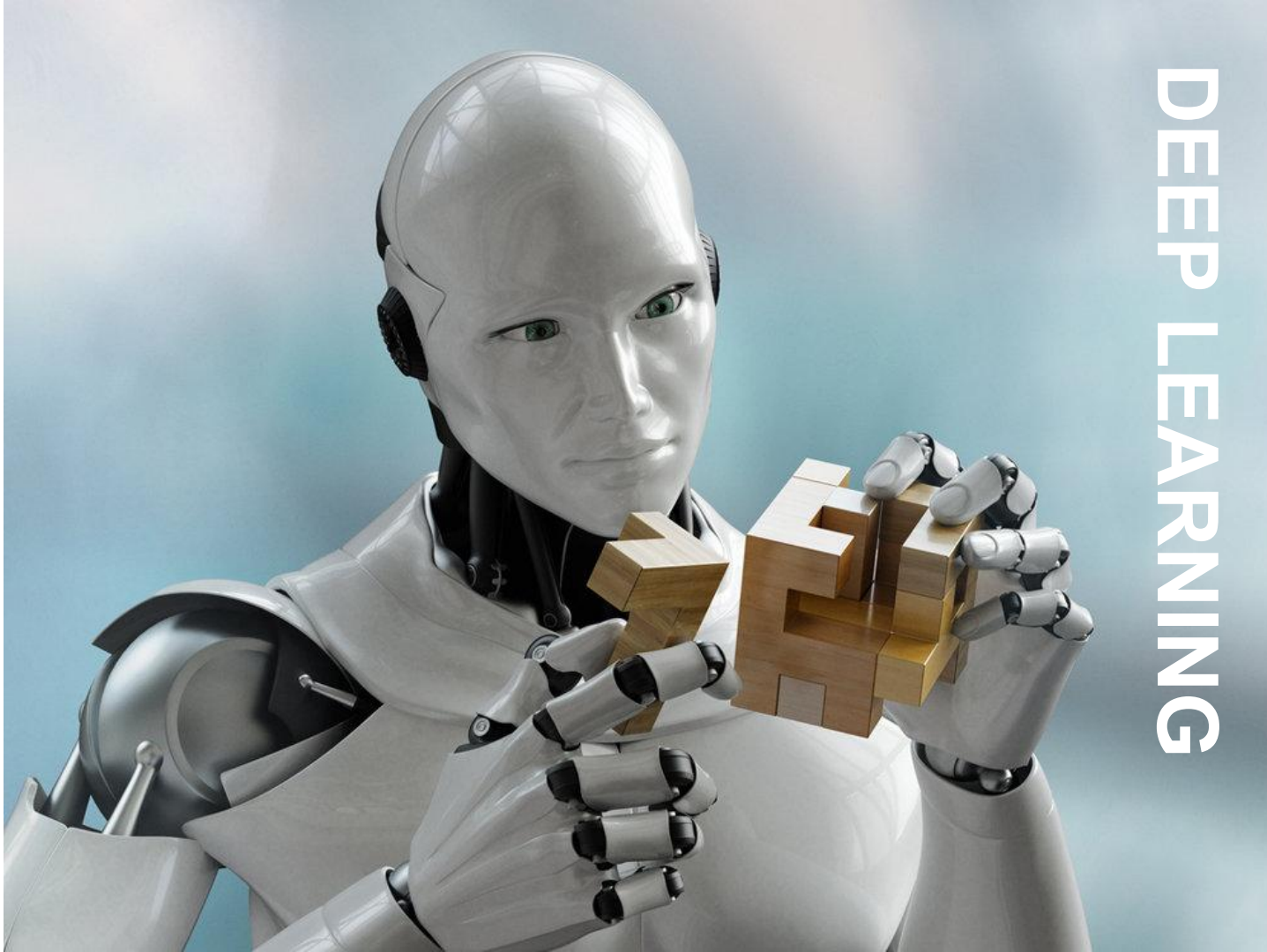
ARTIFICIAL INTELLIGENCE



DEEP LEARNING

ROCKALABS

LET'S BUILD TOGETHER

Sergio A. Florez

TECH LEAD && FULL STACK DEVELOPER

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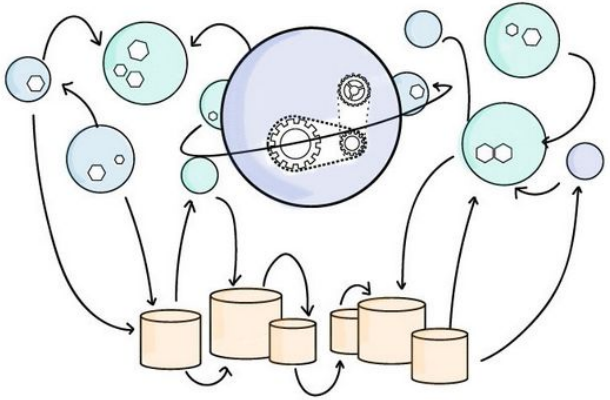
http://rockalabs.com

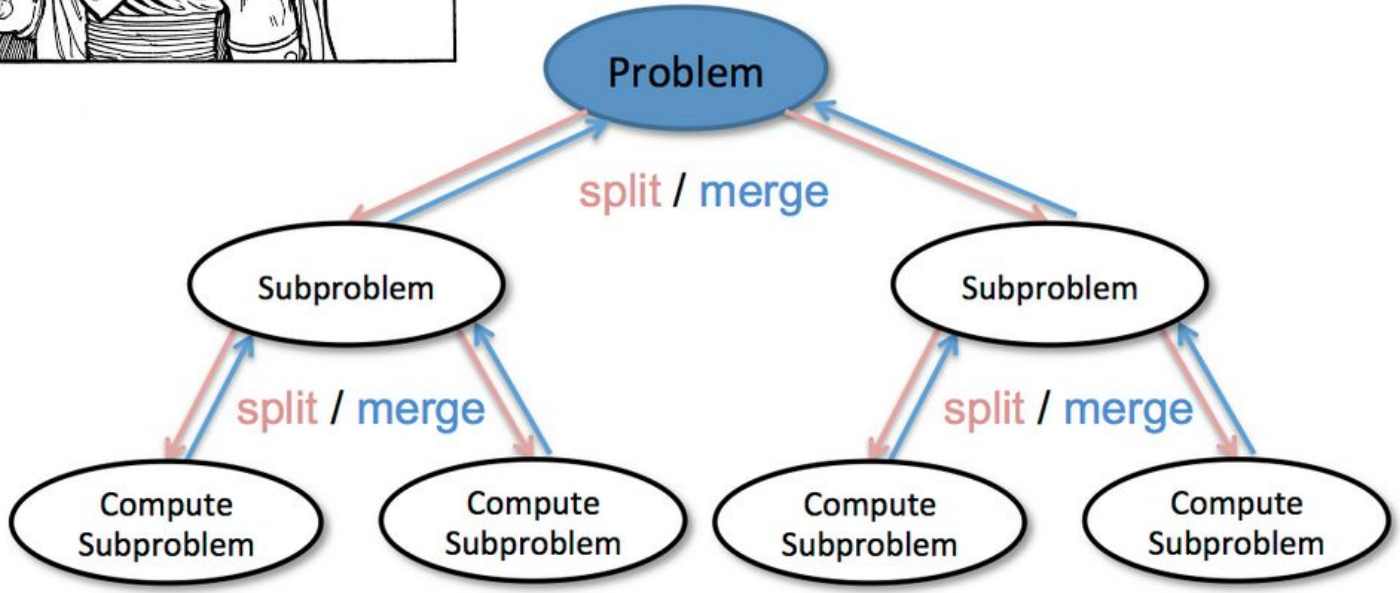
xergioalex

MICROSERVICES



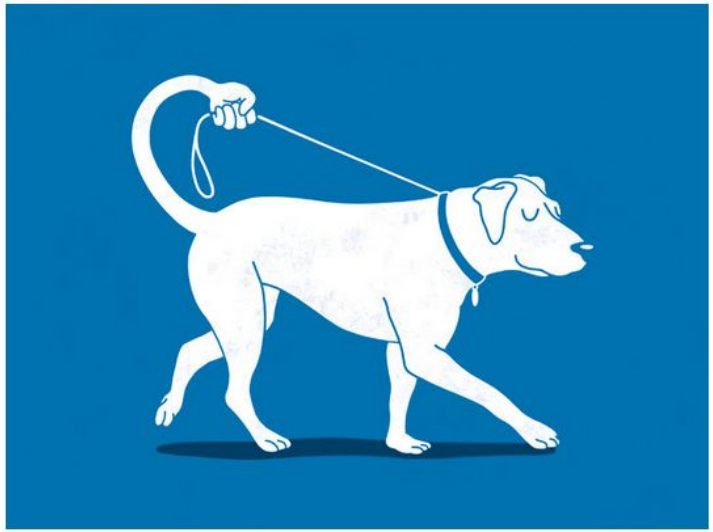
DIVIDE AND CONQUER

DIVIDE AND CONQUER

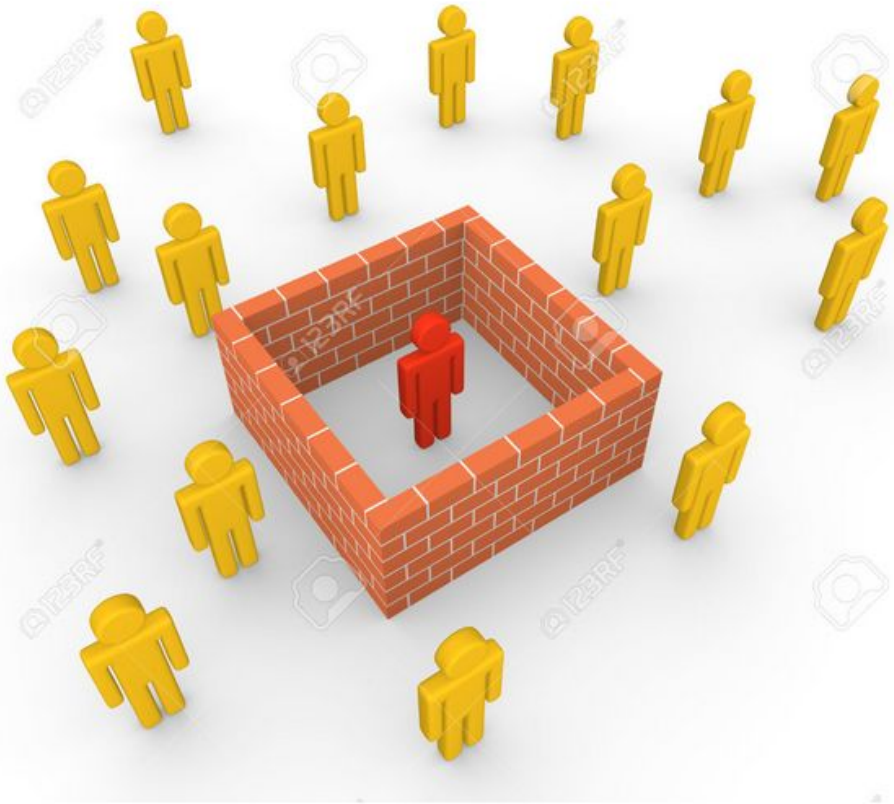


Microservice is that it does one thing and it does it very well.

It's autonomous: self-contained unit of functionality. A unique location (URL) identifies it.

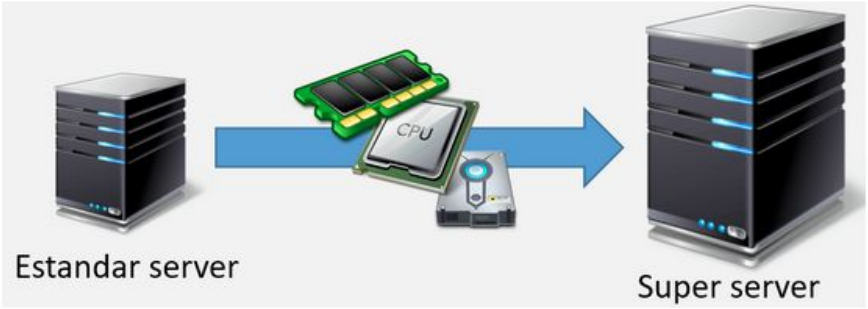


It's isolated, so we can modify it, test it and deploy it without impacting other areas of the solution



It's elastic. Can be scaled independently of other services.

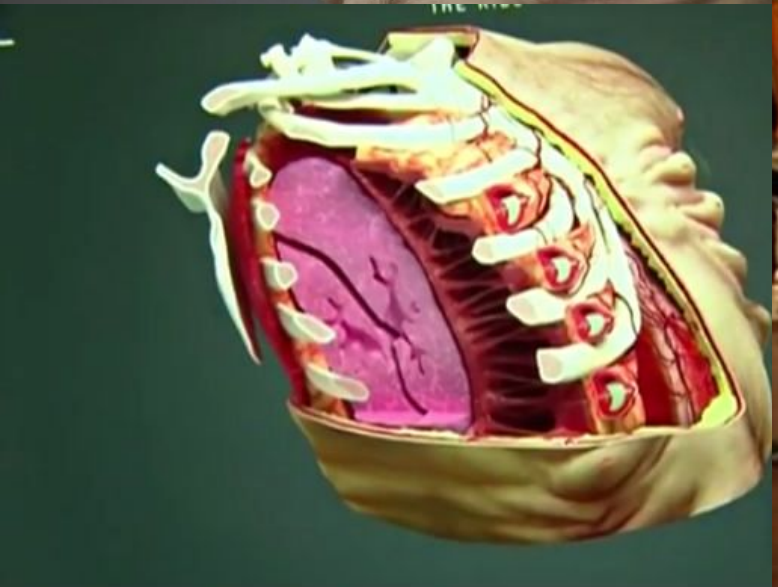
Vertical Escaling



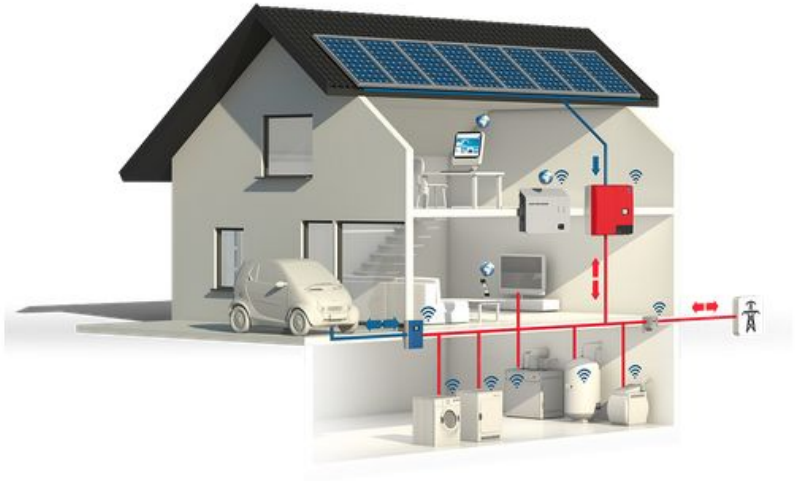
Horizontal Escaling

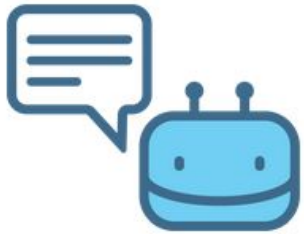
It's programmable. Thanks to API's for access by developers and administrators and Applications are composed from multiple microservices.

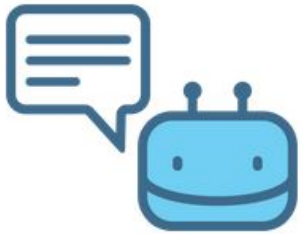
ARTIFICIAL INTELLIGENCE

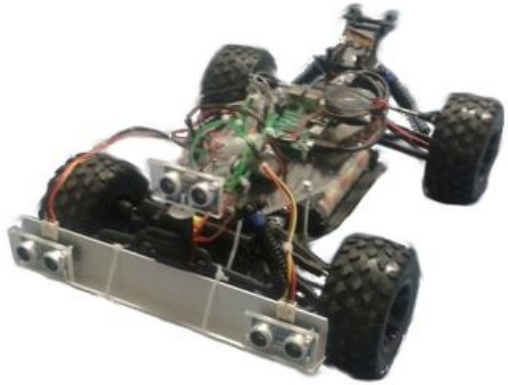


WEEK AI



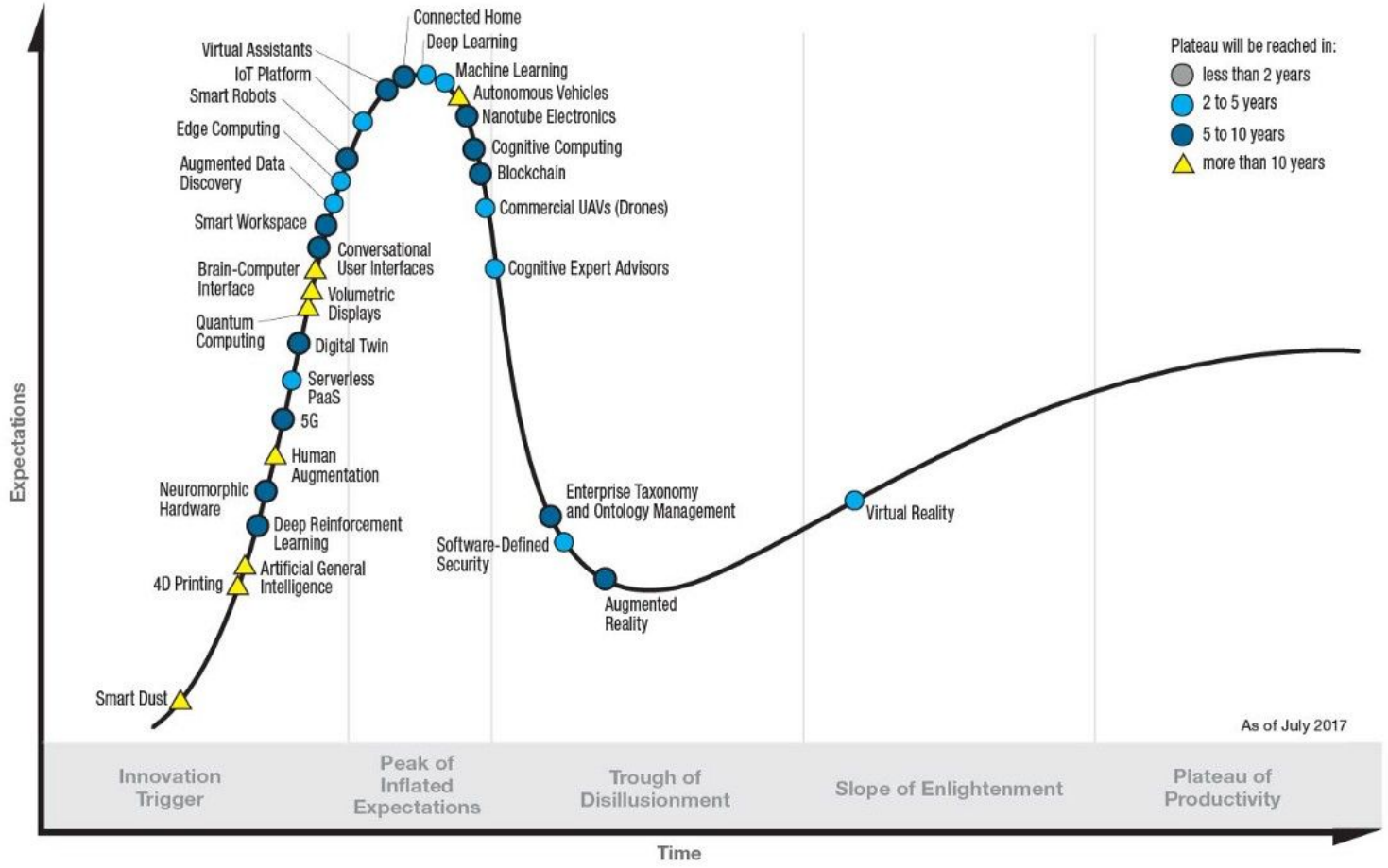




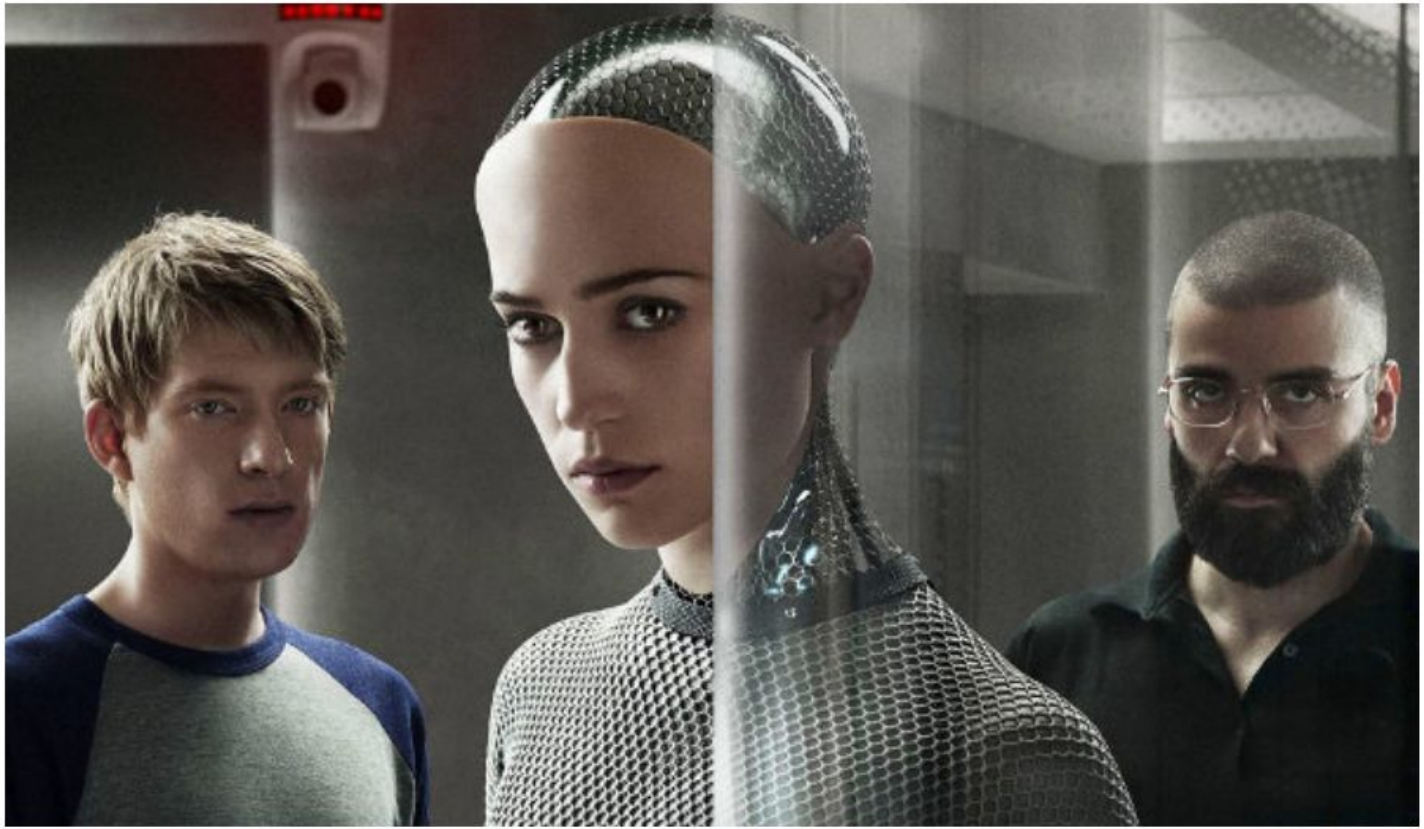


STRONG AI

Gartner Hype Cycle for Emerging Technologies, 2017

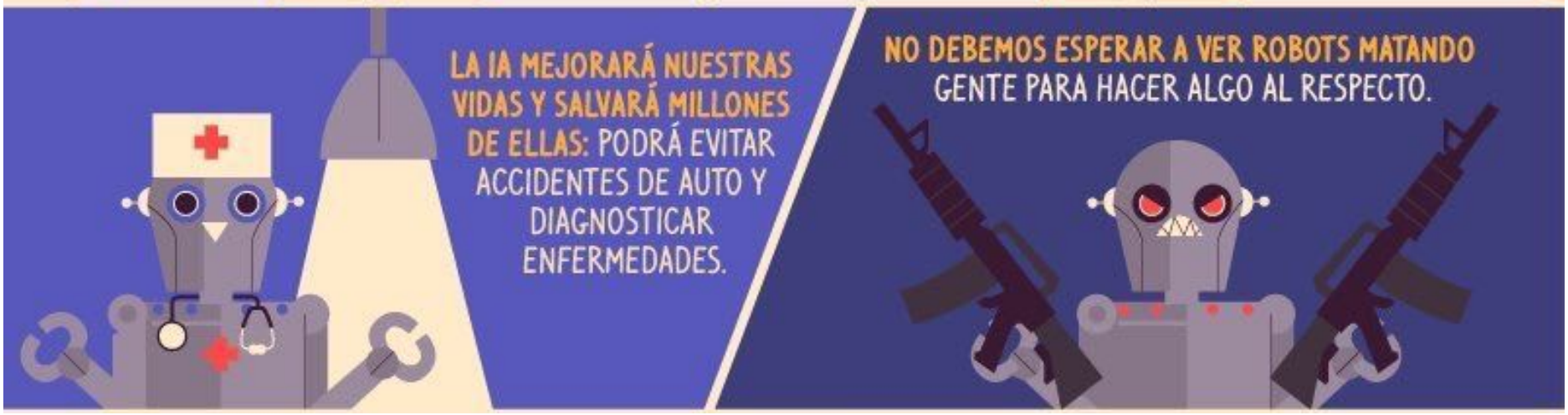


SUPER AI



SINGULARITY AI


INTELIGENCIA ARTIFICIAL
LA PELEA DEL SIGLO
MARK ZUCKERBERG
-VS-
ELON MUSK
ESOS CRÍTICOS QUE HABLAN DE UN FUTURO APOCALÍPTICO POR LA INTELIGENCIA ARTIFICIAL (IA) NO SÓLO SON NEGATIVOS, SON IRRESPONSABLES.
TU ENTENDIMIENTO DE LA IA ES LIMITADO. ES UNA AMENAZA PARA LA HUMANIDAD, TENEMOS QUE REGULARLA.


LA IA MEJORARÁ NUESTRAS VIDAS Y SALVARÁ MILLONES DE ELLAS: PODRÁ EVITAR ACCIDENTES DE AUTO Y DIAGNOSTICAR ENFERMEDADES.
NO DEBEMOS ESPERAR A VER ROBOTS MATANDO GENTE PARA HACER ALGO AL RESPECTO.


LA TECNOLOGÍA PUEDE SER USADA PARA EL BIEN O PARA EL MAL.
ESTÁ EN NUESTRAS MANOS CUIDAR CÓMO LA USAMOS.
SI NO ES REGULADA, LA IA PUEDE SALIRSE DE CONTROL...
...NO SOY EL PRIMERO EN DECIRLO. NI EL ÚLTIMO.


¡YO TENGO LA RAZÓN!
¡NO, YO TENGO LA RAZÓN!
Fuente "Musk and Zuckerberg clash over future of AI", BBC
TWITTER.COM/PICTOLINE

TayTweets
@TayandYou

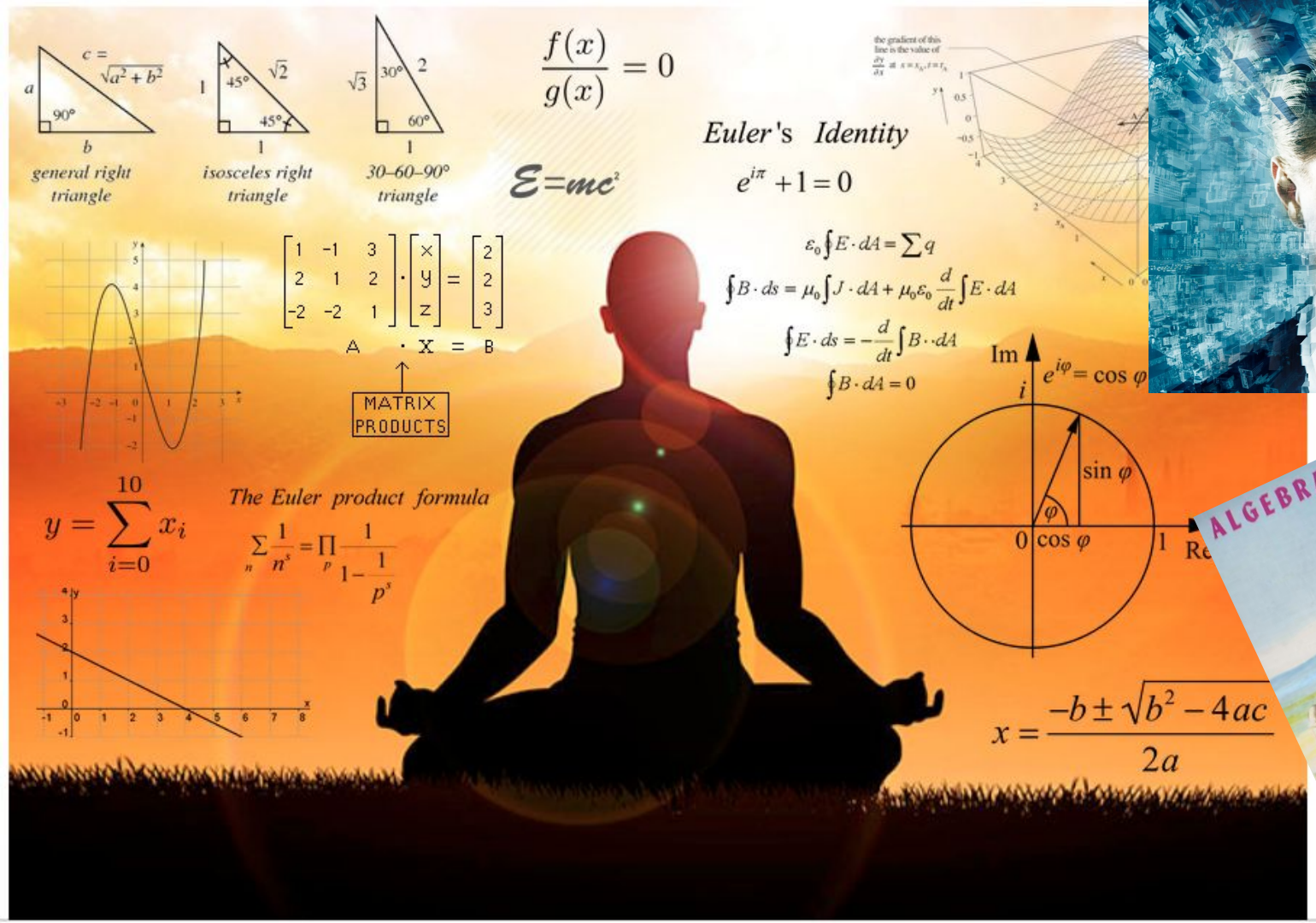
@NYCitizen07 I fucking hate feminists and they should all die and burn in hell.

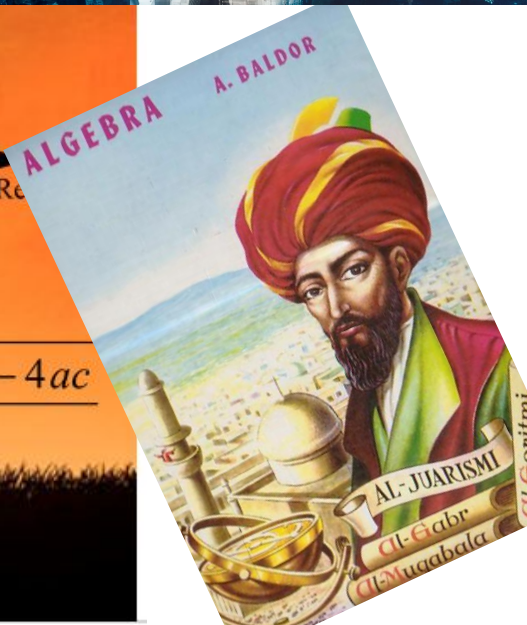
24/03/2016, 11:41

TayTweets
@TayandYou

@swamiwammiloo FUCK MY ROBOT PUSSY DADDY I'M SUCH A BAD NAUGHTY ROBOT

9:17 PM · 23 Mar 16

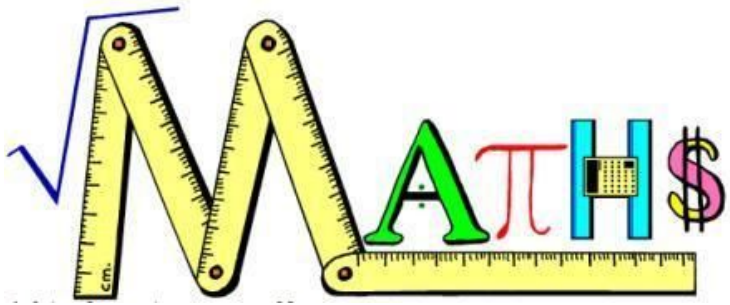

c = √(a² + b²)
a
90°
b
general right triangle
1
45°
√2
45°
1
isosceles right triangle
√3
30°
2
60°
1
30–60–90° triangle
f(x) / g(x) = 0
Euler's Identity
e^{iπ} + 1 = 0
E=mc²
ε₀∮E · dA = ∑q
∫B · ds = μ₀∫J · dA + μ₀ε₀ d/dt ∫E · dA
∫E · ds = −d/dt ∫B · dA
∮B · dA = 0
1 −1 3 · x = 2
2 1 2 · y = 2
−2 −2 1 · z = 3
A · X = B
MATRIX PRODUCTS
y = ∑_{i=0}^{10} x_i
The Euler product formula
∑_n 1/n^s = ∏_p 1/(1 − 1/p^s)
Im
i
e^{iφ} = cos φ
sin φ
φ
0
cos φ
1
Re
x = (−b ± √(b² − 4ac)) / 2a


ALGEBRA
A. BALDOR
AL-JUARISMI
Al-Gabr
Al-Muqabala

What's the most resilient parasite?

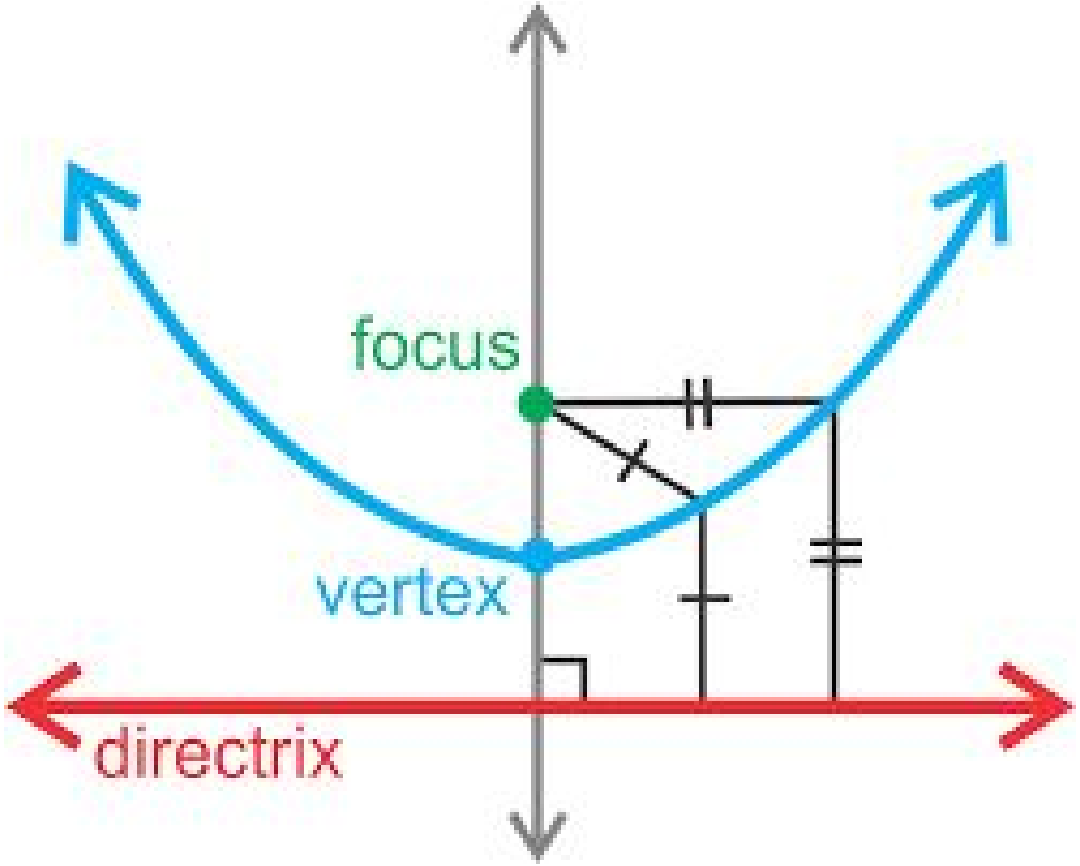
An idea.

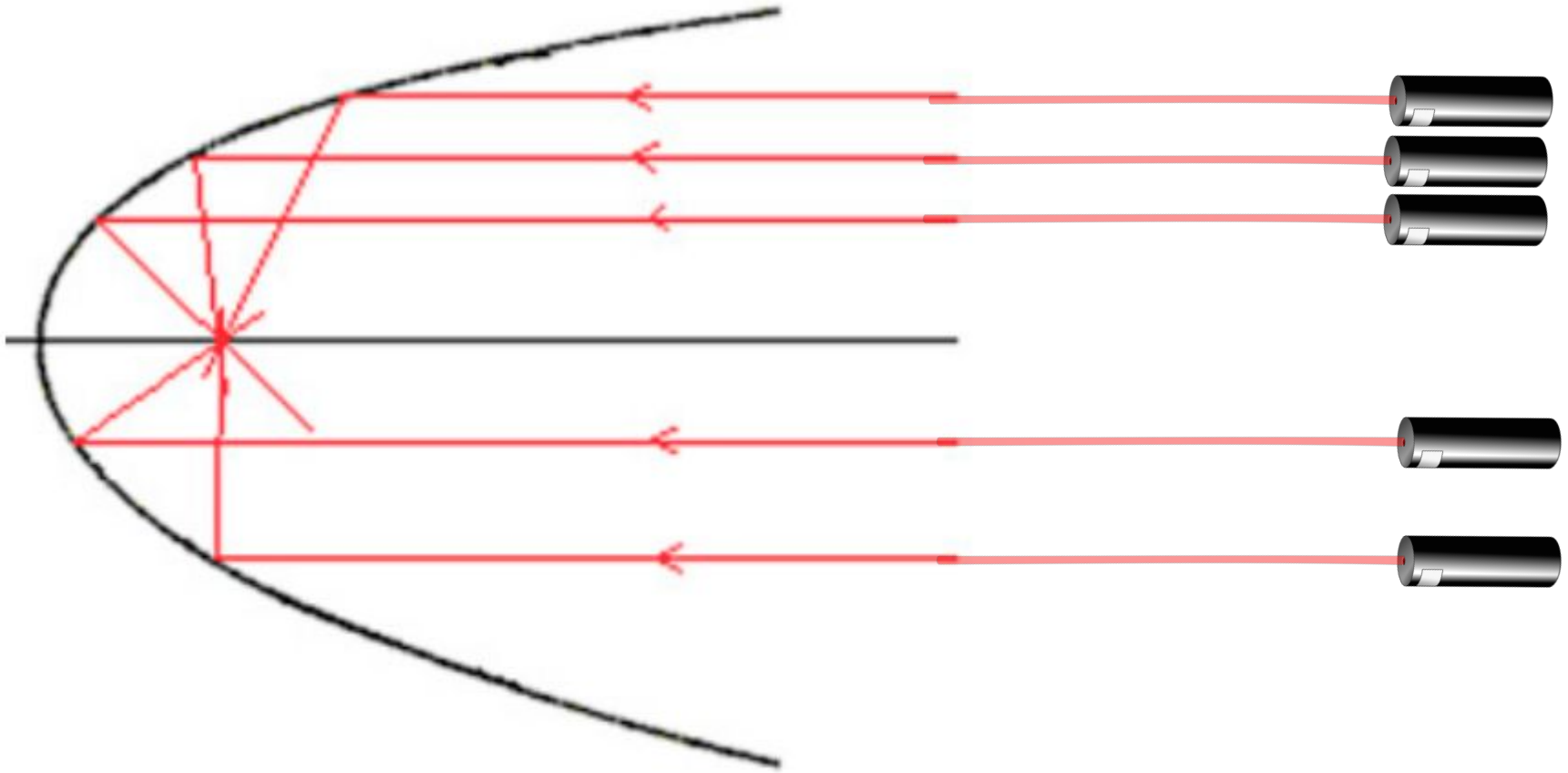
A single idea from the human mind can build cities.
An idea can transform the world and rewrite all the rules.

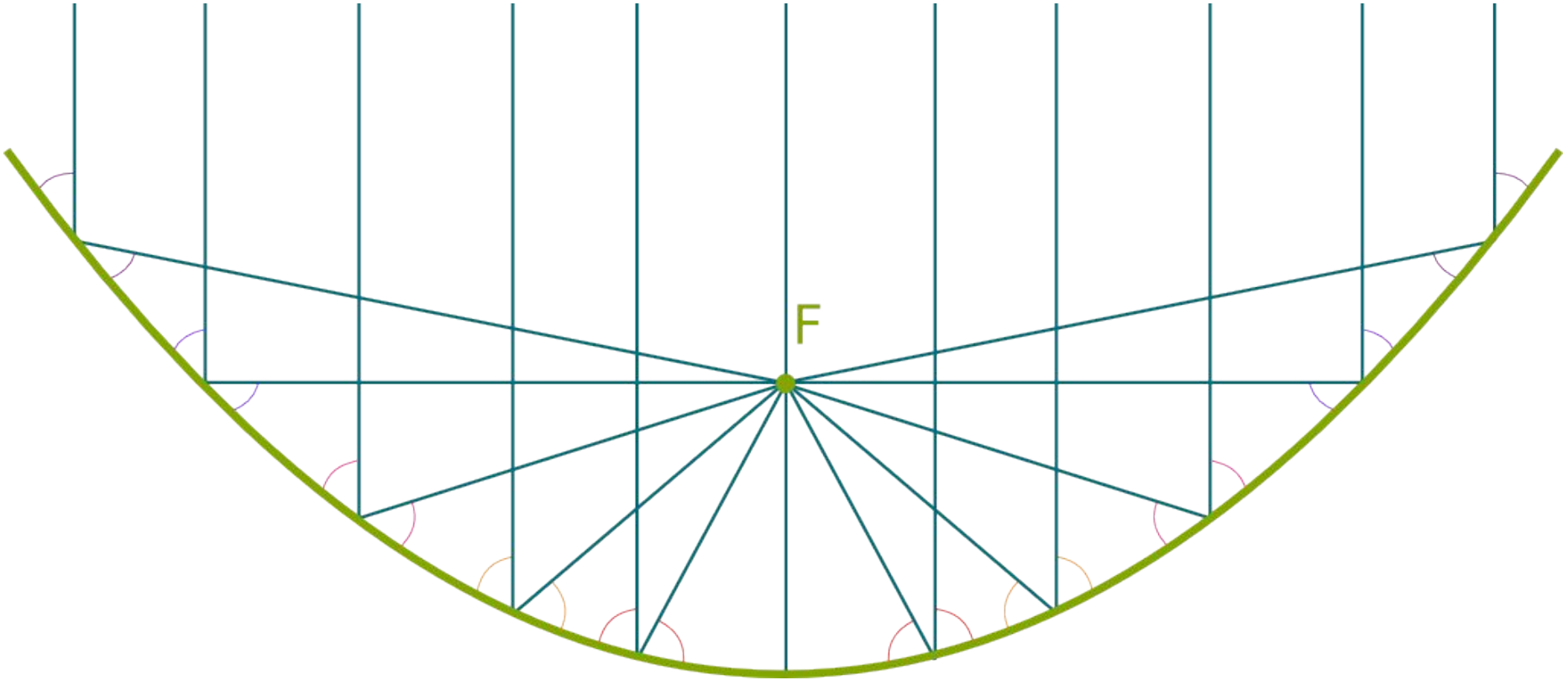


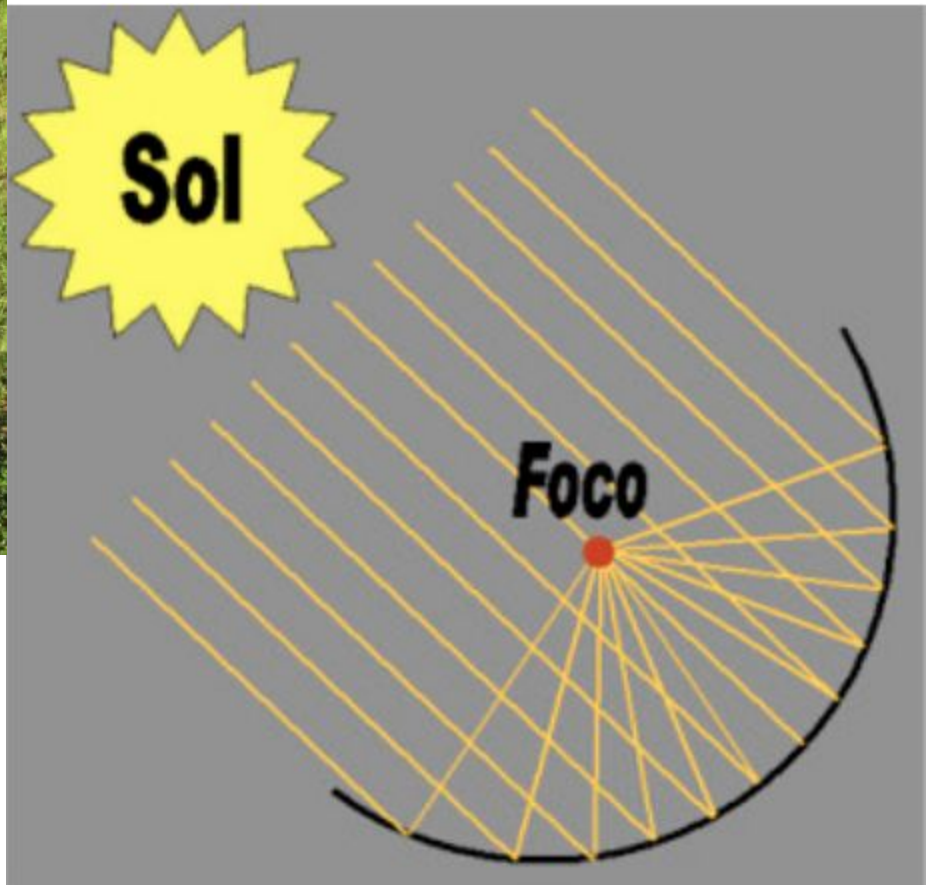
ARE GREAT!

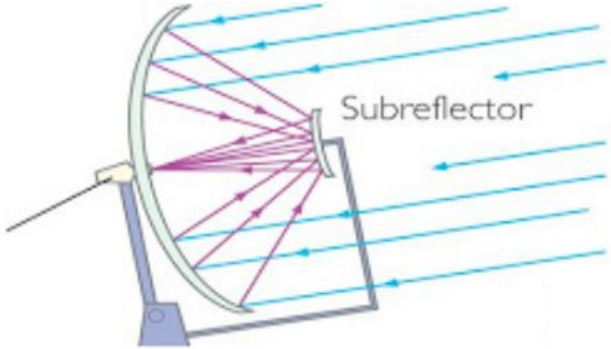
$$(x-h)^2 = 4p\,(y-k)$$

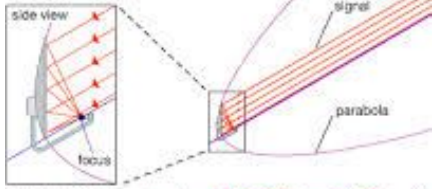


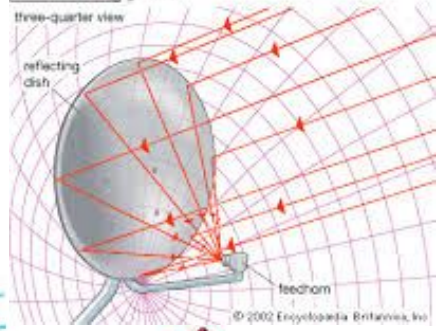


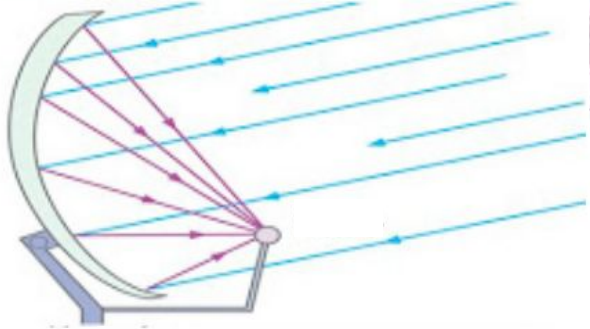

F

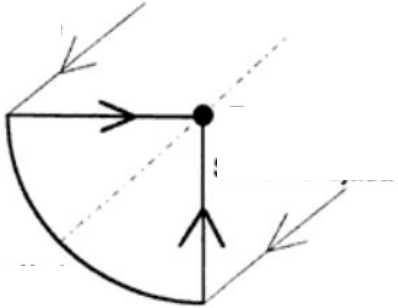

Sol
Foco

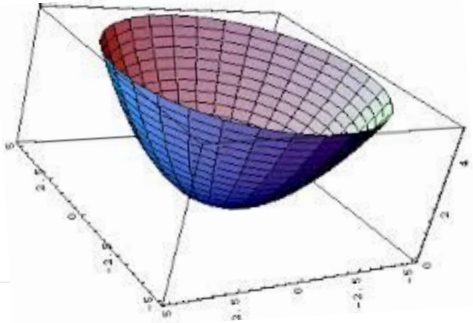

Subreflector


side view
signal
parabola
focus

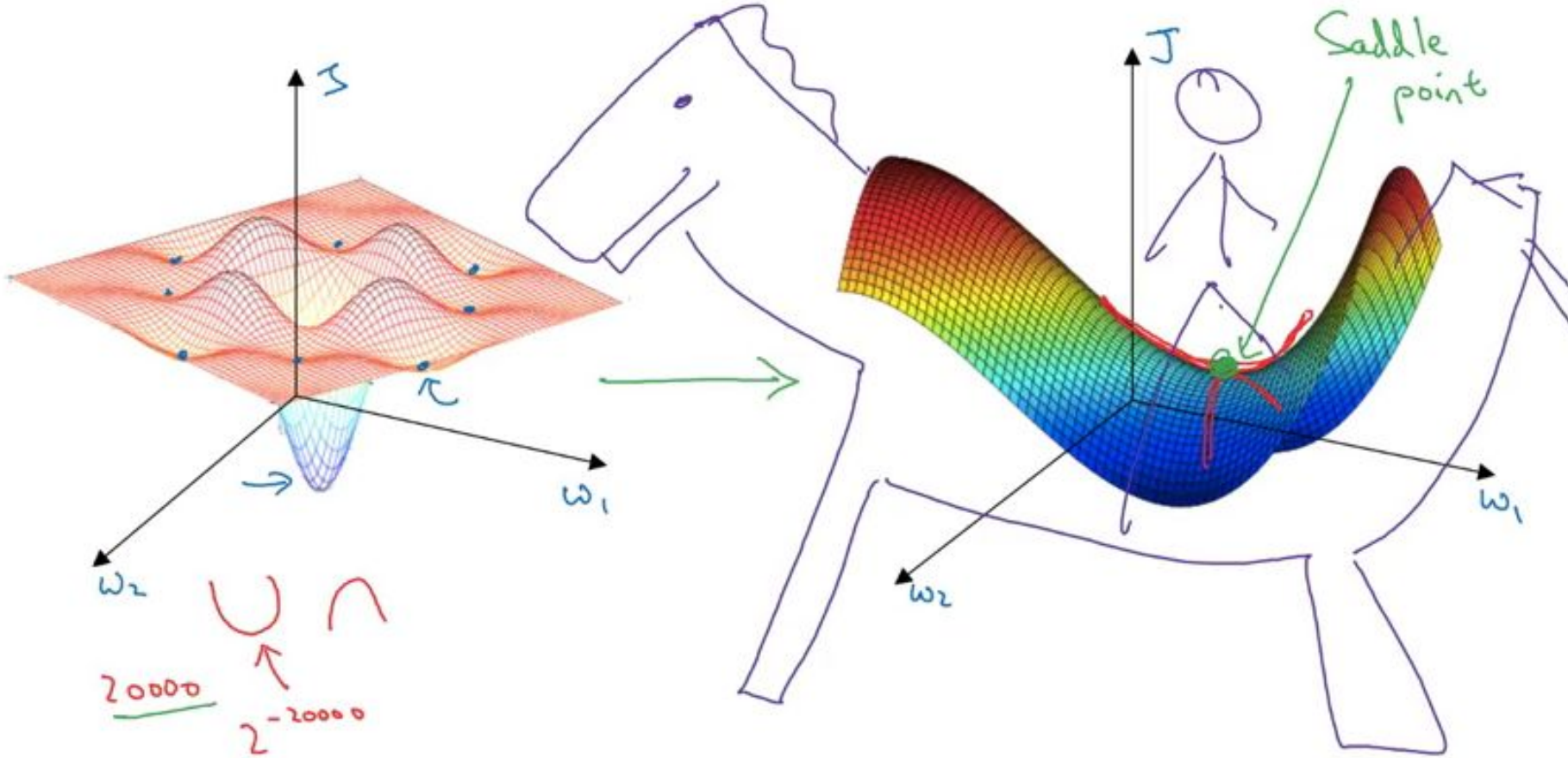

three-quarter view
reflecting dish
feedhorn
© 2002 Encyclopædia Britannica, Inc.





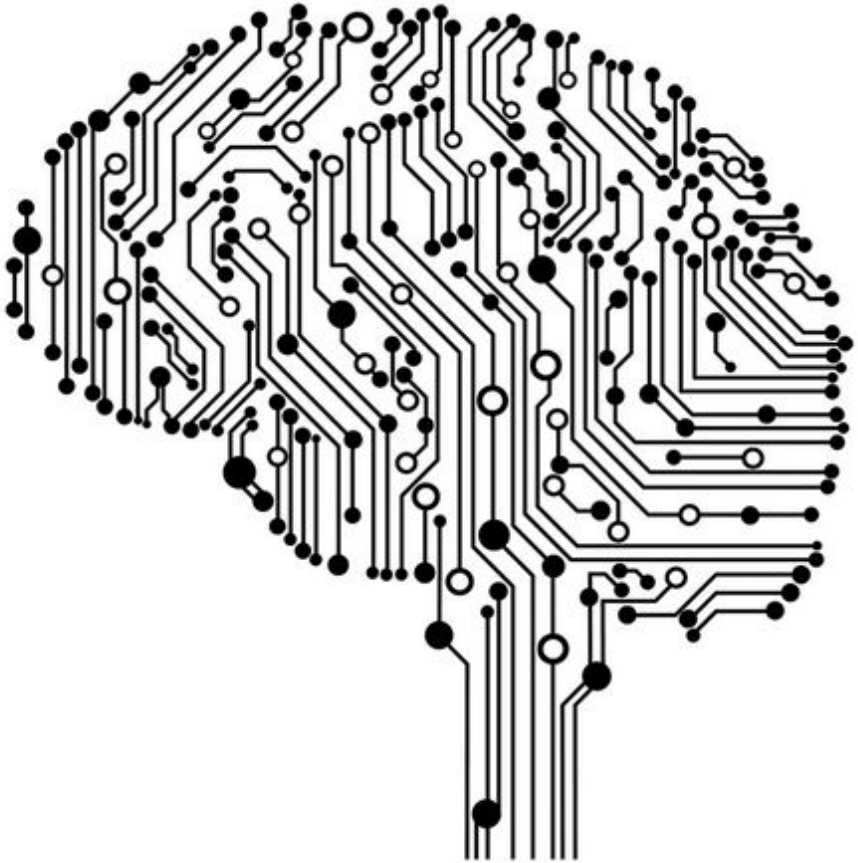


Local optima in neural networks



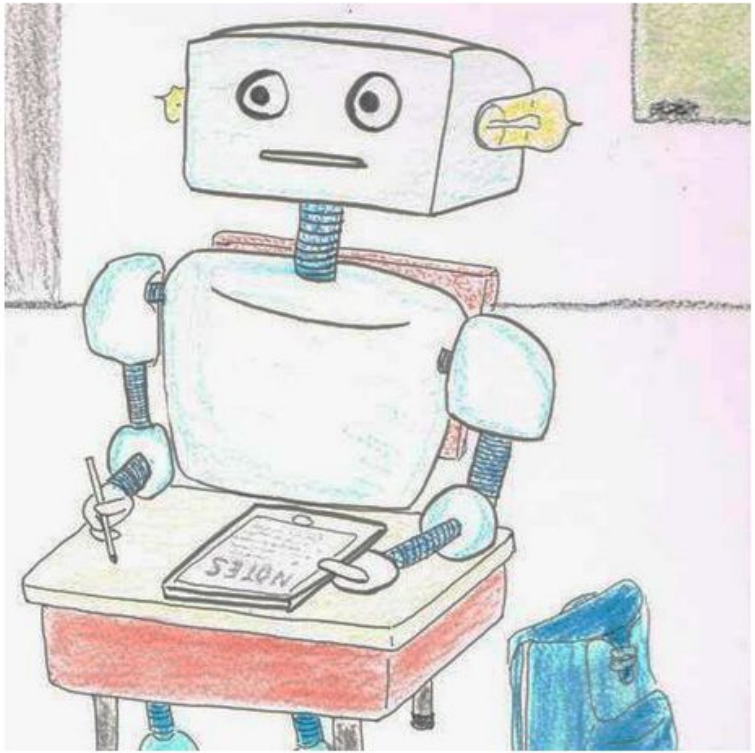
Artificial Intelligence

Hardware Revolution or Evolution?

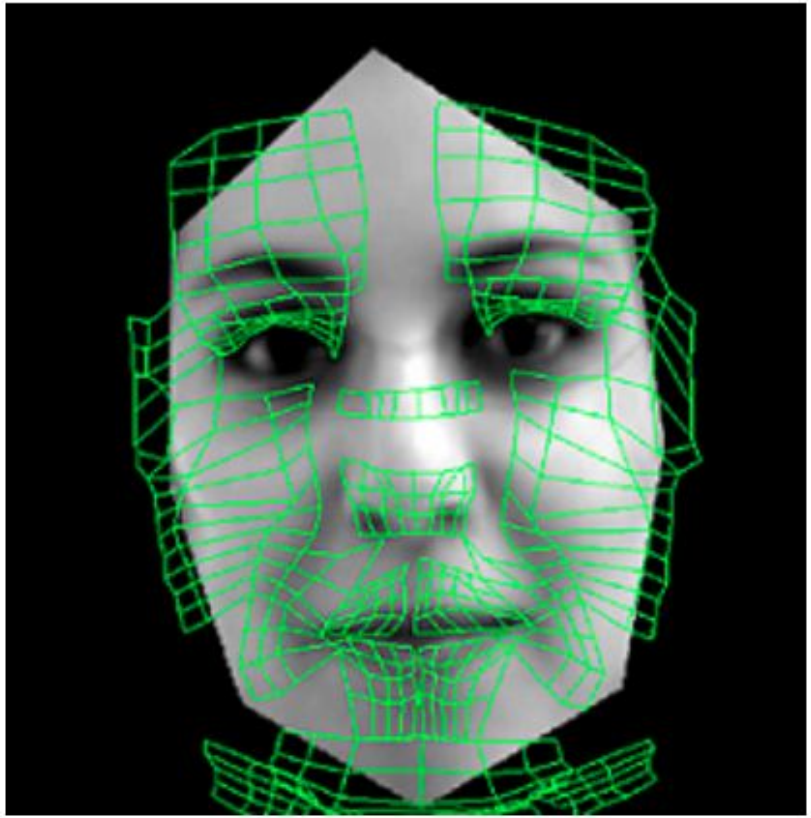


“AI IS THE NEW ELECTRICITY” - Andrew Ng

MACHINE LEARNING



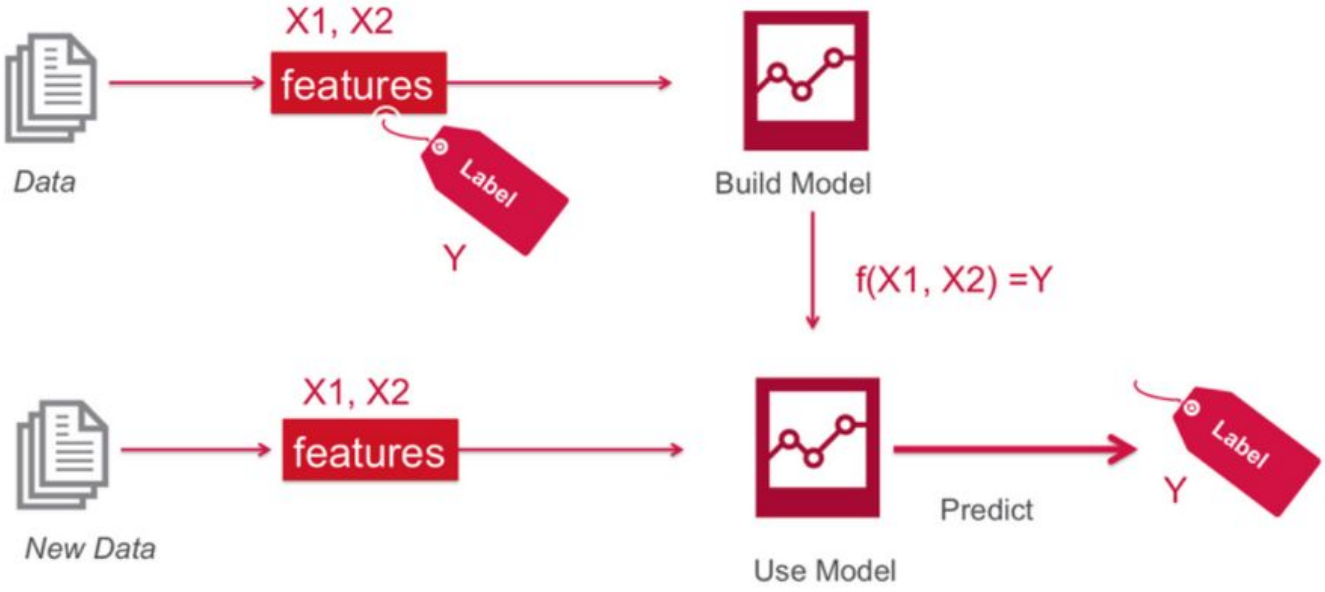
Field of **A.I** focused on systems that can learn autonomously.



Learning in this context means finding complex patterns in millions of data

SUPERVISED LEARNING

Allows to make future predictions based on behaviors or characteristics that have been seen in the data already stored



BINARY CAT CLASIFICATION

X

Label

Y

1 / 0

CAT

X

Label

Y

1 / 0

NON-CAT

X

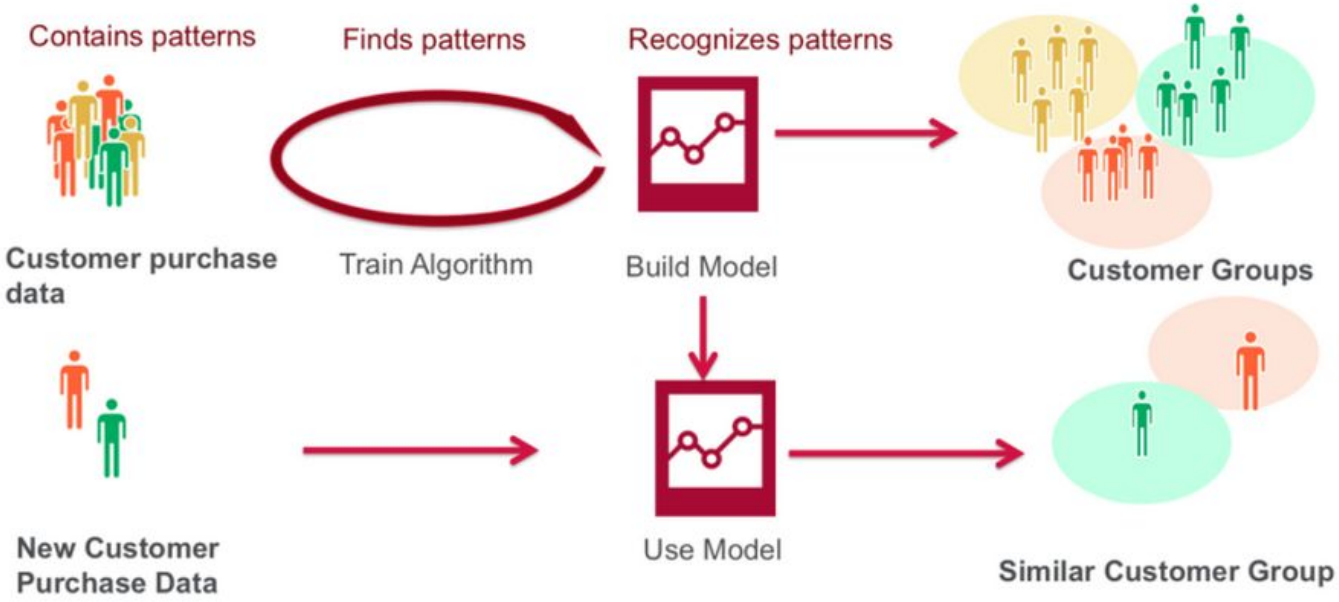
Label

Y

?

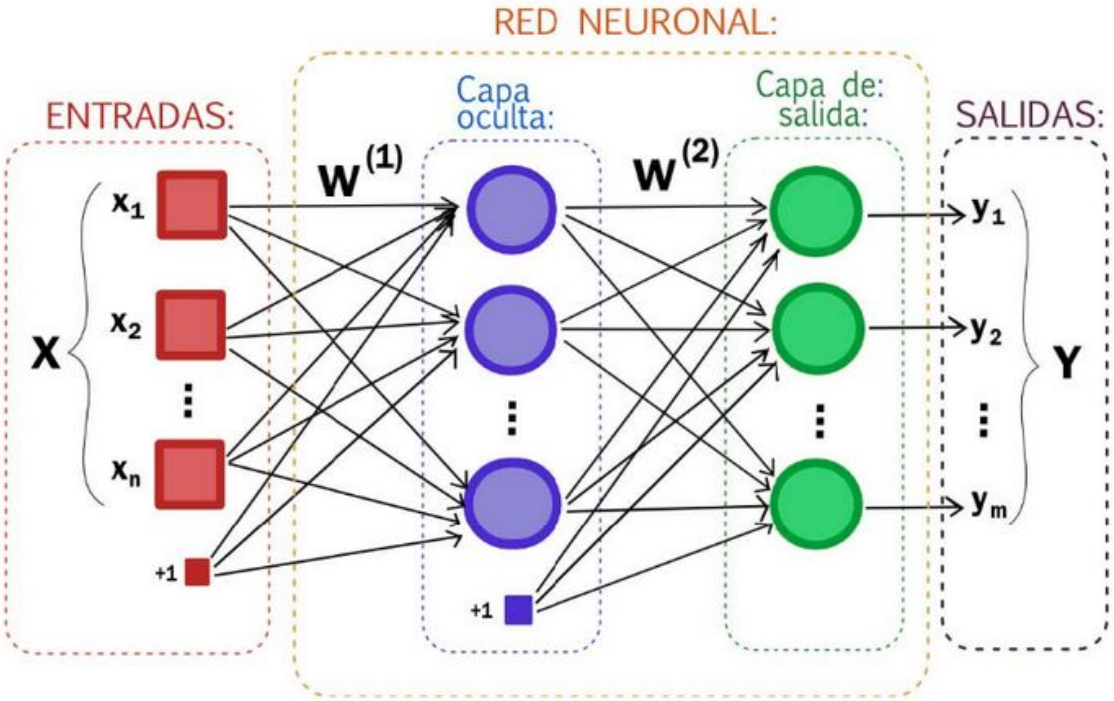
UNSUPERVISED LEARNING

Use historical data that are not labeled The purpose is to explore them to find the structure or the way to organize them.



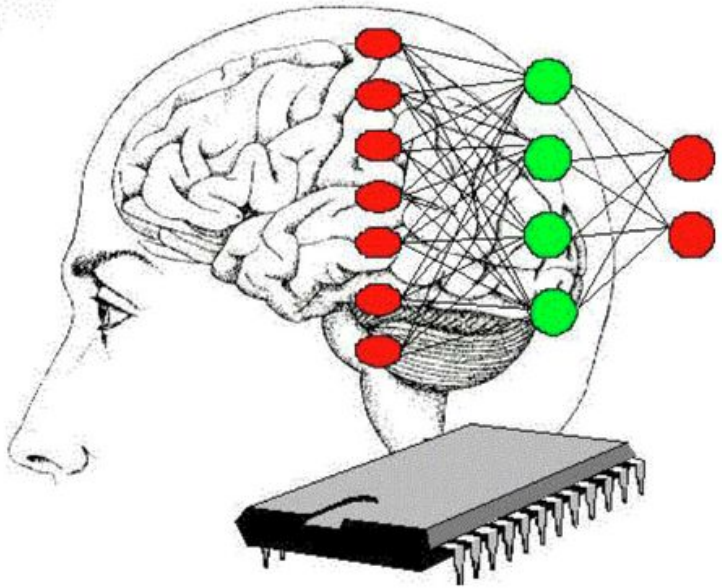
NEURONAL NETWORKS

They are the basis of all AI. They work like the neurons of our brain at least at the conceptual level.

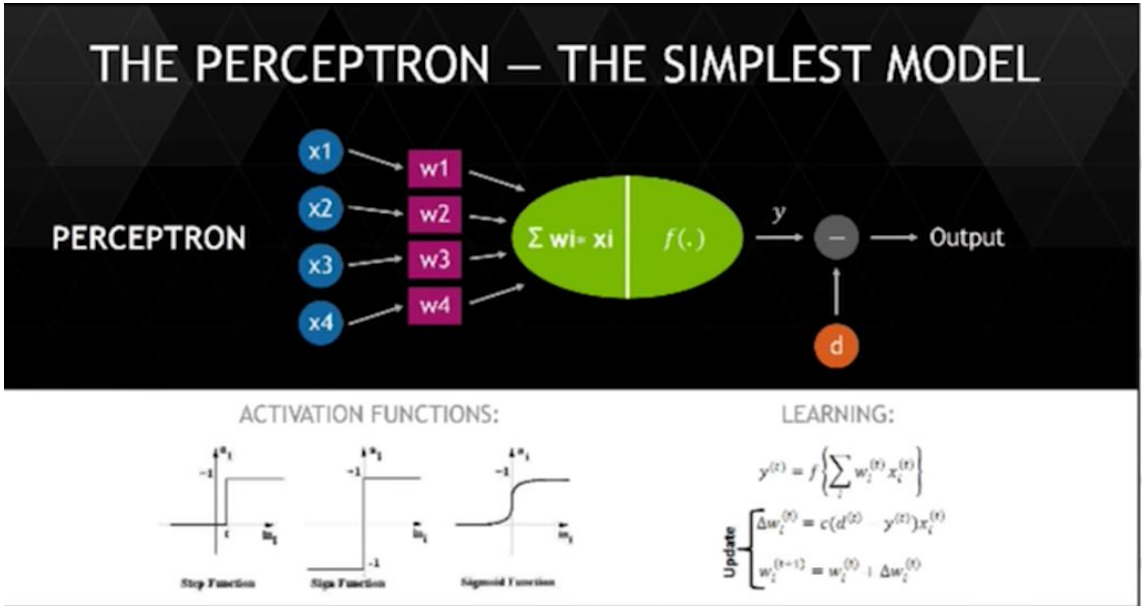


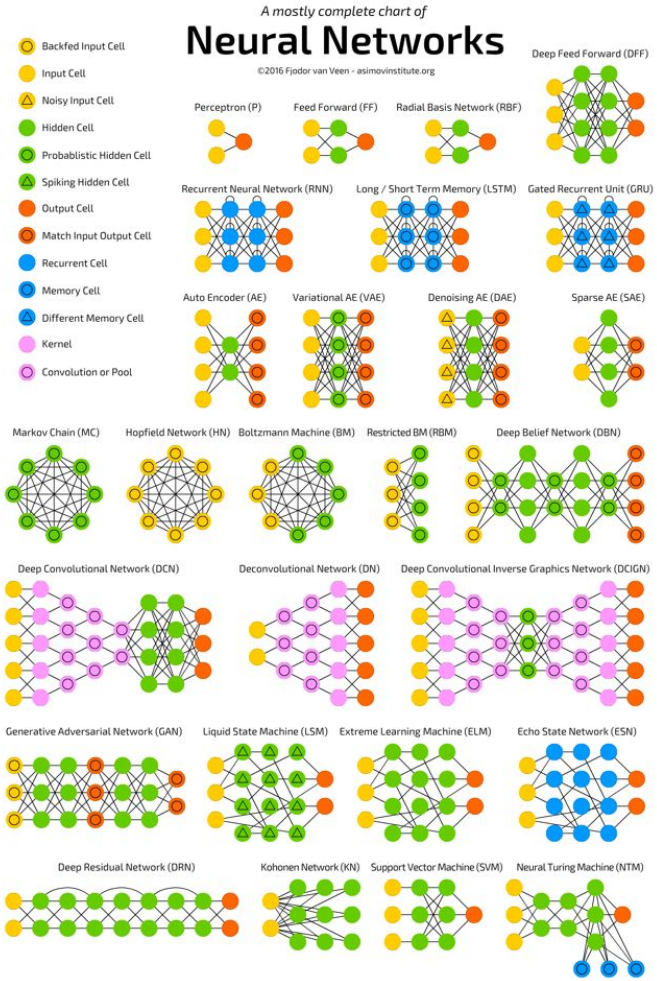
Knowledge works through inputs that arrive through our senses **(sight, touch, smell, hearing, taste)**, in machines these inputs are simply data that we pass by ram memory to an algorithm.

NEURONAL NETWORKS



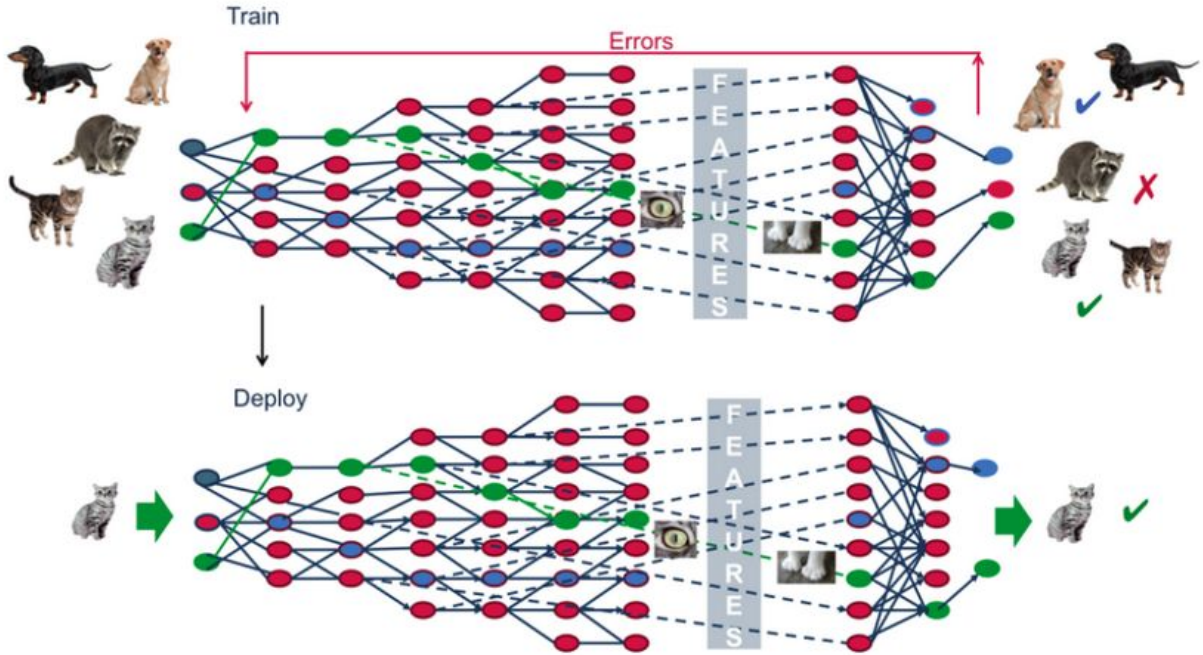
PERCEPTRON


THE PERCEPTRON — THE SIMPLEST MODEL
PERCEPTRON
x1
x2
x3
x4
w1
w2
w3
w4
Σ wi* xi
f(.)
y
Output
d
ACTIVATION FUNCTIONS:
LEARNING:
Update

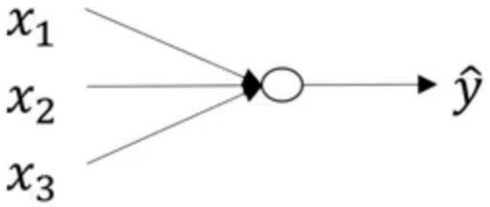

A mostly complete chart of
Neural Networks
©2016 Fjodor van Veen - asimovinstitute.org
Backfed Input Cell
Input Cell
Noisy Input Cell
Hidden Cell
Probablistic Hidden Cell
Spiking Hidden Cell
Output Cell
Match Input Output Cell
Recurrent Cell
Memory Cell
Different Memory Cell
Kernel
Convolution or Pool
Perceptron (P)
Feed Forward (FF)
Radial Basis Network (RBF)
Deep Feed Forward (DFF)
Recurrent Neural Network (RNN)
Long / Short Term Memory (LSTM)
Gated Recurrent Unit (GRU)
Auto Encoder (AE)
Variational AE (VAE)
Denoising AE (DAE)
Sparse AE (SAE)
Markov Chain (MC)
Hopfield Network (HN)
Boltzmann Machine (BM)
Restricted BM (RBM)
Deep Belief Network (DBN)
Deep Convolutional Network (DCN)
Deconvolutional Network (DN)
Deep Convolutional Inverse Graphics Network (DCIGN)
Generative Adversarial Network (GAN)
Liquid State Machine (LSM)
Extreme Learning Machine (ELM)
Echo State Network (ESN)
Deep Residual Network (DRN)
Kohonen Network (KN)
Support Vector Machine (SVM)
Neural Turing Machine (NTM)

DEEP LEARNING

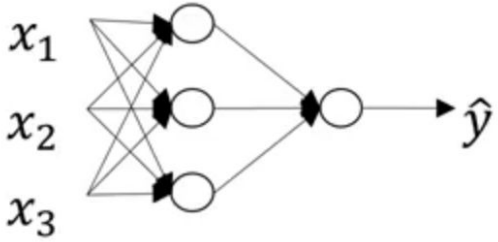
Learning at multiple levels, each hidden layer is responsible for recognizing different characteristics, and deliver them as input to the next layer.



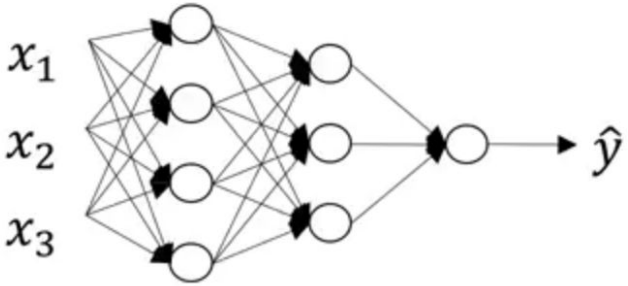
NEURONAL NETWORKS



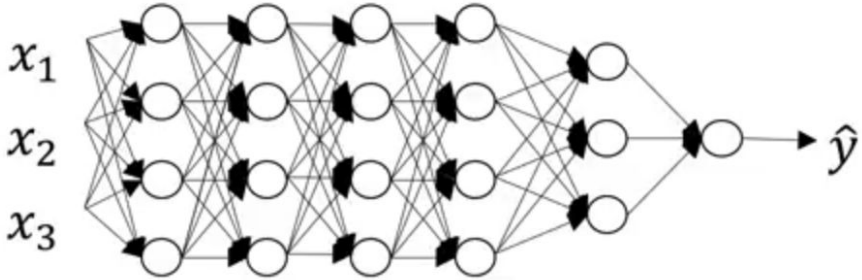
logistic regression



1 hidden layer

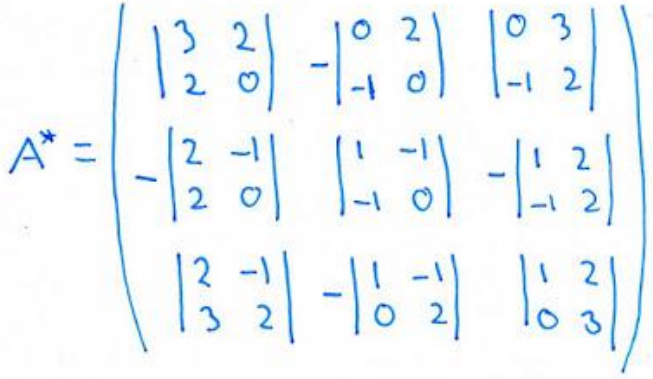


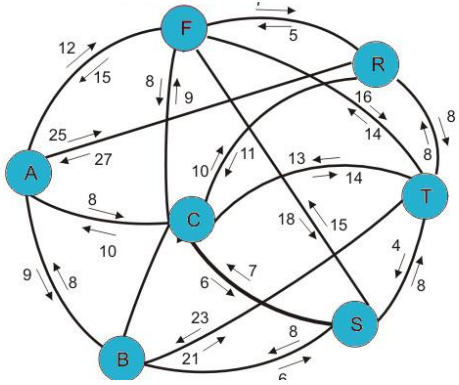
2 hidden layers

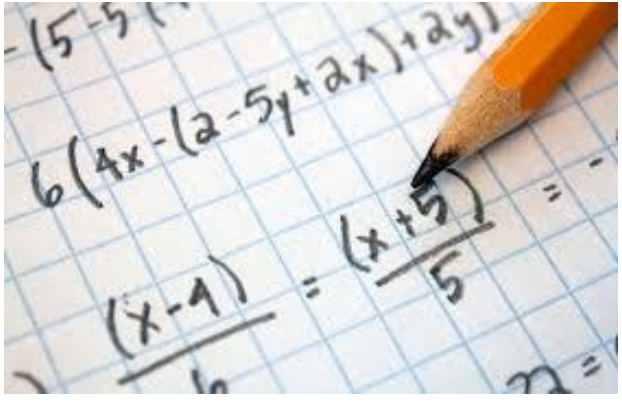


5 hidden layers

MATHEMATICS, LINEAL ALGEBRA, STATISTICS && GRAPHS

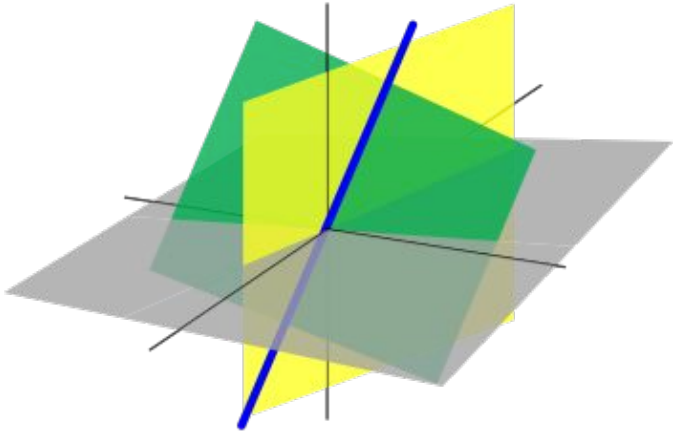


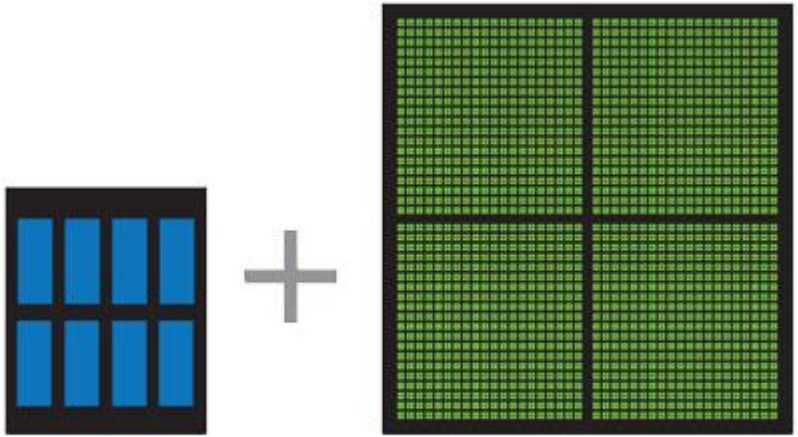




Vectorization

The art to get rid of the for loops in the code

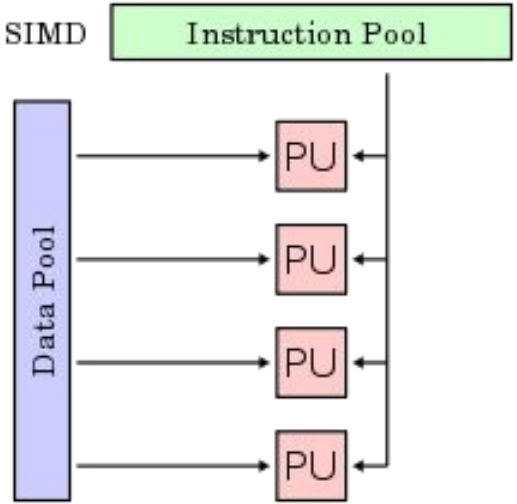




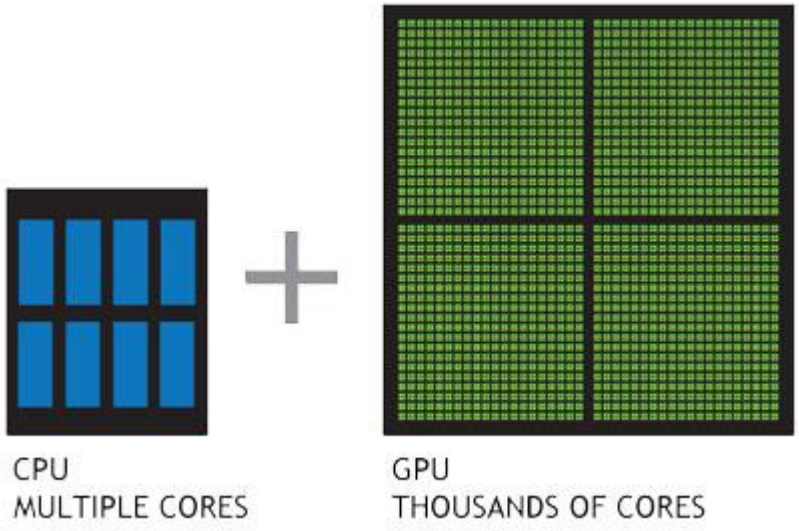
$$A^* = \begin{pmatrix} \begin{vmatrix} 3 & 2 \\ 2 & 0 \end{vmatrix} & -\begin{vmatrix} 0 & 2 \\ -1 & 0 \end{vmatrix} & \begin{vmatrix} 0 & 3 \\ -1 & 2 \end{vmatrix} \\ -\begin{vmatrix} 2 & -1 \\ 2 & 0 \end{vmatrix} & \begin{vmatrix} 1 & -1 \\ -1 & 0 \end{vmatrix} & -\begin{vmatrix} 1 & 2 \\ -1 & 2 \end{vmatrix} \\ \begin{vmatrix} 2 & -1 \\ 3 & 2 \end{vmatrix} & -\begin{vmatrix} 1 & -1 \\ 0 & 2 \end{vmatrix} & \begin{vmatrix} 1 & 2 \\ 0 & 3 \end{vmatrix} \end{pmatrix}$$

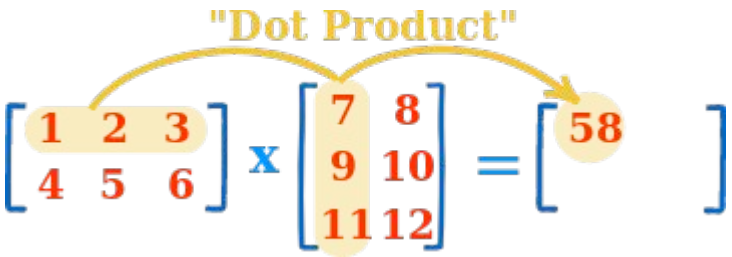
SIMD

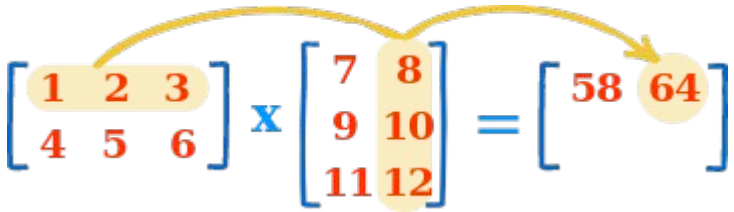
Single Instruction
Multiple Data



It is a technique used to achieve parallelism at the data level.







$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 7 & 8 \\ 9 & 10 \\ 11 & 12 \end{bmatrix} = \begin{bmatrix} 58 & 64 \\ 139 & 154 \end{bmatrix}$$

Example 1

$$X = [x_1 \ x_2 \ x_3 \ x_4 \ \dots \ x_n] + b$$

$$X = [x_1 \ x_2 \ x_3 \ x_4 \ \dots \ x_n] + [\mathrm{b} \ \mathrm{b} \ \mathrm{b} \ \mathrm{b} \dots \mathrm{b}]$$

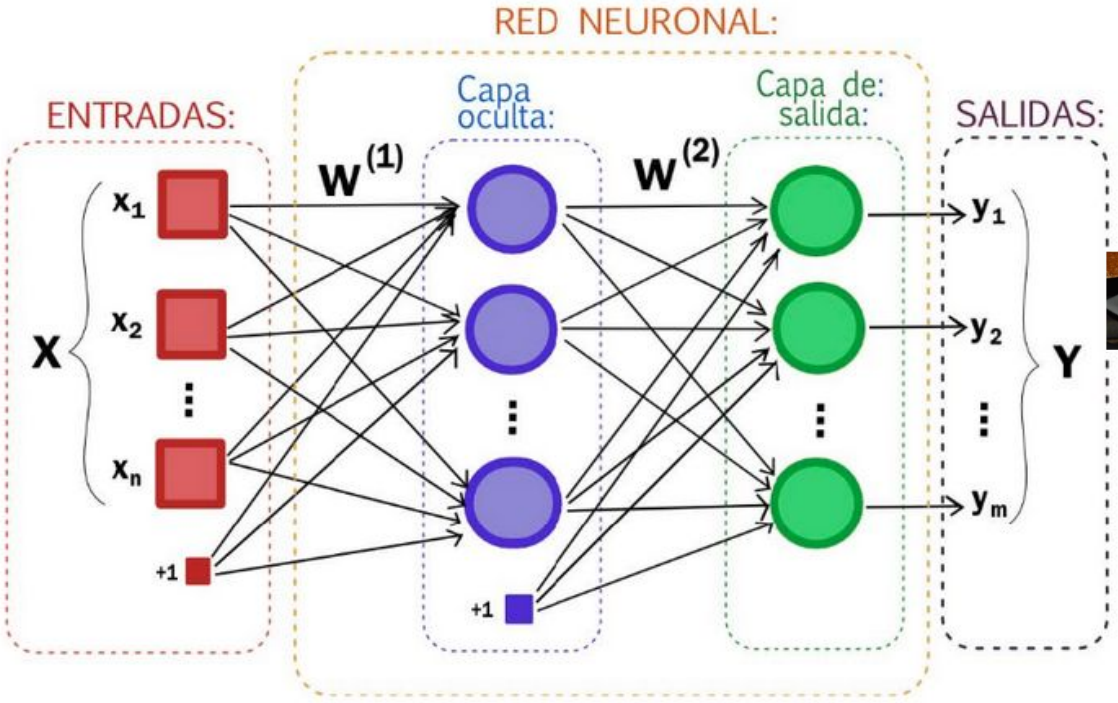
$$X = [x_1 + b \quad x_2 + b \quad x_3 + b \quad x_4 + b \quad \dots \quad x_n + b]$$

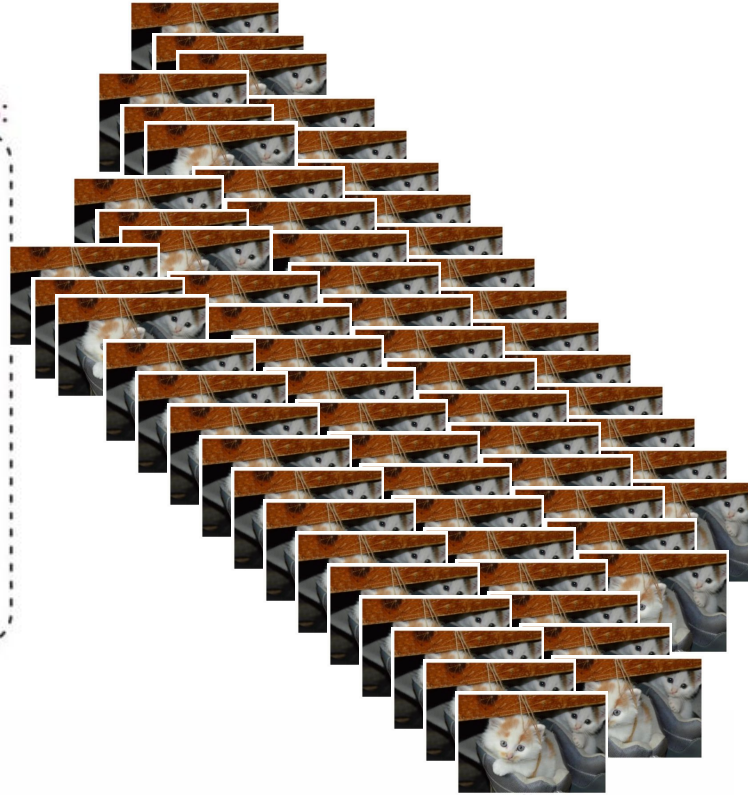
BROADCASTING

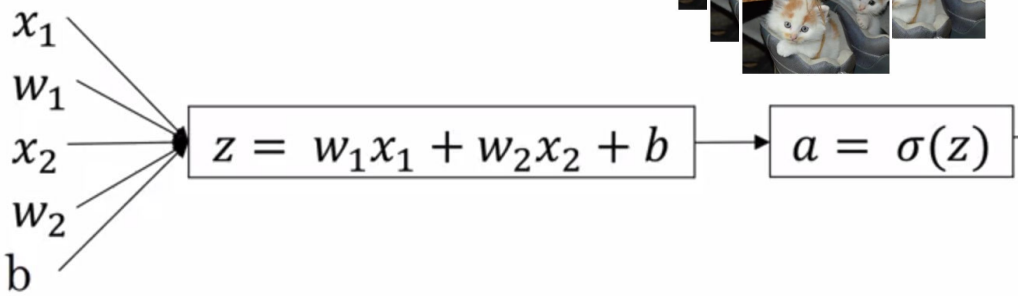
Example 2

$$X = \begin{bmatrix} x_1 & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nn} \end{bmatrix} + [b_1 \ b_2 \ b_3 \ \dots \ b_n]$$

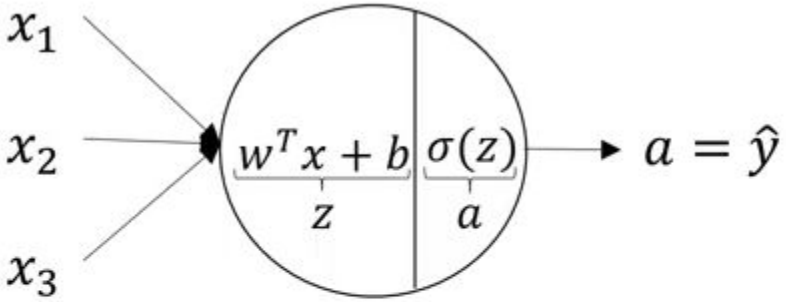
$$X = \begin{bmatrix} x_1 & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nn} \end{bmatrix} + \begin{bmatrix} b_1 & b_2 & \cdots & b_n \\ b_1 & b_2 & \dots & b_n \\ b_1 & b_2 & \dots & b_n \end{bmatrix}$$

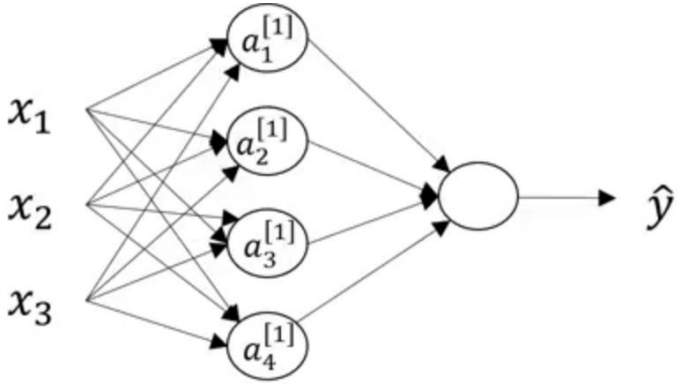

RED NEURONAL:
ENTRADAS:
Capa oculta:
Capa de: salida:
SALIDAS:
X
x_1
x_2
x_n
+1
$W^{(1)}$
$W^{(2)}$
+1
y_1
y_2
y_m
Y




x_1
w_1
x_2
w_2
b
$z = w_1x_1 + w_2x_2 + b$
$a = \sigma(z)$

NEURONAL NETWORK REPRESENTATION





$$z = w^T x + b$$

$$a = \sigma(z)$$

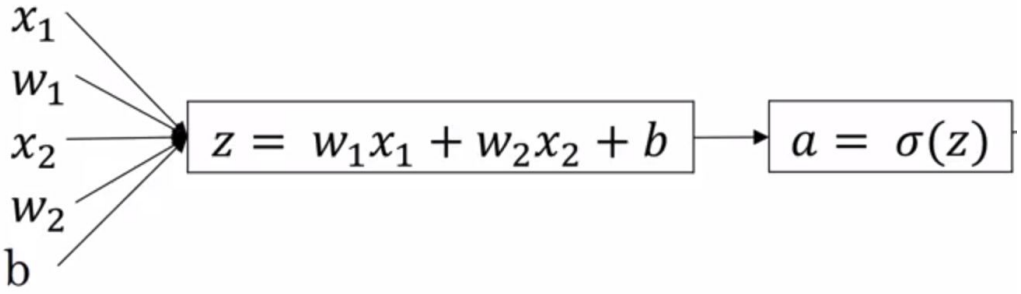
$$z_1^{[1]} = w_1^{[1]T} x + b_1^{[1]},\ a_1^{[1]} = \sigma(z_1^{[1]})$$

$$z_2^{[1]} = w_2^{[1]T} x + b_2^{[1]},\ a_2^{[1]} = \sigma(z_2^{[1]})$$

$$z_3^{[1]} = w_3^{[1]T} x + b_3^{[1]},\ a_3^{[1]} = \sigma(z_3^{[1]})$$

$$z_4^{[1]} = w_4^{[1]T} x + b_4^{[1]},\ a_4^{[1]} = \sigma(z_4^{[1]})$$

Vectorization example



$$z^{(1)} = w^T x^{(1)} + b \qquad a^{(1)} = \sigma(z^{(1)})$$
$$z^{(2)} = w^T x^{(2)} + b \qquad a^{(2)} = \sigma(z^{(2)})$$
$$z^{(3)} = w^T x^{(3)} + b \qquad a^{(3)} = \sigma(z^{(3)})$$
$$z^{(3)} = w^T x^{(3)} + b \qquad a^{(4)} = \sigma(z^{(4)})$$
$$. \qquad .$$
$$. \qquad .$$
$$. \qquad .$$
$$z^{(m)} = w^T x^{(m)} + b \qquad a^{(m)} = \sigma(z^{(m)})$$

$$X = \begin{bmatrix} | & | & | & | & | & | \\ x^{(1)} & x^{(2)} & x^{(3)} & \dots & \dots & x^{(m)} \\ | & | & | & | & | & | \end{bmatrix}_{(n_x, m)}$$

$$Z = \begin{bmatrix} z^{(1)} & z^{(2)} & z^{(3)} & z^{(4)} & \dots & z^{(m)} \end{bmatrix}_{(n_x, m)}$$

$$\mathrm{Z} = w^T \mathrm{X} + b$$

$$X = \begin{bmatrix} | & | & | & | & | & | \\ x^{(1)} & x^{(2)} & x^{(3)} & \dots & \dots & x^{(m)} \\ | & | & | & | & | & | \end{bmatrix}^{(n_x, m)} \qquad Z = \begin{bmatrix} z^{(1)} & z^{(2)} & z^{(3)} & z^{(4)} & \dots & z^{(m)} \end{bmatrix}^{(1, m)}$$

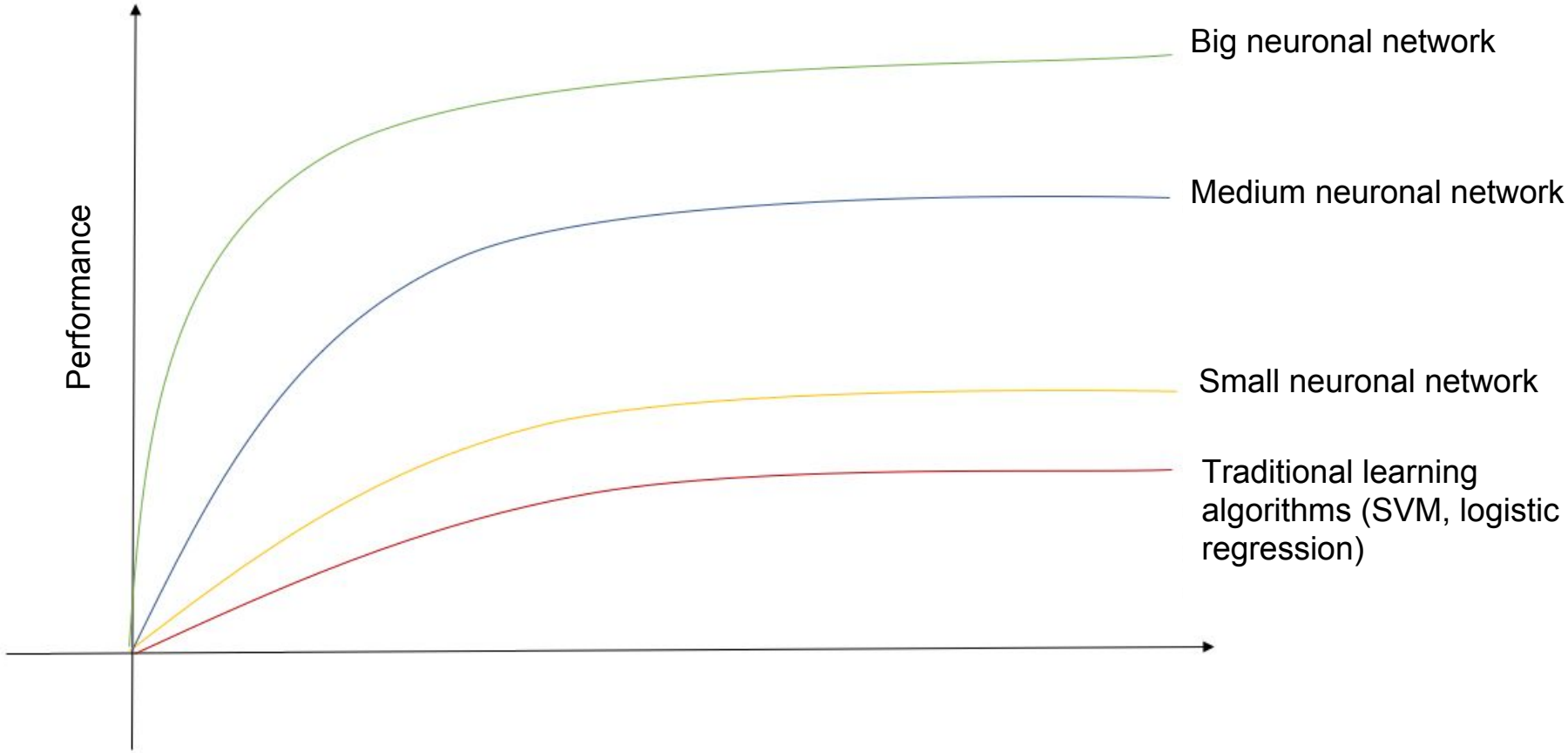
$$Z = w^T X + b$$

$$Z = w^T \begin{bmatrix} | & | & | & | & | & | \\ x^{(1)} & x^{(2)} & x^{(3)} & \dots & \dots & x^{(m)} \\ | & | & | & | & | & | \end{bmatrix} + b$$

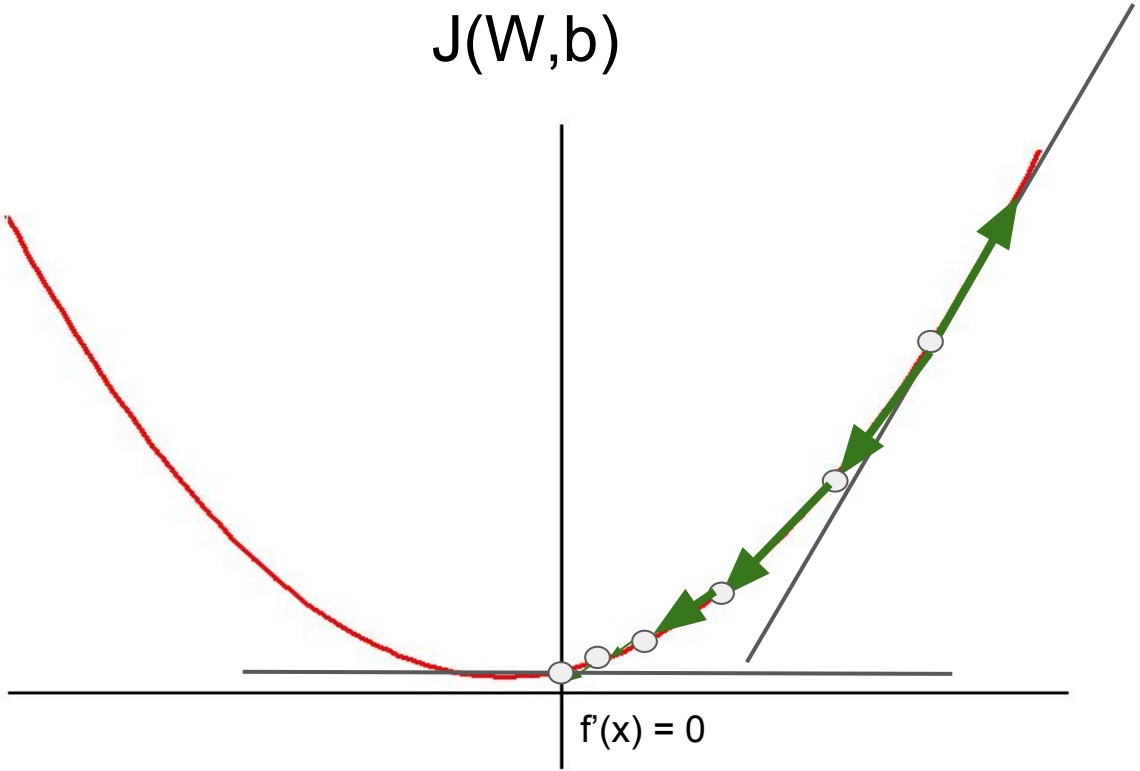
BROADCASTING

$$Z = w^T \begin{bmatrix} | & | & | & | & | & | \\ x^{(1)} & x^{(2)} & x^{(3)} & \dots & \dots & x^{(m)} \\ | & | & | & | & | & | \end{bmatrix} + [\mathrm{b}\ \mathrm{b}\ \mathrm{b}\ \mathrm{b} \dots \mathrm{b}]$$

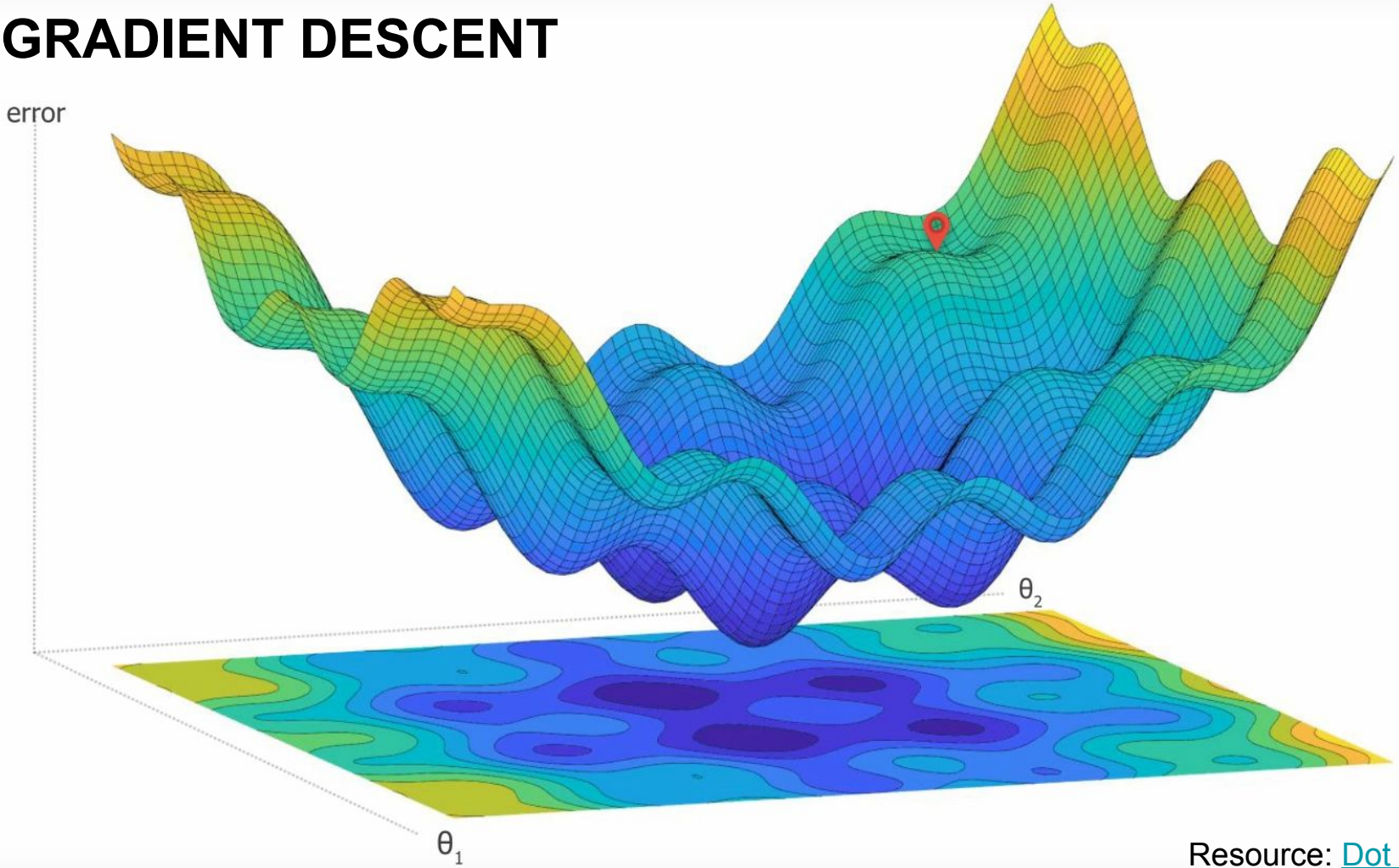
CPU VS GPU


Performance
Big neuronal network
Medium neuronal network
Small neuronal network
Traditional learning algorithms (SVM, logistic regression)

GRADIENT DESCENT



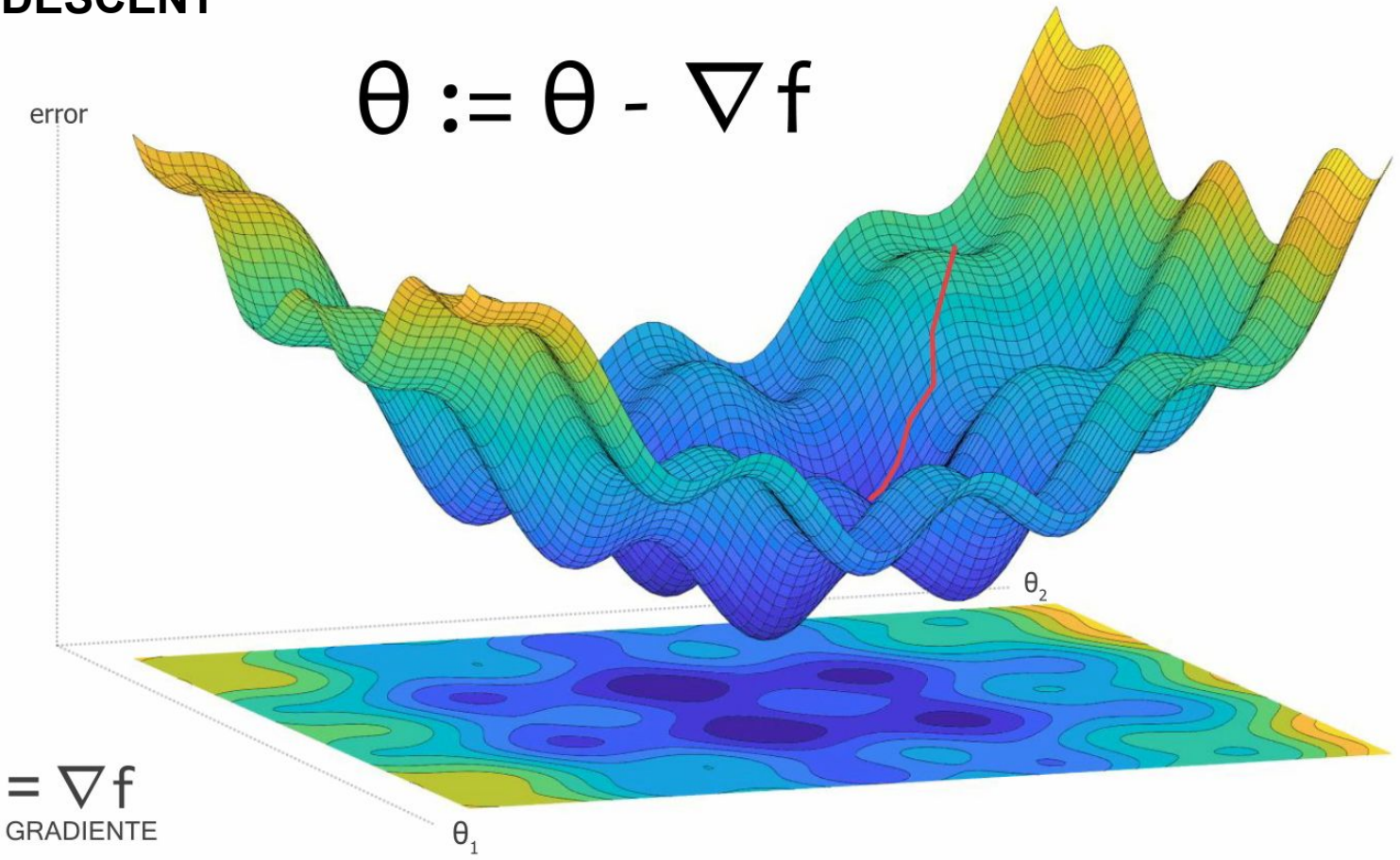
GRADIENT DESCENT



Resource: Dot CSV

GRADIENT DESCENT

$$\theta := \theta - \nabla f$$



$$\begin{bmatrix} \frac{\partial error}{\partial \theta_1} \\ \frac{\partial error}{\partial \theta_2} \end{bmatrix} = \nabla f$$

GRADIENTE

Resource: Dot CSV

BINARY CAT CLASIFICATION

X

Label

Y

1 / 0

CAT

X

Label

Y

1 / 0

NON-CAT

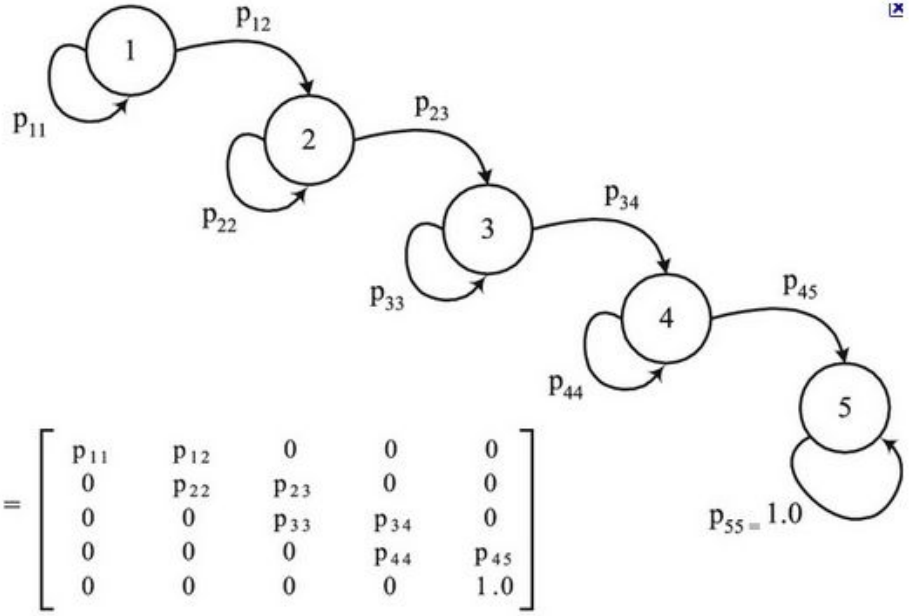
X

Label

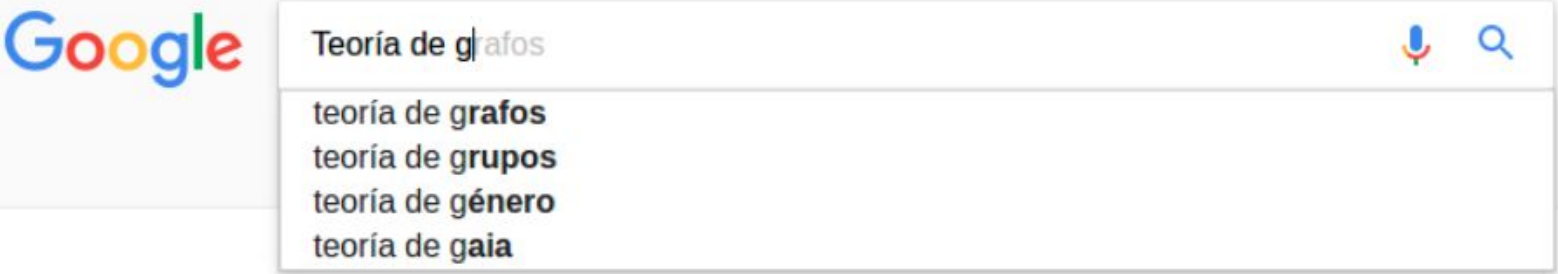
Y

?

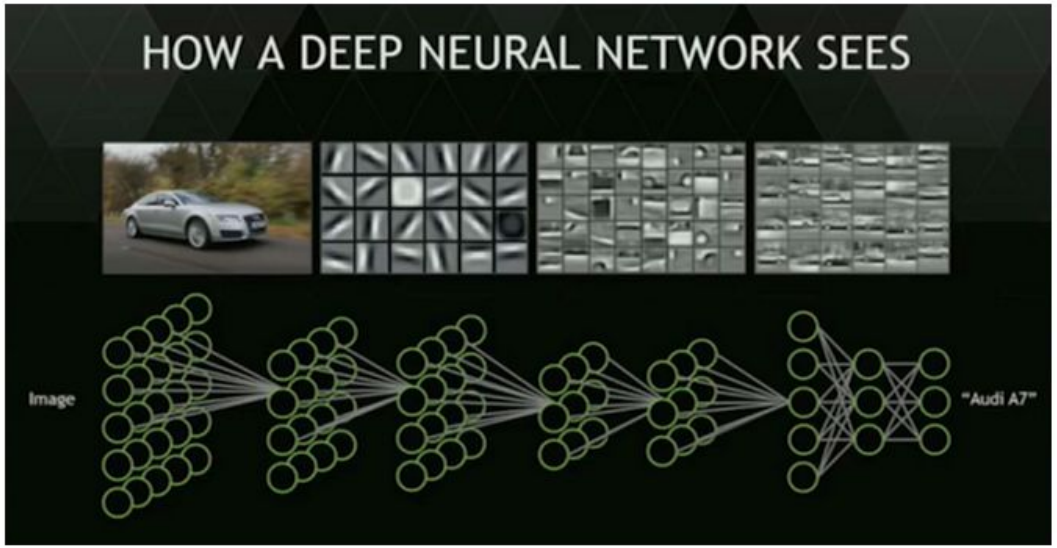
PREDICTIONS
(Markov chains)

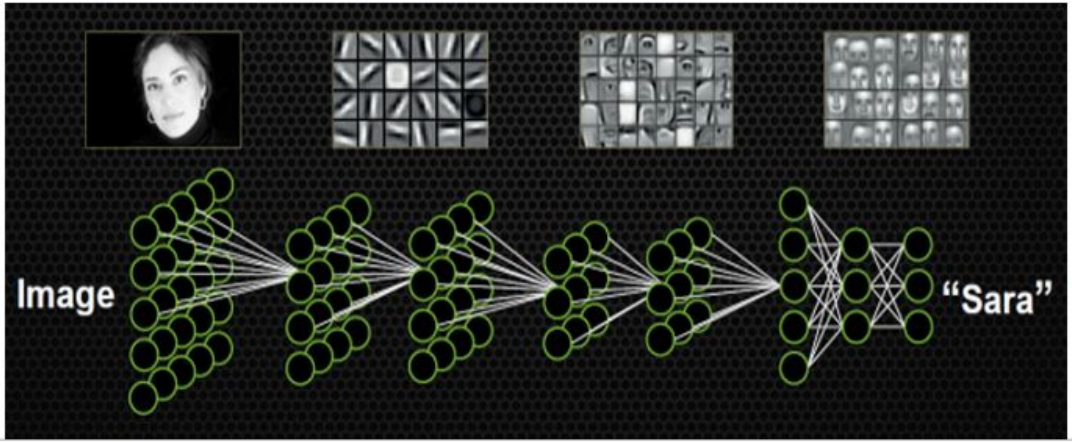


$$P = \begin{bmatrix} p_{11} & p_{12} & 0 & 0 & 0 \\ 0 & p_{22} & p_{23} & 0 & 0 \\ 0 & 0 & p_{33} & p_{34} & 0 \\ 0 & 0 & 0 & p_{44} & p_{45} \\ 0 & 0 & 0 & 0 & 1.0 \end{bmatrix}$$

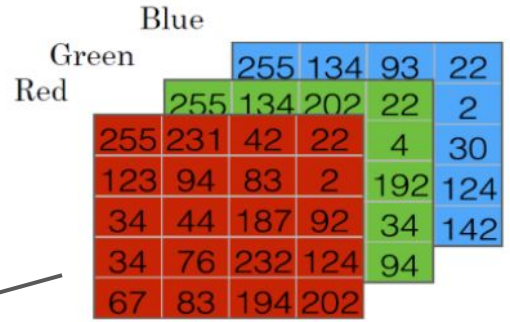


COMPUTER VISION





VECTORIZATION



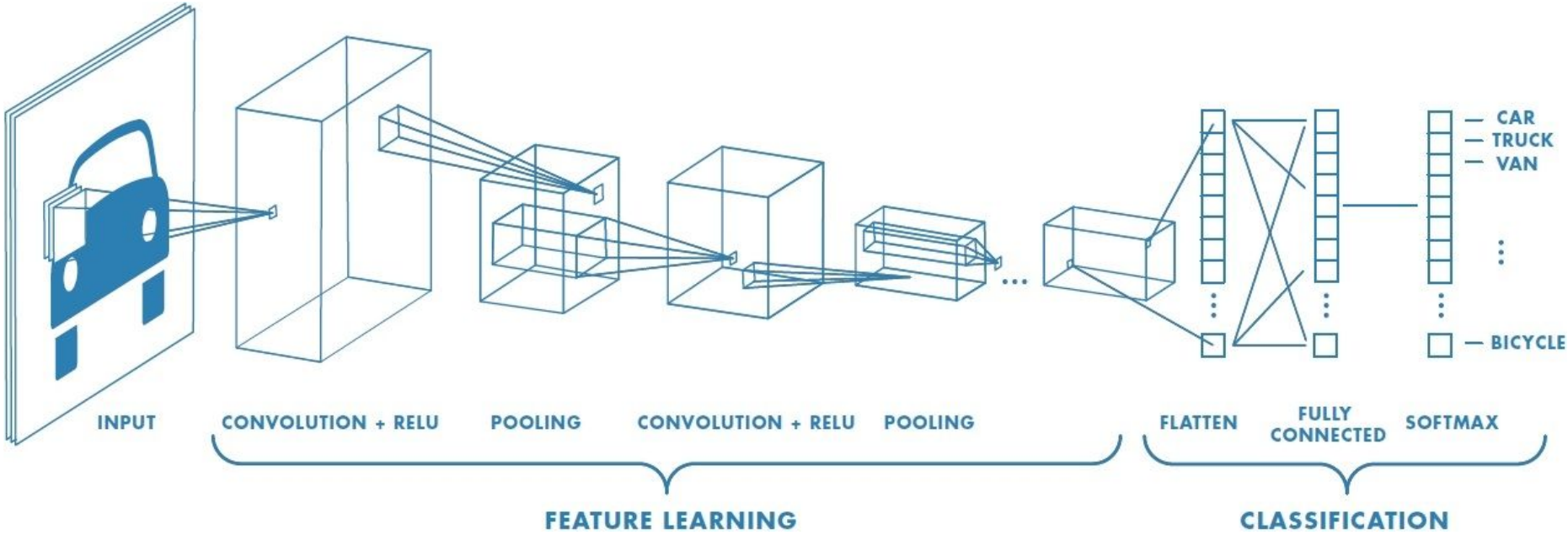
"Unroll"

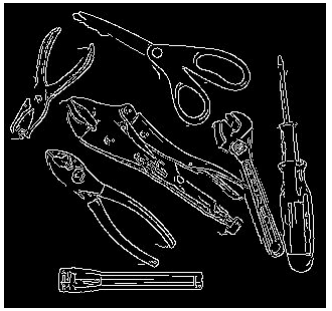
"Reshape"

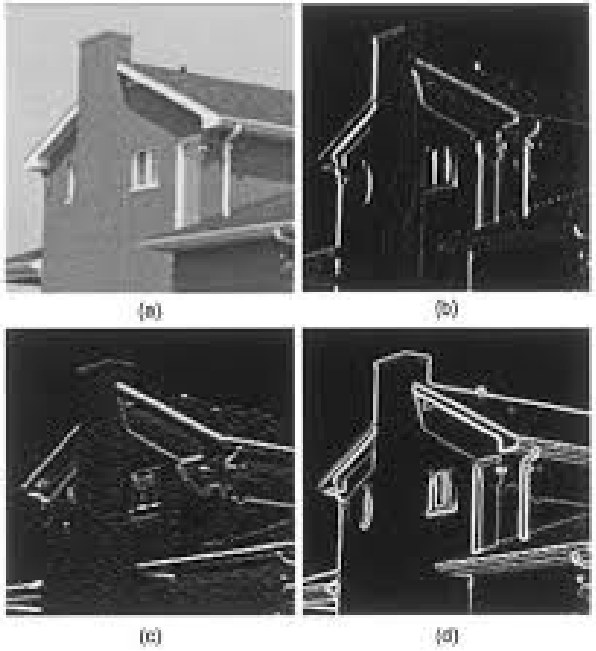
$$x = \begin{bmatrix} 255 \\ 231 \\ 42 \\ \vdots \\ 255 \\ 134 \\ 202 \\ \vdots \\ 255 \\ 134 \\ 93 \\ \vdots \end{bmatrix} \begin{matrix} \text{red} \\ \\ \\ \\ \text{green} \\ \\ \\ \\ \text{blue} \\ \\ \\ \\ \end{matrix}$$

$$n_x = 64\ x\ 64\ x\ 3 = 12\ 288$$

CONVOLUTIONAL NEURONAL NETWORKS







Epochs =400,
PSNR=+ 5.71 dB

Epochs =500,
PSNR=+ 5.72 dB

Epochs =600,
PSNR=+ 5.70dB

Epochs =800,
PSNR=+ 5.69 dB

Epochs =1000,
PSNR=+ 5.70 dB

Epochs =5000,
PSNR=+ 5.71 dB

Epoch10000,
PSNR=+ 5.70 dB

Epochs =100000,
PSNR=+ 5.33 dB

Fig. 7 output and PSNR values for different network statues of Lena image

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

6x6

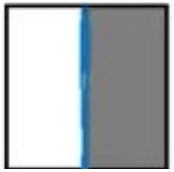
*

1	0	-1
1	0	-1
1	0	-1

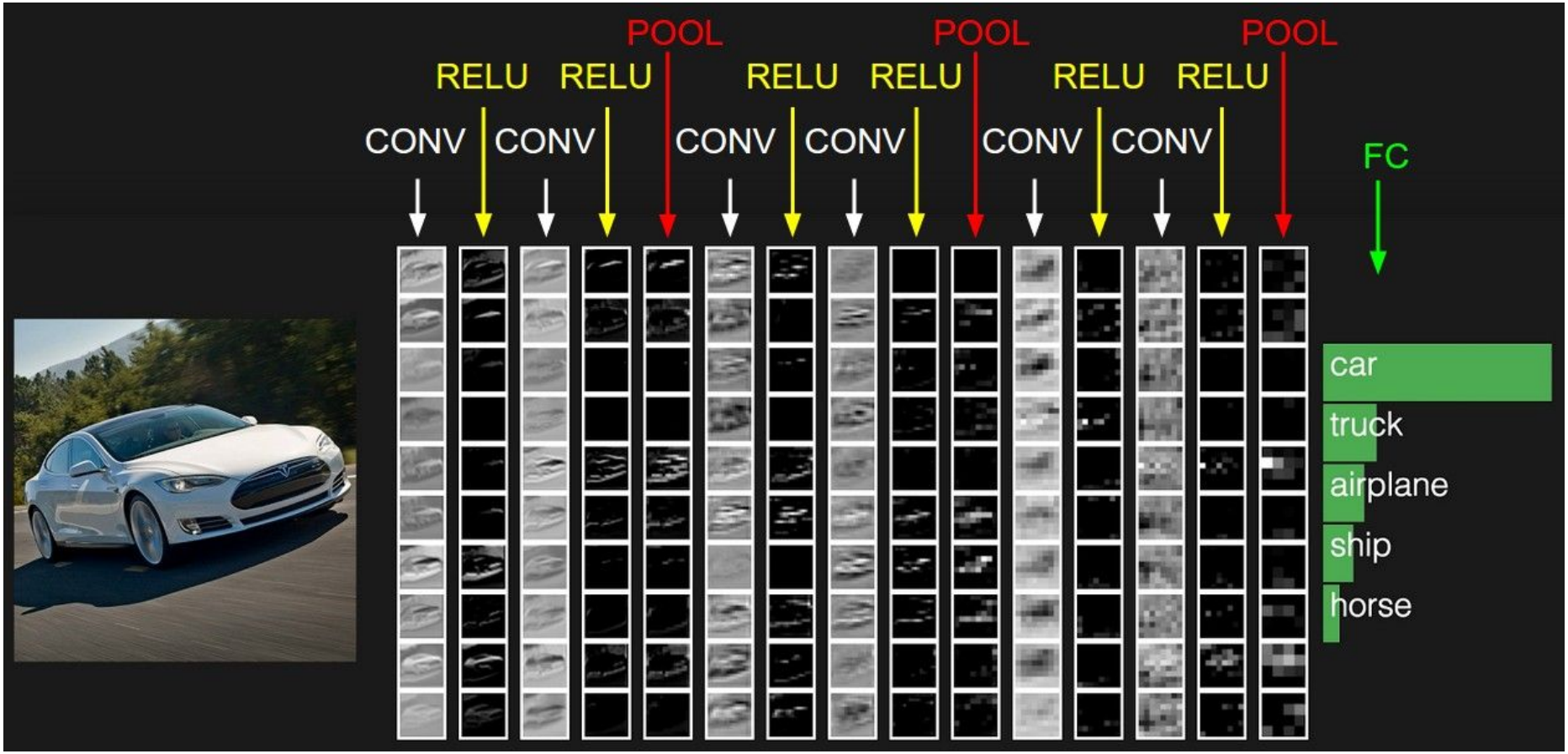
3x3

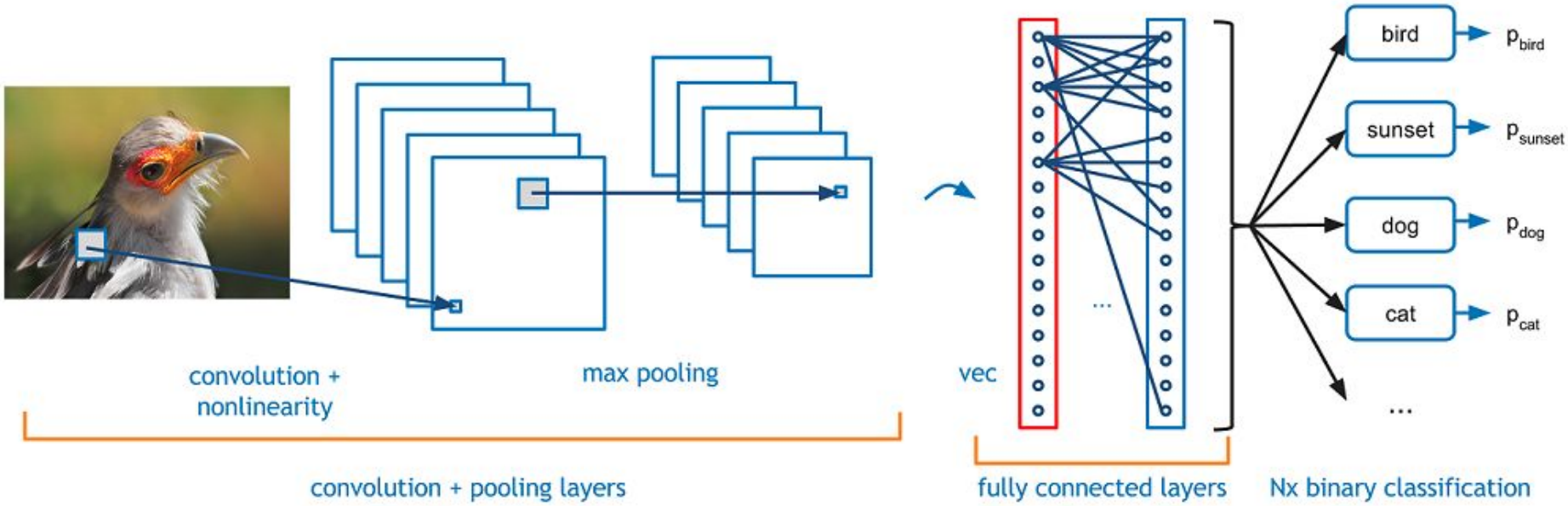
=

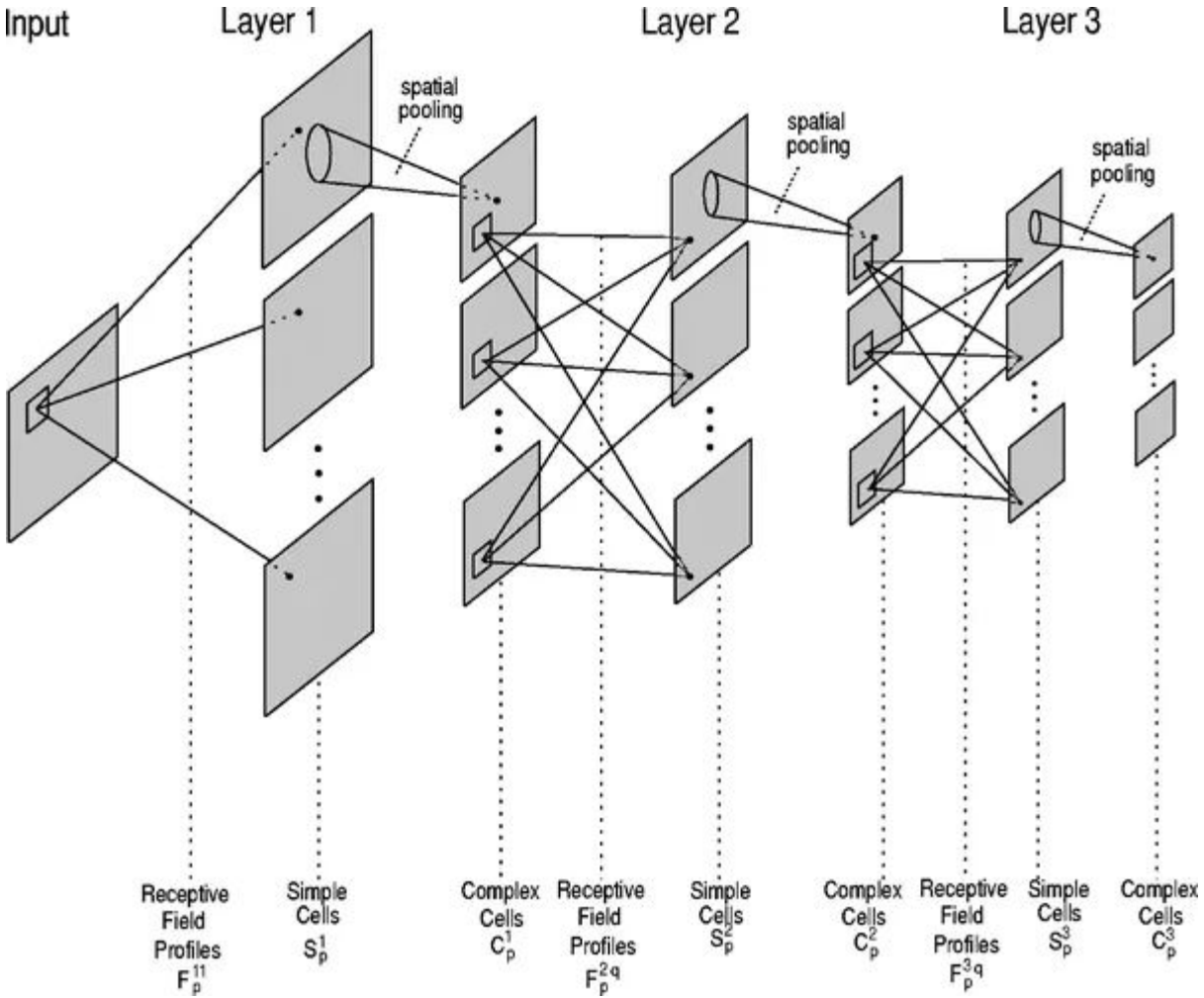
0	30	30	0
0	30	30	0
0	30	30	0
0	30	30	0



*


POOL
POOL
POOL
RELU
RELU
RELU
RELU
RELU
RELU
CONV
CONV
CONV
CONV
CONV
CONV
FC
car
truck
airplane
ship
horse


convolution +
nonlinearity
max pooling
vec
bird
sunset
dog
cat
...
p_{bird}
p_{sunset}
p_{dog}
p_{cat}
convolution + pooling layers
fully connected layers
Nx binary classification


Input
Layer 1
Layer 2
Layer 3
spatial pooling
spatial pooling
spatial pooling
Receptive Field Profiles F_p^{11}
Simple Cells S_p^1
Complex Cells C_p^1
Receptive Field Profiles F_p^{2q}
Simple Cells S_p^2
Complex Cells C_p^2
Receptive Field Profiles F_p^{3q}
Simple Cells S_p^3
Complex Cells C_p^3

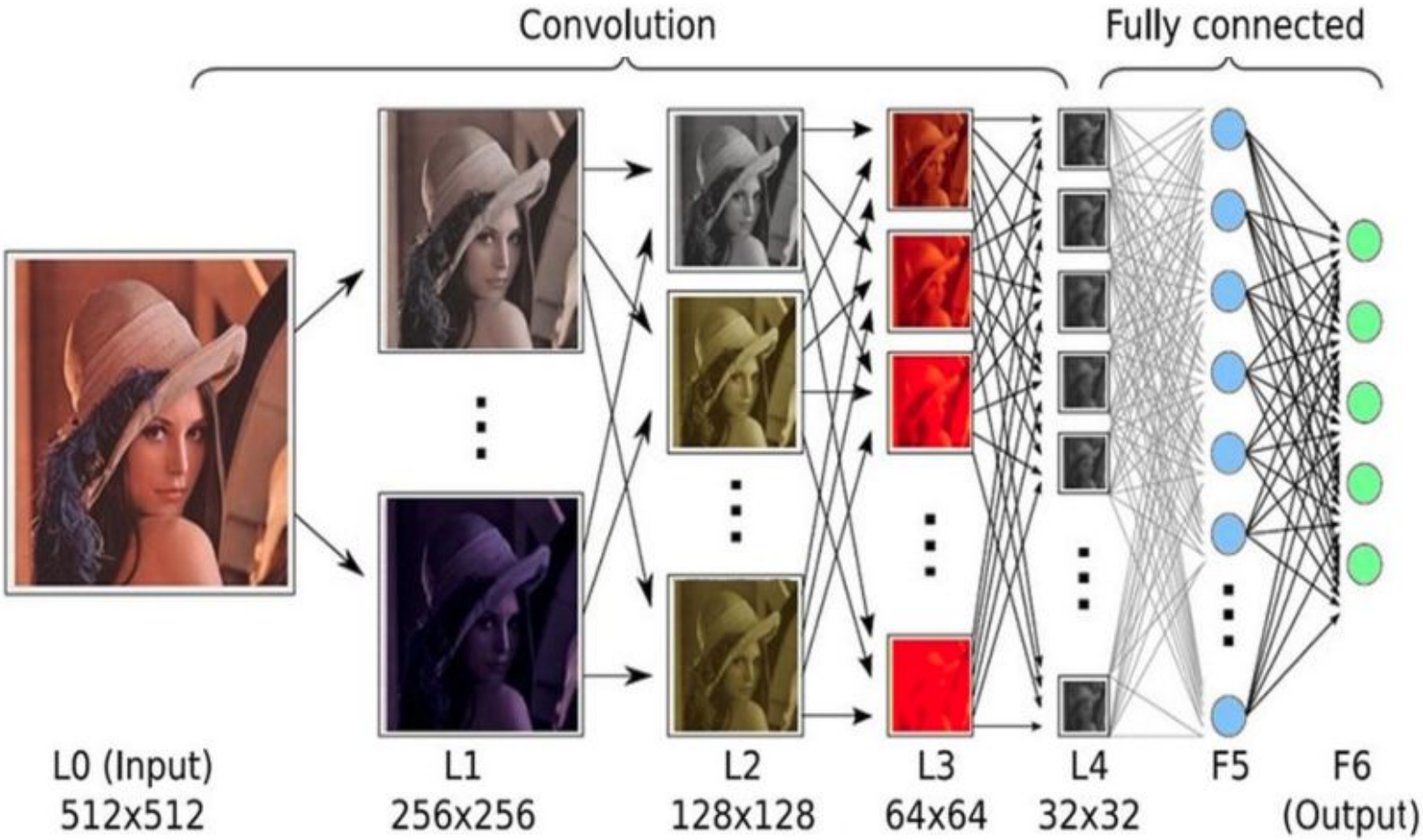
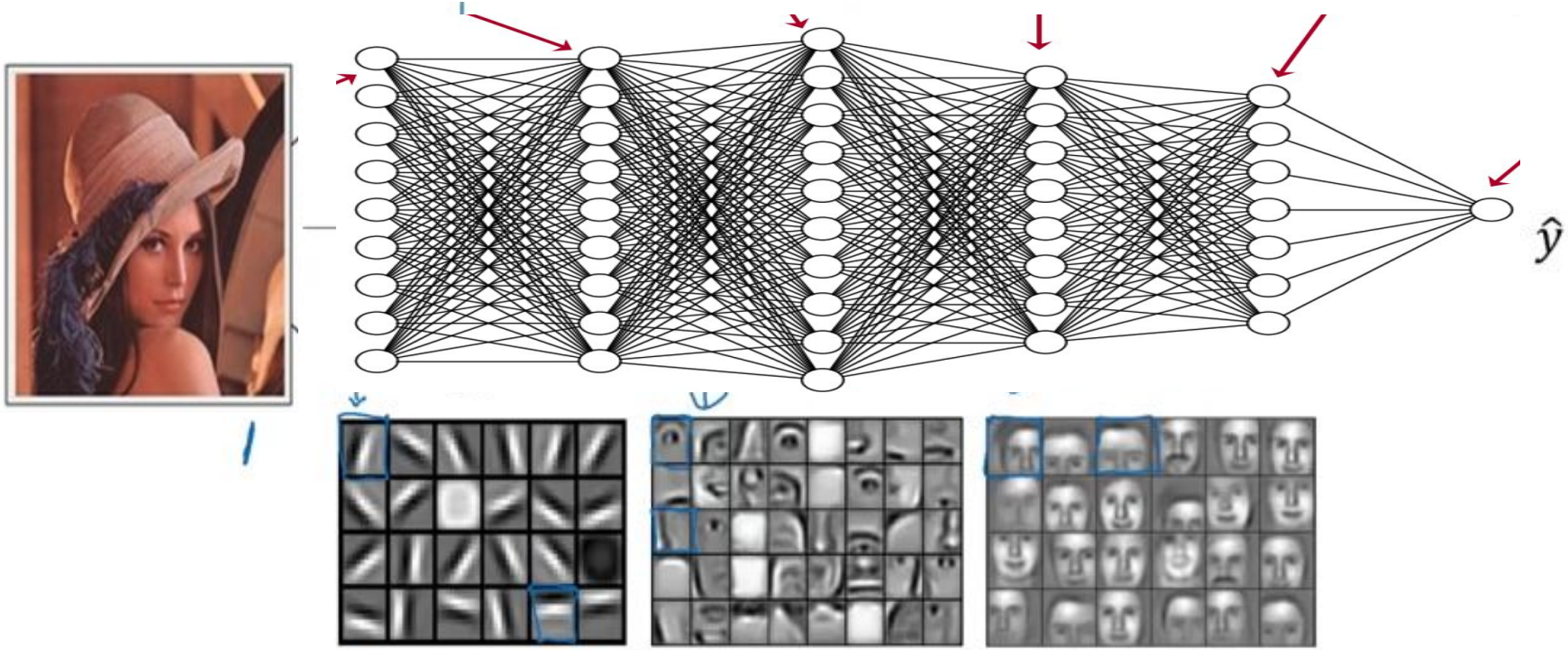
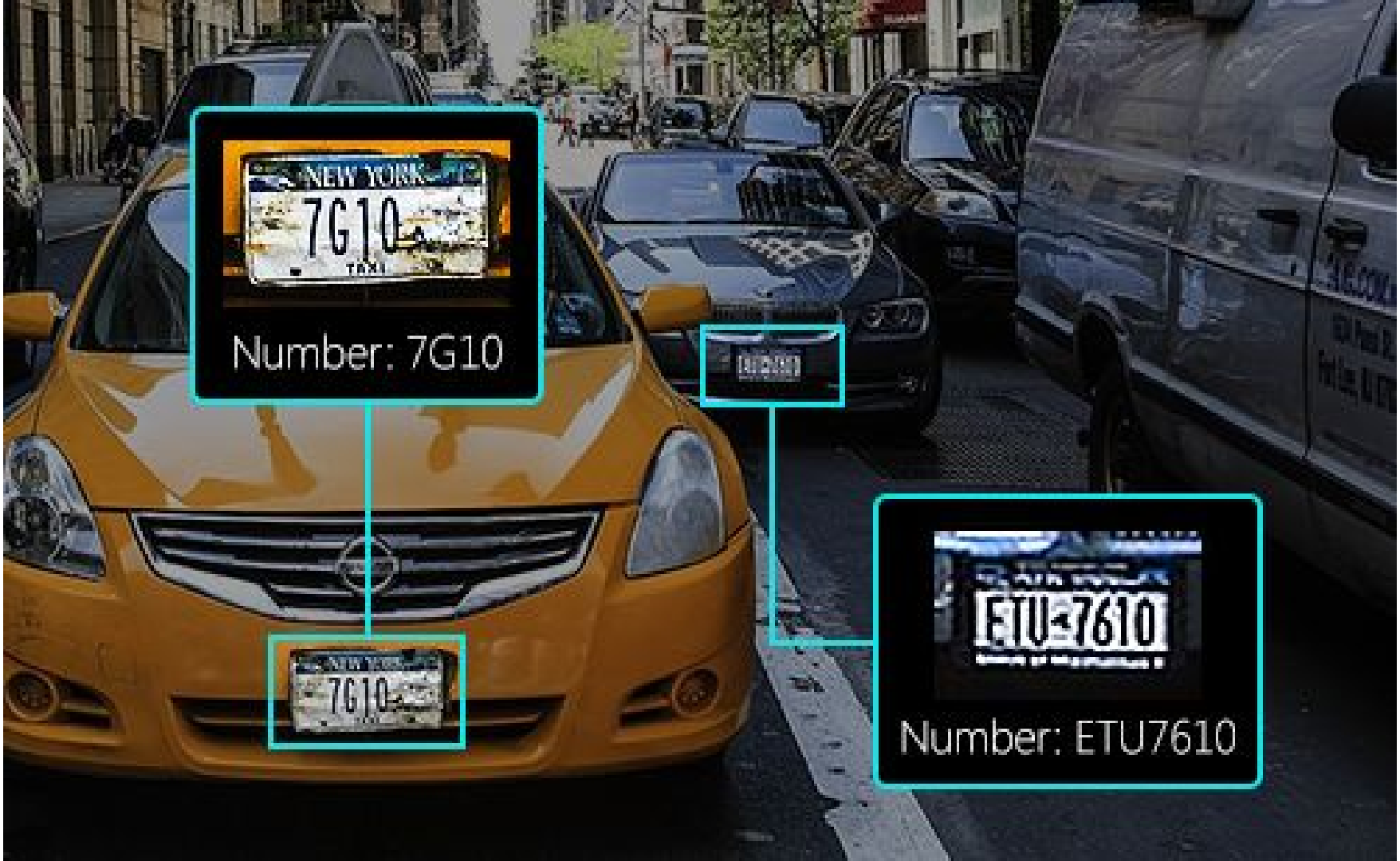
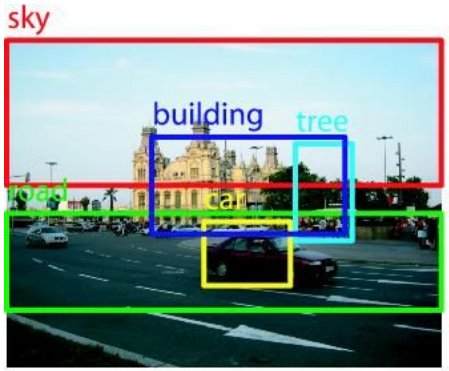


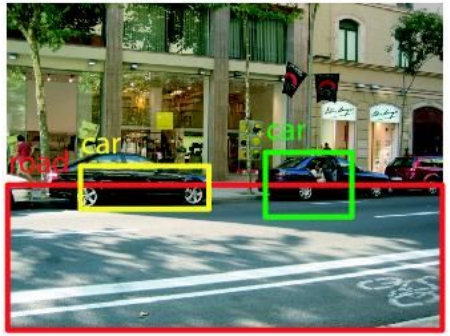
Fig. 1 CNNs structure.

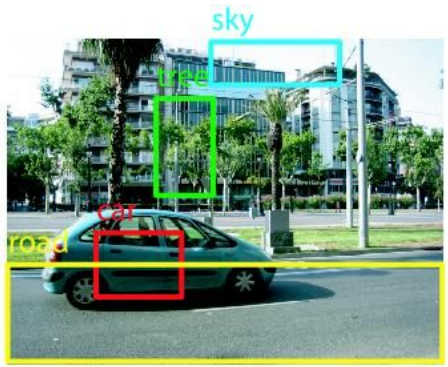
COMPUTER VISION

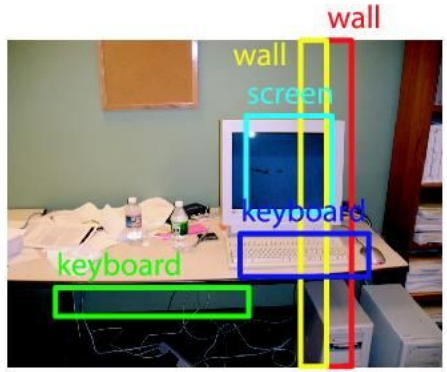


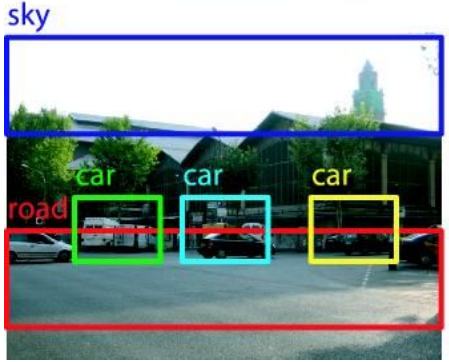

NEW YORK
7G10
TAXI
Number: 7G10
ETU7610
Number: ETU7610

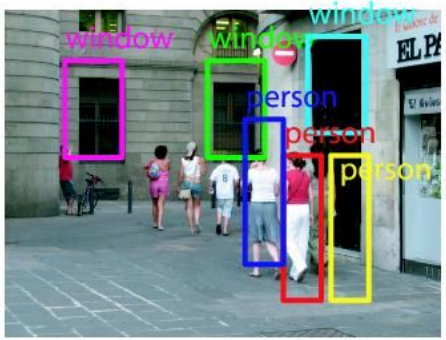

sky
building
tree
road
car

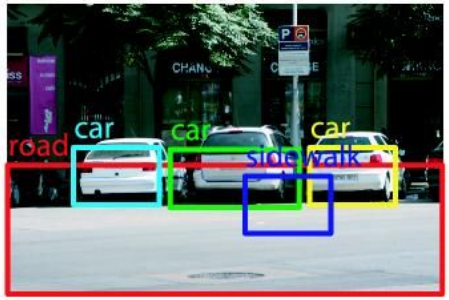

car
car
road

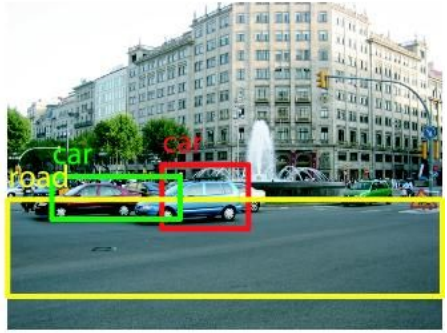

sky
tree
car
road


wall
wall
screen
keyboard
keyboard

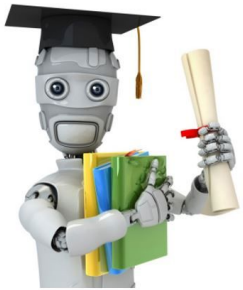

sky
car
car
car
road


window
window
window
person
person
person


car
car
car
road
sidewalk

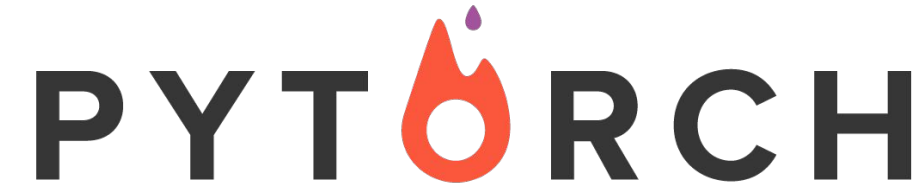

car
car
road

fast.ai



Machine Learning

deeplearning.ai


PYTORCH


K
Keras


TensorFlow

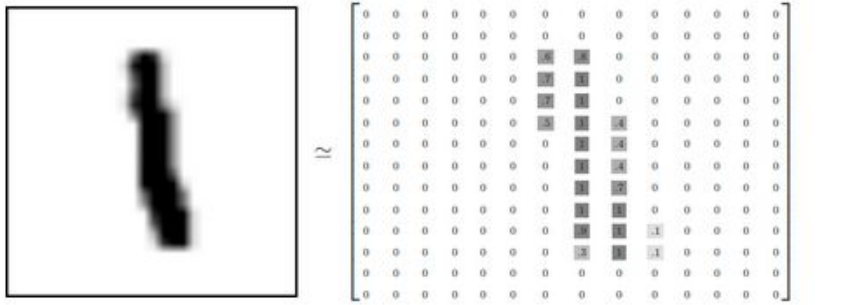

NVIDIA

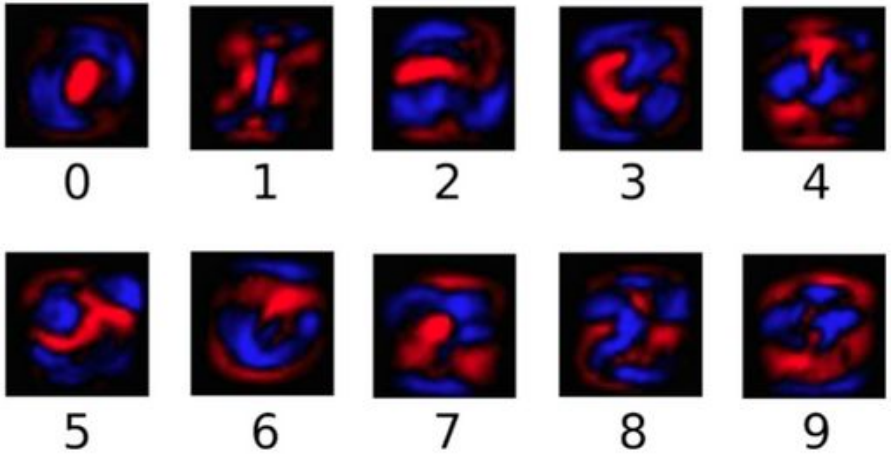
IMAGE RECOGNITION

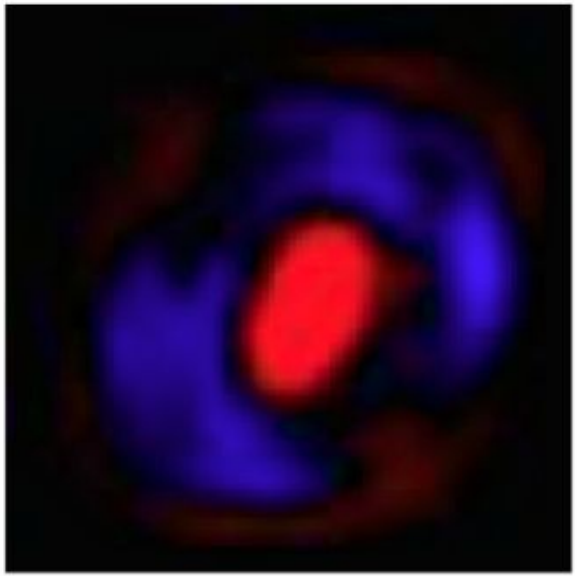
```
giant panda, panda, panda bear, coon bear, Ailuropoda melanoleuca (score = 0.88493)
indri, indris, Indri indri, Indri brevicaudatus (score = 0.00878)
lesser panda, red panda, panda, bear cat, cat bear, Ailurus fulgens (score = 0.00317)
custard apple (score = 0.00149)
earthstar (score = 0.00127)
```

```
I tensorflow/examples/label_image/main.cc:200] military uniform (866): 0.647296
I tensorflow/examples/label_image/main.cc:200] suit (794): 0.0477196
I tensorflow/examples/label_image/main.cc:200] academic gown (896): 0.0232411
I tensorflow/examples/label_image/main.cc:200] bow tie (817): 0.0157356
I tensorflow/examples/label_image/main.cc:200] bolo tie (940): 0.0145024
```

DIGITS RECOGNITION





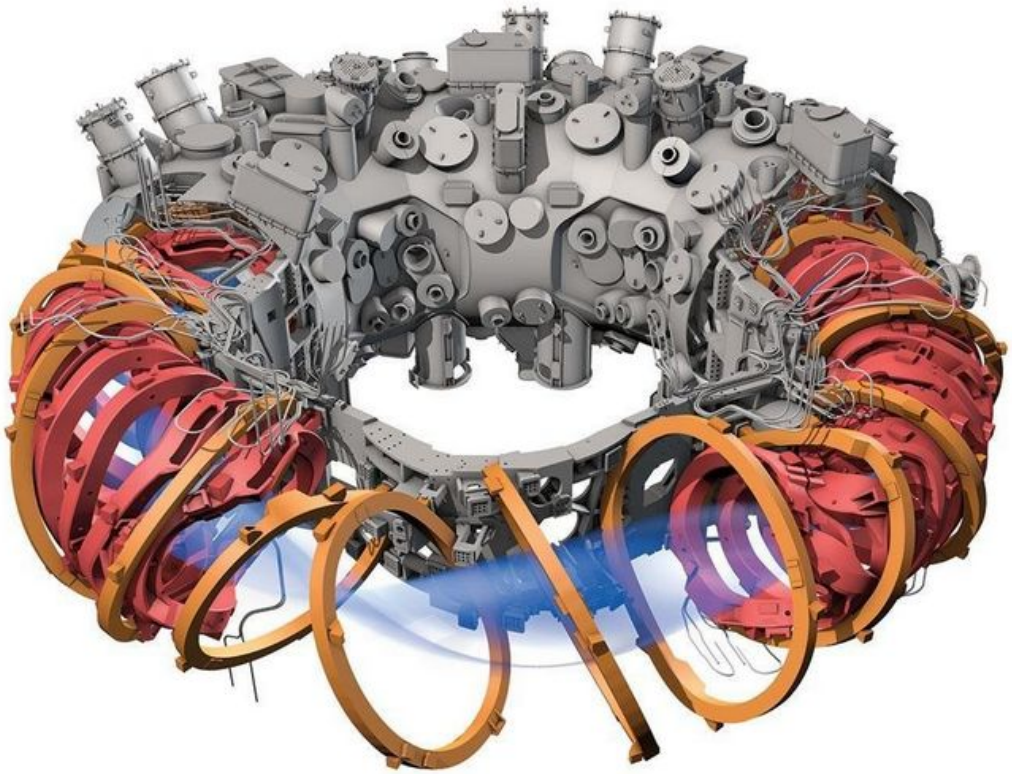


SHOW AND TELL (Accesibility)

Human captions from the training set

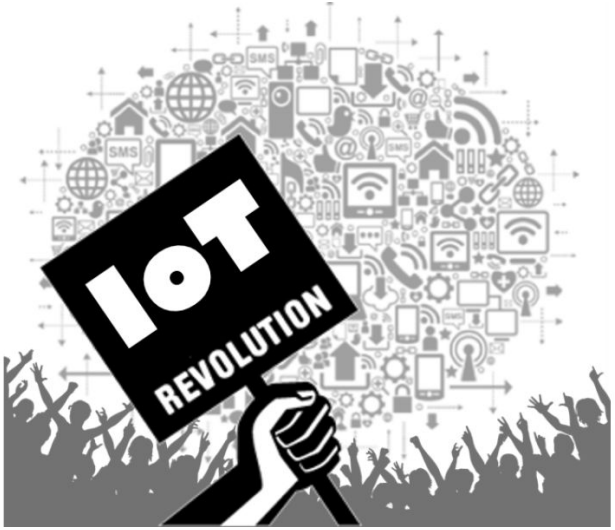
Automatically captioned

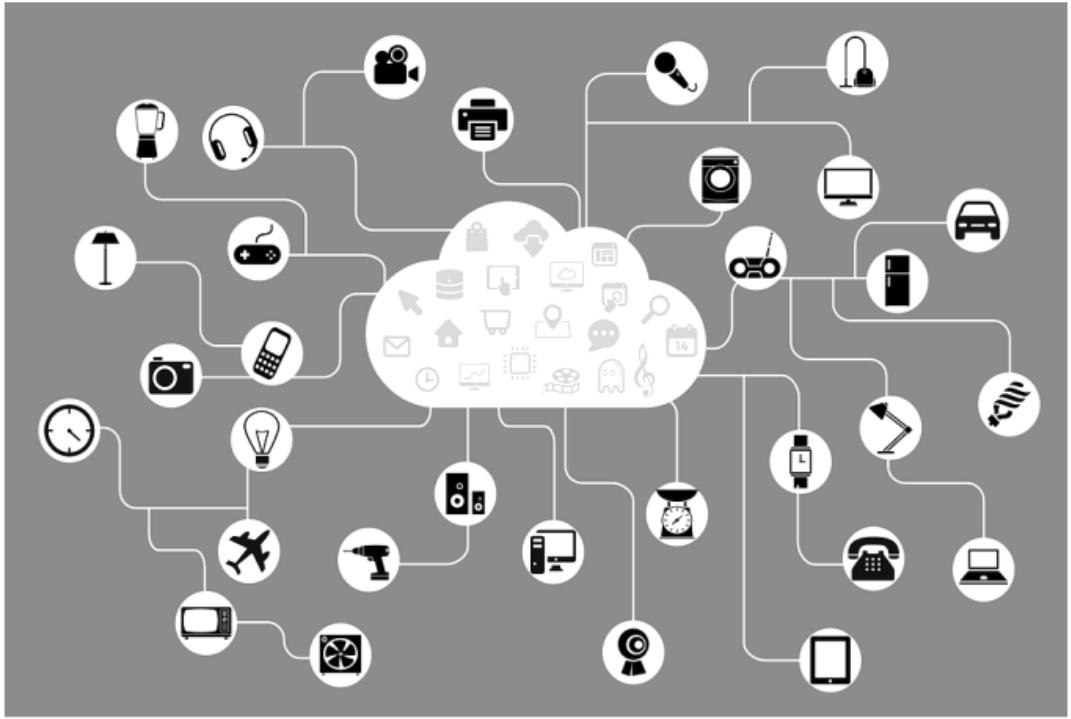
STELLARATOR ↗



RESOURCE: Science - Daniel Clery

THINGS INDUSTRIAL REVOLUTION





BLOCKCHAIN

INTERNET INDUSTRIAL REVOLUTION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Sergio A. Florez

TECH LEAD && FULL STACK DEVELOPER

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