Deep Learning Workshop

"...what we want is a machine
that can learn from experience."

Alan Turing, 1947

Xenofon Karagiannis

This workshop...

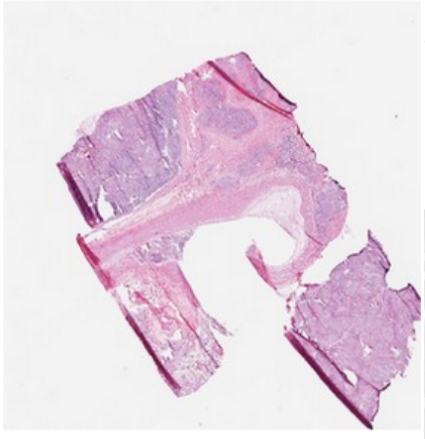
- Introduction to Deep Learning - TOO MANY slides!
- Hands on with Keras
- Thesis mini-presentation

Goals

- Deep Learning != Magic
- Deep Learning != Black box

MEGAN MOLTENI SCIENCE 09.17.18 11:00 AM

GOOGLE AI TOOL IDENTIFIES A TUMOR'S MUTATIONS FROM AN IMAGE

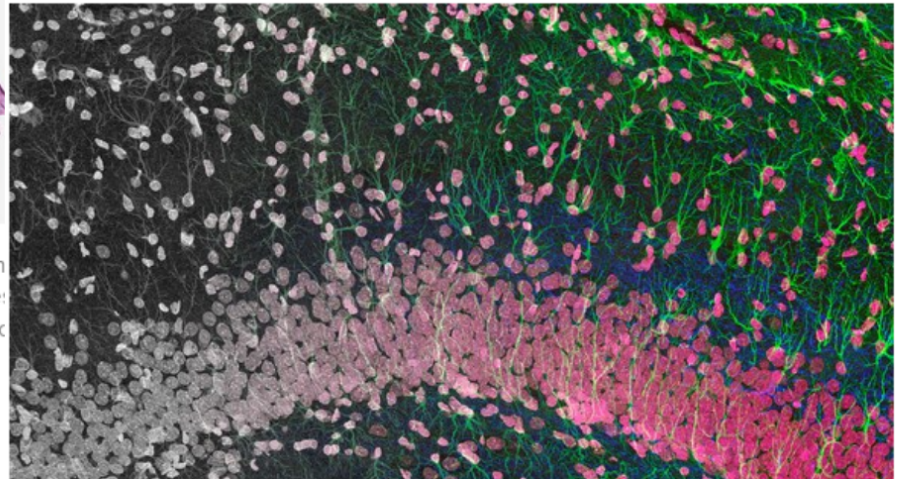


The image shows the process by which an
a map that tells apart two lung cancer type
cell carcinoma in red, lung squamous cell c

NYU SCHOOL OF MEDICINE

ROBBIE GONZALEZ SCIENCE 04.12.18 12:00 PM

AI LEARNS A NEW TRICK: MEASURING BRAIN CELLS



A.I. Shows Promise Assisting Physicians

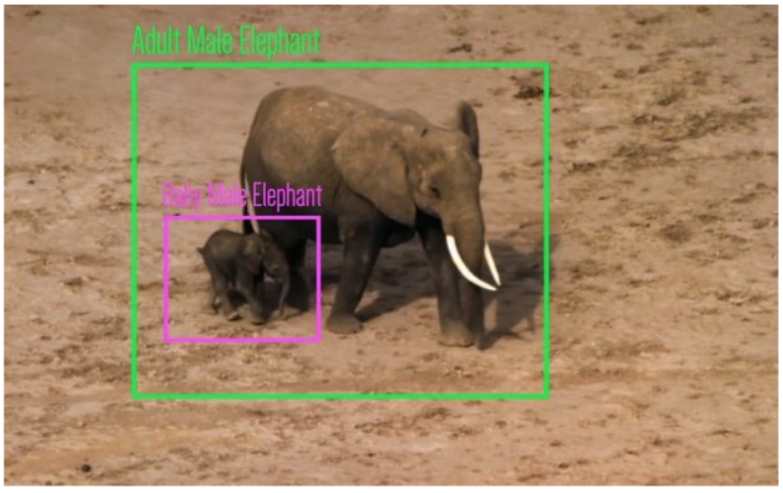
ers to recognize illnesses on magnetic resonance images of a
Beijing last year. The human doctors lost.

A.I. Is Helping Scientists Predict When and Where the Next Big Earthquake Will Be

Paul Allen enlists machine-learning tools for monitoring wildlife and ecosystems

BY ALAN BOYLE on September 26, 2018 at 10:54 am

Post a Comment | Email



Machine-learning technology can contribute to image recognition programs that could identify elephants in aerial imagery on their own. (Vulcan Photo)

The Google Pixel 3 Review: Phone's Smarts Shine Through Its A.I.-Driven Camera

Hardware innovations? Nope. Instead, Google is emphasizi software improvements — particularly for images — with i newest Pixel smartphones.

By Brian X. Chen

Oct. 15, 2018

CADE METZ BUSINESS 05.22.17 03:12 PM

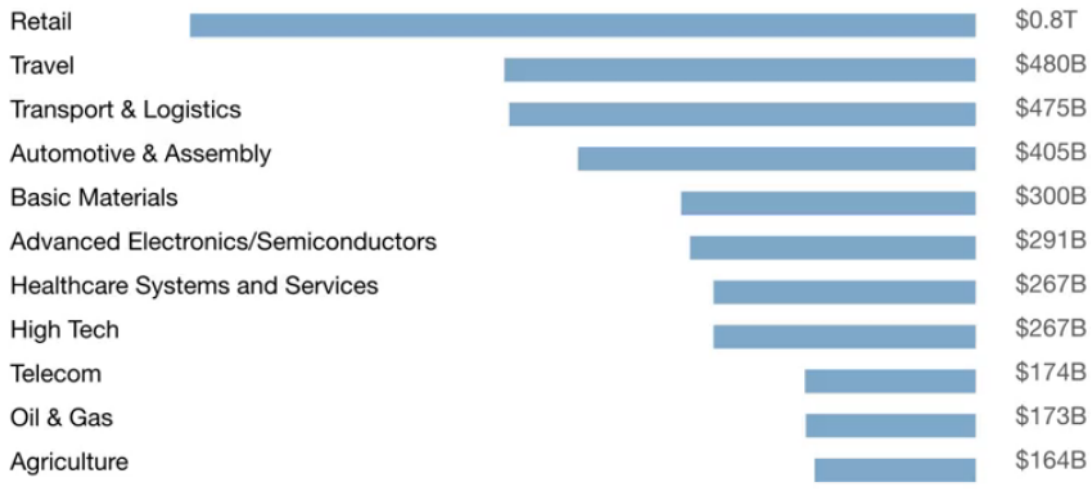
ALPHAGO IS BACK TO BATTLE MERE HUMANS—AND IT'S SMARTER THAN EVER

“AI is the new electricity”

Andrew NG

AI value creation by 2030

$13 trillion



[Source: McKinsey Global Institute.]

Buzzword Bingo!

Data Science	Cloud Computing	Machine Learning
Artificial Intelligence	Big Data	IoT
Reinforcement Learning	Deep Learning	Blockchain

Machine Learning

“Field of study that gives computers the ability to learn without being explicitly programmed.”

-Arthur Samuel (1959)

An ML projects results in a piece of software that runs.

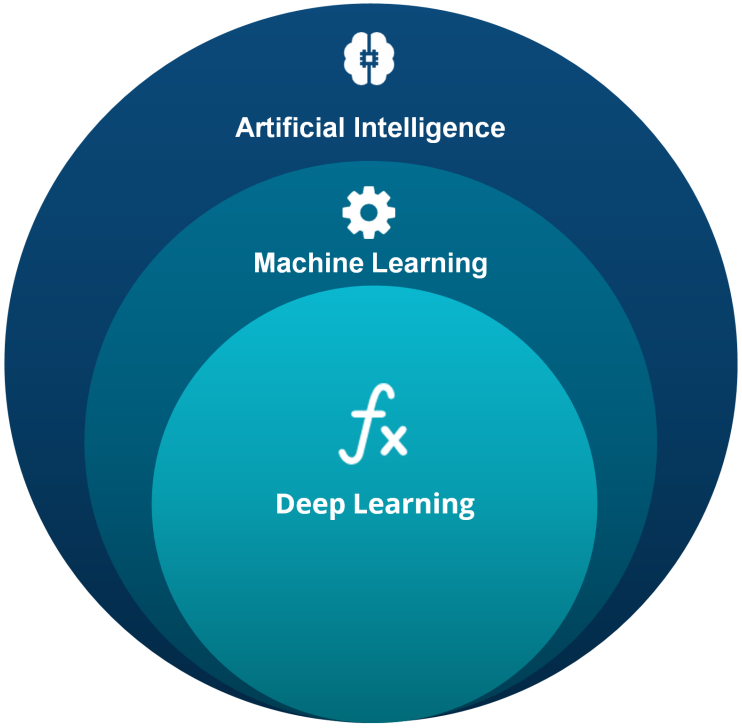
Data Science

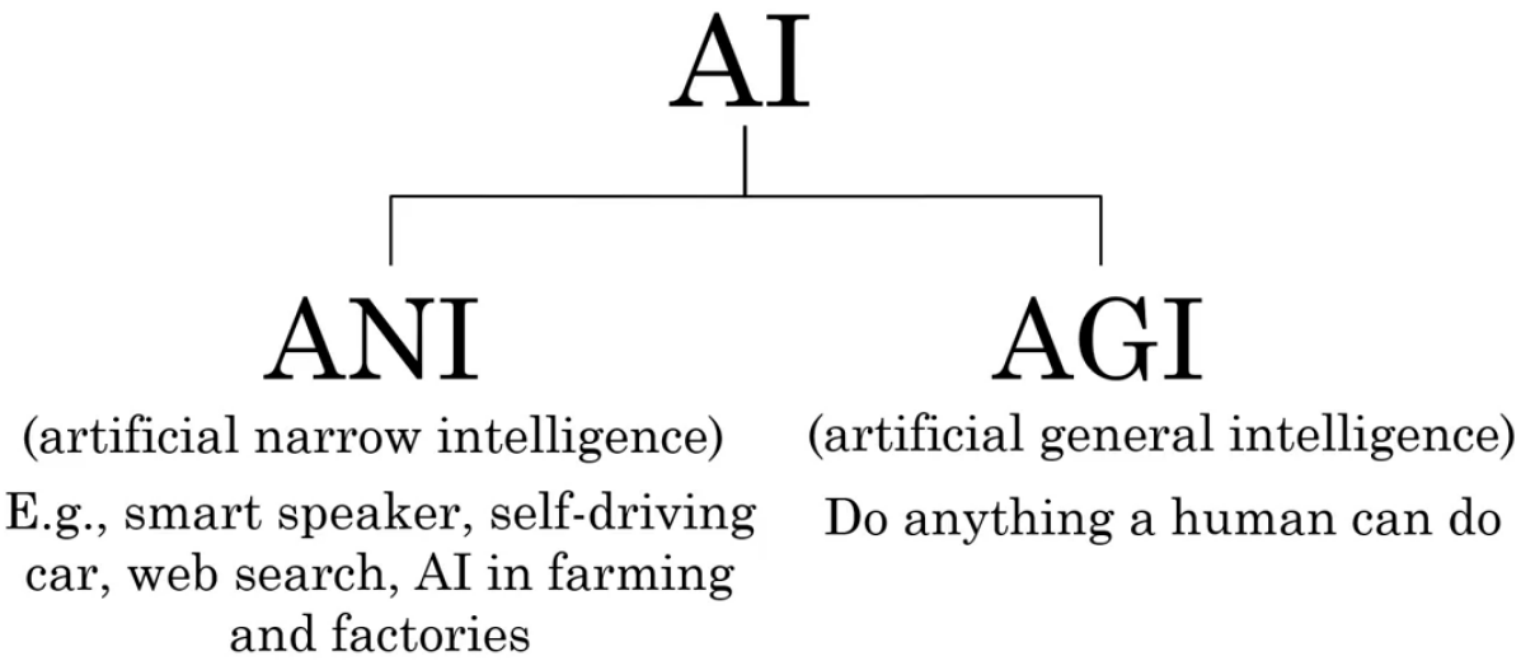
Science of extracting knowledge and insights from data.

A Data Science projects is often a presentation that summarizes conclusions for executives to take business actions or that summarizes conclusions for a product team to decide how to improve a website.

Artificial Intelligence

“the study and design of intelligent agents” where an intelligent agent is a system that perceives its environment and takes actions which maximizes its chances of success.




AI
ANI
(artificial narrow intelligence)
E.g., smart speaker, self-driving car, web search, AI in farming and factories
AGI
(artificial general intelligence)
Do anything a human can do

Color Restoration [link]

Automatic colorization and color restoration in black and white images.

(a) Colorado National Park, 1941 *(b) Textile Mill, June 1937* *(c) Berry Field, June 1909* *(d) Hamilton, 1936*

Figure 1: *Colorization results of historical black and white photographs from the early 20th century. Our model can obtain realistic colorization results whether it is a picture of landscapes (a), man-made environments (b), human portraits (c), or close-ups (d). Photos taken by Ansel Adams (a) and Lewis Hines (b,c,d), and are taken from the US National Archives (Public Domain).*

Speech Reenactment [link]

Synthesizing Obama: Learning Lip Sync from Audio.

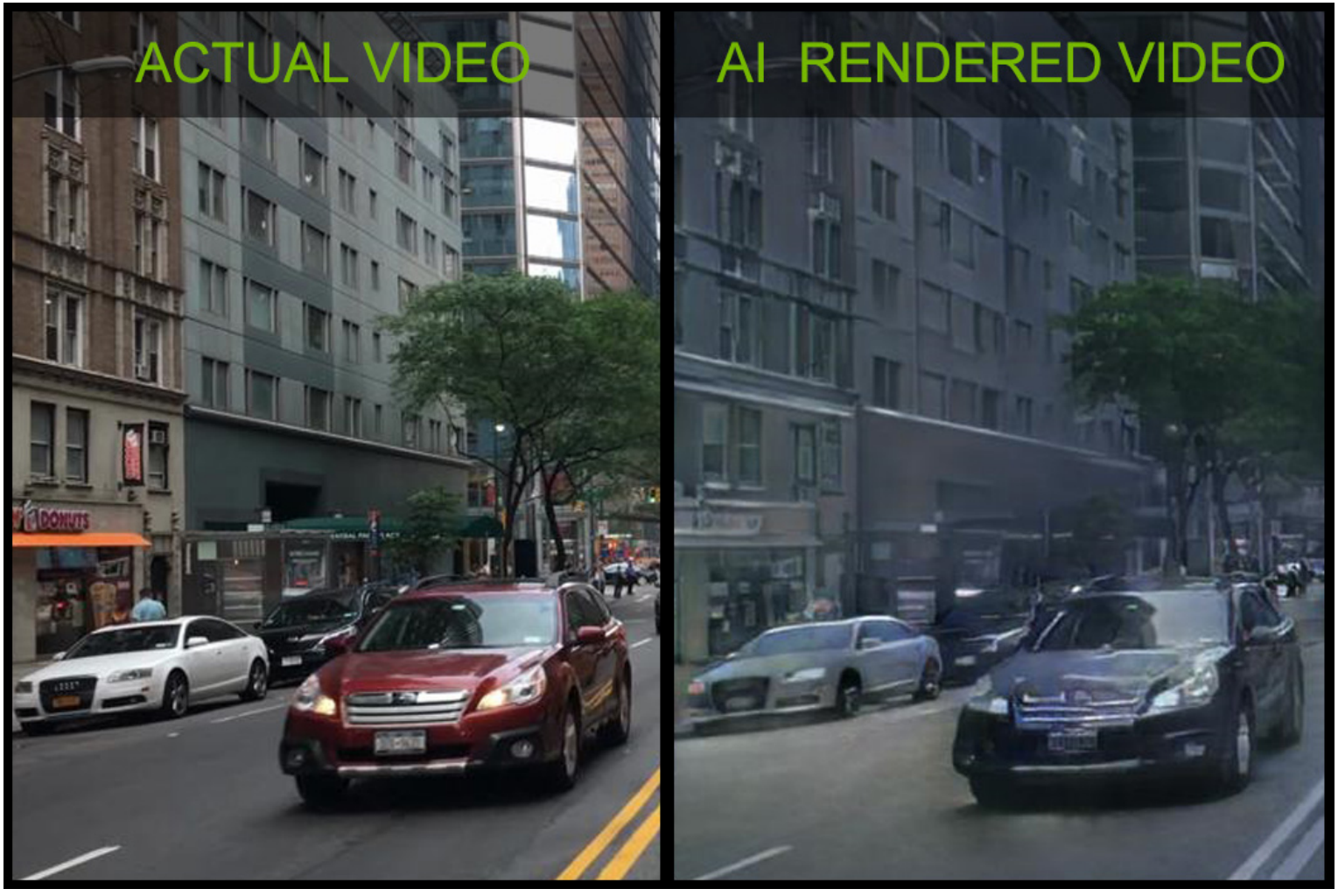
Diagnose crop diseases [link]

Artificial intelligence could help farmers diagnose crop diseases

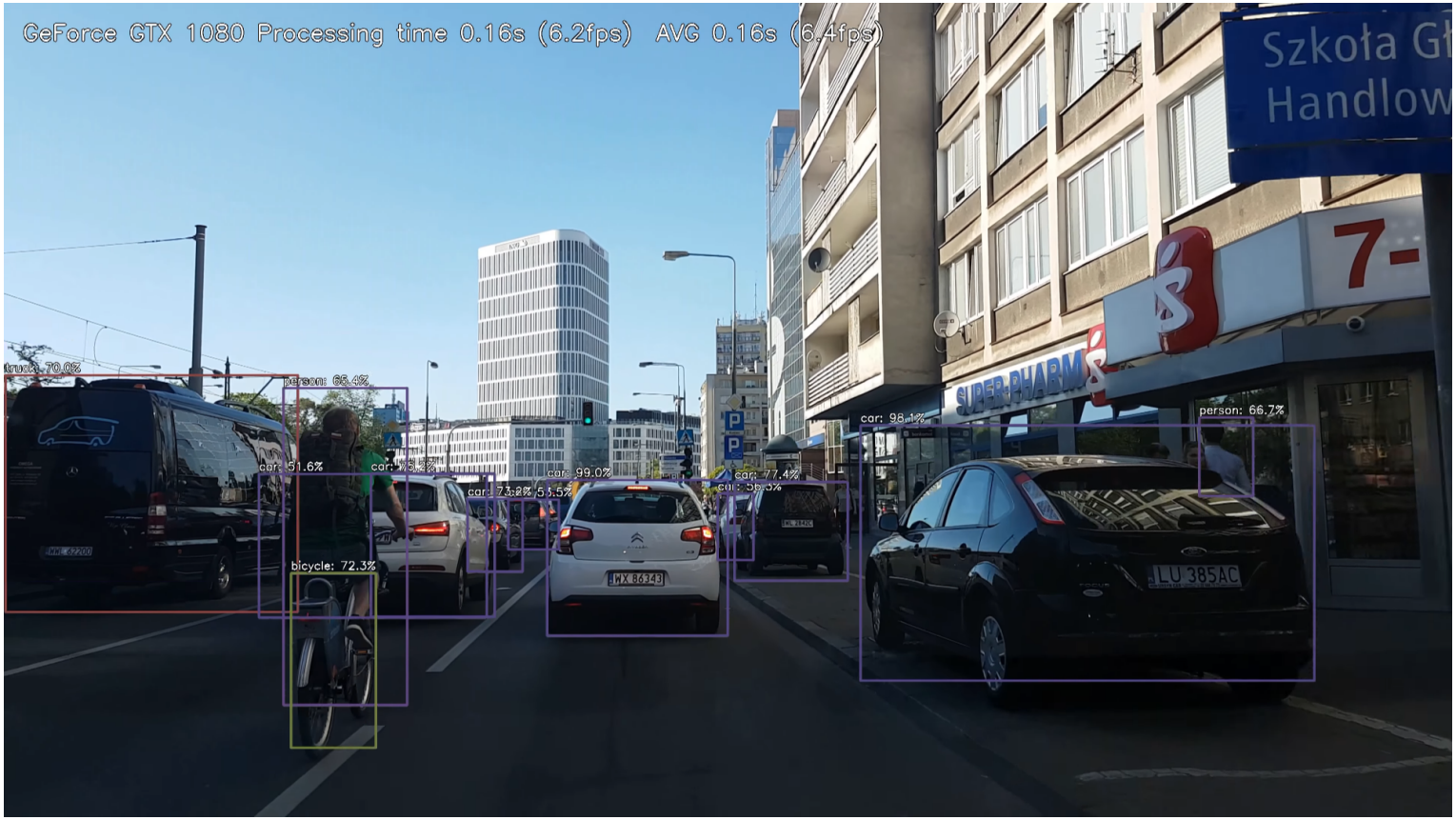
Kelsey Pryze, undergraduate researcher, captures photographs of potato leaves at Penn State's Russell E. Larson Agricultural Research Center at Rock Springs. **IMAGE: PENN STATE / EPFL**

Car Vehicle / Traffic Lights / Pedestrian detection with YOLO [link]

NVIDIA Invents AI Interactive Graphics [link]

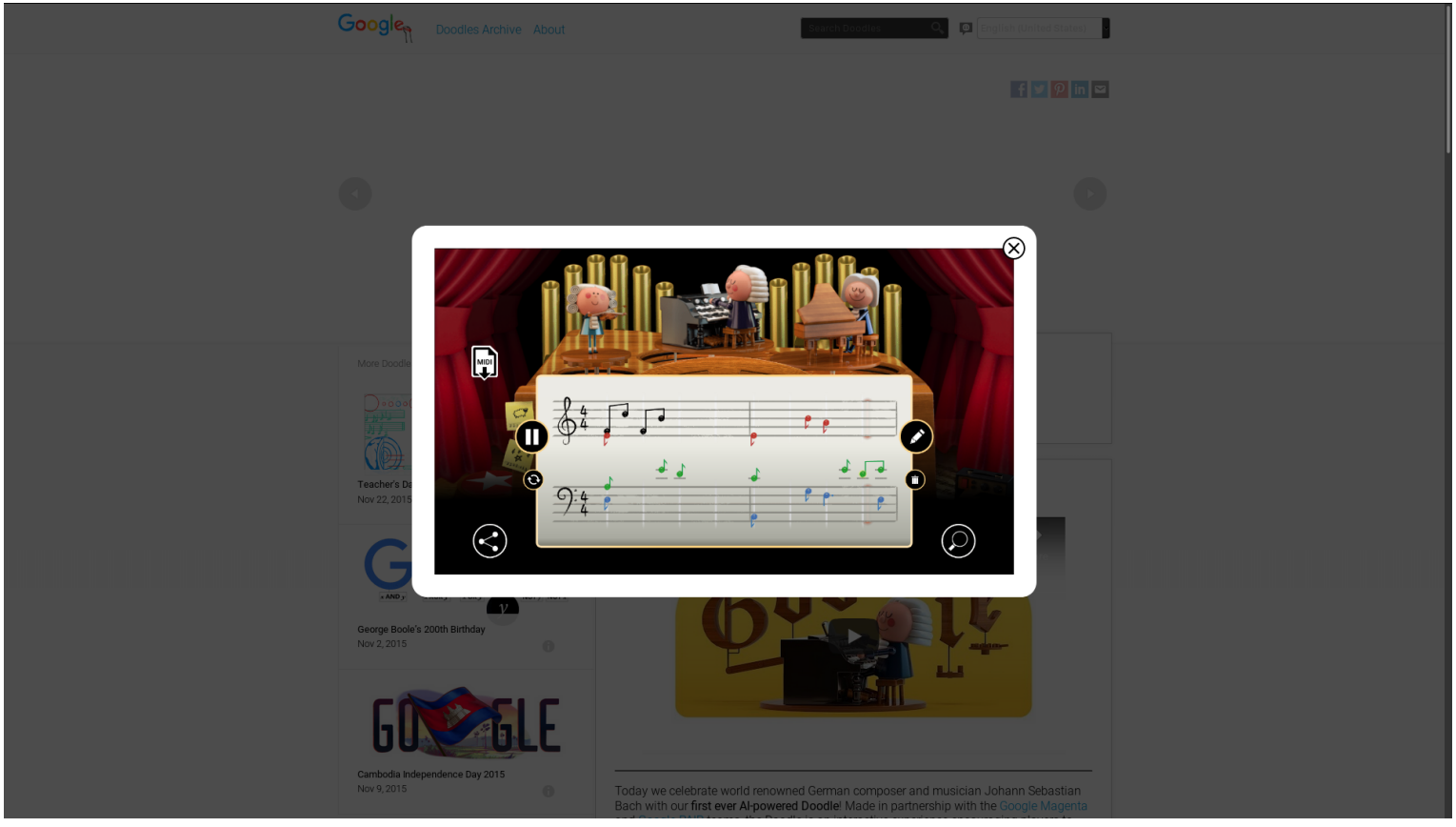


Real Time Object Detection in 4K Video - RetinaNet [link]



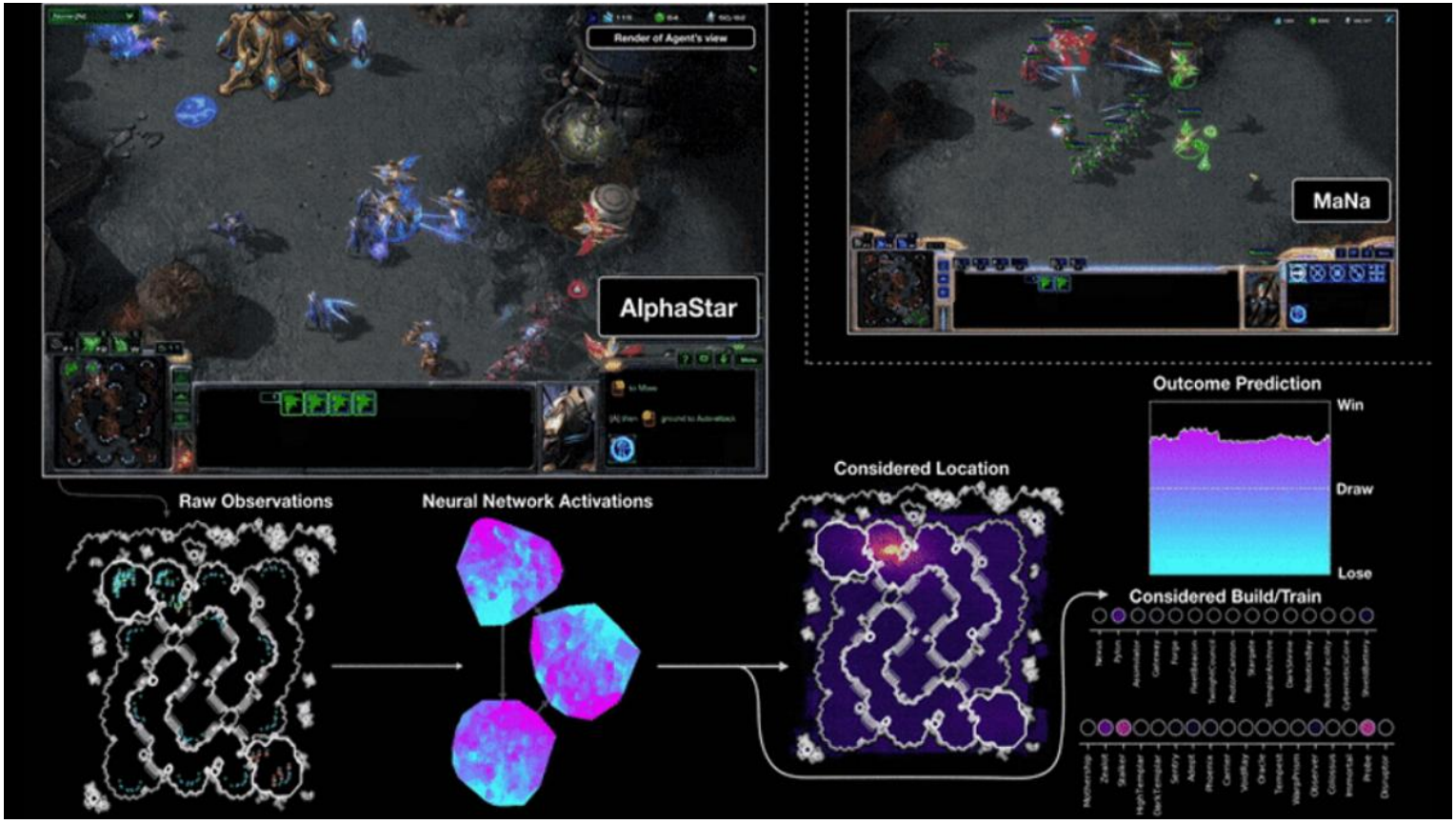
This person does not exist - GAN [link]

Google Doodle - Celebrating Johann Sebastian Bach [link]

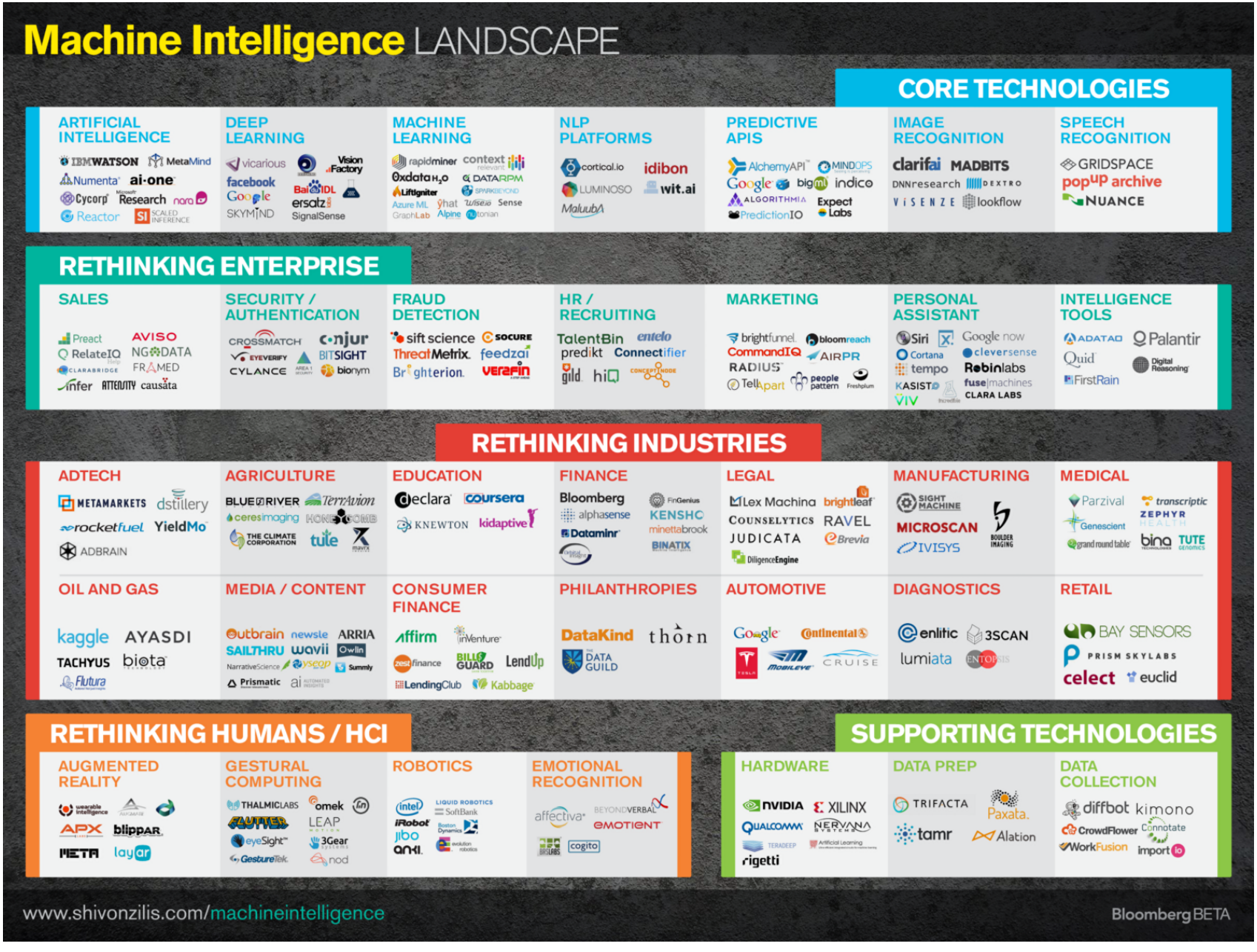


Google DeepMind - AlphaGo [link]

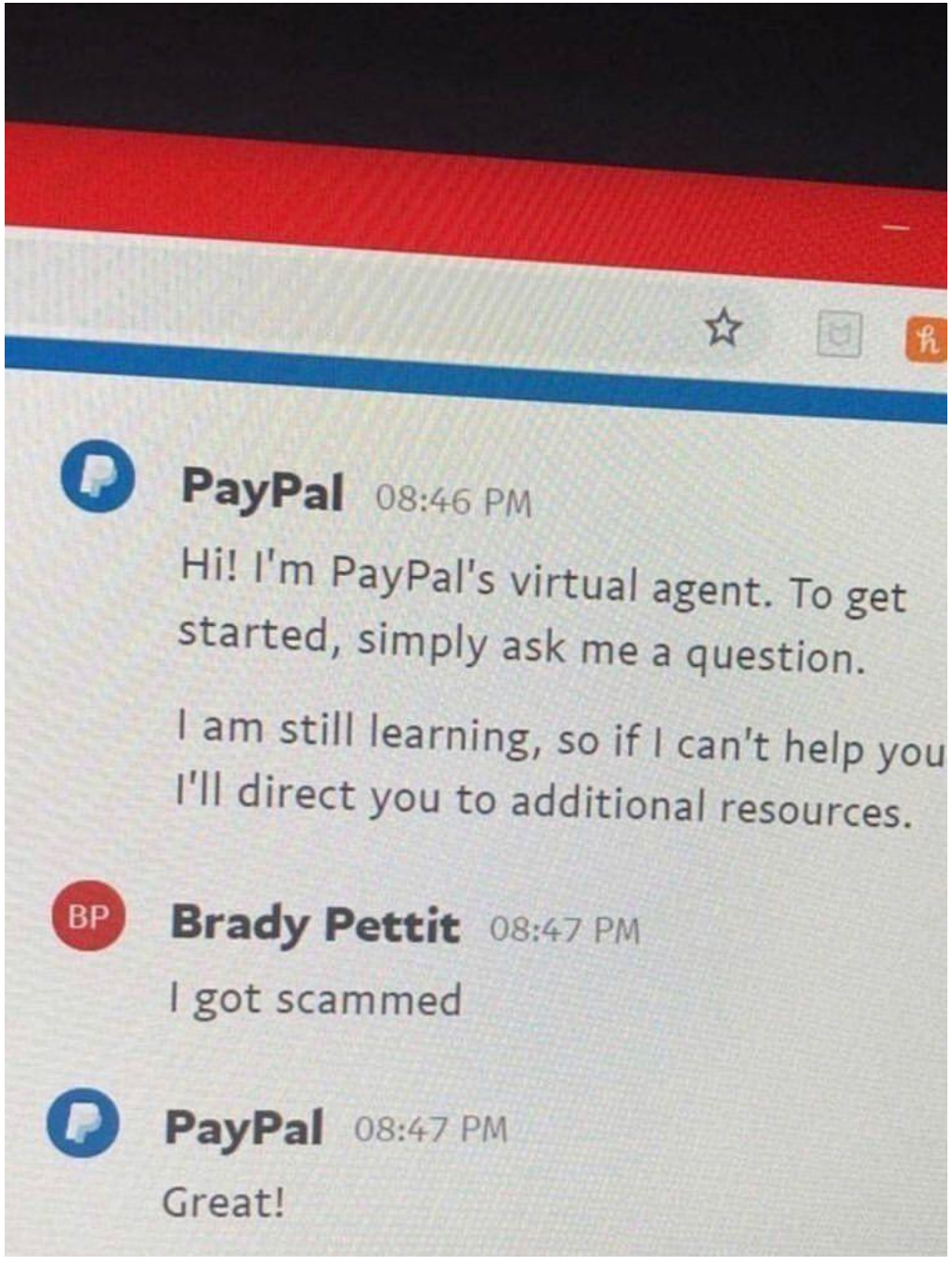
Google DeepMind - AlphaStar Starcraft II [link]

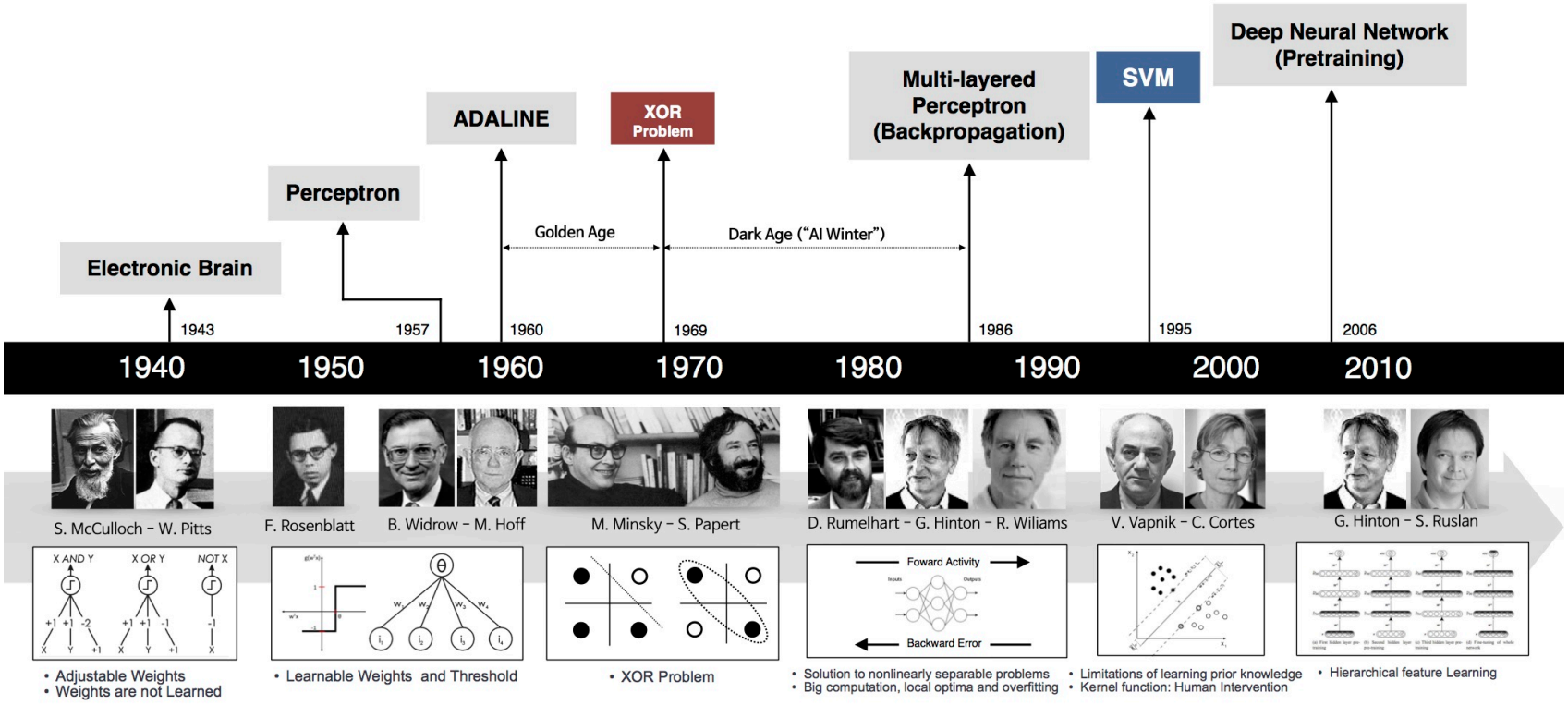


OpenAI Dota2 [link]


Machine Intelligence LANDSCAPE
CORE TECHNOLOGIES
ARTIFICIAL INTELLIGENCE
IBM WATSON
MetaMind
Numenta
ai·one
Cycorp
Microsoft Research
nara
Reactor
SCALED INFERENCE
DEEP LEARNING
vicarious
Vision Factory
facebook
Baidu IDL
Google
ersatz
SKYMIND
SignalSense
MACHINE LEARNING
rapidminer
context relevant
0xdata H2O
DATARPM
Liftigniter
SPARKBEYOND
Azure ML
yhat
wise.io
Sense
GraphLab
Alpine
tonian
NLP PLATFORMS
cortical.io
idibon
LUMINOSO
wit.ai
MaluubA
PREDICTIVE APIS
AlchemyAPI
MINDOPS
Google
bigml
indico
ALGORITHMIA
PredictionIO
Expect Labs
IMAGE RECOGNITION
clarifai
MADBITS
DNNresearch
DEXTRO
ViSENZE
lookflow
SPEECH RECOGNITION
GRIDSPACE
popup archive
NUANCE
RETHINKING ENTERPRISE
SALES
Preact
AVISO
RelateIQ
NGDATA
CLARABRIDGE
FRAMED
infer
ATTENSITY
causata
SECURITY / AUTHENTICATION
CROSSMATCH
cnjur
EYEVERIFY
BITSIGHT
CYLANCE
bionym
FRAUD DETECTION
sift science
SOCURE
ThreatMetrix
feedzai
Brighterion
VERAFIN
HR / RECRUITING
TalentBin
entelo
predikt
Connectifier
gild
hiQ
CONCEPTNODE
MARKETING
brightfunnel
bloomreach
CommandIQ
AIRPR
RADIUS
TellApart
people pattern
Freshplum
PERSONAL ASSISTANT
Siri
Google now
Cortana
cleversense
tempo
Robinlabs
KASISTO
fuse machines
VIV
CLARA LABS
INTELLIGENCE TOOLS
ADATAO
Palantir
Quid
Digital Reasoning
FirstRain
RETHINKING INDUSTRIES
ADTECH
METAMARKETS
dstillery
rocketfuel
YieldMo
ADBRAIN
AGRICULTURE
BLUE RIVER
TerrAvion
ceresimaging
HONEYCOMB
THE CLIMATE CORPORATION
tule
mavrx
EDUCATION
declara
coursera
KNEWTON
kidaptive
FINANCE
Bloomberg
FinGenius
alphasense
KENSHO
Dataminr
minettabrook
BINATIX
LEGAL
Lex Machina
brightleaf
COUNSELYTICS
RAVEL
JUDICATA
Brevia
DiligenceEngine
MANUFACTURING
SIGHT MACHINE
MICROSCAN
IVISYS
BOULDER IMAGING
MEDICAL
Parzival
transcriptic
ZEPHYR HEALTH
Genescient
grand round table
bina
TUTE GENOMICS
OIL AND GAS
kaggle
AYASDI
TACHYUS
biota
Flutura
MEDIA / CONTENT
Outbrain
newsle
ARRIA
SAILTHRU
wavii
Owlin
NarrativeScience
yseop
Summly
Prismatic
ai
CONSUMER FINANCE
affirm
inVenture
zestfinance
BILLGUARD
LendUp
LendingClub
Kabbage
PHILANTHROPIES
DataKind
thorn
DATA GUILD
AUTOMOTIVE
Google
Continental
TESLA
MobileEye
CRUISE
DIAGNOSTICS
enlitic
3SCAN
lumiata
ENTOPSIS
RETAIL
BAY SENSORS
PRISM SKYLABS
celect
euclid
RETHINKING HUMANS / HCI
AUGMENTED REALITY
wearable intelligence
APX
blippar
META
layar
GESTURAL COMPUTING
THALMICLABS
omek
FLUTTER
LEAP MOTION
eyeSight
3Gear
GestureTek
nod
ROBOTICS
intel
LIQUID ROBOTICS
SoftBank
iRobot
Boston Dynamics
jibo
anki
EMOTIONAL RECOGNITION
affectiva
BEYONDVERBAL
EMOTIENT
cogito
SUPPORTING TECHNOLOGIES
HARDWARE
NVIDIA
XILINX
QUALCOMM
NERVANA SYSTEMS
TERADEEP
Artificial Learning
rigetti
DATA PREP
TRIFACTA
Paxata
tamr
Alation
DATA COLLECTION
diffbot
kimono
CrowdFlower
Connotate
WorkFusion
import.io
www.shivonzilis.com/machineintelligence
Bloomberg BETA


Kaenbyou 01/13/2018
60+ hours on 16 GPU nvidia CUDA cluster.
dog


PayPal 08:46 PM
Hi! I'm PayPal's virtual agent. To get started, simply ask me a question.
I am still learning, so if I can't help you I'll direct you to additional resources.
BP
Brady Pettit 08:47 PM
I got scammed
PayPal 08:47 PM
Great!


Deep Neural Network (Pretraining)
SVM
Multi-layered Perceptron (Backpropagation)
XOR Problem
ADALINE
Perceptron
Electronic Brain
Golden Age
Dark Age ("AI Winter")
1943
1957
1960
1969
1986
1995
2006
1940
1950
1960
1970
1980
1990
2000
2010
S. McCulloch - W. Pitts
F. Rosenblatt
B. Widrow - M. Hoff
M. Minsky - S. Papert
D. Rumelhart - G. Hinton - R. Wiliams
V. Vapnik - C. Cortes
G. Hinton - S. Ruslan
X AND Y
X OR Y
NOT X
Foward Activity
Backward Error
• Adjustable Weights
• Weights are not Learned
• Learnable Weights and Threshold
• XOR Problem
• Solution to nonlinearly separable problems
• Big computation, local optima and overfitting
• Limitations of learning prior knowledge
• Kernel function: Human Intervention
• Hierarchical feature Learning

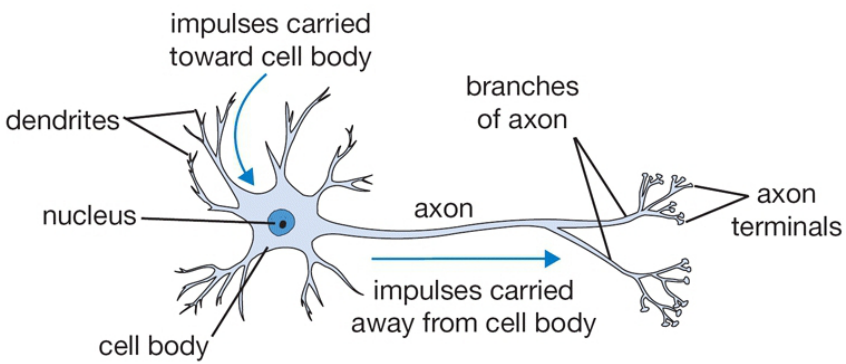
Neuron: The basic computational unit of the brain

Walter Pitts and Warren McCulloch [1943]:

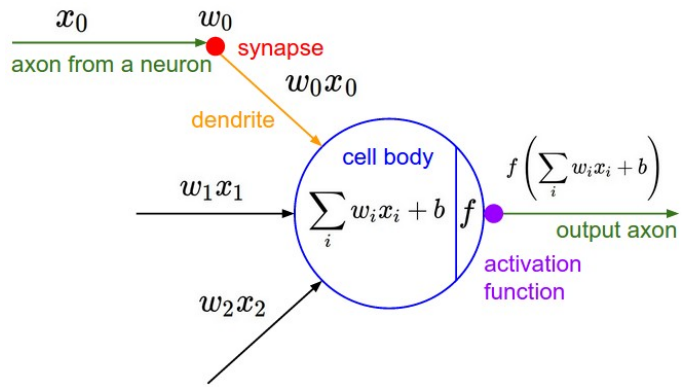
Thresholded logic unit (designed to mimic the way a neuron was thought to work)

adjustable but *not learned* weights

$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{ threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{ threshold} \end{cases}$$



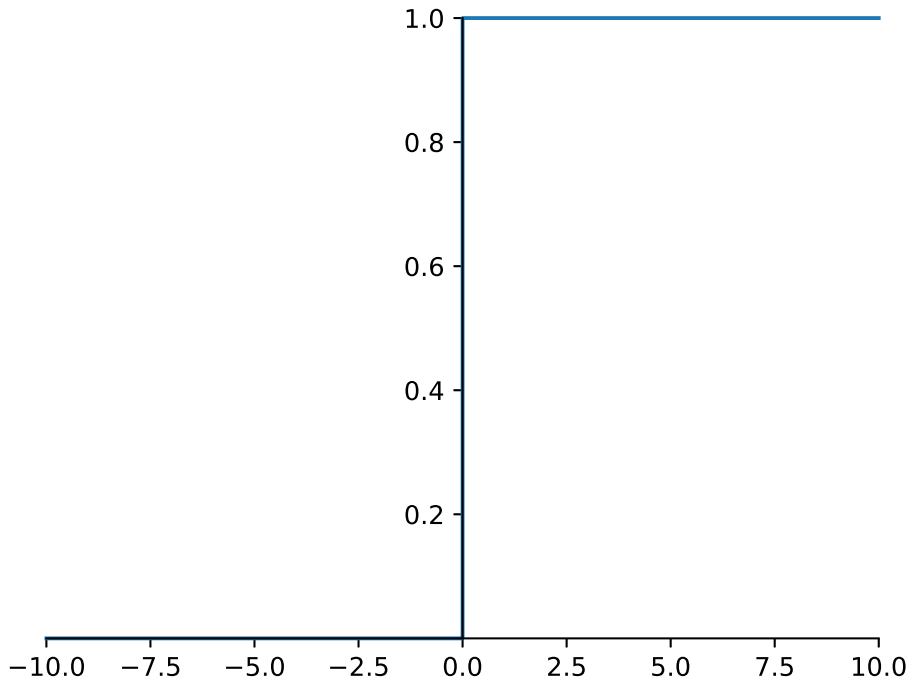
(i) Biological Neuron



(ii) Artificial Neuron

Thresholded logic unit: Maps inputs to 1 or 0

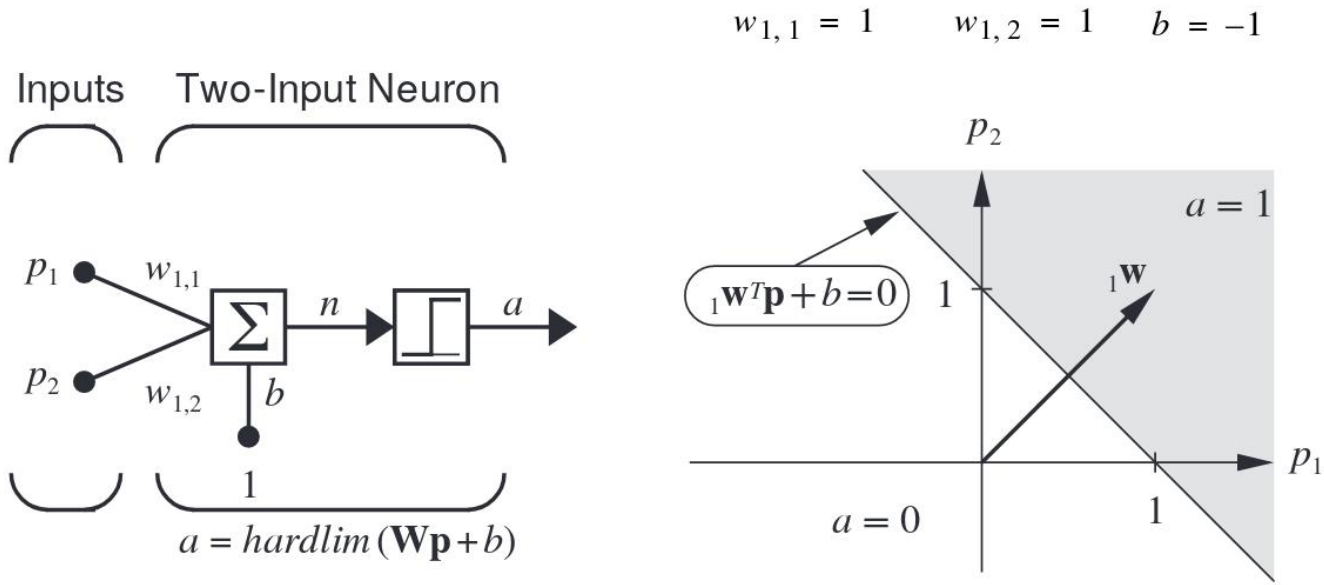
$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{ threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{ threshold} \end{cases}$$



Frank Rosenblatt's "perceptron" [1957]:

First real precursor to modern neural networks

Developed **rule for learning weights**



$$a = hardlim({}_1\mathbf{w}^{\mathrm{T}}\mathbf{p} + b) = hardlim(w_{1,1}p_1 + w_{1,2}p_2 + b)$$

Decision Boundary: $w_{1,1}p_1 + w_{1,2}p_2 + b = 0$

Linear equation: $ax + by + c = 0$

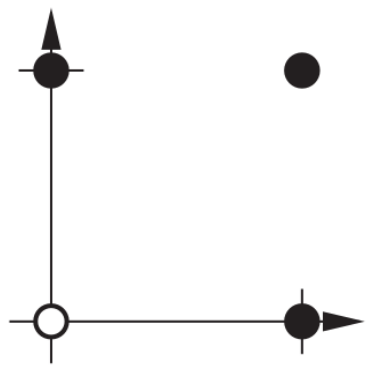
Supervised Learning

Network is provided with a set of examples of proper network behavior (inputs/targets)

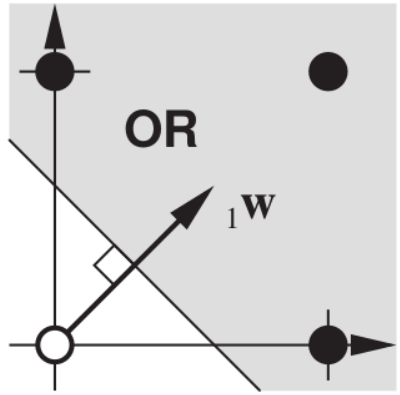
$$\{p_1, t_1\}, \{p_2, t_2\}, \ldots, \{p_Q, t_Q\}$$

Example - OR gate

$$\left\{\mathbf{p}_1 = \begin{bmatrix}0\\0\end{bmatrix}, t_1 = 0\right\} \quad \left\{\mathbf{p}_2 = \begin{bmatrix}0\\1\end{bmatrix}, t_2 = 1\right\} \quad \left\{\mathbf{p}_3 = \begin{bmatrix}1\\0\end{bmatrix}, t_3 = 1\right\} \quad \left\{\mathbf{p}_4 = \begin{bmatrix}1\\1\end{bmatrix}, t_4 = 1\right\}$$



Example - OR gate



Weight vector should be orthogonal to the decision boundary.

$$_1\mathbf{w} = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}$$

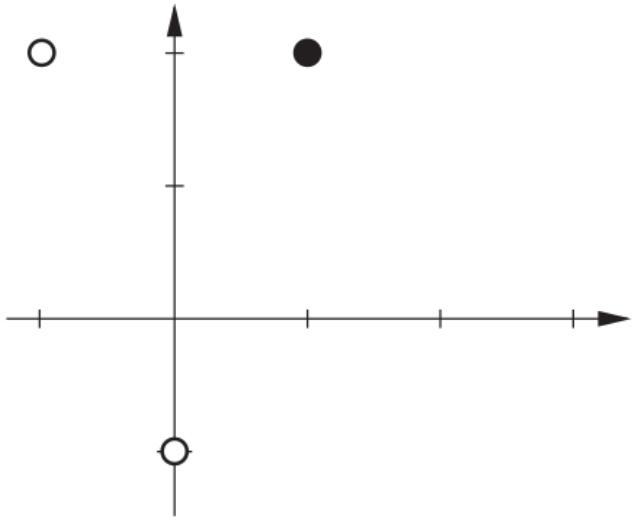
Pick a point on the decision boundary to find the bias.

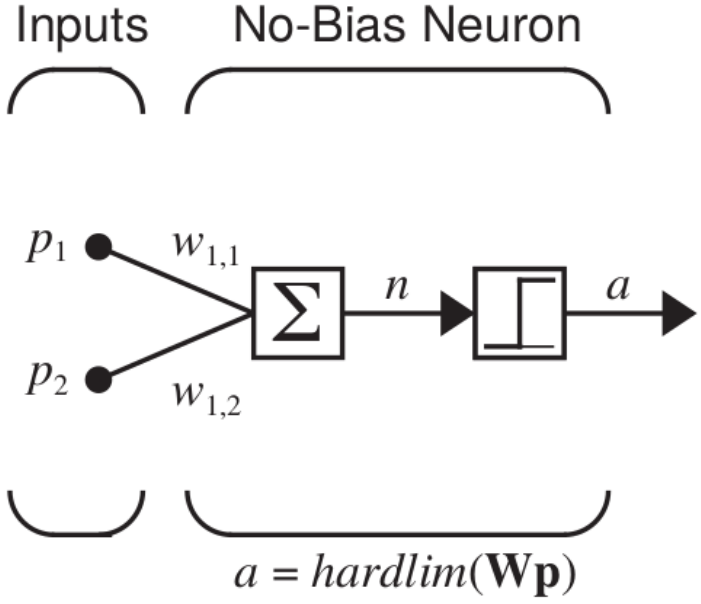
$$_1\mathbf{w}^T\mathbf{p} + b = \begin{bmatrix} 0.5 & 0.5 \end{bmatrix} \begin{bmatrix} 0 \\ 0.5 \end{bmatrix} + b = 0.25 + \mathrm{b} = 0 \quad \Rightarrow \quad b = -0.25$$

Learning Rule Test Problem

$$\{\mathbf{p}_1, \mathbf{t}_1\}, \{\mathbf{p}_2, \mathbf{t}_2\}, \ldots, \{\mathbf{p}_Q, \mathbf{t}_Q\}$$

$$\left\{\mathbf{p}_1 = \begin{bmatrix}1\\2\end{bmatrix}, t_1 = 1\right\} \quad \left\{\mathbf{p}_2 = \begin{bmatrix}-1\\2\end{bmatrix}, t_2 = 0\right\} \quad \left\{\mathbf{p}_3 = \begin{bmatrix}0\\-1\end{bmatrix}, t_3 = 0\right\}$$

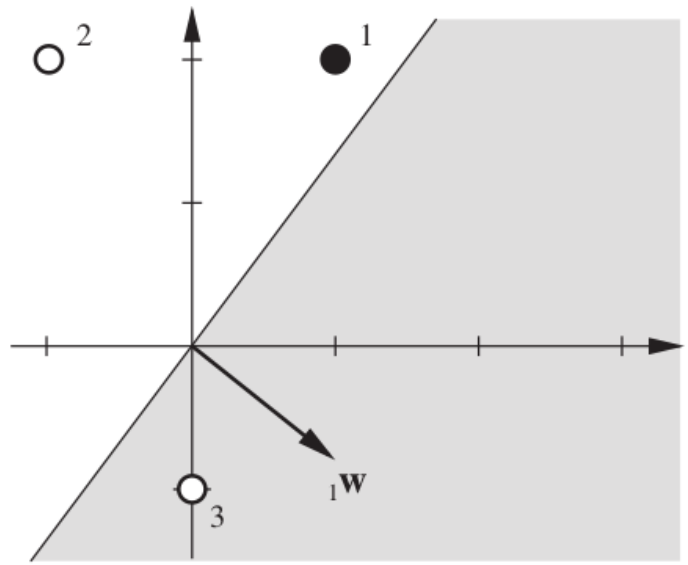




Starting Point

Random initial weight:

$$ {}_1\mathbf{w} = \begin{bmatrix} 1.0 \\ -0.8 \end{bmatrix} $$



Present $\mathbf{p}_1$ to the network:

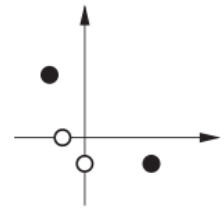
$$ a = hardlim({}_1\mathbf{w}^T \mathbf{p}_1) = hardlim\left(\begin{bmatrix} 1.0 & -0.8 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix} \right) $$

$$ a = hardlim(-0.6) = 0 $$

Incorrect Classification.

Tentative Learning Rule

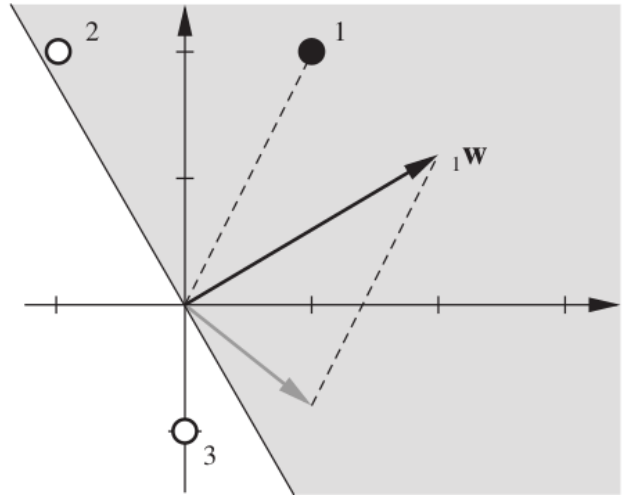
- Set ${}_1\mathbf{w}$ to $\mathbf{p}_1$
  - Not stable ×



- Add $\mathbf{p}_1$ to ${}_1\mathbf{w}$ ✓

Tentative Rule: If $t = 1$ and $a = 0$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} + \mathbf{p}$

$${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} + \mathbf{p}_1 = \begin{bmatrix} 1.0 \\ -0.8 \end{bmatrix} + \begin{bmatrix} 1 \\ 2 \end{bmatrix} = \begin{bmatrix} 2.0 \\ 1.2 \end{bmatrix}$$



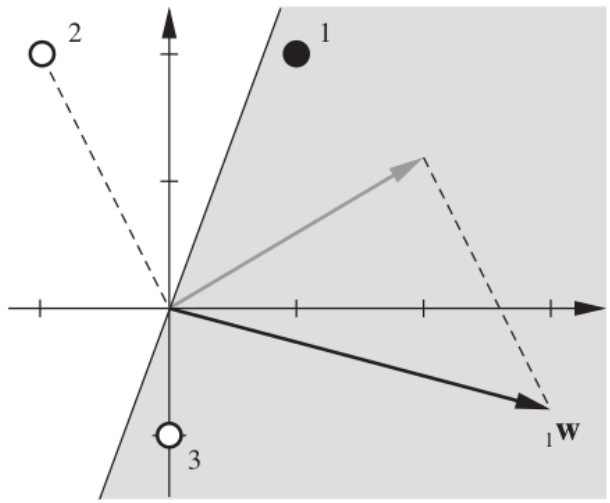
Second Input Vector

$$a = hardlim({}_1\mathbf{w}^{\mathrm{T}}\mathbf{p}_2) = hardlim\left(\begin{bmatrix}2.0 & 1.2\end{bmatrix}\begin{bmatrix}-1\\2\end{bmatrix}\right)$$

$$a = hardlim(0.4) = 1 \quad \text{(Incorrect Classification)}$$

Modification to Rule: If $t = 0$ and $a = 1$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} - \mathbf{p}$

$${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} - \mathbf{p}_2 = \begin{bmatrix}2.0\\1.2\end{bmatrix} - \begin{bmatrix}-1\\2\end{bmatrix} = \begin{bmatrix}3.0\\-0.8\end{bmatrix}$$

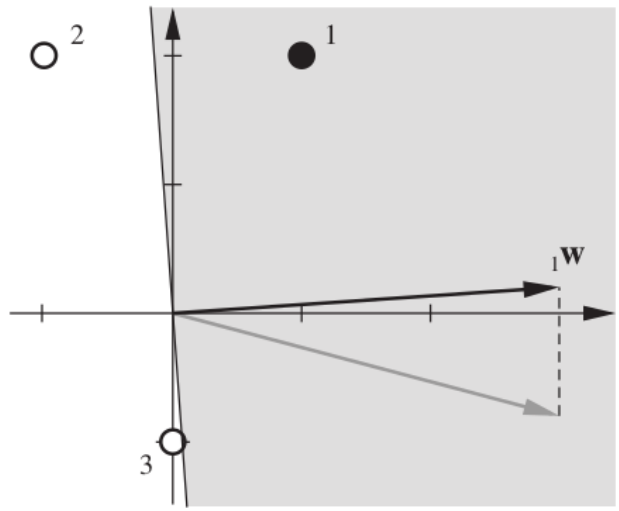


Third Input Vector

$$a = hardlim({}_1\mathbf{w}^T \mathbf{p}_3) = hardlim\left(\begin{bmatrix}3.0 & -0.8\end{bmatrix}\begin{bmatrix}0\\-1\end{bmatrix}\right)$$

$$a = \text{hardlim}(0.8) = 1 \qquad \text{(Incorrect Classification)}$$

$${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} - \mathbf{p}_3 = \begin{bmatrix}3.0\\-0.8\end{bmatrix} - \begin{bmatrix}0\\-1\end{bmatrix} = \begin{bmatrix}3.0\\0.2\end{bmatrix}$$



Patterns are now correctly classified.

If $t = a$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old}$.

Unified Learning Rule

If $t = 1$ and $a = 0$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} + \mathbf{p}$

If $t = 0$ and $a = 1$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} - \mathbf{p}$

If $t = a$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old}$

$$e = t - a$$

If $e = 1$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} + \mathbf{p}$

If $e = -1$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} - \mathbf{p}$

If $e = 0$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old}$

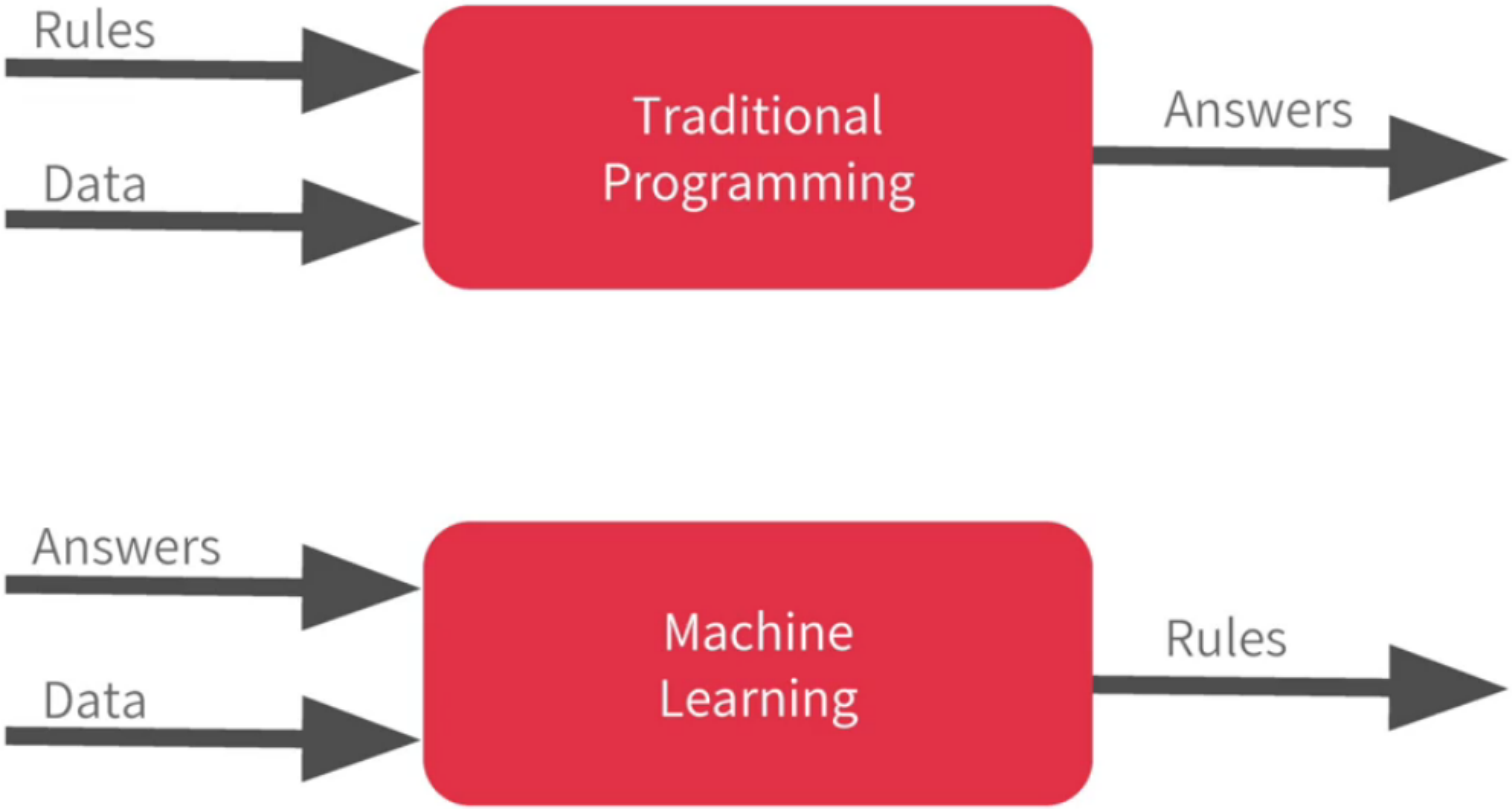
$$ {}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} + e\mathbf{p} = {}_1\mathbf{w}^{old} + (t-a)\mathbf{p} $$

$$ b^{new} = b^{old} + e $$

A bias is a weight with an input of 1.

HANDS ON: Single Perceptron

Run_on_GPU.ipynb
Single_Perceptron_OR_Gate.ipynb
Single_Perceptron_Linear_Regression.ipynb
dlaicourse-master/Course 1 - Part 2 - Lesson 2 - Notebook.ipynb


Rules
Data
Traditional Programming
Answers
Answers
Data
Machine Learning
Rules

Perceptron convergence theorem

The perceptron learning rule will converge to a weight vector (not necessarily unique) that gives the correct response for all training patterns, and it will do so in a finite number of steps.

Rosenblatt was so confident that the perceptron would lead to true AI, that in 1959 he remarked:

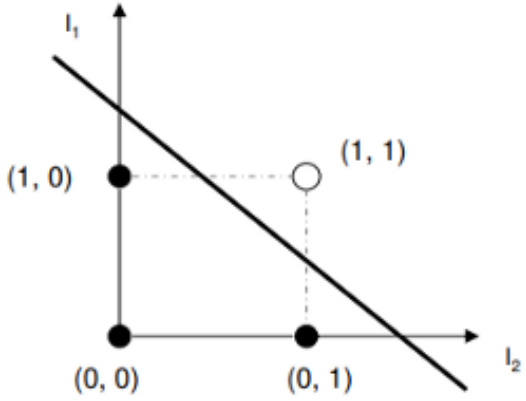
[The perceptron is] the embryo of an electronic computer that [the Navy] expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence.

Marvin Minsky and Seymor Papert - XOR problem [1969]

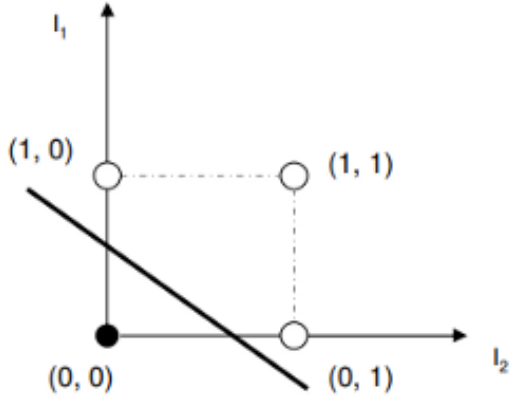
They showed that the perceptron was incapable of learning the simple exclusive-or (XOR) function.
They proved that it was theoretically impossible for it to learn such a function, no matter how long you let it train.
(this isn't surprising to us, as the model implied by the perceptron is a linear one and the XOR function is nonlinear)

At the time this was enough to kill all research on neural nets

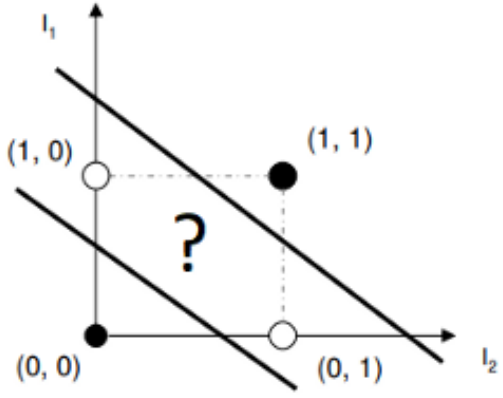
AND		
I_1	I_2	out
0	0	0
0	1	0
1	0	0
1	1	1



OR		
I_1	I_2	out
0	0	0
0	1	1
1	0	1
1	1	1



XOR		
I_1	I_2	out
0	0	0
0	1	1
1	0	1
1	1	0

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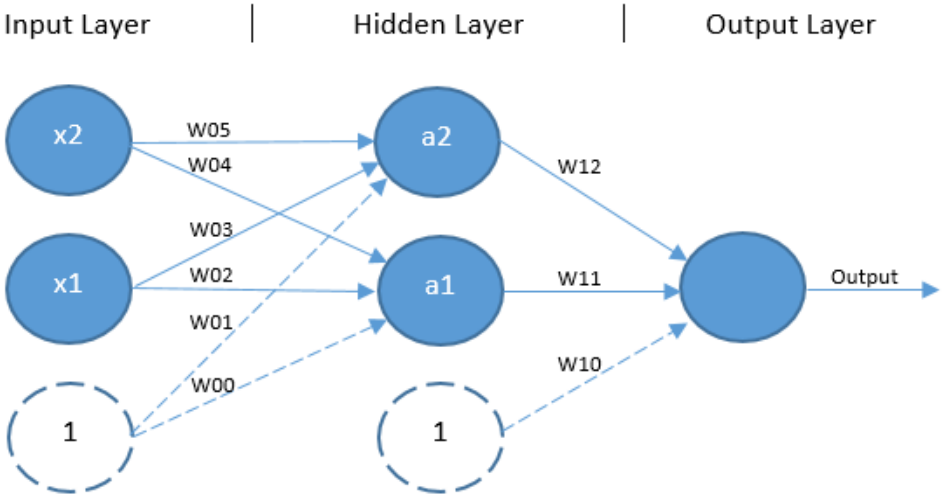
memegenerator.net

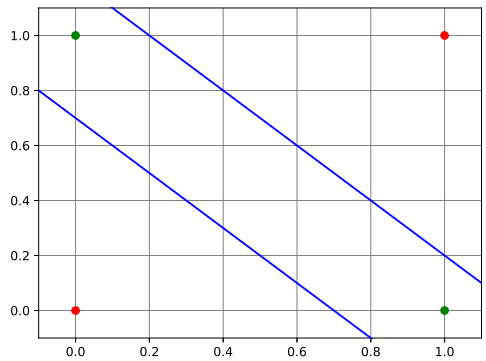
XOR Solution???

One single perceptron neuron: One decision boundary (hyperplane)

Two perceptron neurons: Two decision boundaries

Multi Layer Perceptron (MLP)





A network of perceptrons can be used to simulate a circuit containing many NAND gates. And because NAND gates are universal for computation, it follows that perceptrons are also universal for computation.

In the mathematical theory of artificial neural networks, the universal approximation theorem states that a feed-forward network with a single hidden layer containing a finite number of neurons can approximate continuous functions on compact subsets of R^n, under mild assumptions on the activation function. The theorem thus states that simple neural networks can represent a wide variety of interesting functions when given appropriate parameters

The problem: There was no equally powerfull rule (to the Perceptron's) for learning in networks with hidden units.

David. Rumelhard, Geoffrey. Hinton and Ronald. Williams - Learning Representations by back-propagating errors [1986]
(aka "Backpropagation")

Perceptron's delta rule: $\Delta_p w_{ji} = \eta(t_{pj} - o_{pj}) i_{pi} = \eta \delta_{pj} i_{pi}$

How was this rule derived?
For linear units, this rule minimizes the squares of the differences between the actual and the desired output values summed over the output units and all pairs of input/output vectors. $E = \sum E_p$

$$E_p = \frac{1}{2} \sum_j (t_{pj} - o_{pj})^2$$

We have: input and target data, network architecture
We want: an algorithm which lets us find weights and biases so that the output from the network approximates y(x) (target *t*) for all training inputs x. To quantify how well we're achieving this goal we define a cost function.

$$C(w,b) = \frac{1}{2n}\sum_x (t-\alpha)^2$$

w the collection of all weights in the network, *b* all the biases, *n* the total number of training inputs, α is the vector of outputs from the network when *x* is input, and the sum is over all training inputs, *x*.

The output α depends on *x*, *w* and *b*.
We'll call *C* the quadratic cost function (or mean squared error - MSE).

$C(w,b)$ is non-negative.
$C(w,b)$ becomes small i.e $C(w,b) \approx 0$ when $t \approx \alpha$.

$$C(w,b) = \frac{1}{2n}\sum_x (t-\alpha)^2$$

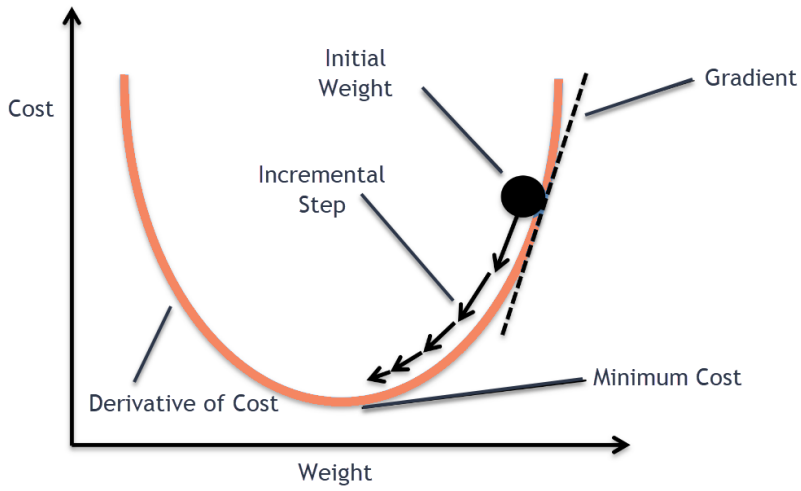
$y = 2x + 4$
$x = [1, 2, 3, 4, 5, 6, 7, 8]$
$t = [6, 8, 10, 12, 14, 16, 18, 20]$
For $w = 3, b = 2$.
$\alpha = [5, 8, 11, 14, 17, 20, 23, 26]$

$C(w,b) = \frac{(6-5)^2+(8-8)^2+(10-11)^2+\ldots+(20-26)^2}{16} = 5.75$

The aim of our training algorithm will be to minimize the cost C(w,b) as a function of the weights and biases. In other words, we want to find a set of weights and biases which make the cost as small as possible. We'll do that using an algorithm known as **gradient descent**.

Minimize some function

The derivative of the function shows us the way the function changes. From Calculus is known that a function has a minimum (or maximum) value when its derivative at that point is zero.

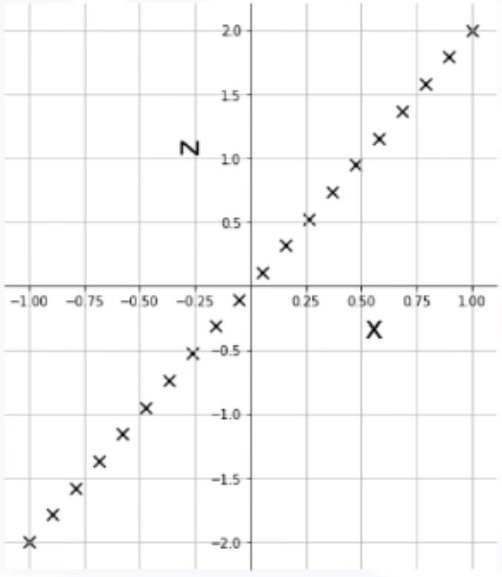


$$f(x+\epsilon) \approx f(x) + \epsilon f'(x)$$

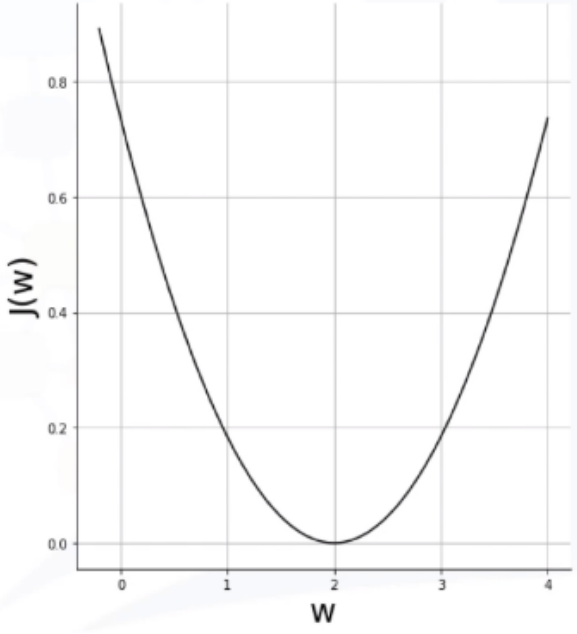
It is useful for minimizing the function because it tells us how to change x in order to make a small improvement in y

Gradient Descent Algorithm

$$Z = wX$$

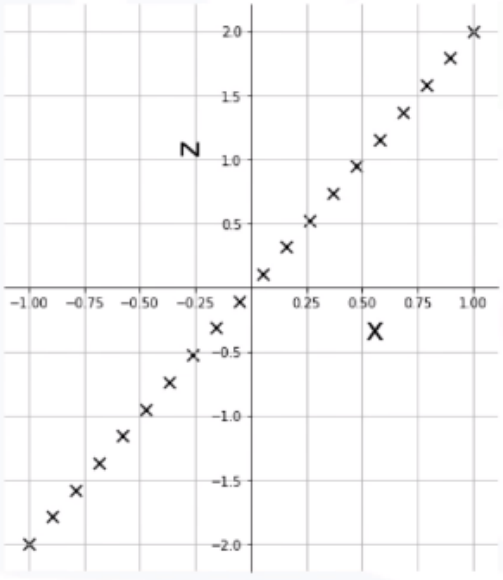


$$J(w) = \frac{1}{2m}\sum_{i=1}^{m}(z_i - wx_i)^2$$

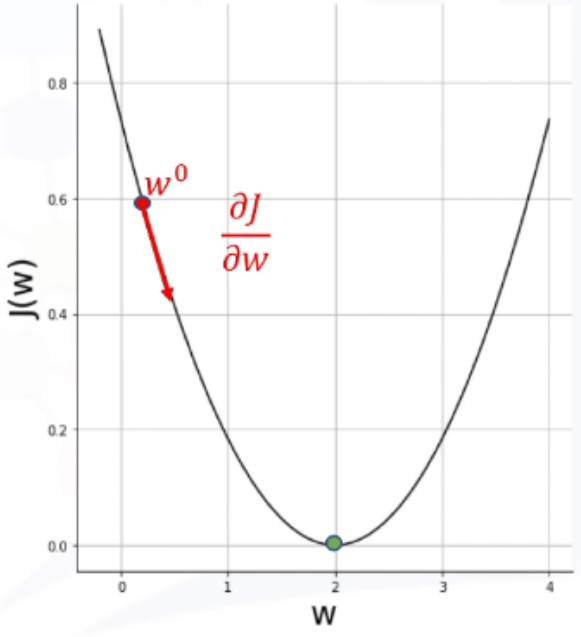


Gradient Descent Algorithm

$$Z = wX$$

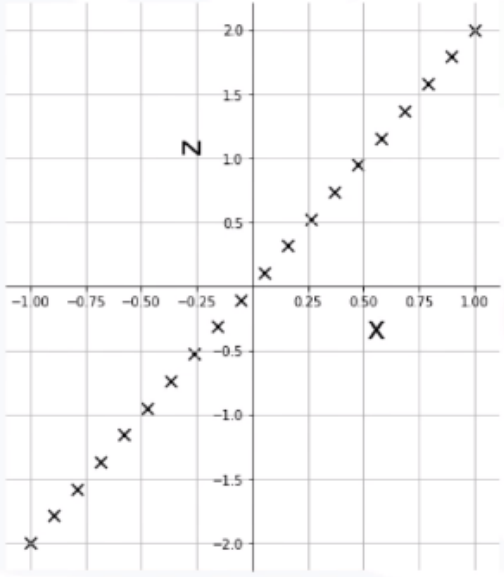


$$J(w) = \frac{1}{2m}\sum_{i=1}^{m}(z_i - wx_i)^2$$

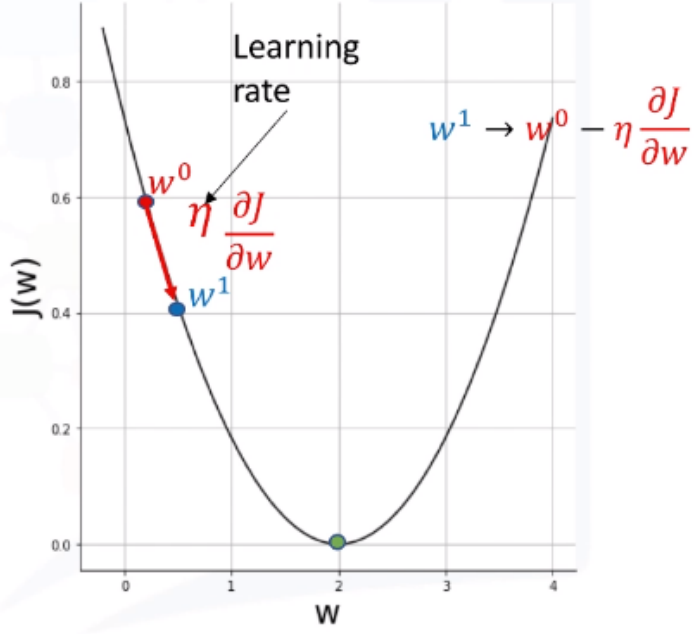


Gradient Descent Algorithm

$$Z = wX$$

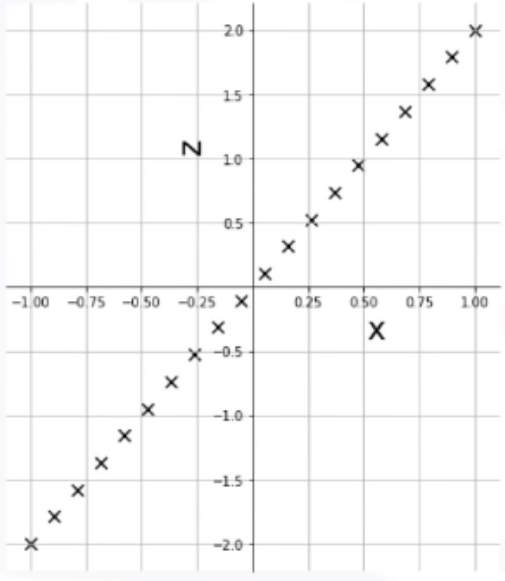


$$J(w) = \frac{1}{2m}\sum_{i=1}^{m}(z_i - wx_i)^2$$

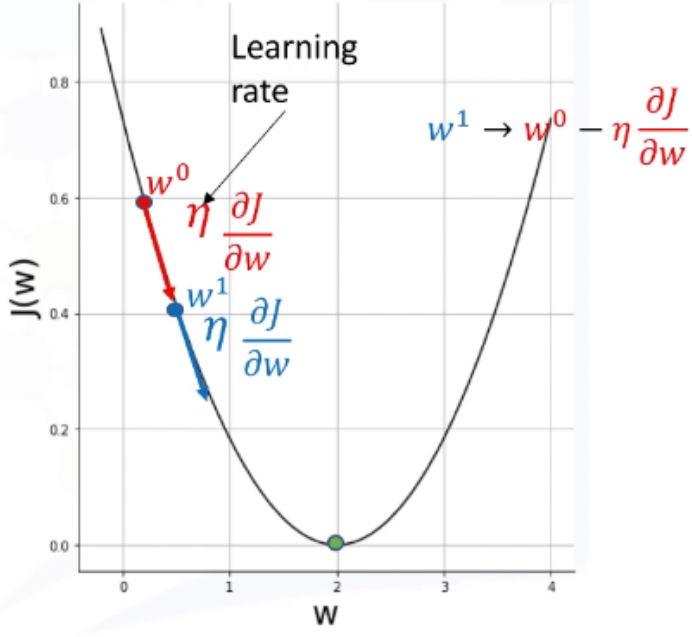


Gradient Descent Algorithm

$$Z = wX$$



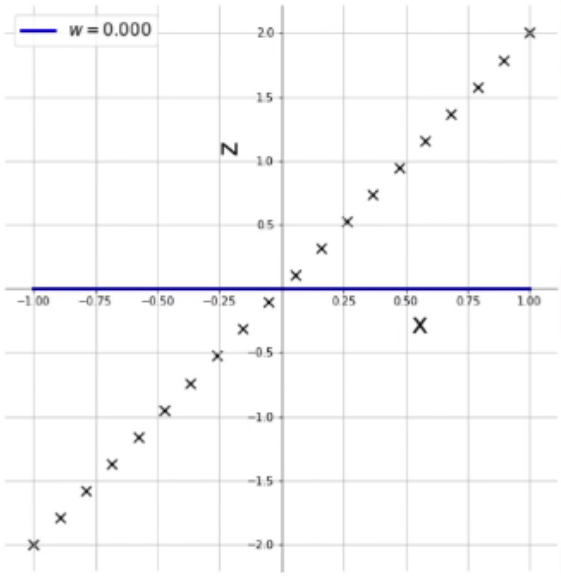
$$J(w) = \frac{1}{2m}\sum_{i=1}^{m}(z_i - wx_i)^2$$

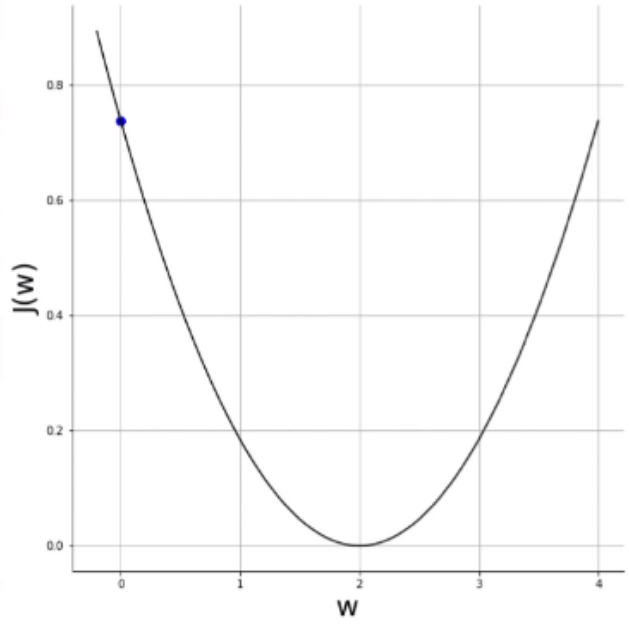


Gradient Descent – Initialization

$$Z = wX$$

$$J(w) = \frac{1}{2m}\sum_{i=1}^{m}(z_i - wx_i)^2$$

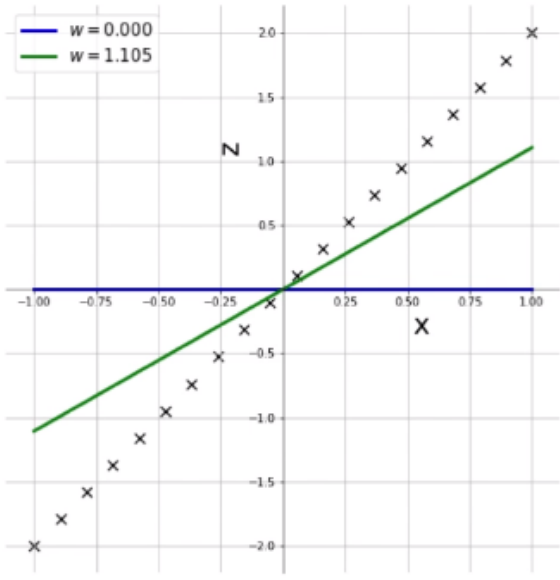


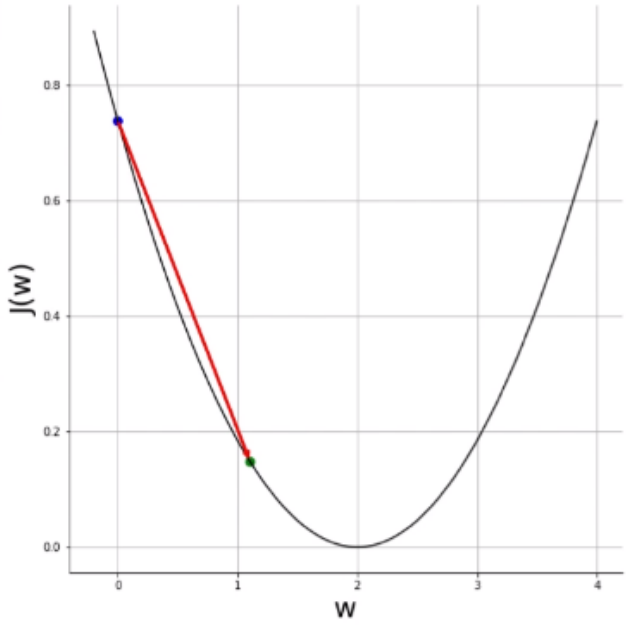


Gradient Descent – 1st Iteration

$$Z = wX$$

$$J(w) = \frac{1}{2m}\sum_{i=1}^{m}(z_i - wx_i)^2$$

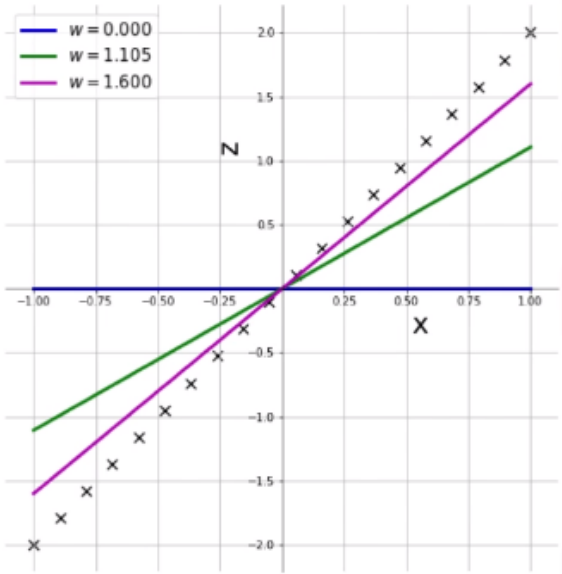


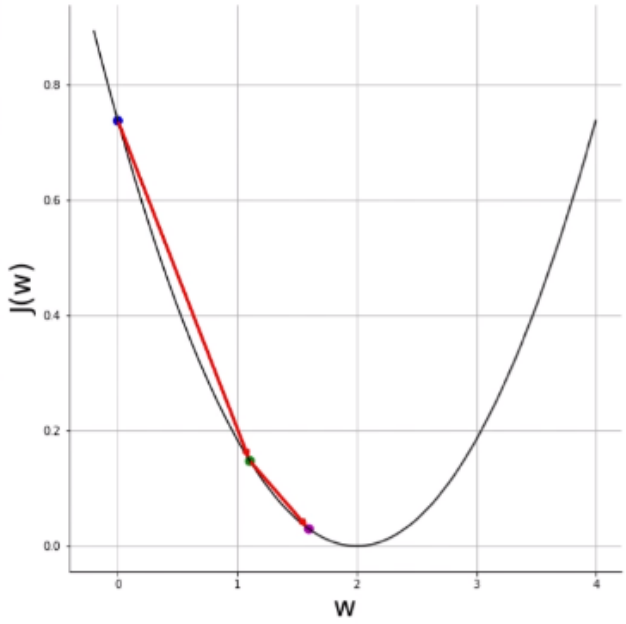


Gradient Descent – 2nd Iteration

$$Z = wX$$

$$J(w) = \frac{1}{2m}\sum_{i=1}^{m}(z_i - wx_i)^2$$

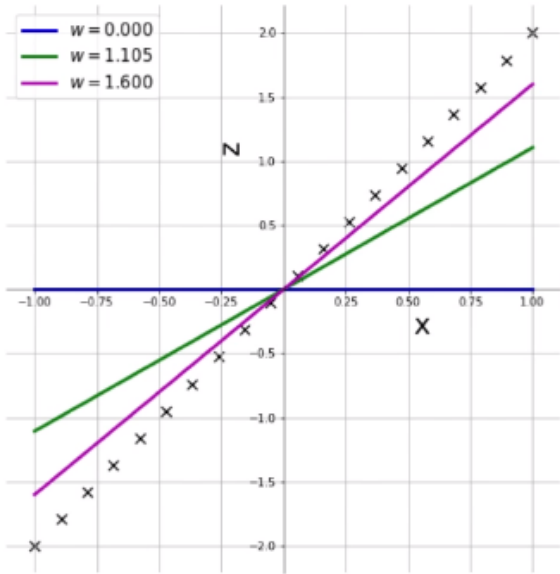


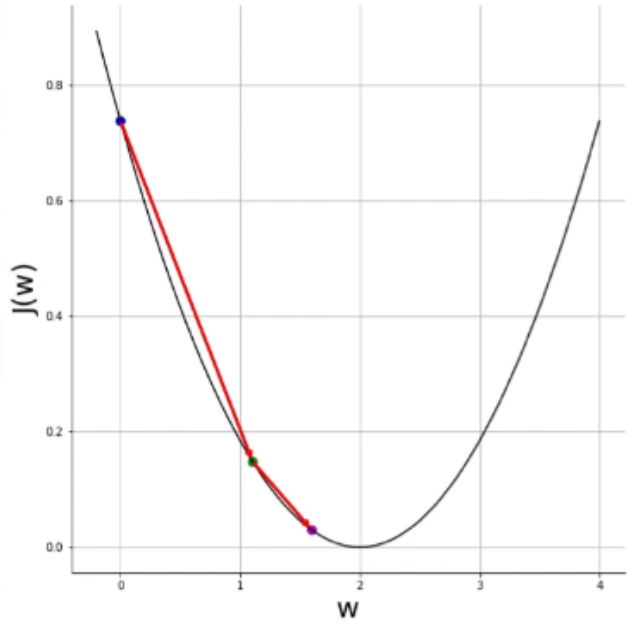


Gradient Descent – 2nd Iteration

$$Z = wX$$

$$J(w) = \frac{1}{2m}\sum_{i=1}^{m}(z_i - wx_i)^2$$

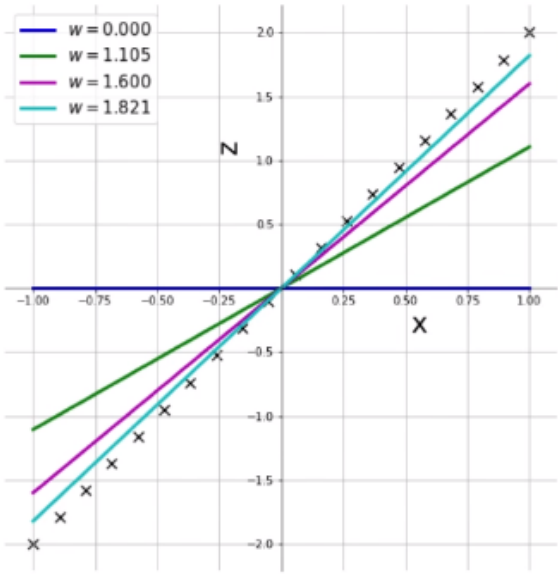


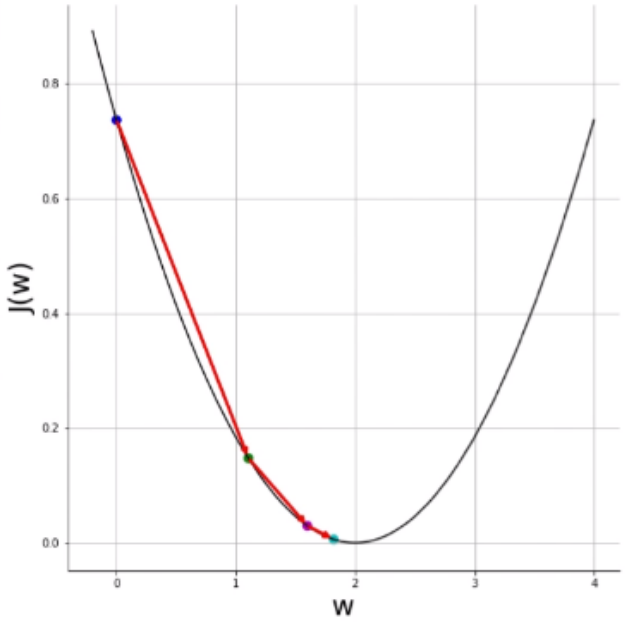


Gradient Descent – 3rd Iteration

$$Z = wX$$

$$J(w) = \frac{1}{2m}\sum_{i=1}^{m}(z_i - wx_i)^2$$

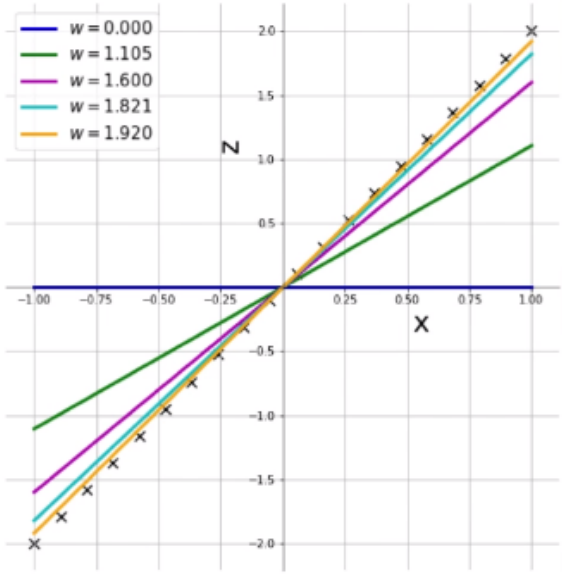


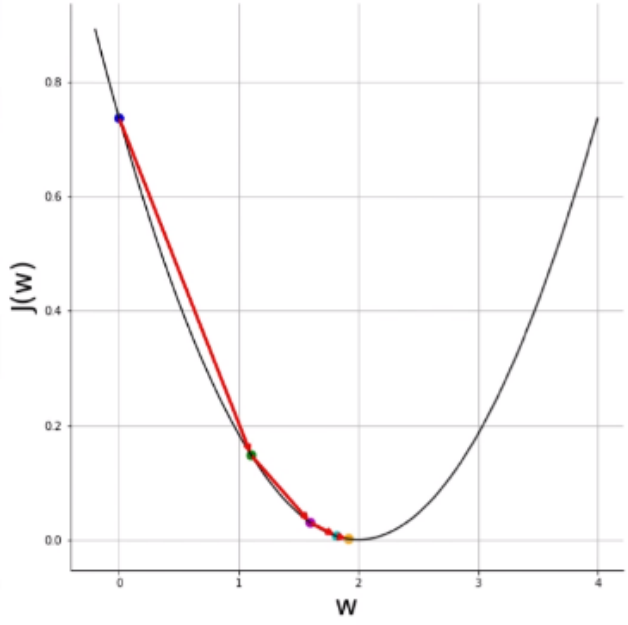


Gradient Descent – 4th Iteration

$$Z = wX$$

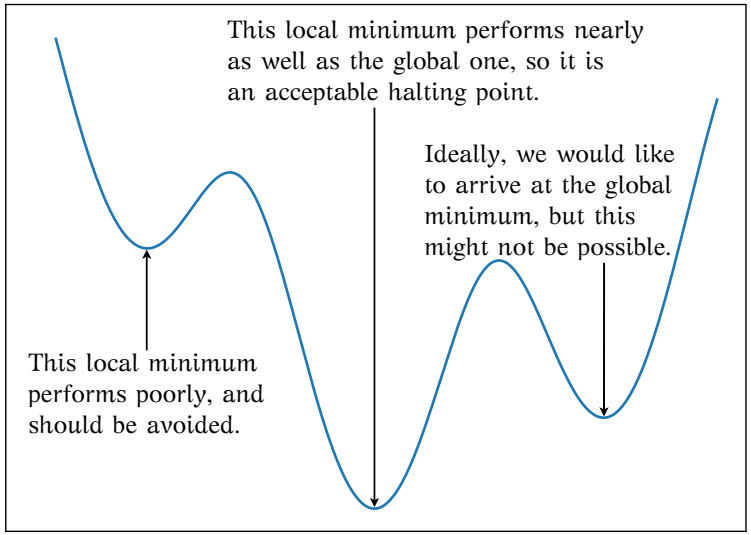
$$J(w) = \frac{1}{2m}\sum_{i=1}^{m}(z_i - wx_i)^2$$



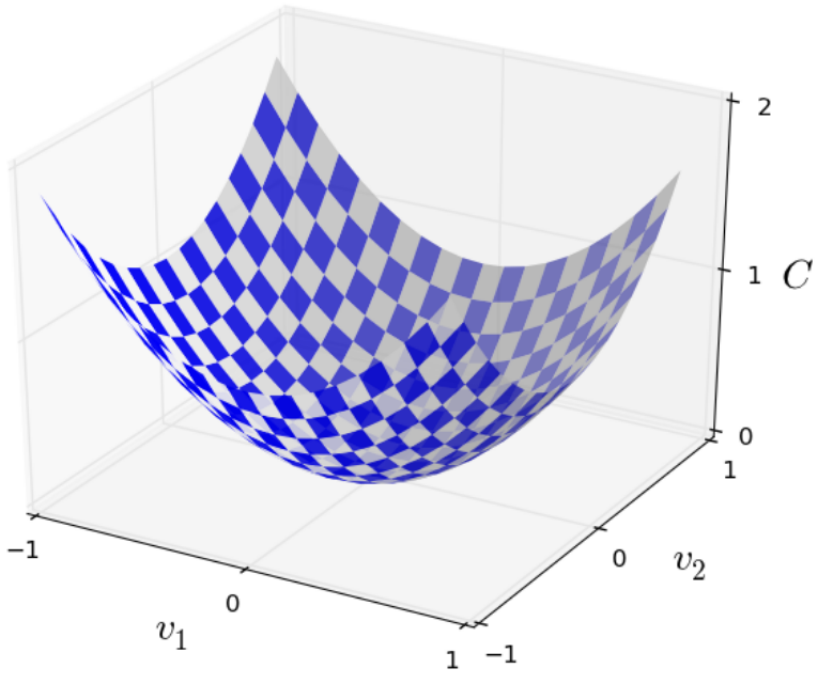


Critical points:

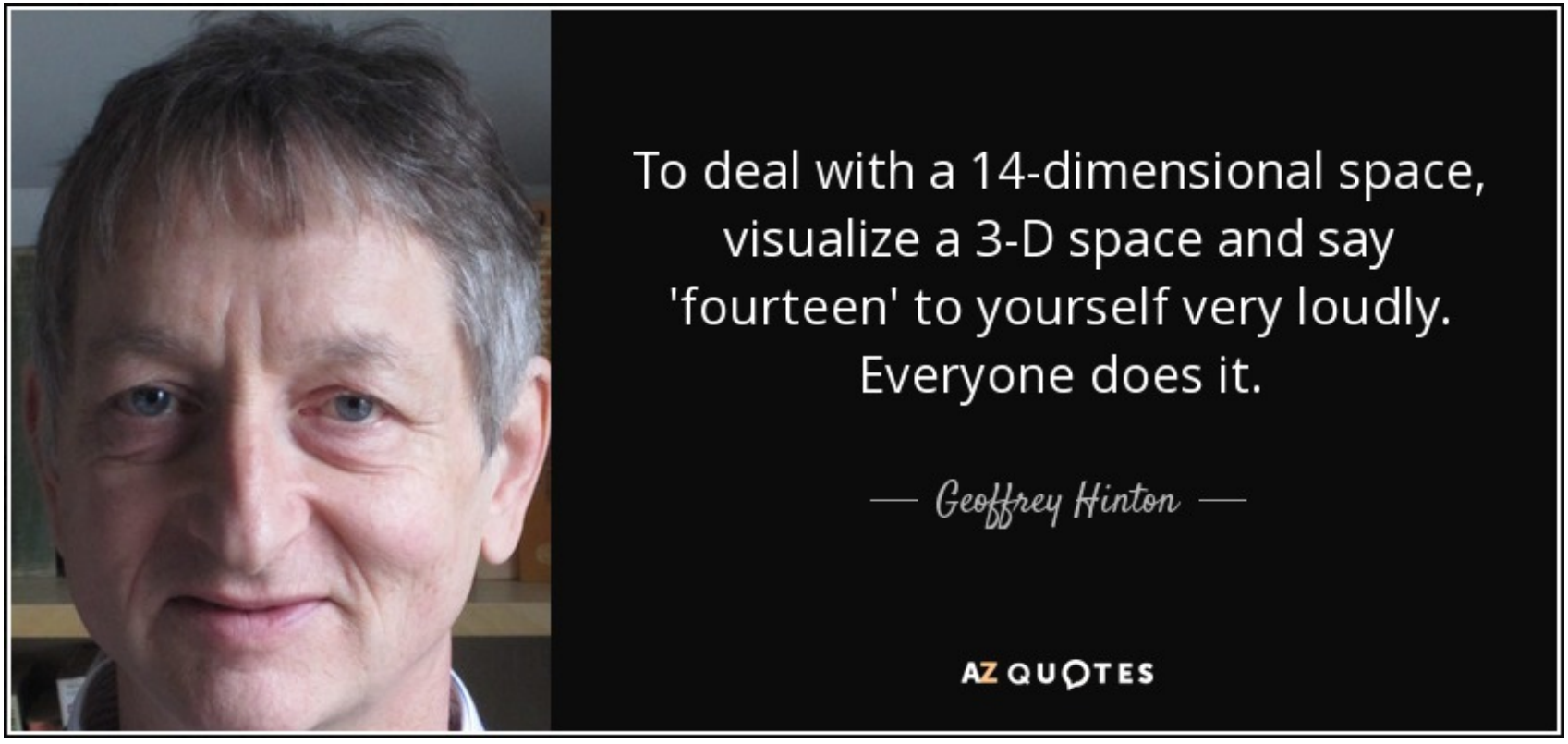
The cost functions may have many local minima that are not optimal.
This makes the optimization difficult, especially when the input is multidimensional.
Usually we settle for finding a value of f which is low, but not necessarily minimal.



Multidimensional inputs:



Usually we have multiple inputs and for that we use partial derivatives.
There is a partial derivative for each input variable.
The gradient of f is the vector containing all the partial derivatives $\nabla_x f(x)$. Element i of the gradient is the partial derivative of f with respect to x_i.
In multiple dimesions, critical points are these where every element of the gradient is equal to zero.


To deal with a 14-dimensional space, visualize a 3-D space and say 'fourteen' to yourself very loudly. Everyone does it.
— Geoffrey Hinton —
AZ QUOTES

Gradient descent:

To minimize f we need to find the direction in which f decreases the fastest.

We can find the direction using the directional derivative.

Moving in the direction of the negative gradient we can decrease f. This method is known as gradient descent.

$$x' = x - \epsilon \nabla_x f(x)$$

ϵ is the learning rate, a positive scalar determing the size of the step.

There are many ways to set the value of this parameter

Stochastic Gradient Descent:

Deep Learning needs large datasets which increase the computational cost of the gradient descent method.

For the cost function:

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m} L(x^{(i)}, y^{(i)}, \theta)$$

the gradient descent method needs to calculate the:

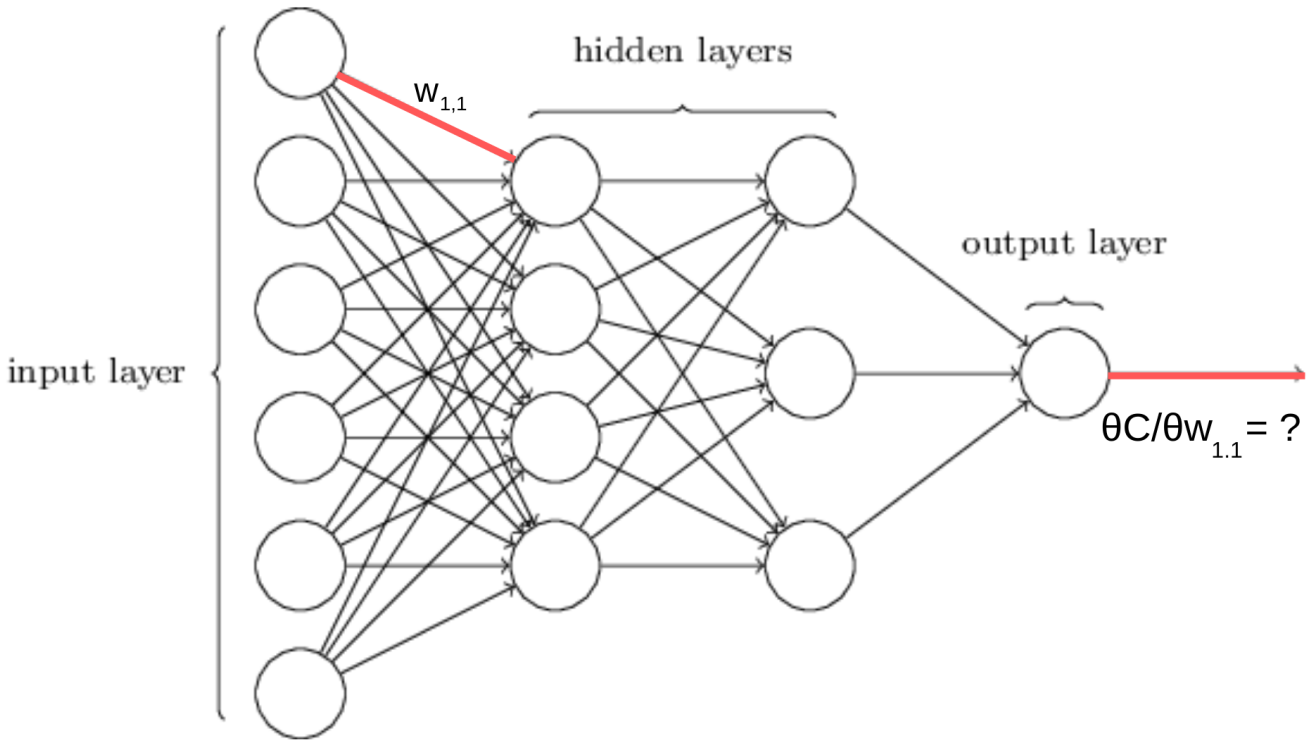
$$\nabla_\theta J(\theta) = \frac{1}{m}\sum_{i=1}^{m} \nabla_\theta L(x^{(i)}, y^{(i)}, \theta)$$

which is $O(m)$ However, the gradient is a prediction and because of that it can be an approximation using a small subset of the training dataset.

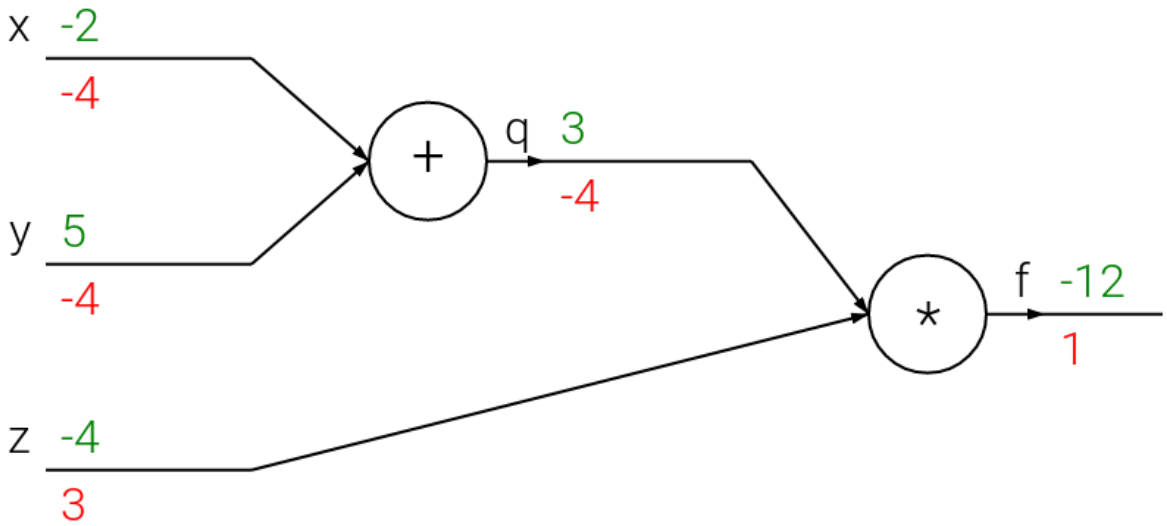
This is the Stochastic Gradient Descent methods which is an extension of the gradient descent.

So, how do we train a Multi Layer Perceptron?

$$w_{1.1}^{new} = w_{1.1}^{old} - \eta \frac{\partial C}{\partial w_{1.1}}$$



Back Propagation: PROPAGATE the errors BACK to the input weights!



Chain rule to the rescue!

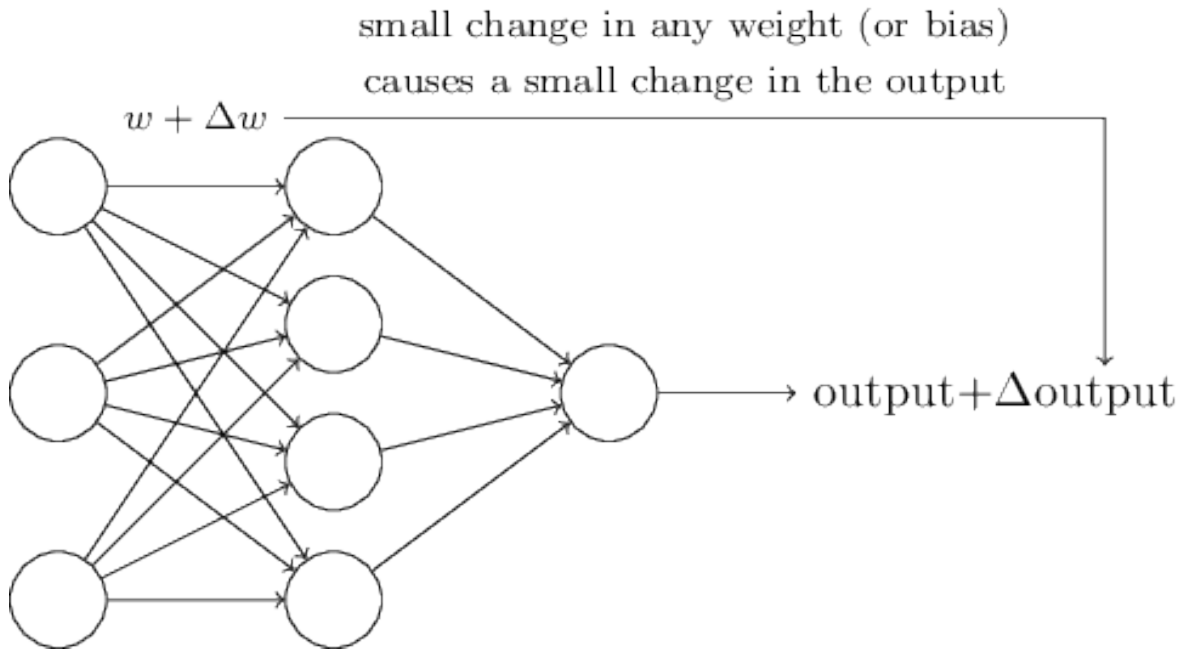
$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q}\frac{\partial q}{\partial x} = \frac{\partial (q \cdot z)}{\partial q}\frac{\partial (x + y)}{\partial x} = z \cdot 1 = z = -4$$

$$\frac{\partial f}{\partial z} = \frac{\partial (q \cdot z)}{\partial z} = q = 3$$

Sigmoid neurons - Sigmoid activation function

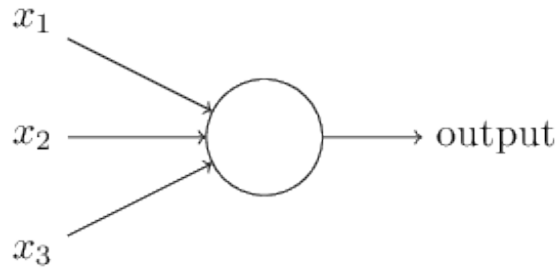
We want a small change in weight to cause only a small corresponding change in the output from the network.

Not possible with perceptrons! - a small change in the weights or bias of any single perceptron in the network can sometimes cause the output of that perceptron to completely flip, say from 0 to 1

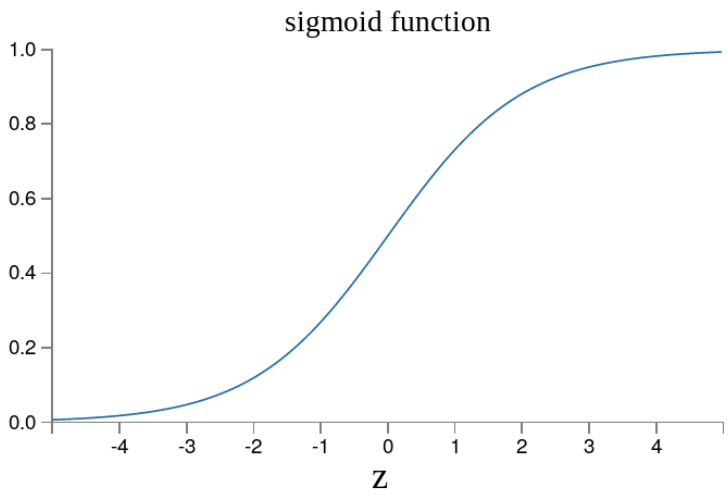


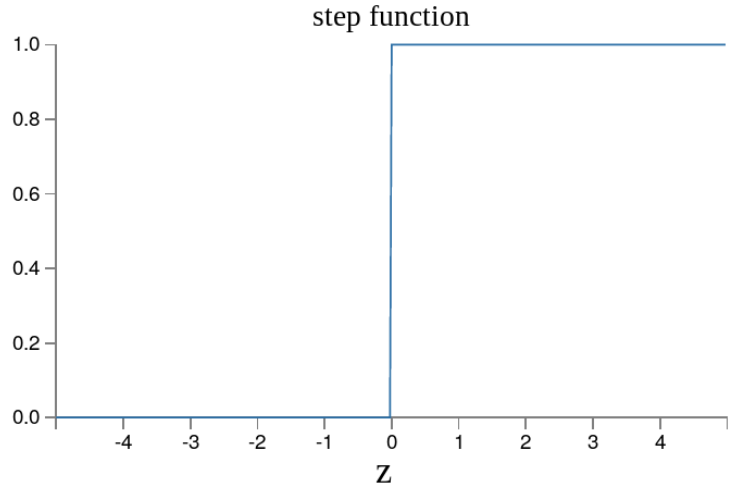
The ouputs of the sigmoid neuron is NOT 0 or 1.

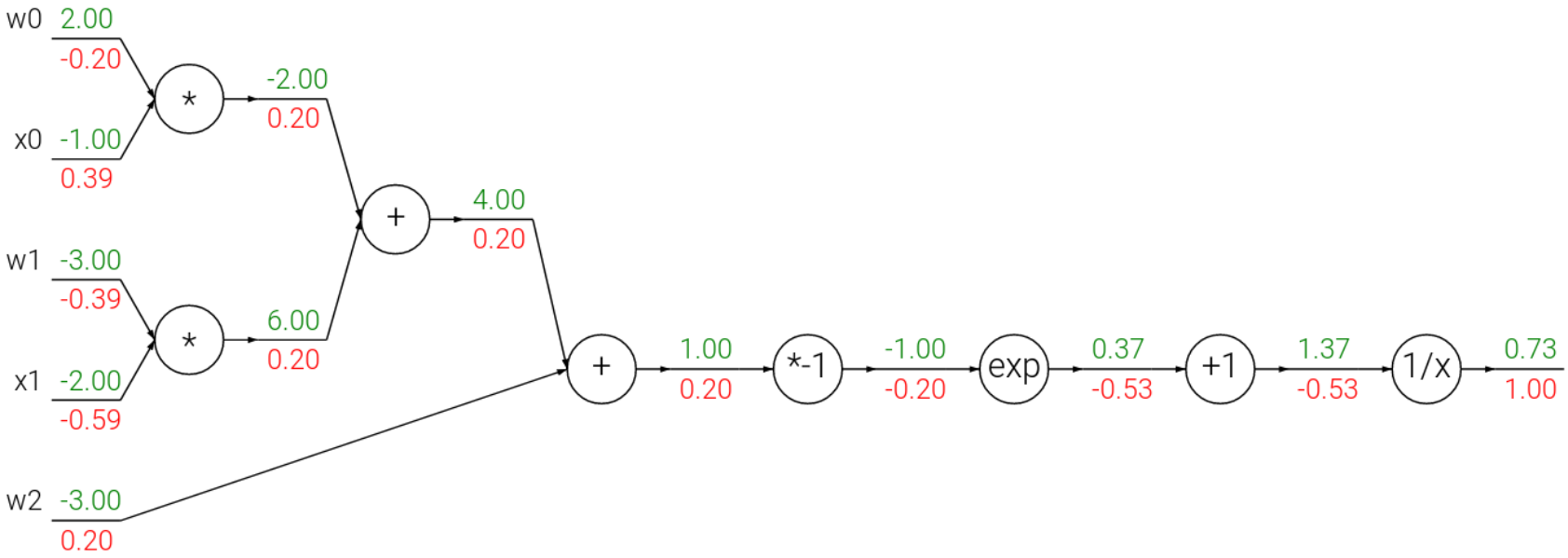
$output = \sigma(w \cdot x + b)$, where σ is the sigmoid function.



$$\sigma(z) = \frac{1}{1+e^{-z}} = \frac{1}{1+exp(-\sum_j w_j x_j - b)}$$







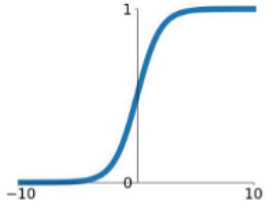
$q = w_0 \cdot x_0, \quad p = w_1 \cdot x_1, \quad s = q + p, \quad t = w_2 + s, \quad r = -t, \quad u = e^r,$
$v = u + 1$ and $z = \frac{1}{v}$

$$\frac{\partial z}{\partial w_0} = \frac{\partial z}{\partial v}\frac{\partial v}{\partial u}\frac{\partial u}{\partial r}\frac{\partial r}{\partial t}\frac{\partial t}{\partial s}\frac{\partial s}{\partial q}\frac{\partial q}{\partial w_0} =$$
$$-0.53 \cdot 1 \cdot 0.37 \cdot (-1) \cdot 1 \cdot 1 \cdot x_0 = -0.1961 \approx -0.20$$

Activation Functions

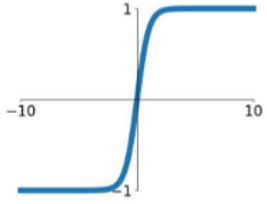
Sigmoid

$\sigma(x) = \frac{1}{1+e^{-x}}$



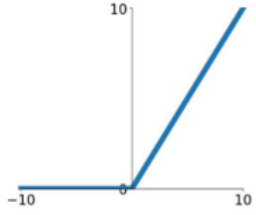
tanh

$\tanh(x)$



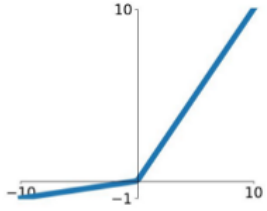
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$

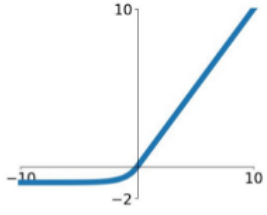


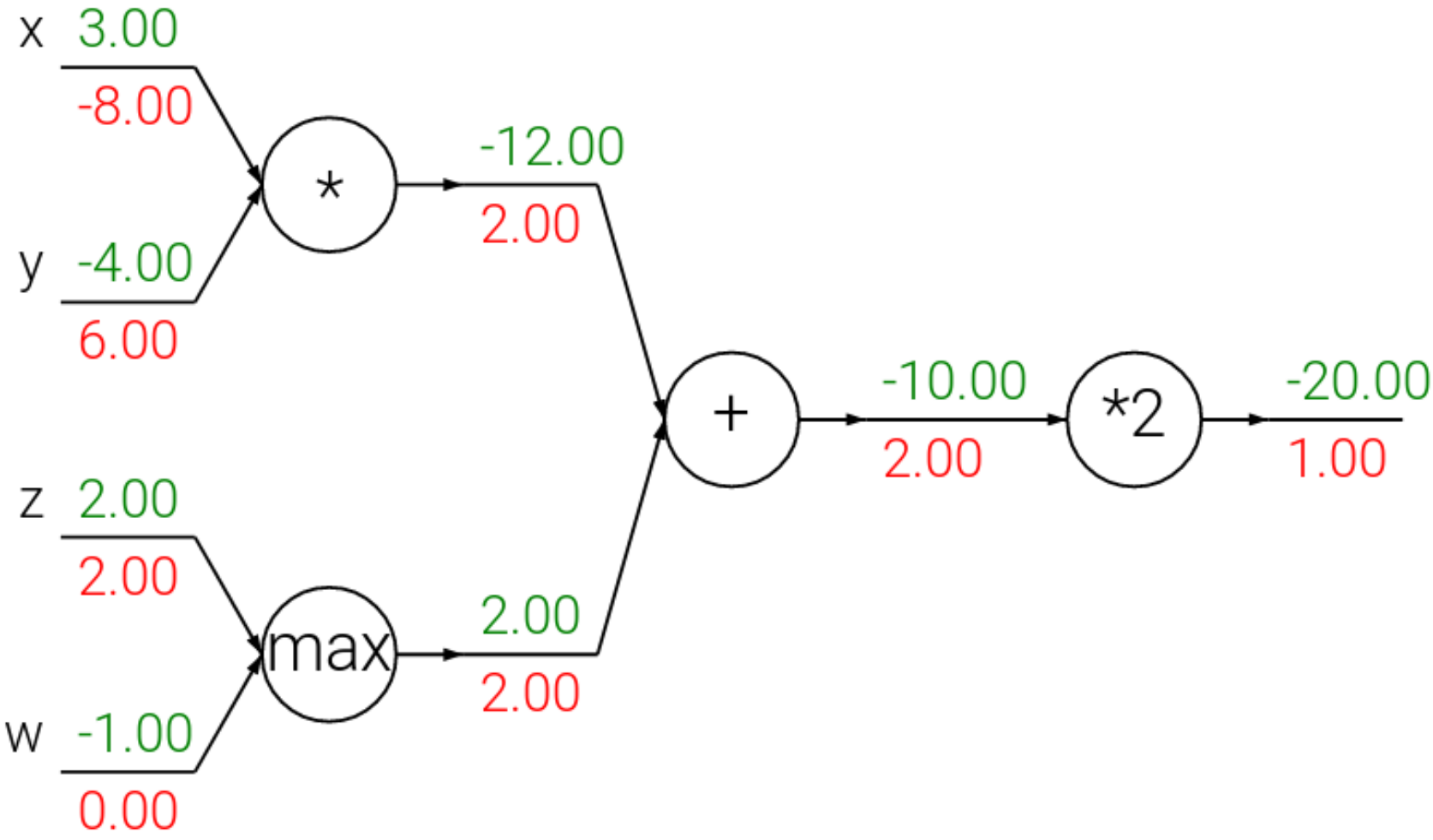
Maxout

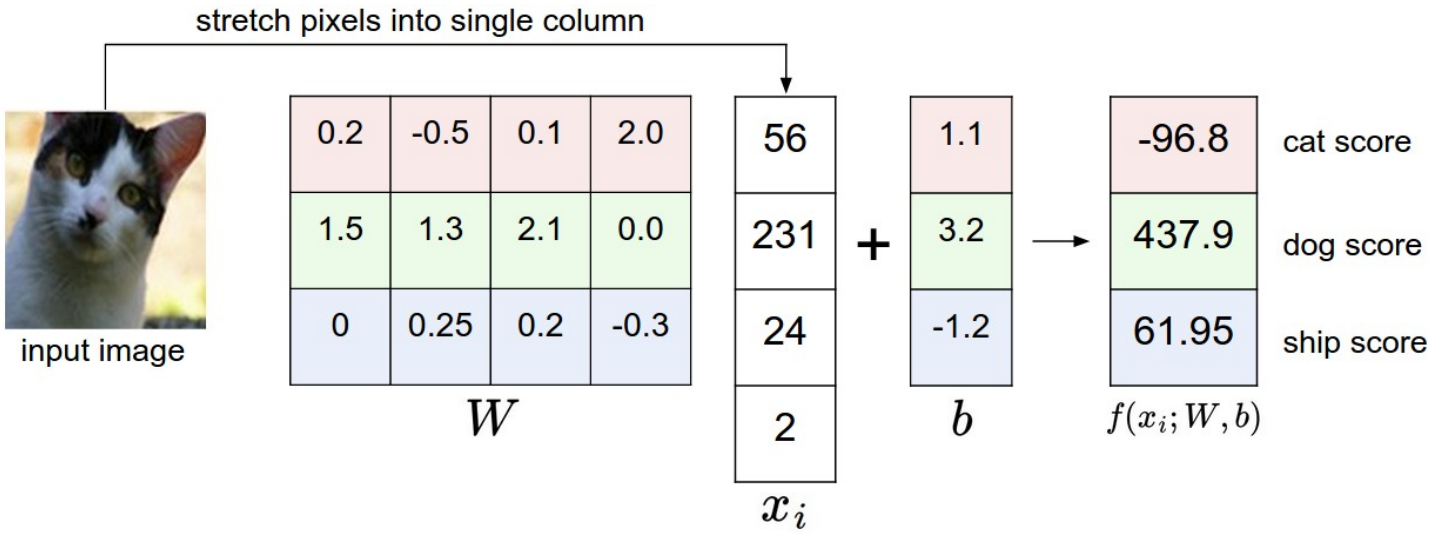
$\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



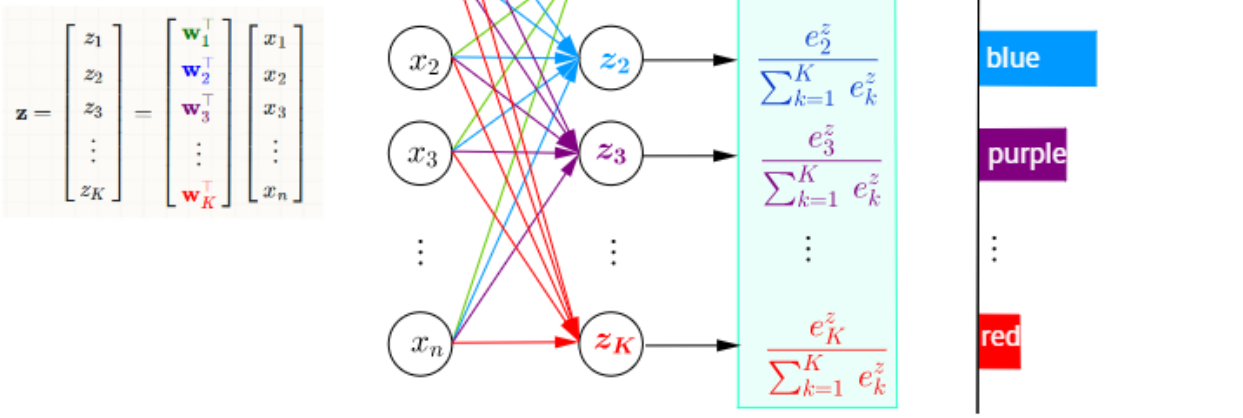

x
3.00
-8.00
y
-4.00
6.00
*
-12.00
2.00
z
2.00
2.00
w
-1.00
0.00
max
2.00
2.00
+
-10.00
2.00
*2
-20.00
1.00

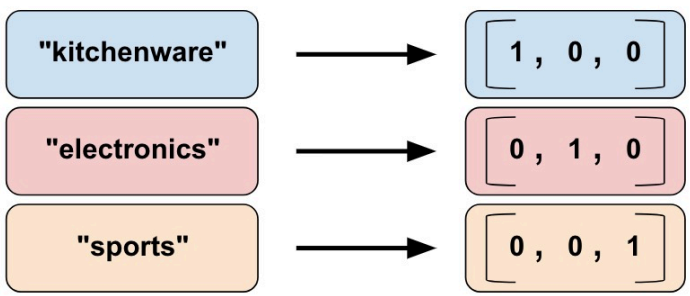


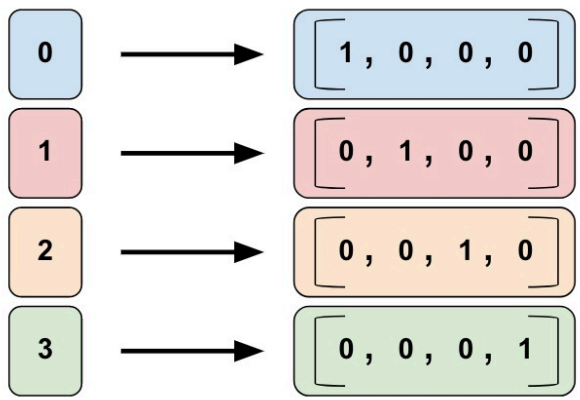
Softmax function

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

$$\begin{bmatrix} 1.2 \\ 0.9 \\ 0.4 \end{bmatrix} \rightarrow \boxed{\text{Softmax}} \rightarrow \begin{bmatrix} 0.46 \\ 0.34 \\ 0.20 \end{bmatrix}$$


bias
$z_j = \mathbf{w}_j^\top \cdot \mathbf{x}$
SoftMax
probabilities
green
blue
purple
red

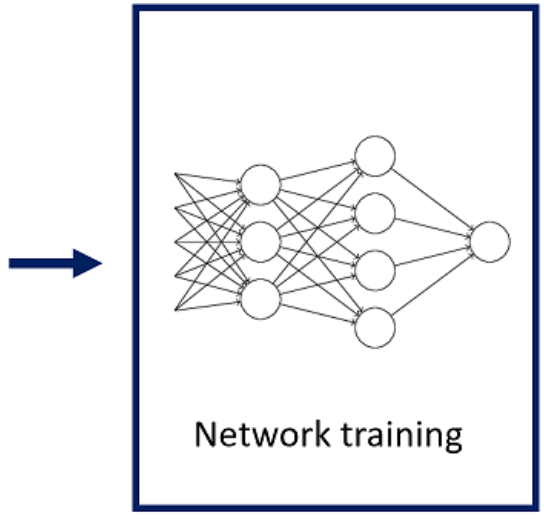

"kitchenware"
"electronics"
"sports"
1 , 0 , 0
0 , 1 , 0
0 , 0 , 1


0
1
2
3
1 , 0 , 0 , 0
0 , 1 , 0 , 0
0 , 0 , 1 , 0
0 , 0 , 0 , 1

https://cs.stanford.edu/people/karpathy/convnetjs/demo/classify2d.html


Ankle boot
T-shirt/top
T-shirt/top
Dress
T-shirt/top
Pullover
Sneaker
Pullover
Sandal
Sandal
T-shirt/top
Ankle boot
Sandal
Sandal
Sneaker
Ankle boot
Trouser
T-shirt/top
Shirt
Coat
Dress
Trouser
Coat
Bag
Coat

Data & Labels



0
1
2
3
4
5
6
7
8
9

HANDS ON: Fully Connected Networks

_____

2-Layer_Sigmoid_XOR.ipynb

Course 1 - Part 4 - Lesson 2 - Notebook_No_answers.ipynb

Course 1 - Part 4 - Lesson 4 - Notebook.ipynb (callbacks)

DL0101EN-3-2-Classification-with-Keras-py-v1.0.ipynb

DL0101EN-3-1-Regression-with-Keras-py-v1.0.ipynb

What is cross entropy?

172

Cross-entropy is commonly used to quantify the difference between two probability distributions. Usually the "true" distribution (the one that your machine learning algorithm is trying to match) is expressed in terms of a one-hot distribution.

For example, suppose for a specific training instance, the label is B (out of the possible labels A, B, and C). The one-hot distribution for this training instance is therefore:

```
Pr(Class A)  Pr(Class B)  Pr(Class C)
        0.0          1.0          0.0
```

You can interpret the above "true" distribution to mean that the training instance has 0% probability of being class A, 100% probability of being class B, and 0% probability of being class C.

Now, suppose your machine learning algorithm predicts the following probability distribution:

```
Pr(Class A)  Pr(Class B)  Pr(Class C)
      0.228        0.619        0.153
```

How close is the predicted distribution to the true distribution? That is what the cross-entropy loss determines. Use this formula:

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

Where `p(x)` is the wanted probability, and `q(x)` the actual probability. The sum is over the three classes A, B, and C. In this case the loss is **0.479** :

```
H = - (0.0*ln(0.228) + 1.0*ln(0.619) + 0.0*ln(0.153)) = 0.479
```

So that is how "wrong" or "far away" your prediction is from the true distribution.

What is cross entropy?

Cross entropy is one out of many possible loss functions (another popular one is SVM hinge loss). These loss functions are typically written as J(theta) and can be used within gradient descent, which is an iterative algorithm to move the parameters (or coefficients) towards the optimum values. In the equation below, you would replace `J(theta)` with `H(p, q)`. But note that you need to compute the derivative of `H(p, q)` with respect to the parameters first.

$$\text{Repeat until convergence } \{$$

$$\theta_j \leftarrow \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

$$\}$$

So to answer your original questions directly:

> Is it only a method to describe the loss function?

Correct, cross-entropy describes the loss between two probability distributions. It is one of many possible loss functions.

> Then we can use, for example, gradient descent algorithm to find the minimum.

Yes, the cross-entropy loss function can be used as part of gradient descent.

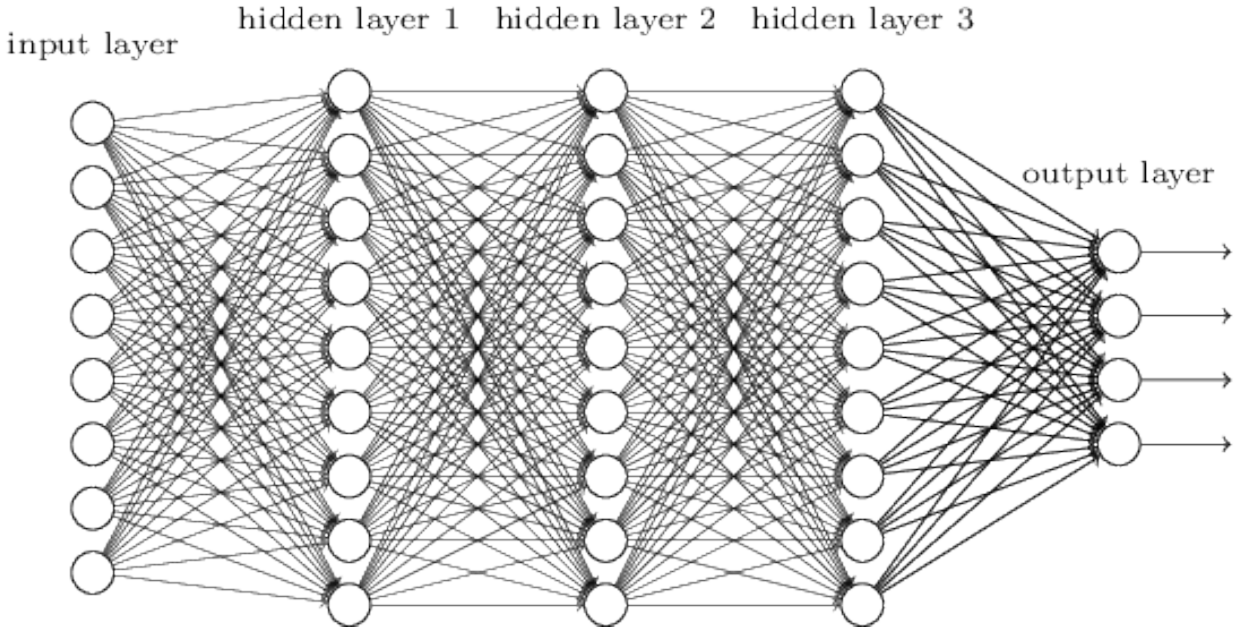
Recap

- Neural Networks are made up of neurons that have learnable weights and biases.
- Each neuron receives some inputs, performs a dot product and usually follows it with a non-linearity.
- The whole network still expresses a single differentiable score function: from the raw input data on one end to class scores at the other - the network transforms the input through a series of hidden layers
- Each hidden layer is made up of a set of neurons, where each neuron is fully connected to all neurons in the previous layer, and where neurons in a single layer function completely independently and do not share any connections.
- The last fully-connected layer is called the “output layer” and in classification settings it represents the class scores.
- And networks have a loss function on the last layer.

Convolutional Neural Networks (CNNs

- Convolutional Neural Networks are very similar to ordinary Neural Networks
- BUT CNN architectures make the explicit assumption that the inputs are images
- vastly reduce the amount of parameters in the network.

Fully Connected neural nets can recognize images of handwritten digits.



Input: 28 x 28 pixels = 784 neurons

Output: 10 neurons (10 classes)

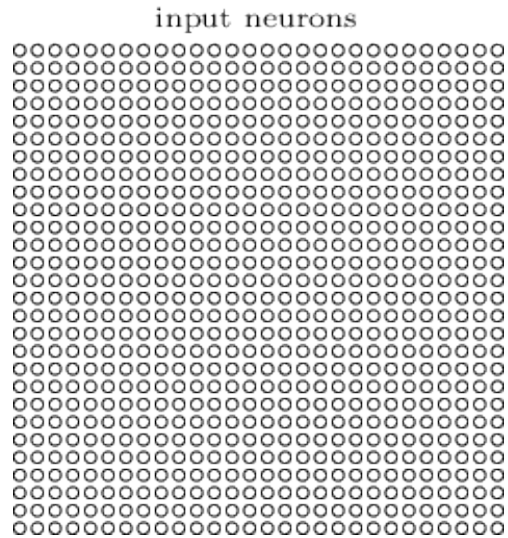
images aka 2D aka spatial structure
BUT a FC model does not take into account this spatial structure of the images.

Convolutional neural networks use three basic ideas:

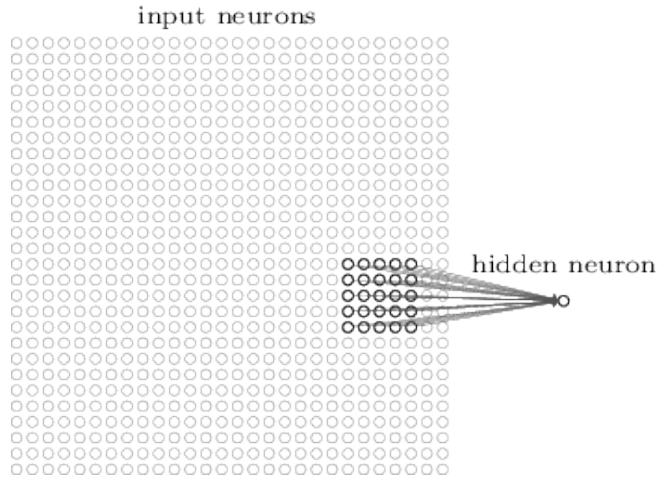
- local receptive fields
- shared weights
- pooling

Local receptive fields

Think of the input (image) as 28 x 28 square of neurons

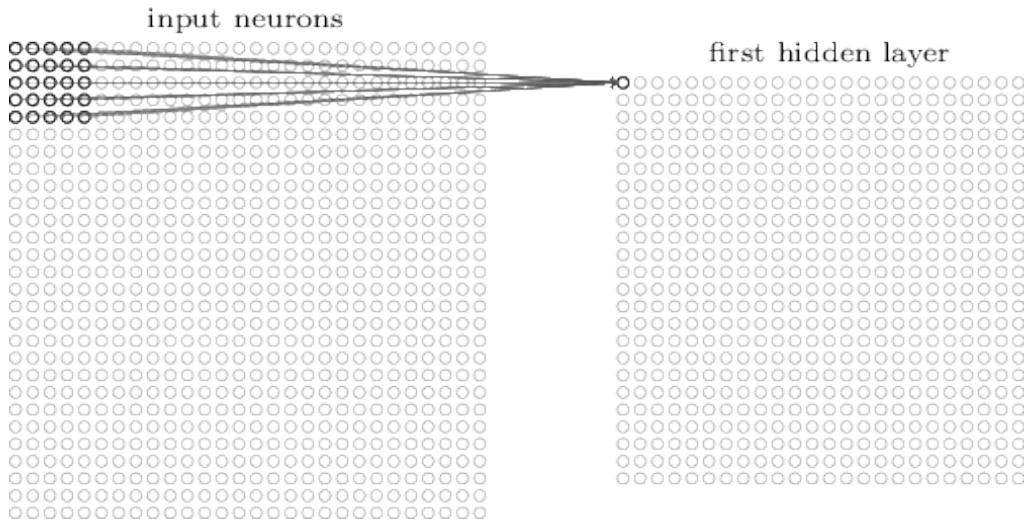


We connect the inputs pixels to a layer of hidden neurons.
Each neuron in the first hidden layer will be connected to a small region of the input neurons, e.g. a 5×5 region, corresponding to 25 input pixels.



- Each connection learns a weight.
- The hidden neuron learns an overall bias.
- We slide the local receptive field across the entire input image.
- For each local receptive field, there is a different hidden neuron in the first hidden layer.

If we have a 28×28 input image, and 5×5 local receptive fields, then there will be 24×24 neurons in the hidden layer.



Shared weights and biases

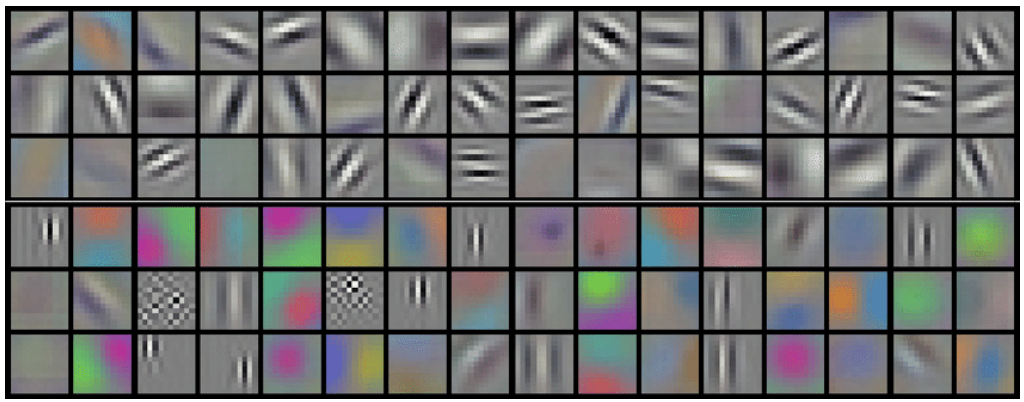
Each hidden neuron has a bias and 5 x 5 weights connected to its local receptive field.
!!! Each of the 24 x 24 hidden neuron in the first hidden layer uses the smae weights and bias!

$$\sigma\left(b + \sum_{l=0}^{4}\sum_{m=0}^{4} w_{l,m} a_{j+l,k+m}\right).$$

where σ is the activation function, b is the shared bias, $w_{l,m}$ is the 5 x 5 array of shared weights and $a_{x,y}$ the input activation at position x, y.
This 5 x 5 weight (+ bias) array is defines a **kernel** or **filter**.

What does this mean???

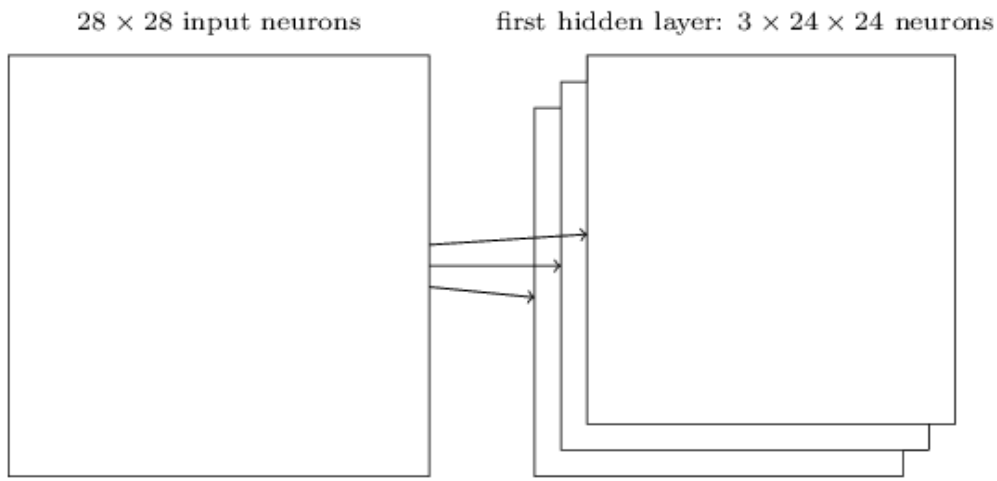
All the neurons in the first hidden layer detect exactly the same **feature**. *(think of the feature detected by a hidden neuron as the kind of input pattern that will cause the neuron to activate: it might be an edge in the image, for instance, or maybe some other type of shape.)*



Example filters by Krizhevsky et al. Because these filters were learned using the first convolutional layer of the neural network, the represented features are simple, such as the edge orientation and frequency

The filters extract features (e.g. edges).
=> **A filter is a feature detector!!!**

For this reason, we sometimes call the map from the input layer to the hidden layer a **feature map**.
To do image recognition we'll need more than one feature map.

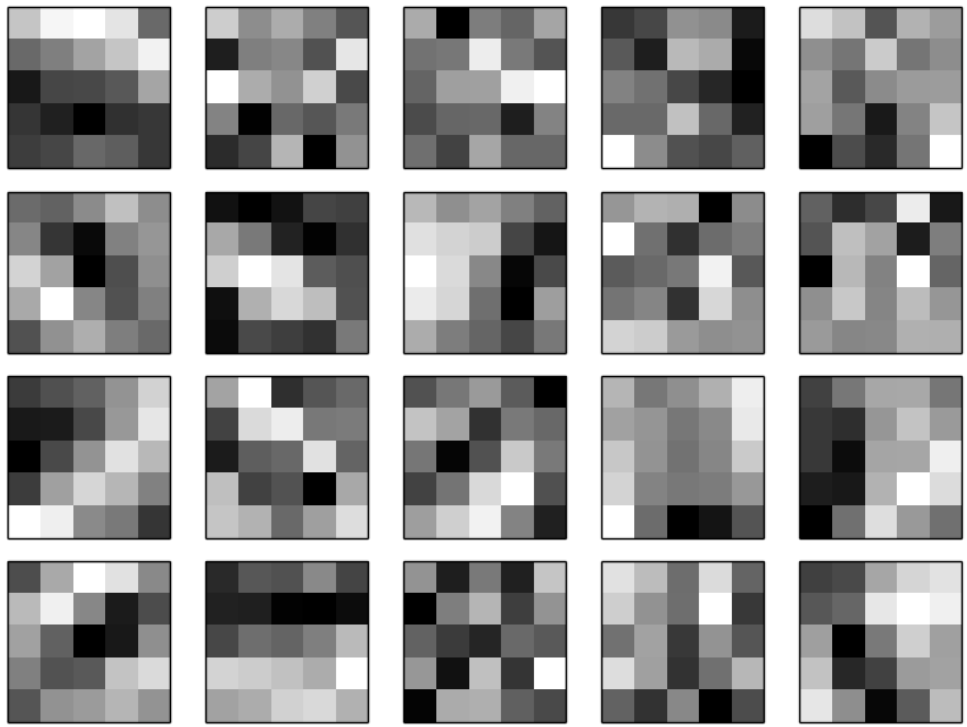


3 feature maps means the network can detect 3 different kinds of features.

The 20 images correspond to 20 different feature maps (or filters, or kernels). Each map is represented as a 5×5 block image, corresponding to the 5×5 weights in the local receptive field.

Whiter blocks mean a smaller (typically, more negative) weight, so the feature map responds less to corresponding input pixels.

Darker blocks mean a larger weight, so the feature map responds more to the corresponding input pixels.



Sharing weights and biases greatly reduces the number of parameters involved!

CNN

5 x 5 (weights) + 1 (bias) = 26 parameters for each feature map.

20 feature maps

Total: 20 x 26=520 parameters defining the convolutional layer.

FCN

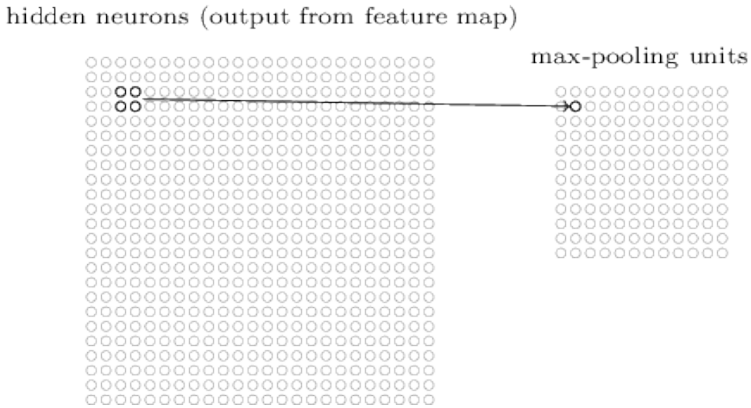
28×28 = 784 input neurons

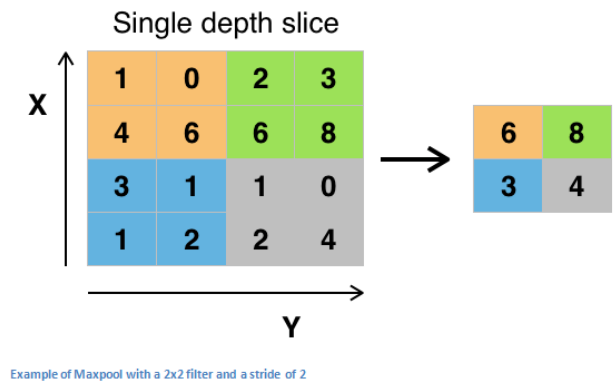
30 hidden neurons

Total: 784 x 30 (weights) + 30 (biases) = 23,550 parameters > 40 x 520!!!

Pooling

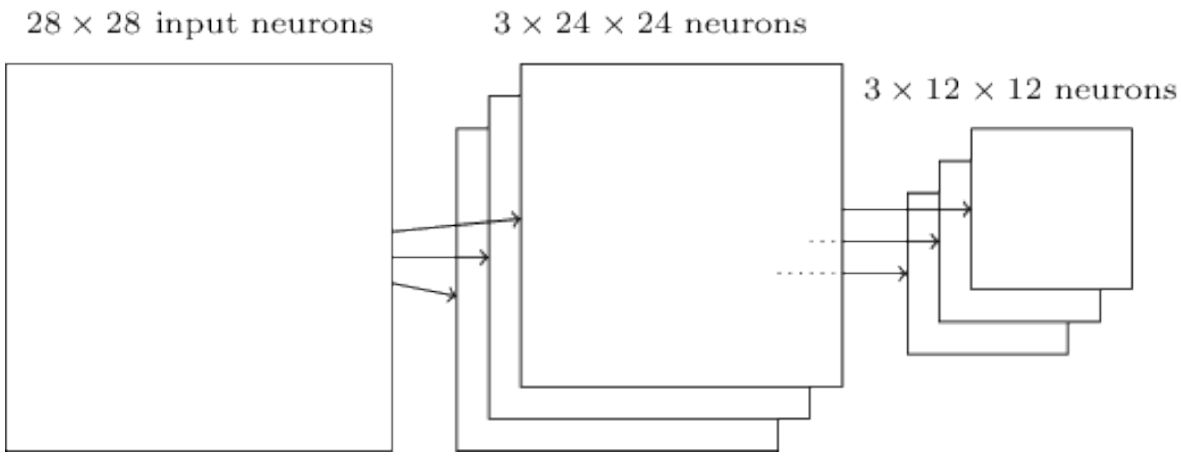
- Usually used immediately after convolutional layers.
- Simplify the information in the output from the convolutional layer





(Many pooling techniques: Max-Pooling, Avg-Pooling, L2-Pooling, etc.)

We apply max-pooling to each feature map separately.



Intuition: Once a feature has been found, its exact location isn't as important as its rough location relative to other features.

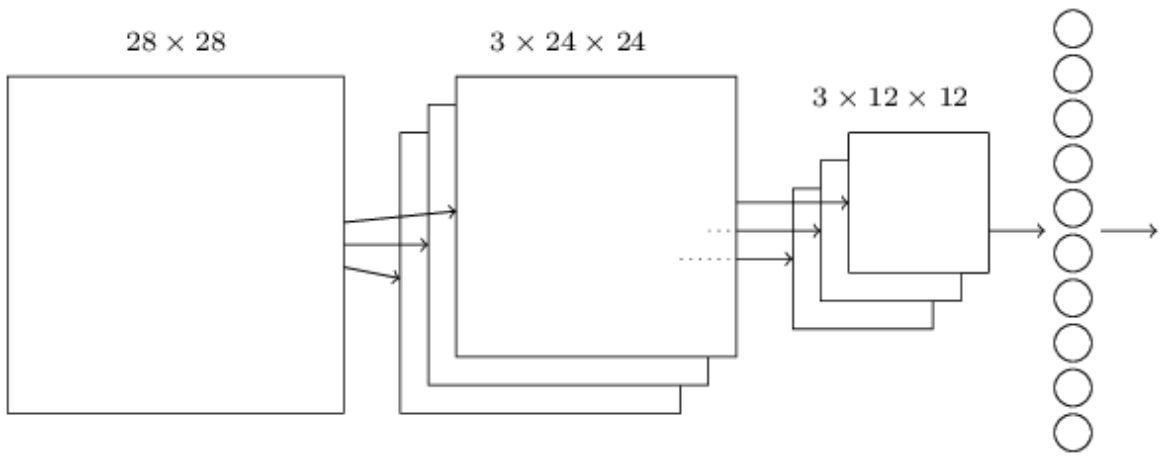
This (among other things) makes CNNs invariant to image translation: move a picture of a cat a little ways, and it's still an image of a cat.

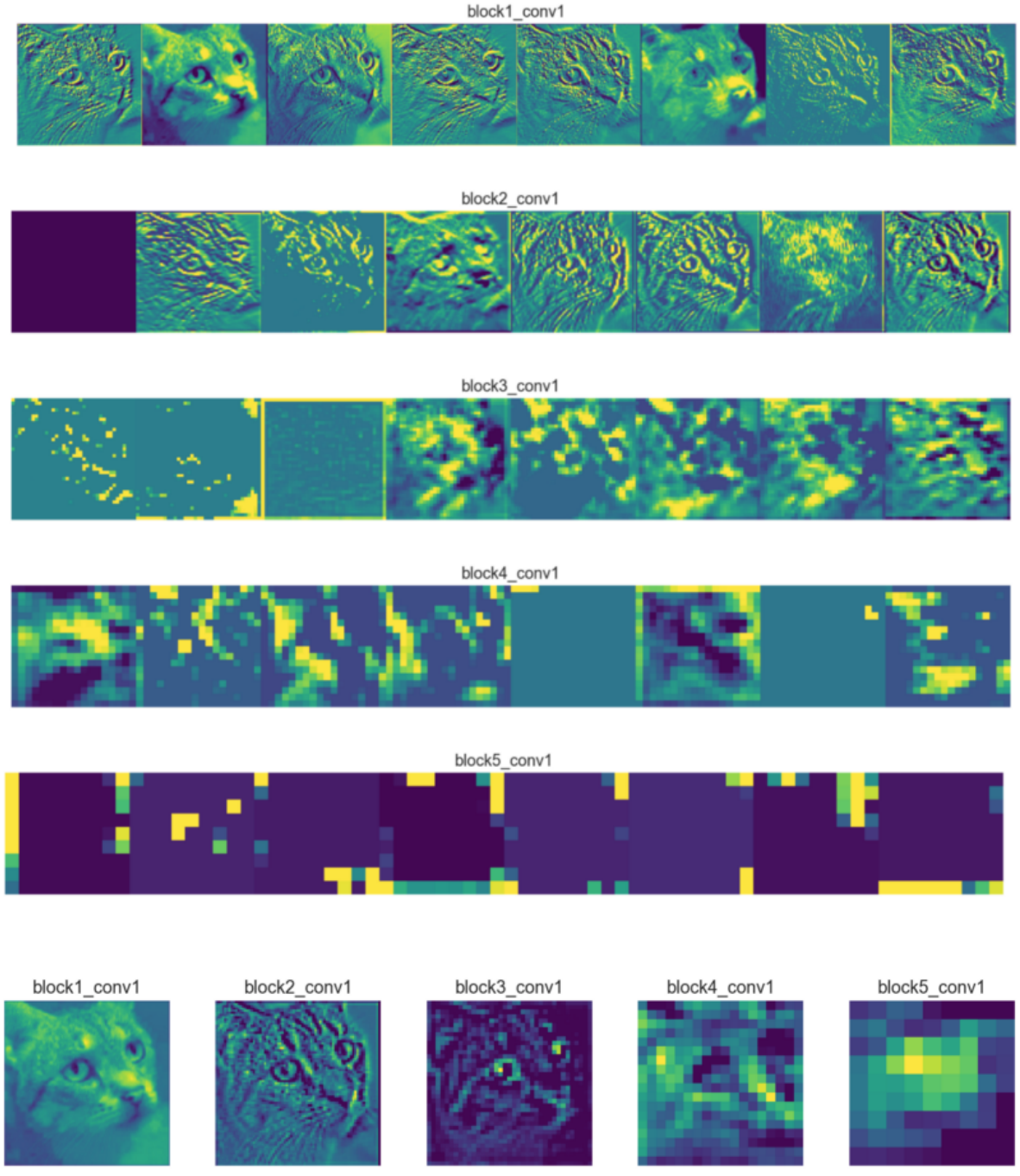
Putting it all together

28×28 input neurons (MNIST), followed by a convolutional layer using a 5×5 local receptive field and 3 feature maps. The result is a layer of 3×24×24 hidden feature neurons.

Max-pooling layer, applied to 2×2 regions, across each of the 3 feature maps. The result is a layer of 3×12×12 hidden feature neurons.

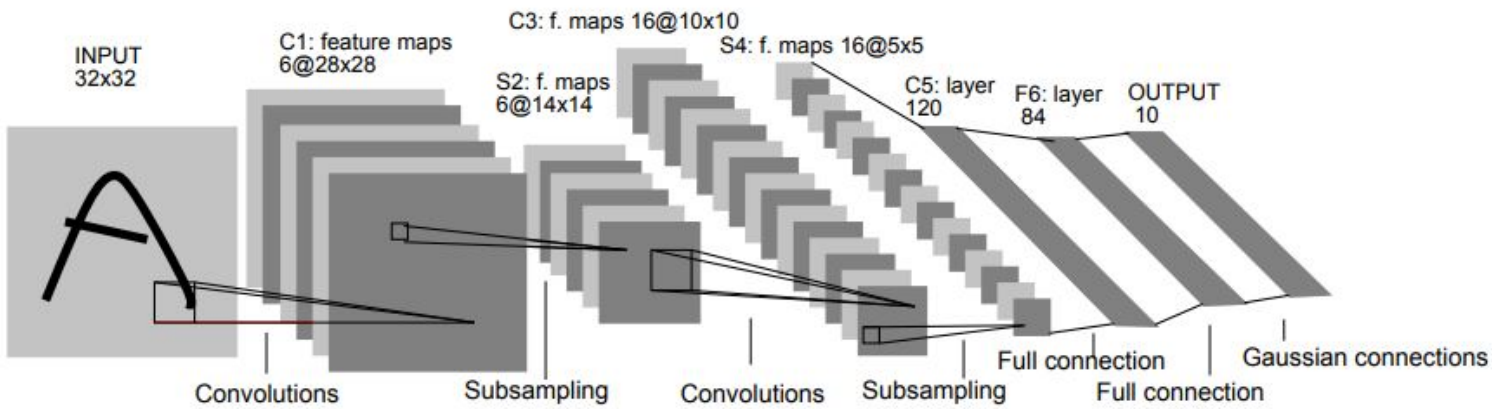
The final layer of connections in the network is a fully-connected layer - 10 output neurons.




block1_conv1
block2_conv1
block3_conv1
block4_conv1
block5_conv1
block1_conv1
block2_conv1
block3_conv1
block4_conv1
block5_conv1

Le-Net 5 [1998]

Yann LeCun, Leon Bottou, Yosuha Bengio and Patrick Haffner proposed a neural network architecture for handwritten and machine-printed character recognition in 1990’s which they called LeNet-5.



HANDS ON: CNN

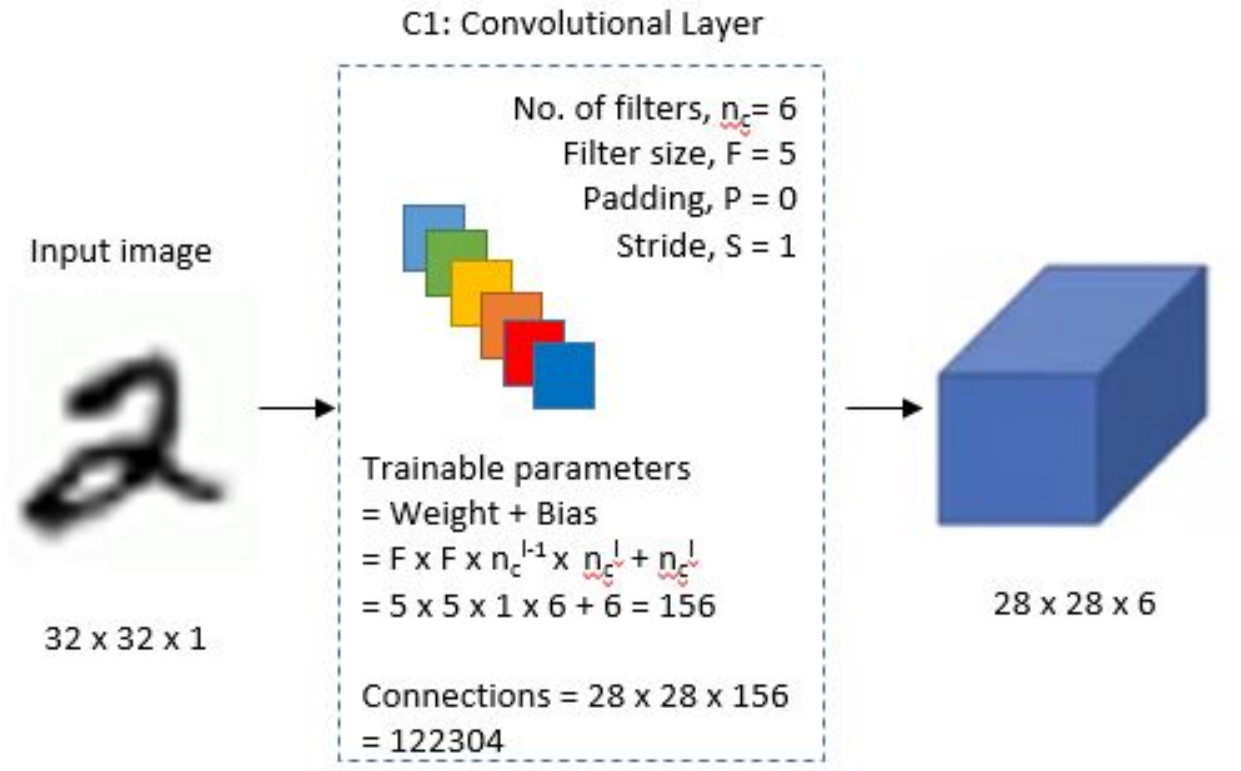
DL0101EN-4-1-Convolutional-Neural-Networks-with-Keras-py-v1.0.ipynb

Course 1 - Part 6 - Lesson 2 - Notebook.ipynb

Course 1 - Part 6 - Lesson 3 - Notebook.ipynb (basic conv)

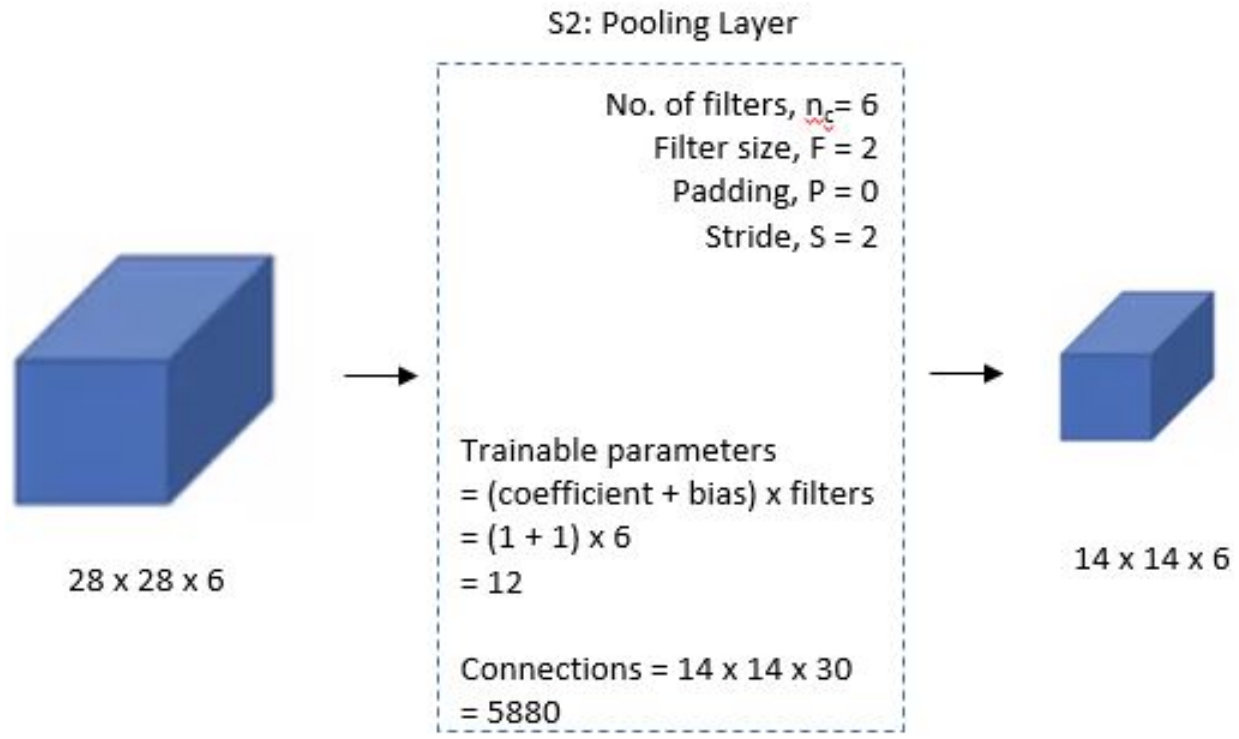
Le-Net 5 - First Layer

The input for LeNet-5 is a 32×32 grayscale image which passes through the first convolutional layer with 6 feature maps or filters having size 5×5 and a stride of one. The image dimensions changes from 32x32x1 to 28x28x6.



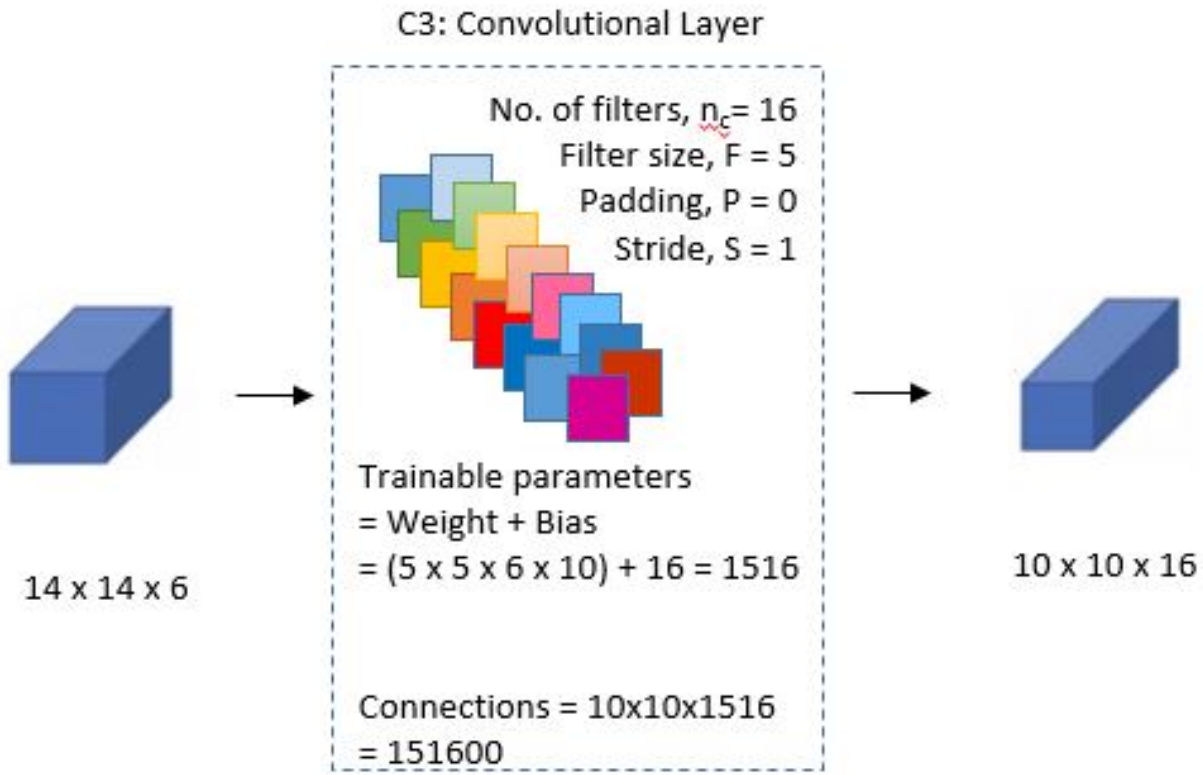
Le-Net 5 - Second Layer

Then the LeNet-5 applies average pooling layer or sub-sampling layer with a filter size 2×2 and a stride of two. The resulting image dimensions will be reduced to 14x14x6.



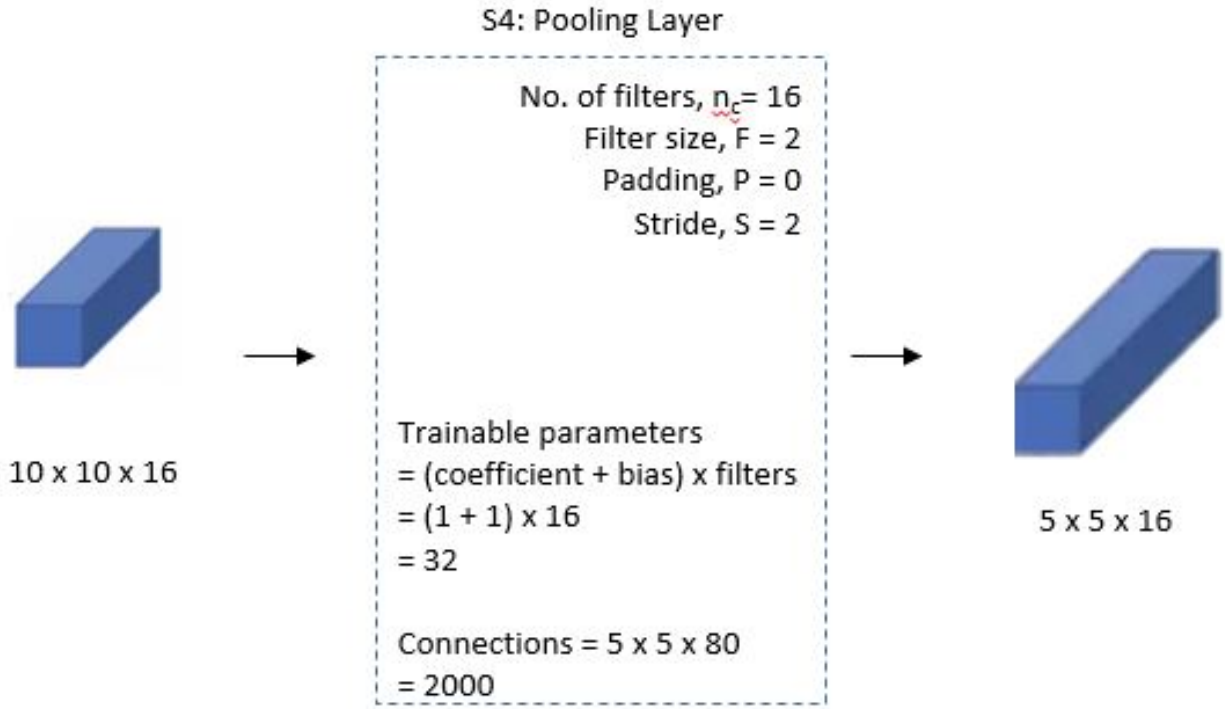
Le-Net 5 - Third Layer

Next, there is a second convolutional layer with 16 feature maps having size 5×5 and a stride of 1.



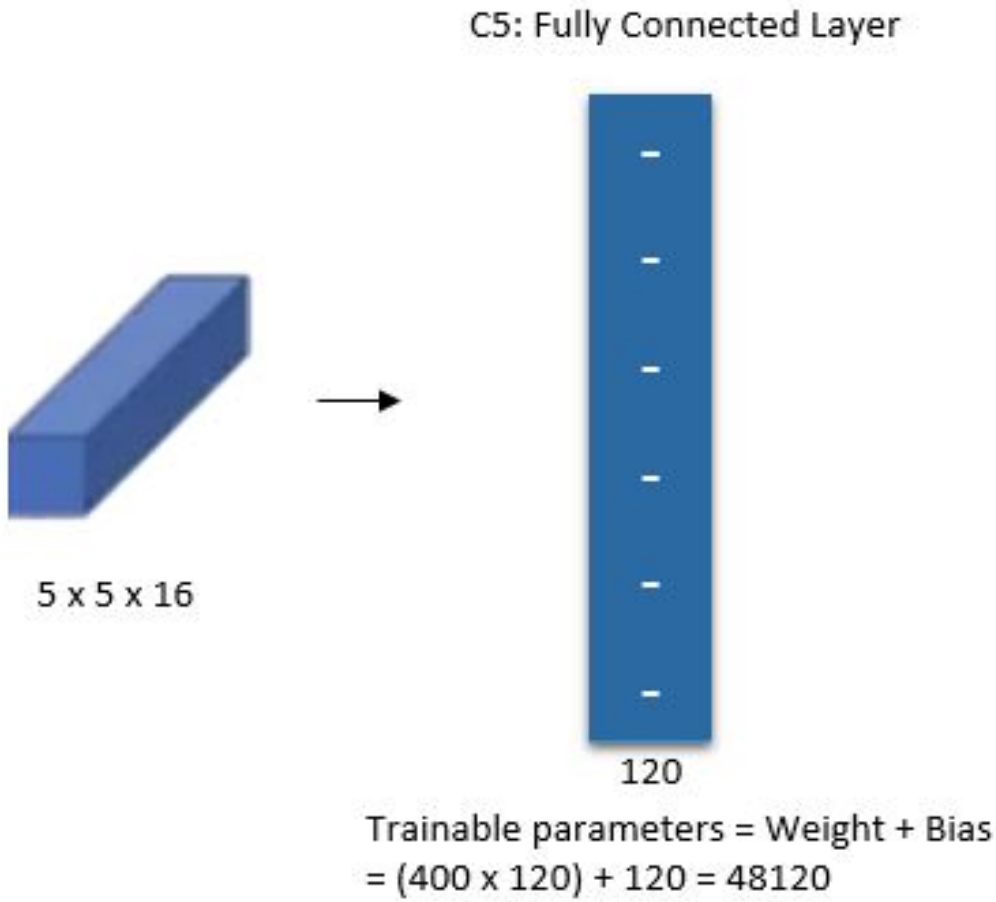
Le-Net 5 - Fourth Layer

The fourth layer (S4) is again an average pooling layer with filter size 2×2 and a stride of 2. This layer is the same as the second layer (S2) except it has 16 feature maps so the output will be reduced to 5x5x16.



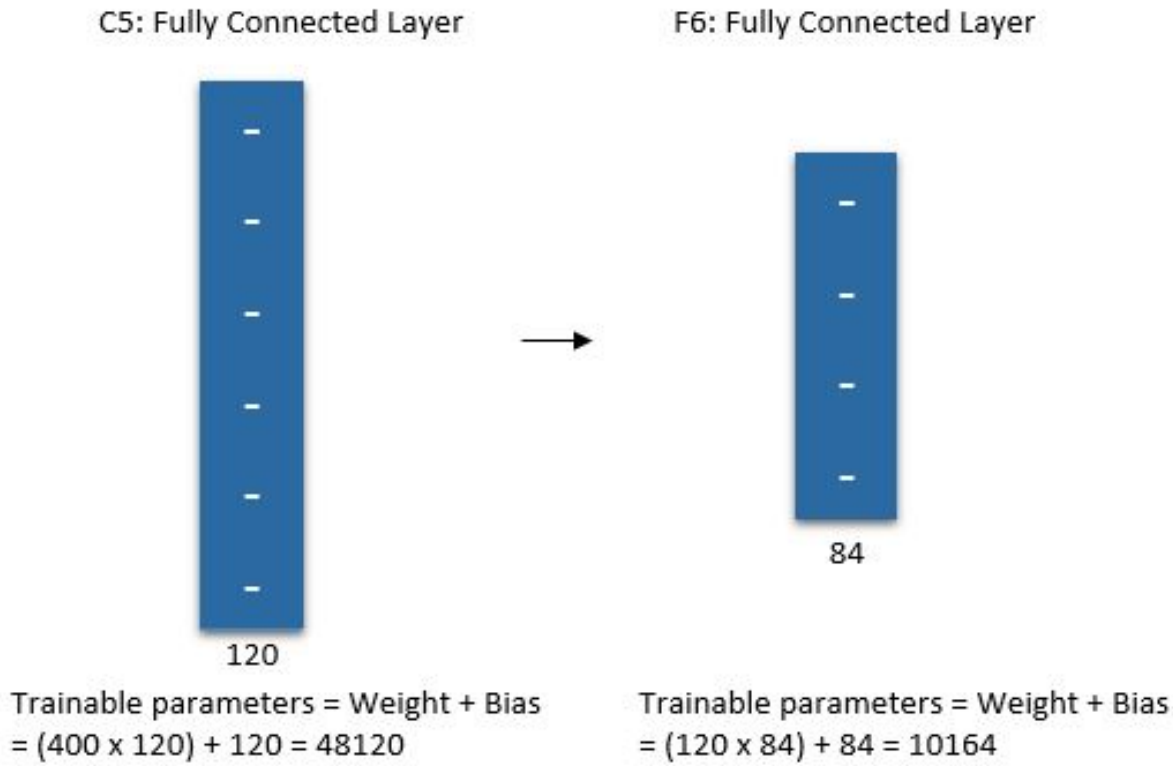
Le-Net 5 - Fifth Layer

The fifth layer (C5) is a fully connected convolutional layer with 120 feature maps each of size 1×1. Each of the 120 units in C5 is connected to all the 400 nodes (5x5x16) in the fourth layer S4.



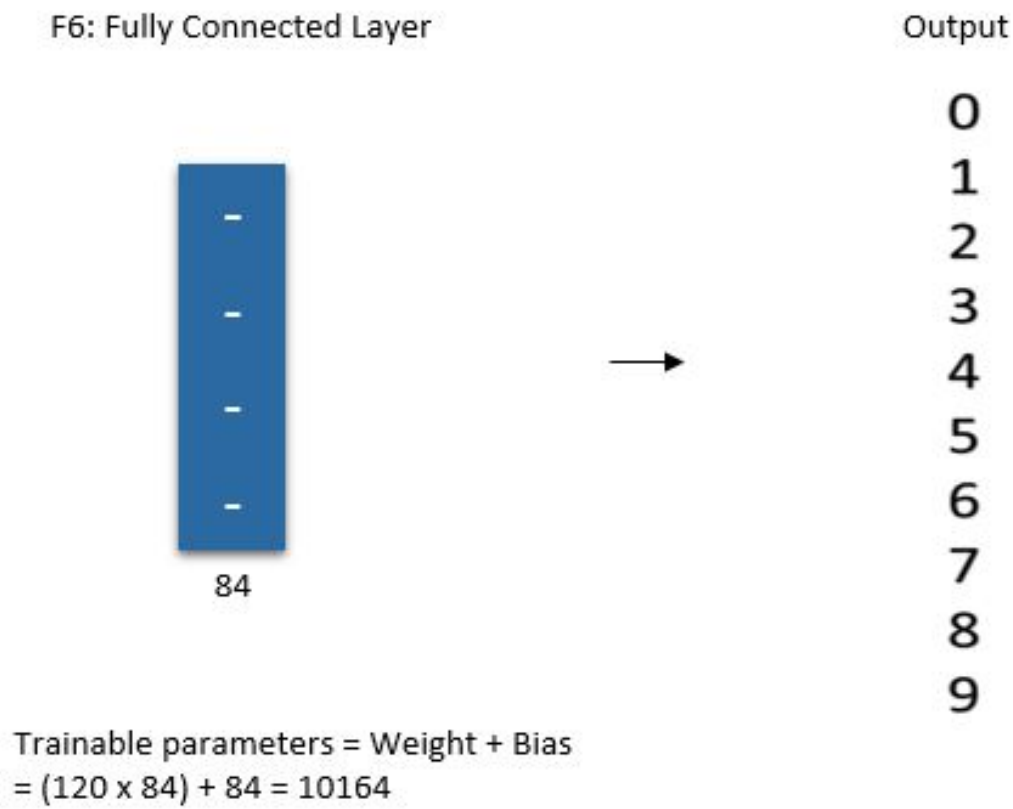
Le-Net 5 - Sixth Layer

The sixth layer is a fully connected layer (F6) with 84 units.



Le-Net 5 - Output Layer

Finally, there is a fully connected softmax output layer ŷ with 10 possible values corresponding to the digits from 0 to 9.



Summary of LeNet-5 Architecture

Layer		Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	32x32	-	-	-
1	Convolution	6	28x28	5x5	1	tanh
2	Average Pooling	6	14x14	2x2	2	tanh
3	Convolution	16	10x10	5x5	1	tanh
4	Average Pooling	16	5x5	2x2	2	tanh
5	Convolution	120	1x1	5x5	1	tanh
6	FC	-	84	-	-	tanh
Output	FC	-	10	-	-	softmax

HANDS ON: LeNet - MNIST

LeNet.ipynb

AlexNet

In the year 2010 Deep Learning was... uncool...

That was the year ImageNet Large Scale Visual Recognition Challenge (ILSVRC) was launched.
In 2012 Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton published the paper “ImageNet Classification with Deep Convolutional Neural Networks”.
AlexNet was the winning entry in ILSVRC 2012.
The paper used a CNN to get a Top-5 error rate (rate of not finding the true label of a given image among its top 5 predictions) of 15.3%. The next best result trailed far behind (26.2%).
When the dust settled, Deep Learning was cool again.

Imagenet classification with deep convolutional neural networks

A Krizhevsky, I Sutskever, GE Hinton - Advances in neural ..., 2012 - papers.nips.cc

We trained a large, deep convolutional neural network to classify the 1.3 million high-resolution images in the LSVRC-2010 ImageNet training set into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 39.7\% and 18.9\% which is considerably better than the previous state-of-the-art results. The neural network, which has 60 million parameters and 500,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and two globally connected layers with a final ...

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