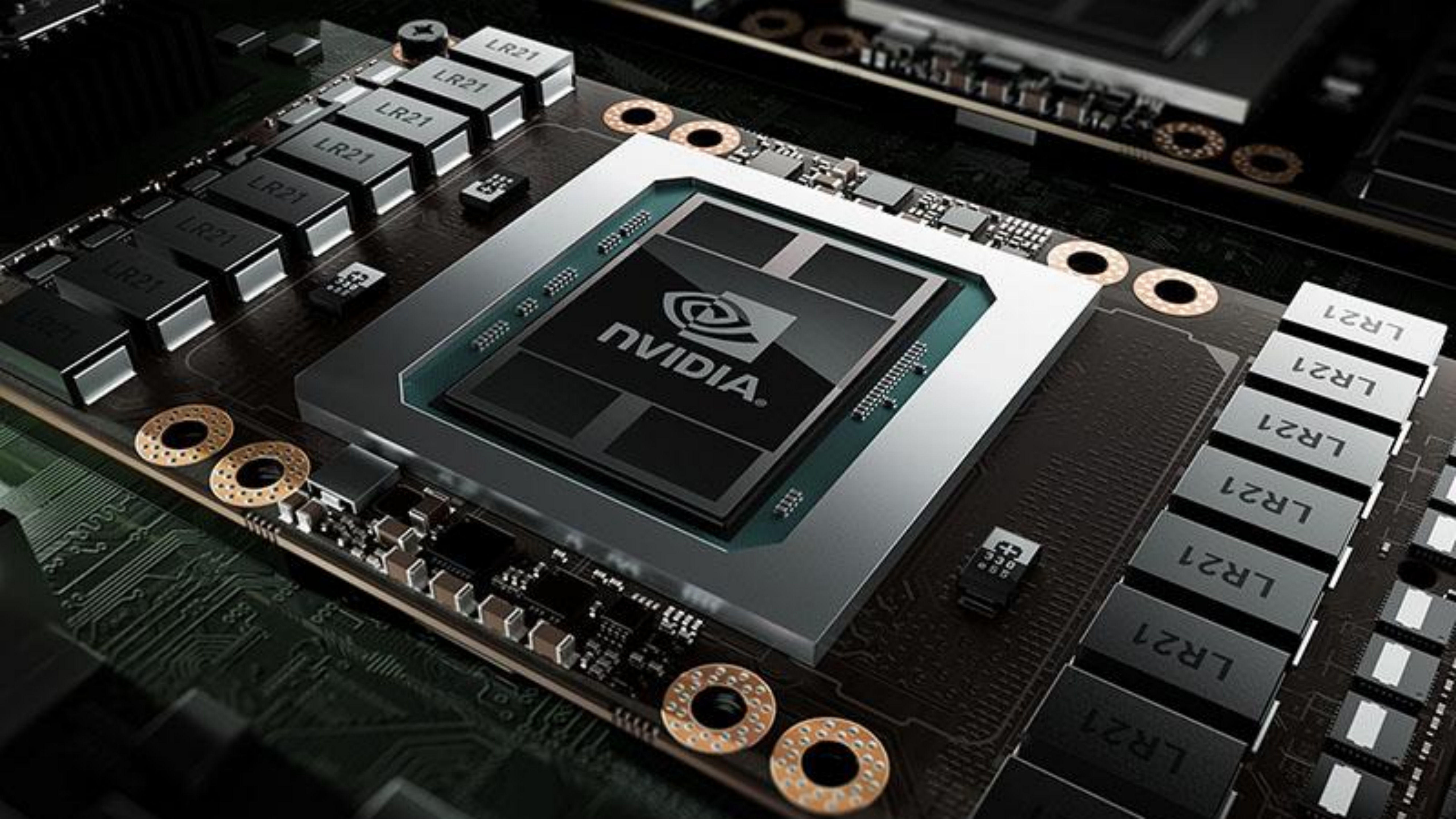


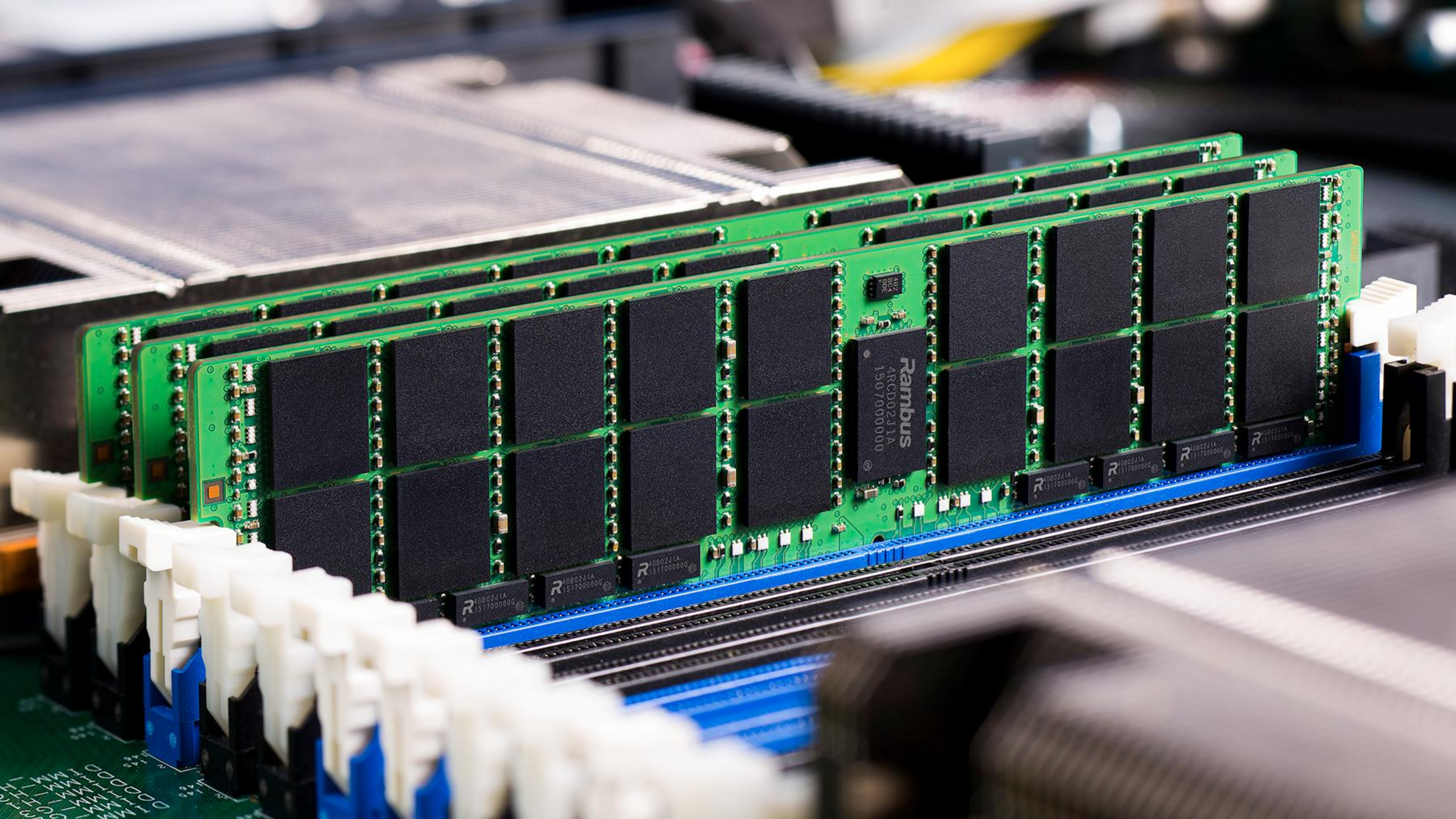
HOW DOES THIS WORK?




SHUT UP AND TAKE MY MONEY


0
10
20
30
40
50
60
70
80
10
20
30
40
50
60
70
80
90


NVIDIA
LR21


Rambus
4RCD02J1A
1507000000

Caffe

Chainer

DL4J
Deeplearning4j

K
KERAS

Microsoft
CNTK

MatConvNet

MINERVA

mxnet

Purine

TensorFlow

theano

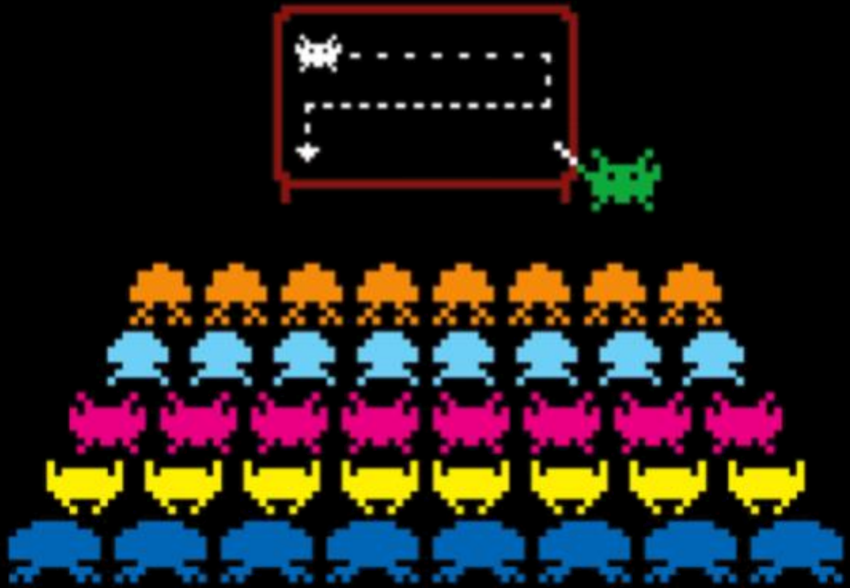
torch

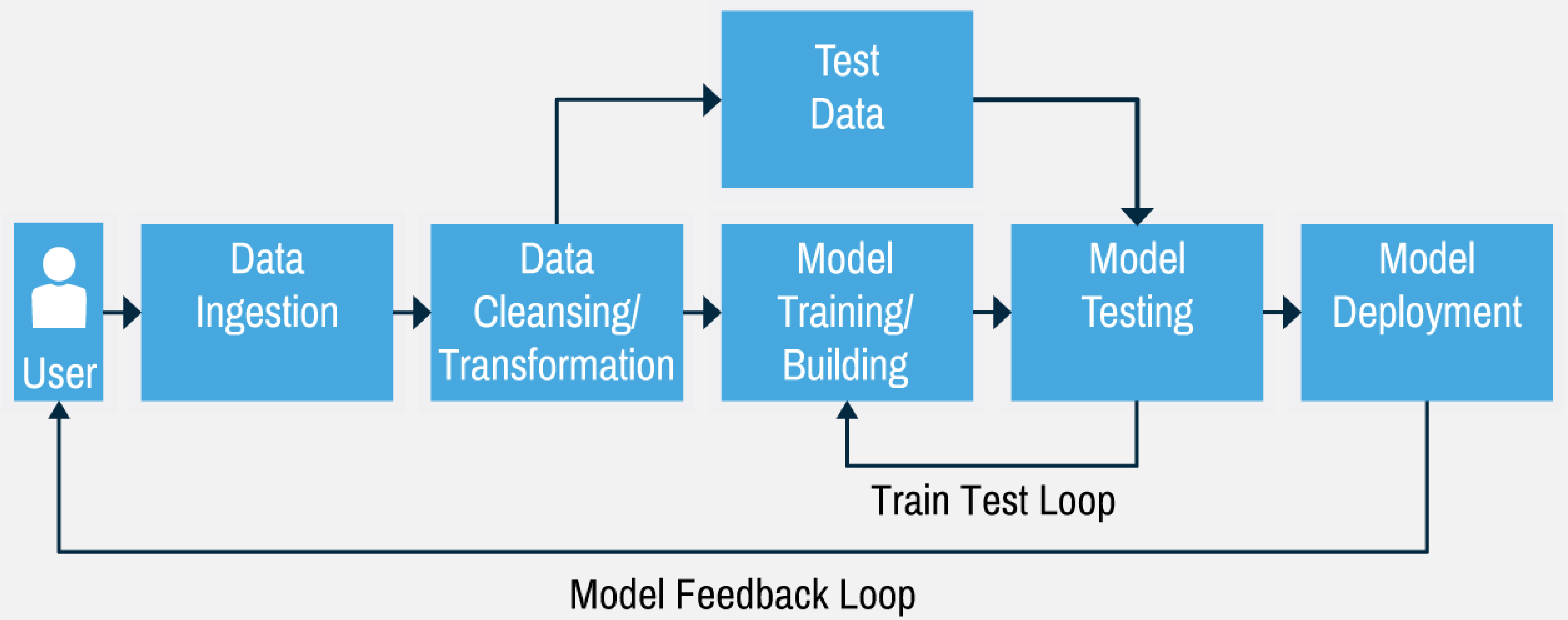
ONNX

OPEN NEURAL NETWORK EXCHANGE FORMAT

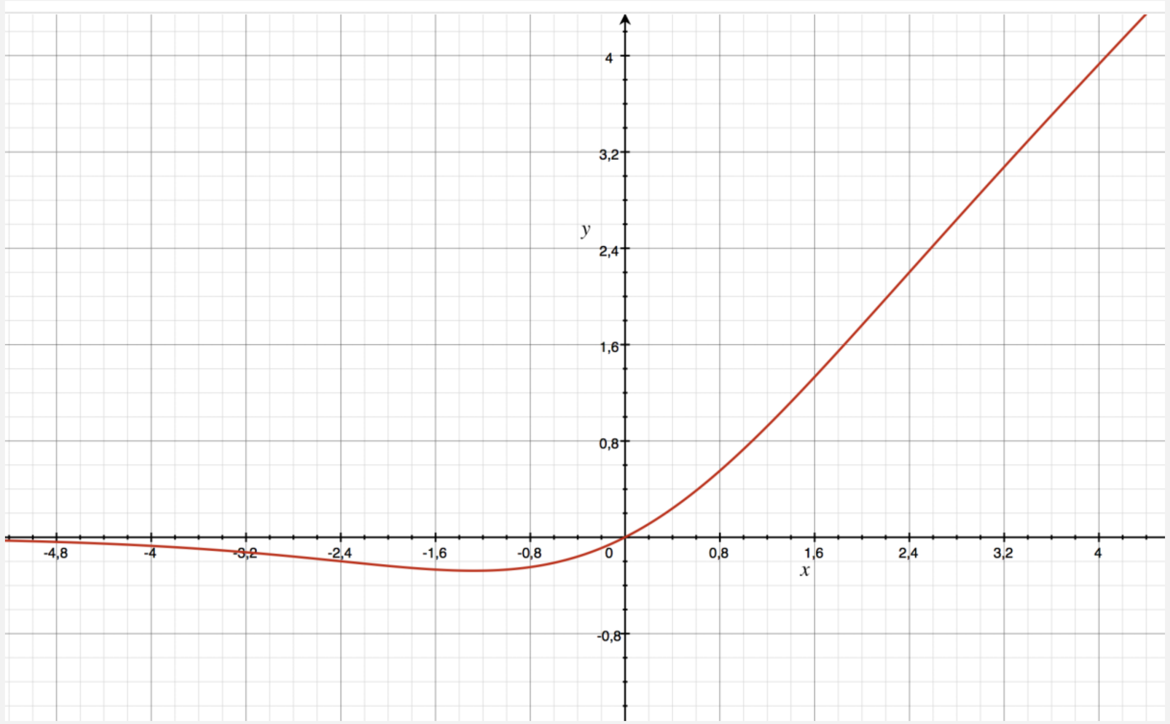
The new open ecosystem for interchangeable AI models


NIKE
plain concepts

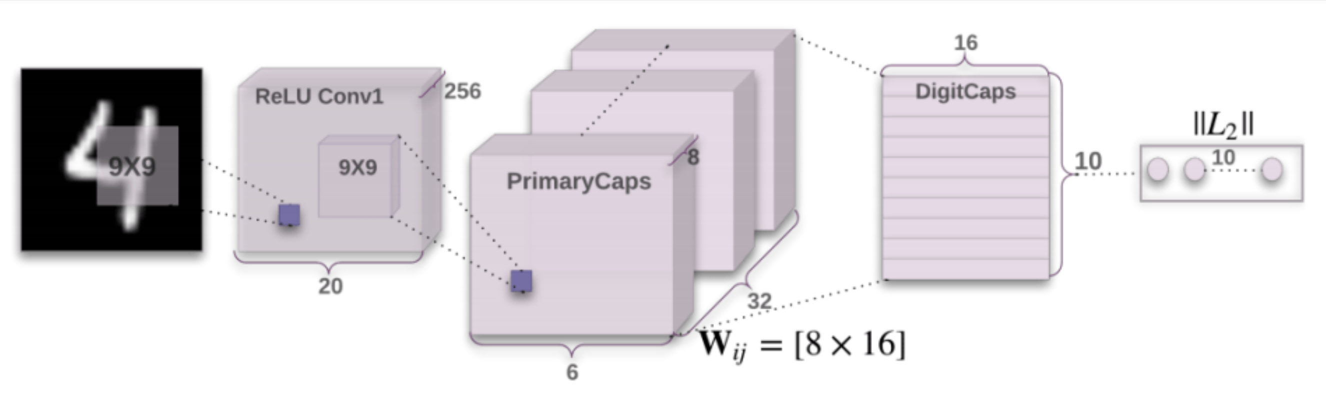



Test
Data
User
Data
Ingestion
Data
Cleansing/
Transformation
Model
Training/
Building
Model
Testing
Model
Deployment
Train Test Loop
Model Feedback Loop

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

Thanks!

Next up...

Production Python Machine Learning in SQL Server

Terry McCann

GLOBAL AI
LONDON 2018

GLOBAL AI
LONDON 2018