Introduction to ML

George Igwegbe
Artificial Intelligence
Saturday (AI6), Lagos

BUZZWORD

Non-Linear hypothesis

Neuron

Perceptron

OR Gate

Higher Order features

XOR Gate

Cortex

LeNet

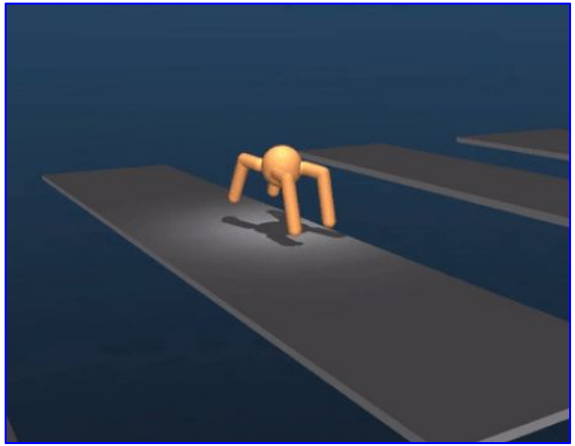
One-hot encoding

AND Gate

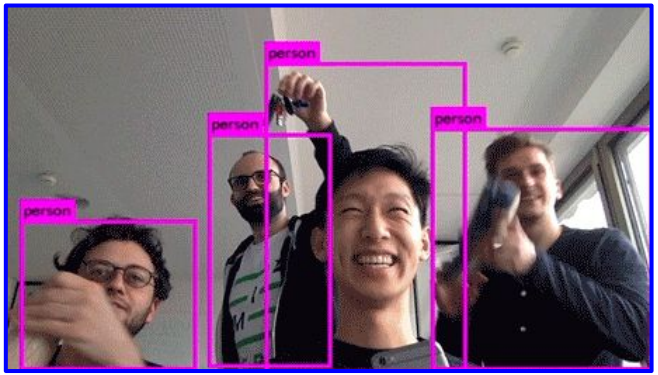
Activation function

Multi-classification

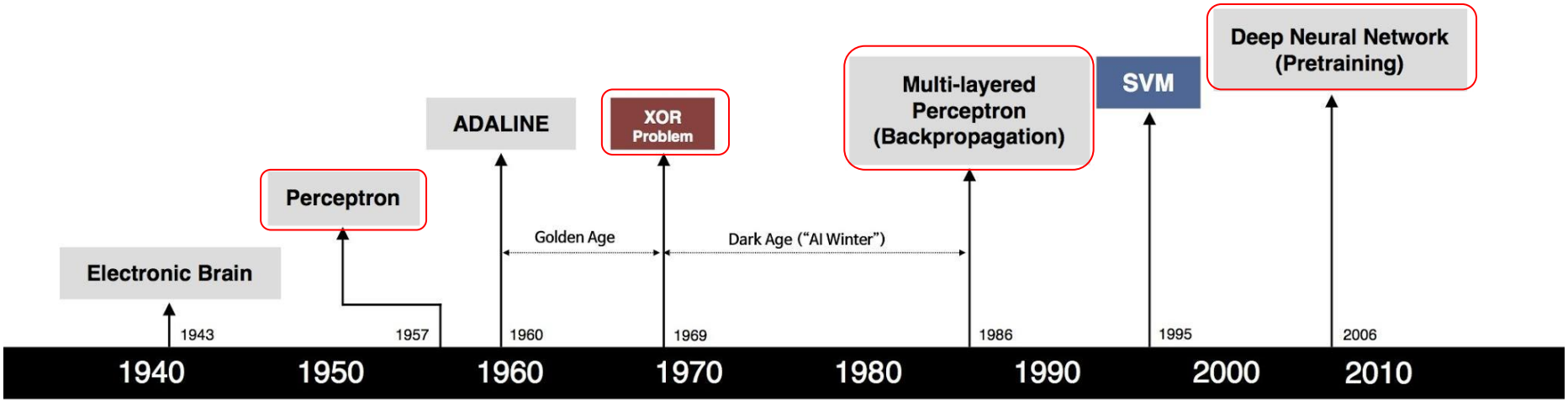
“One learning algorithm”’



What do they have in common?



HISTORY



- 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

Documentary:[The Rise of AI]

1958 Perceptron

1974 Backpropagation

Convolution Neural Networks for Handwritten Recognition

1998

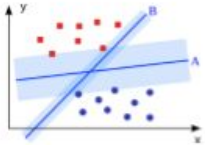
awkward silence (AI Winter)

Google Brain Project on 16k Cores

2012

1969
Perceptron criticized

1995
SVM reigns



2006
Restricted Boltzmann Machine

2012
AlexNet wins

ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky
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Ilya Sutskever
University of Toronto
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Geoffrey E. Hinton
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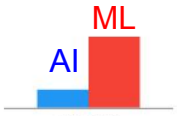
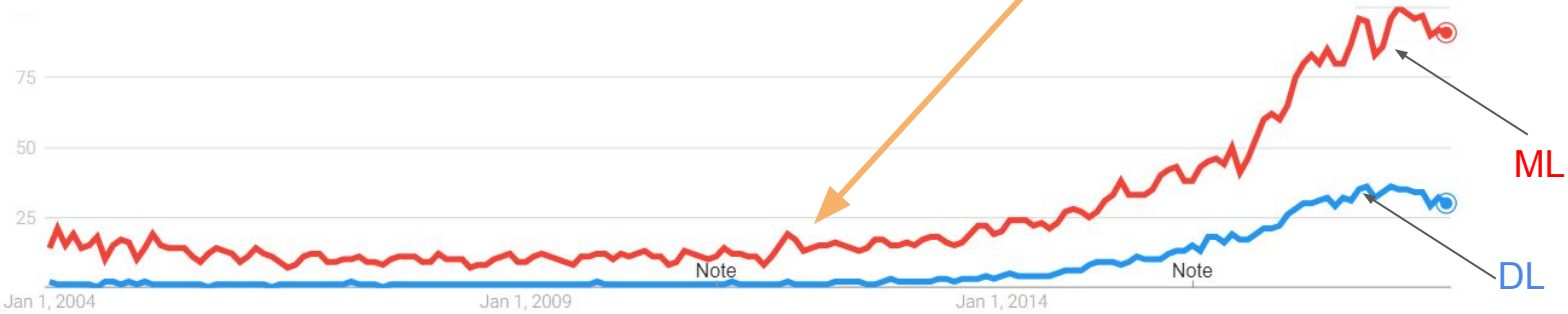


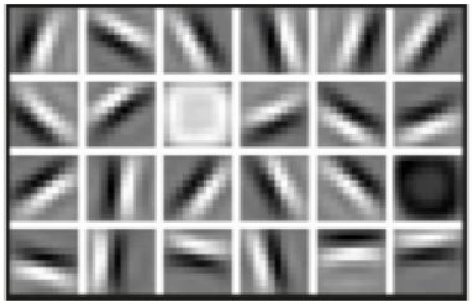


Why Deep Learning?

Hand engineered features are time consuming, brittle and not scalable in practice

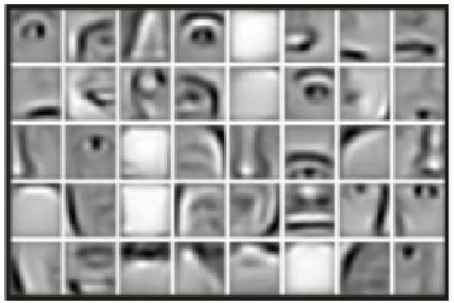
Can we learn the **underlying features** directly from data?

Low Level Features



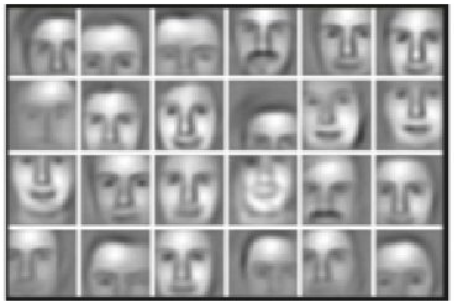
Lines & Edges

Mid Level Features



Eyes & Nose & Ears

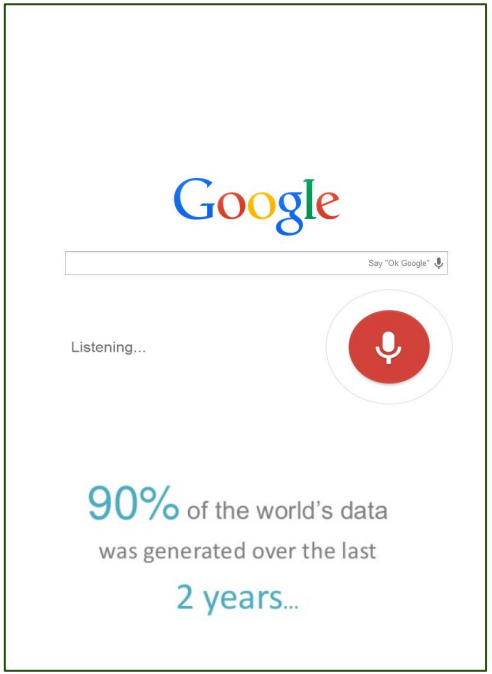
High Level Features



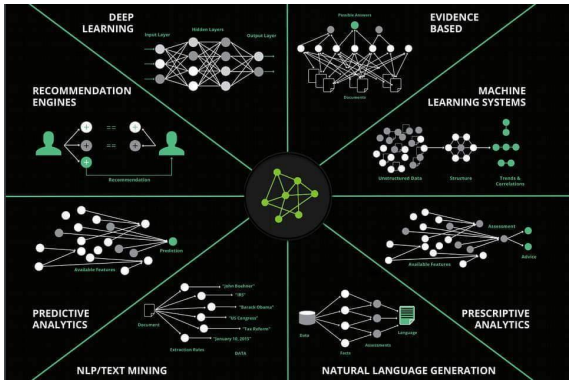
Facial Structure

Why deep learning is having great impact in the world?

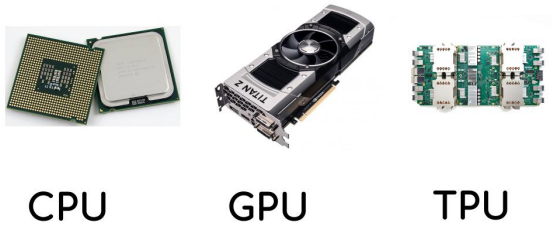
Massive Data



Modern Algorithms



Computational Powerhouse

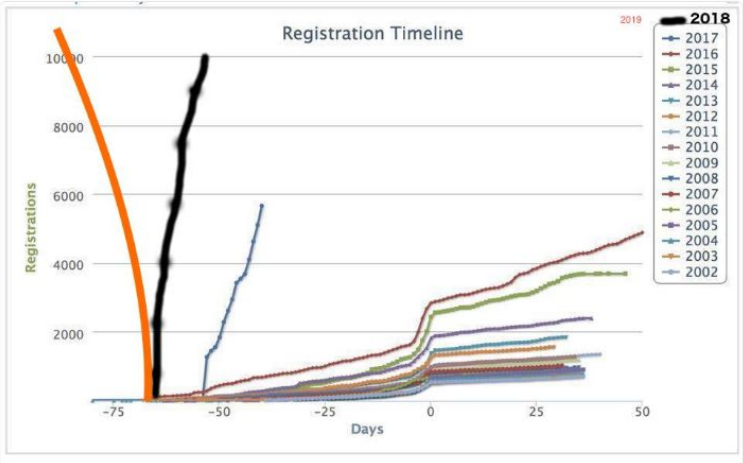


CPU GPU TPU

Soumith Chintala ✓
@soumithchintala

Following

NIPS Conference Registrations 2002 thru 2019.
[2018] War erupts for tickets
[2019] AI researchers discover time travel



6:13 AM - 16 Sep 2017

NIPS @NipsConference · 18 Sep 2017
Replying to @soumithchintala @mikiobraun
The singularity happens in late 2018

1 8 44

Julia Schnabel @ja_schnabel · Sep 4
Replying to @NipsConference

1 6

NIPS
@NipsConference

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#NIPS2018 The main conference sold out in 11 minutes 38 seconds

8:17 AM - 4 Sep 2018

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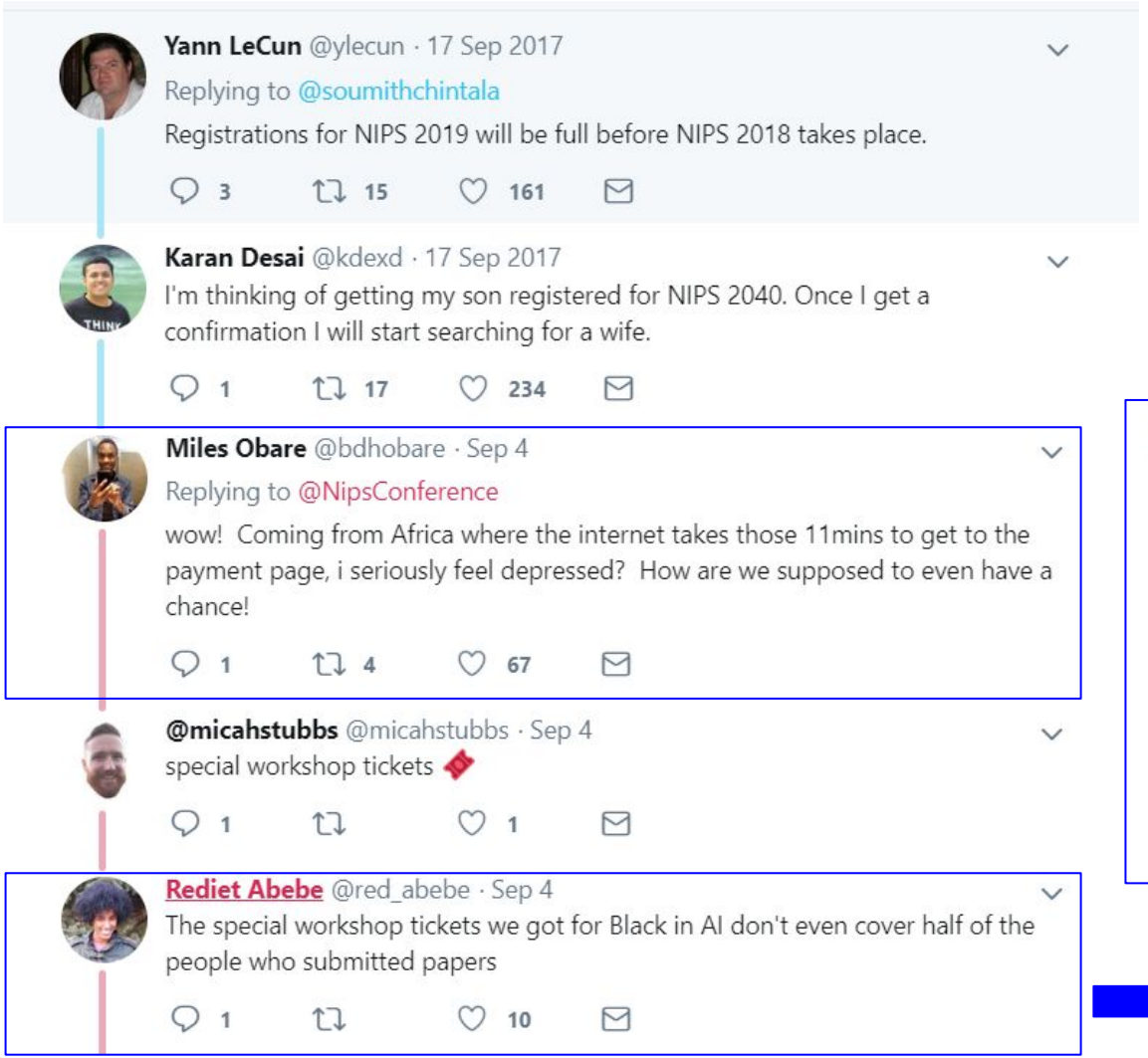
*Neural Information Processing Systems

WHY REPRESENTATION MATTERS?



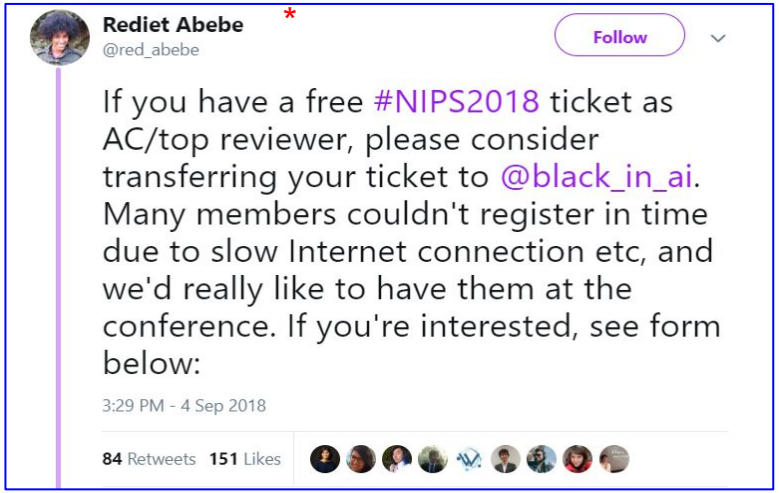
Yann LeCun @ylecun · 17 Sep 2017
Replying to @soumithchintala
Registrations for NIPS 2019 will be full before NIPS 2018 takes place.
3 15 161

Karan Desai @kdexd · 17 Sep 2017
I'm thinking of getting my son registered for NIPS 2040. Once I get a confirmation I will start searching for a wife.
1 17 234

Miles Obare @bdhobare · Sep 4
Replying to @NipsConference
wow! Coming from Africa where the internet takes those 11mins to get to the payment page, i seriously feel depressed? How are we supposed to even have a chance!
1 4 67

@micahstubbs @micahstubbs · Sep 4
special workshop tickets
1 1

Rediet Abebe @red_abebe · Sep 4
The special workshop tickets we got for Black in AI don't even cover half of the people who submitted papers
1 10



Rediet Abebe *
@red_abebe
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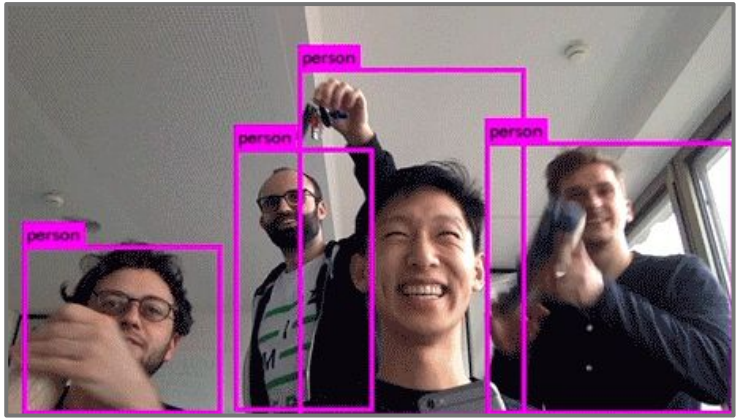
If you have a free #NIPS2018 ticket as AC/top reviewer, please consider transferring your ticket to @black_in_ai. Many members couldn't register in time due to slow Internet connection etc, and we'd really like to have them at the conference. If you're interested, see form below:

3:29 PM - 4 Sep 2018

84 Retweets 151 Likes

*My AI crush

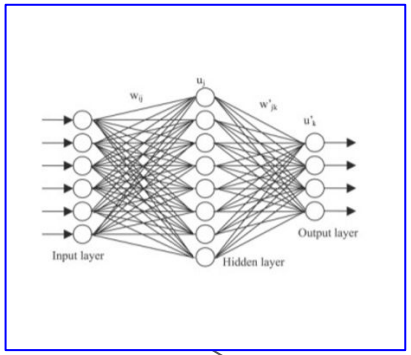


Game state → Neural Net → Next Move

What are these boxes?

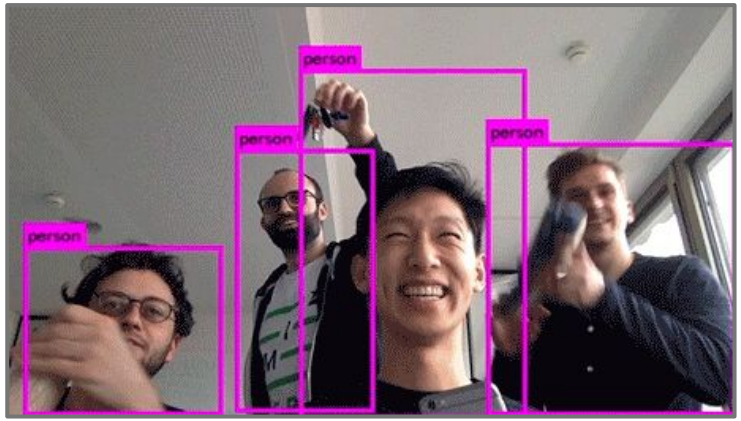
Images → Neural Net → Object Classification

Game state

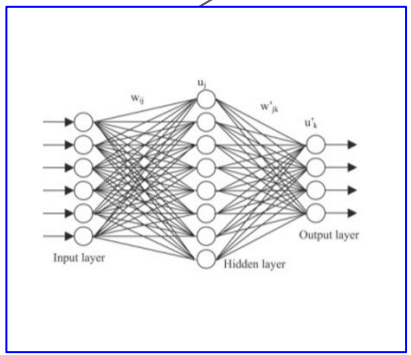


Next Move

Neural Networks

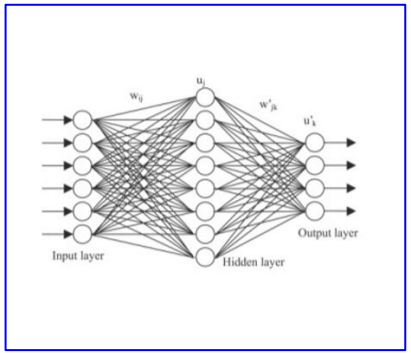


Images



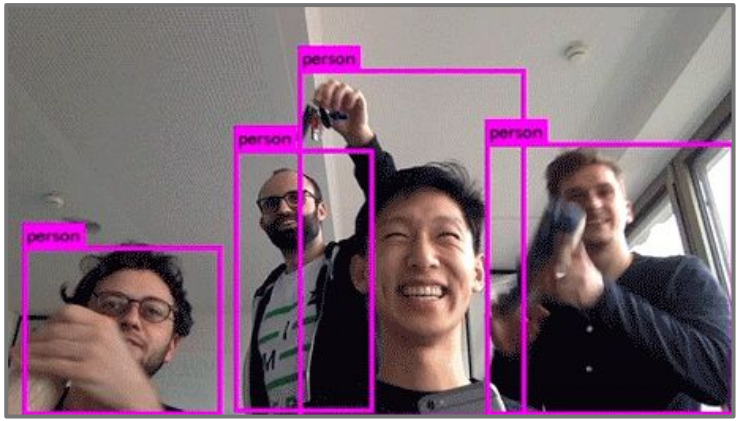
Object Classification

Game state



Next Move

Each of these boxes is actually a function – E.g
f: Image = Image classification



Images

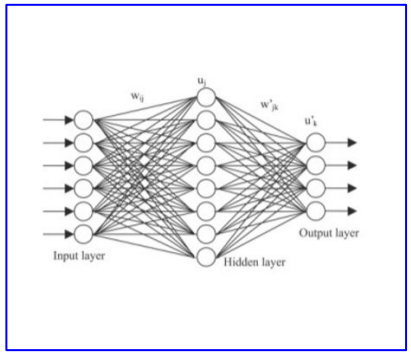
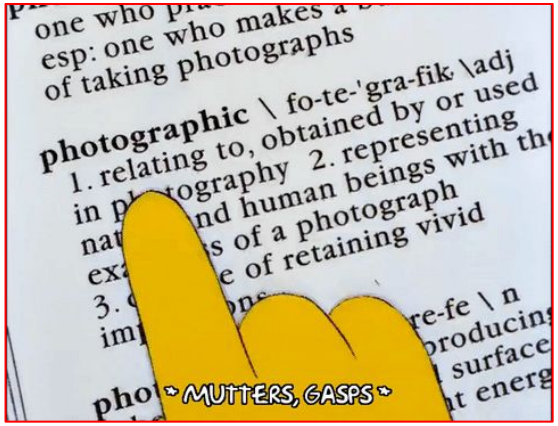
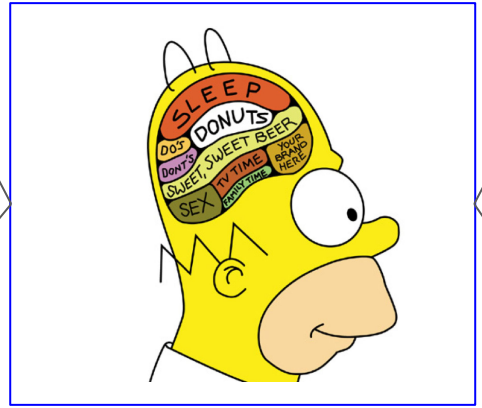


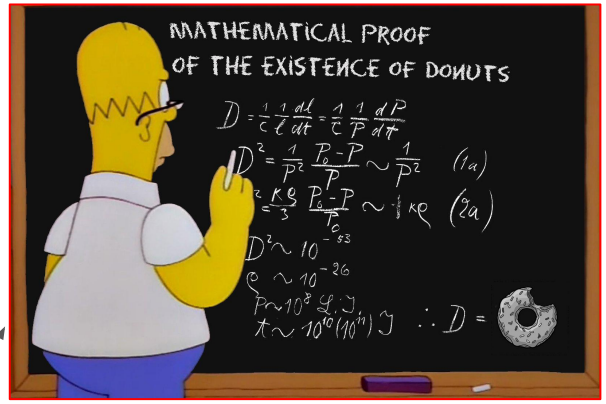
Image Classification

- **It can be approximated by a neural network**

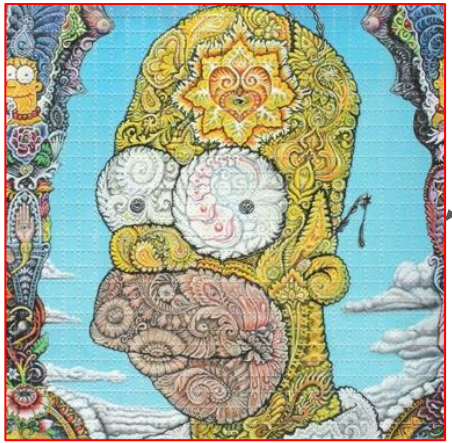


- Learn





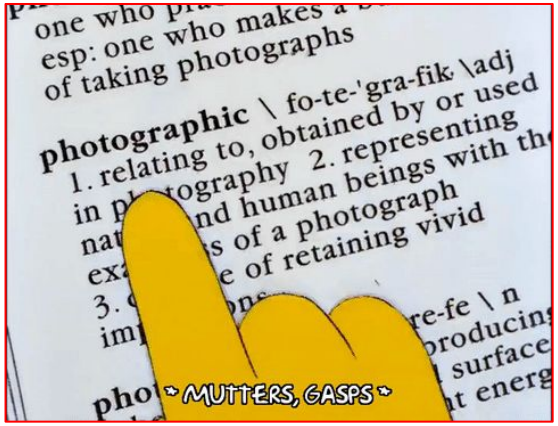
- Solve problem



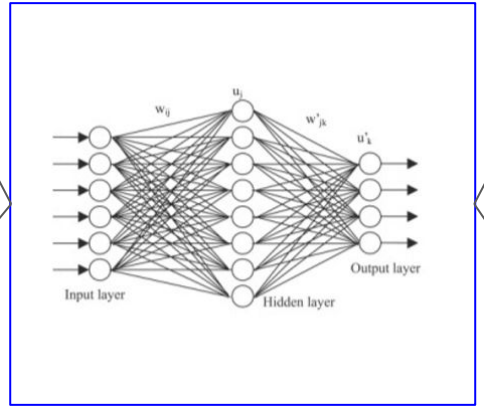
- Recognize pattern

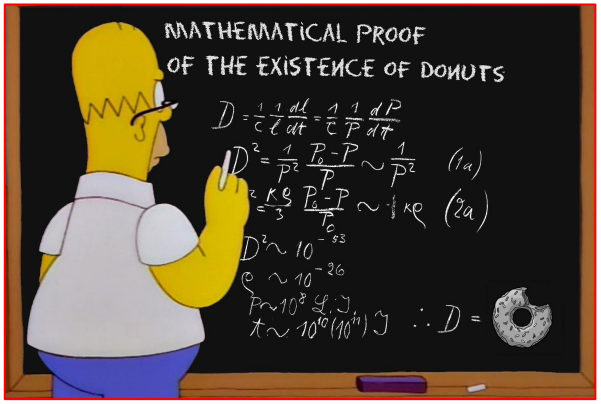
All these are powered by the **BRAIN**.

- Create stuffs

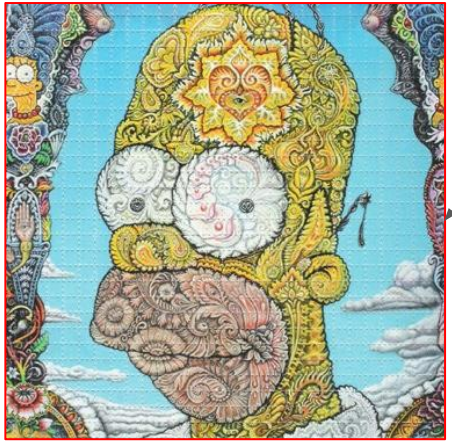


- Learn





- Solve problem

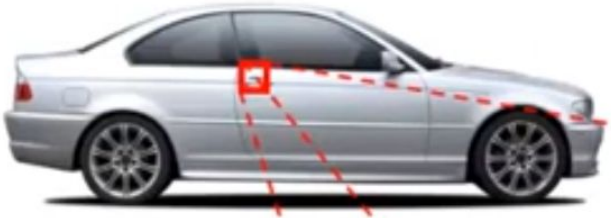


- Recognize pattern

What can you do with Neural Network?

- Create stuffs

You see this:



Semantic Gap

But the camera sees this:

194	210	201	212	199	213	215	195	178	158	182	209
180	189	190	221	209	205	191	167	147	115	129	163
114	126	140	188	176	165	152	140	170	106	78	88
87	103	115	154	143	142	149	153	173	101	57	57
102	112	106	131	122	138	152	147	128	84	58	66
94	95	79	104	105	124	129	113	107	87	69	67
68	71	69	98	89	92	98	95	89	88	76	67
41	56	68	99	63	45	60	82	58	76	75	65
20	43	69	75	56	41	51	73	55	70	63	44
50	50	57	69	75	75	73	74	53	68	59	37
72	59	53	66	84	92	84	74	57	72	63	42
67	61	58	65	75	78	76	73	59	75	69	50

Why computer Vision is hard?

Computer Vision: Car detection






Cars

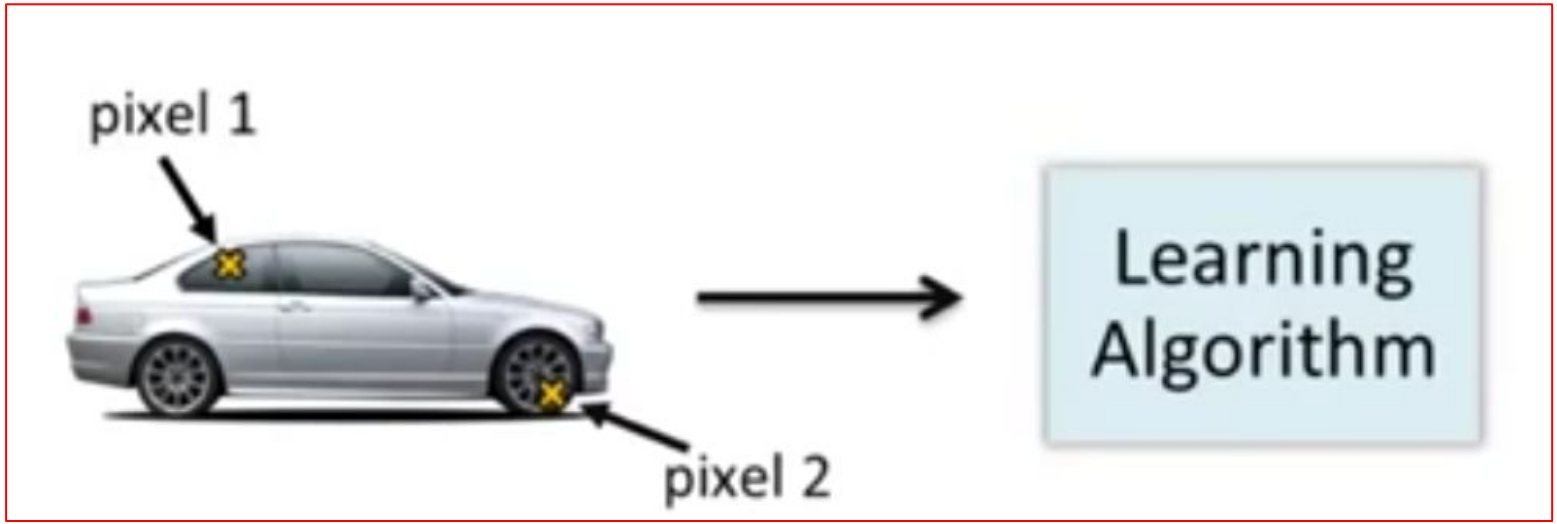


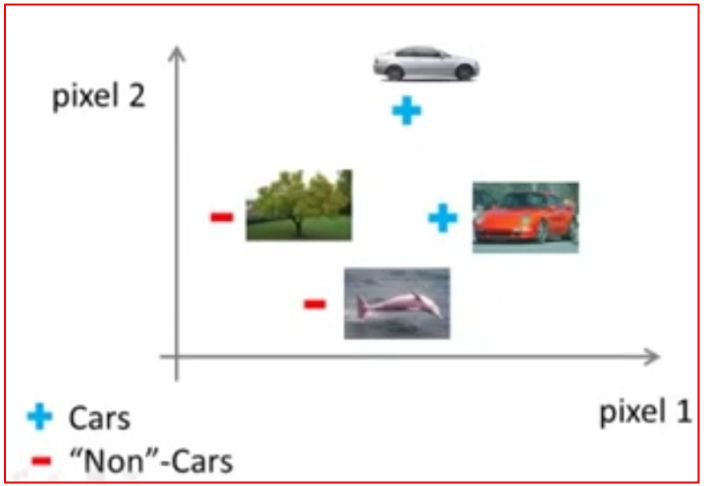


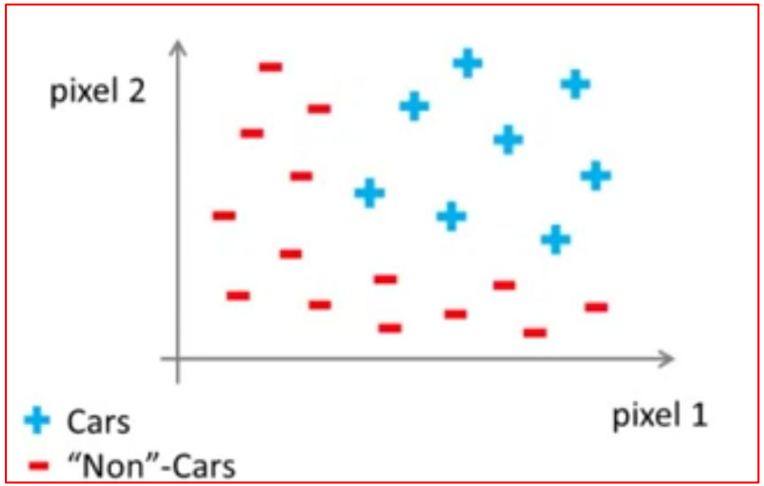

Not a car

Testing:

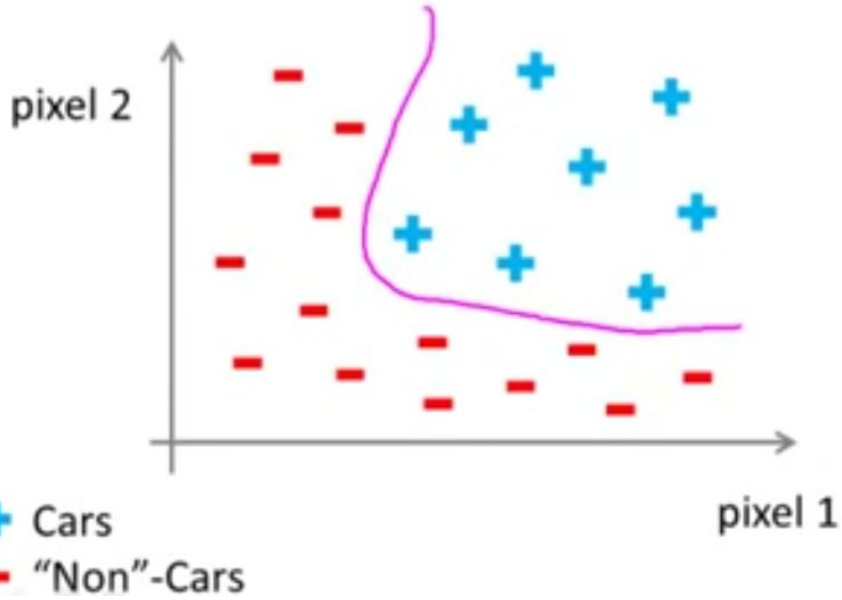
What is this?


pixel 1
pixel 2
Learning Algorithm


pixel 2
pixel 1
Cars
"Non"-Cars


pixel 2
pixel 1
Cars
"Non"-Cars

Learning Algorithm



50 x 50 pixel images→ 2500 pixels

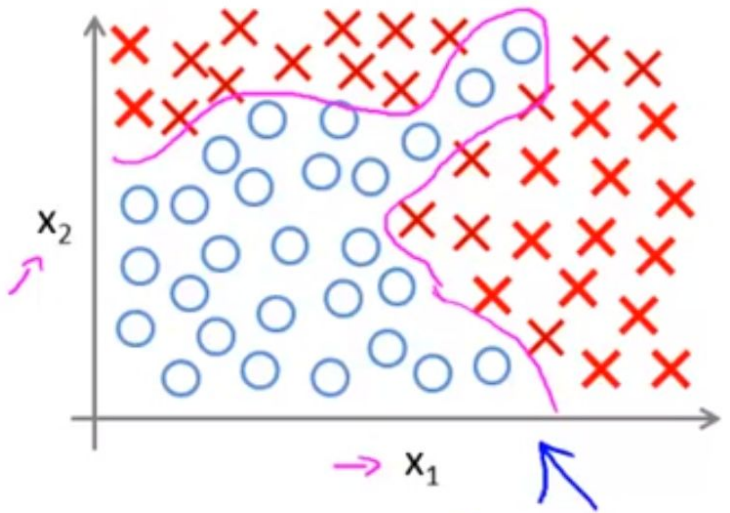
$n = 2500$ (7500 if RGB)

$$x = \begin{bmatrix} \text{pixel 1 intensity} \\ \text{pixel 2 intensity} \\ \vdots \\ \text{pixel 2500 intensity} \end{bmatrix}$$

0 - 255

Quadratic features ($x_i \times x_j$): ≈3 million features

Non-linear Classification



$$g(\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1 x_2 + \theta_4 x_1^2 x_2 + \theta_5 x_1^3 x_2 + \theta_6 x_1 x_2^2 + \dots)$$

$x_1^2, x_1x_2, x_1x_3, x_1x_4 \dots x_1x_{100}$
$x_2^2, x_2x_3 \dots$
≈ 5000 feature $O(n^2)$

x_1 = size
x_2 = # bedrooms
x_3 = # floors
x_4 = age
...
x_{100}

$n = 100$

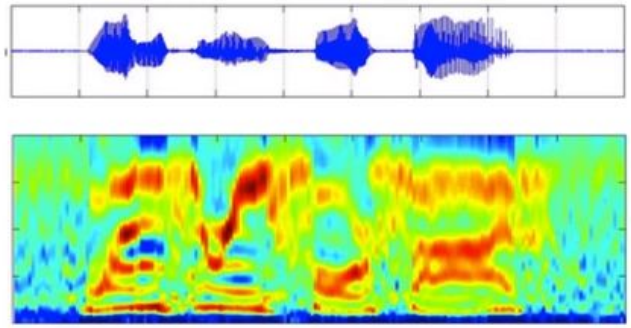
$x_1^2, x_2^2, x_3^2, \dots, x_{100}^2$ $\approx \frac{n^2}{2}$ 10

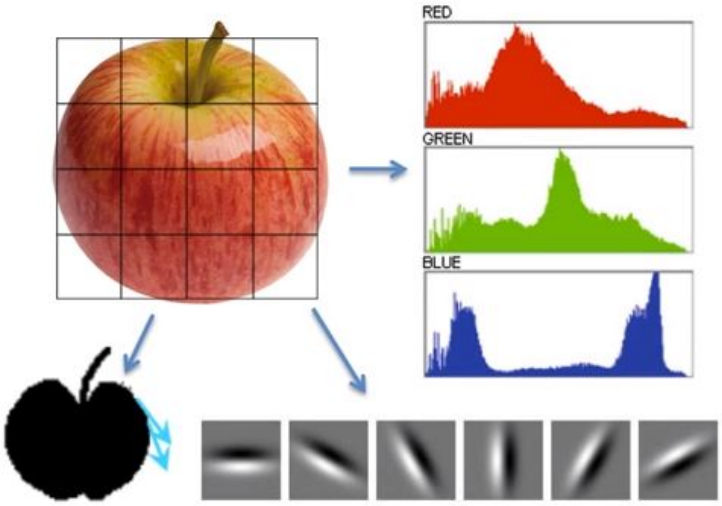
$x_1x_2x_3, x_1^2x_2, x_{10}x_{11}x_{17}, \dots$
$O(n^3)$ 170,000

- **Higher order poly. features - Overfitting and Computationally expensive**

Features in Machine Learning

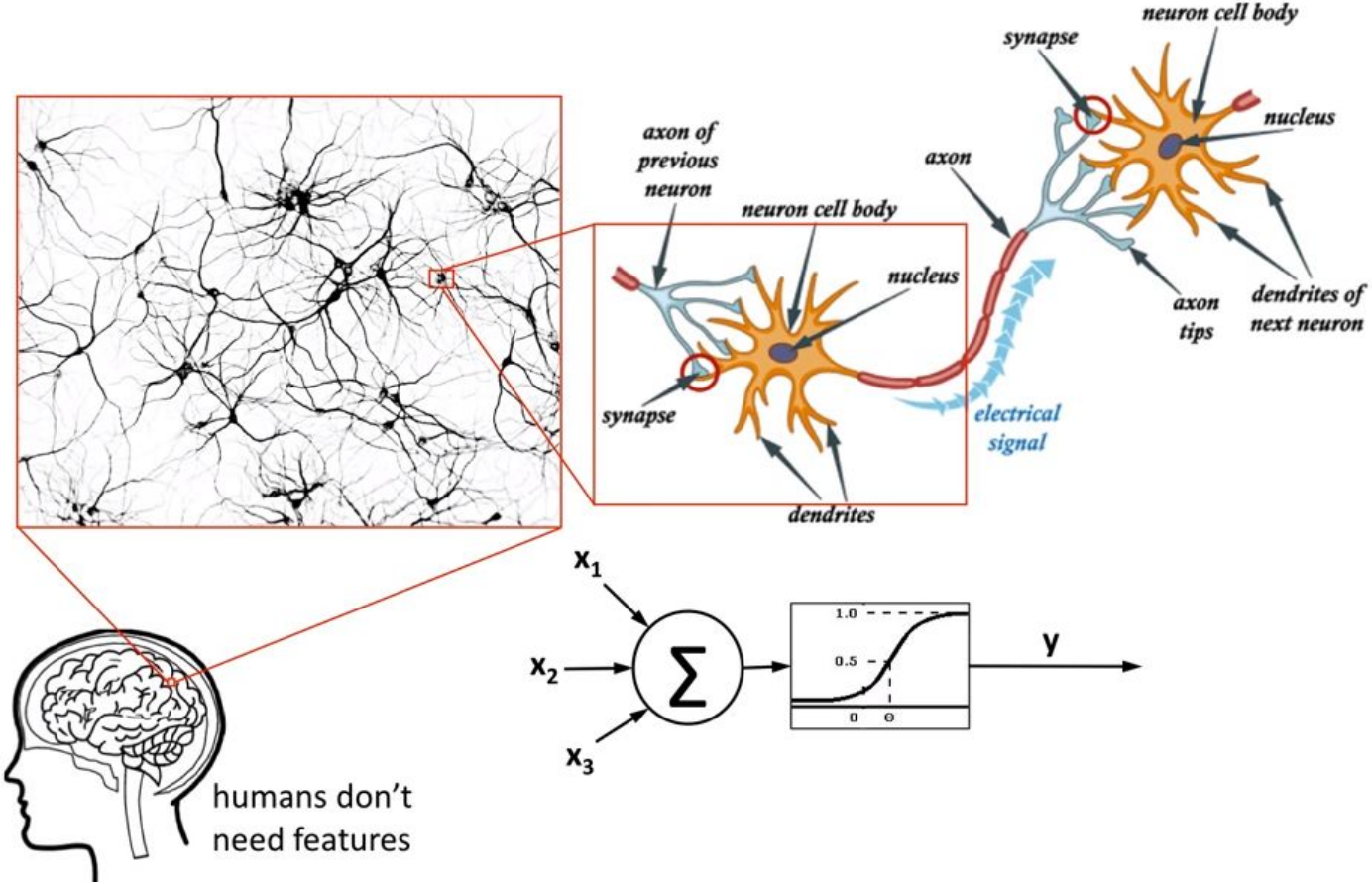
- 1-line summary of ML: $y = \mathrm{sgn}(\mathbf{w}^T\mathbf{x} + b)$
  - SVM can learn very effective weights **w**
  - … if you use the right representation **x**





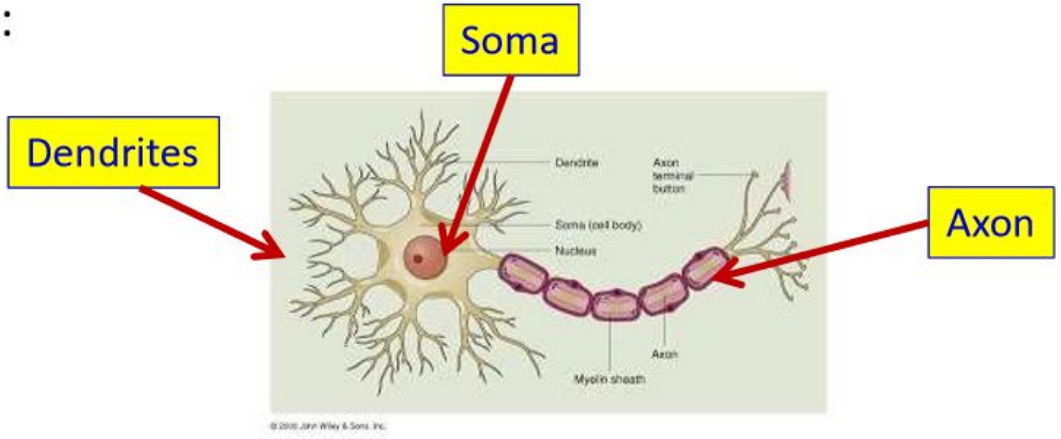
Would be nice to "learn" these representations automatically…

Neurons and the brain



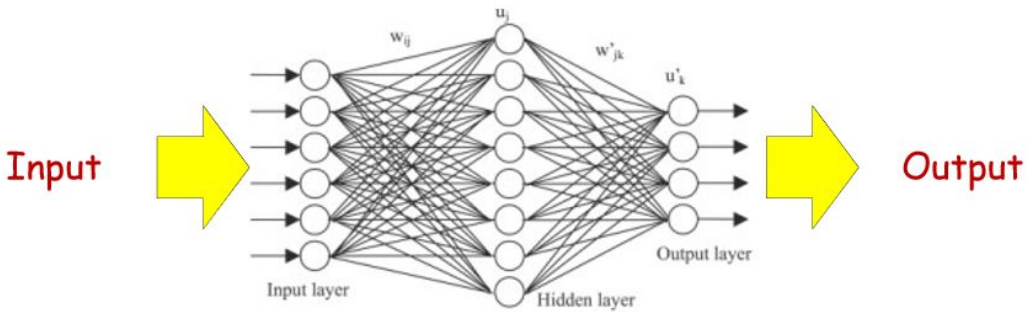
Biological Inspiration

- What are the units?
- A neuron:



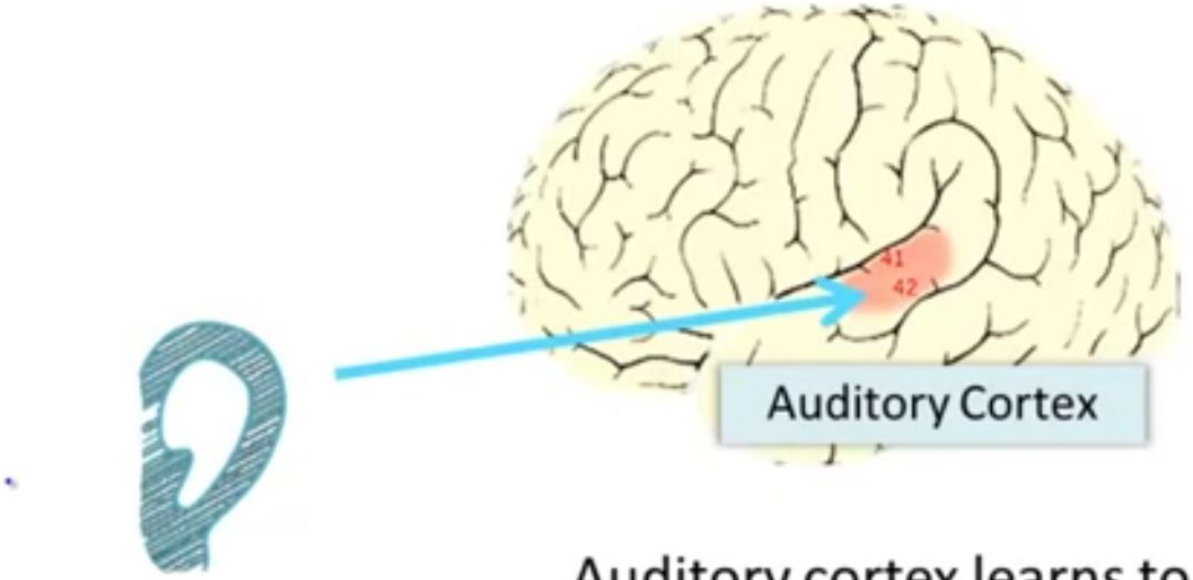
- Signals comes in through the dendrites into the Soma
- A signals goes out via the axon to other neurons
- Algorithms that try to mimic the brain. Was very widely used in 80s and early 90s; popularity diminished in late 90s
- Recent resurgence: State-of-the-art for many applications

The network as a function



- Inputs are numeric vectors
  - Numeric representation of input, e.g. audio, image, game state, etc.
- Outputs are numeric scalars or vectors
  - Numeric “encoding” of output from which actual output can be derived
  - E.g. a score, which can be compared to a threshold to decide if the input is a face or not
  - Output may be multi-dimensional, if task requires it

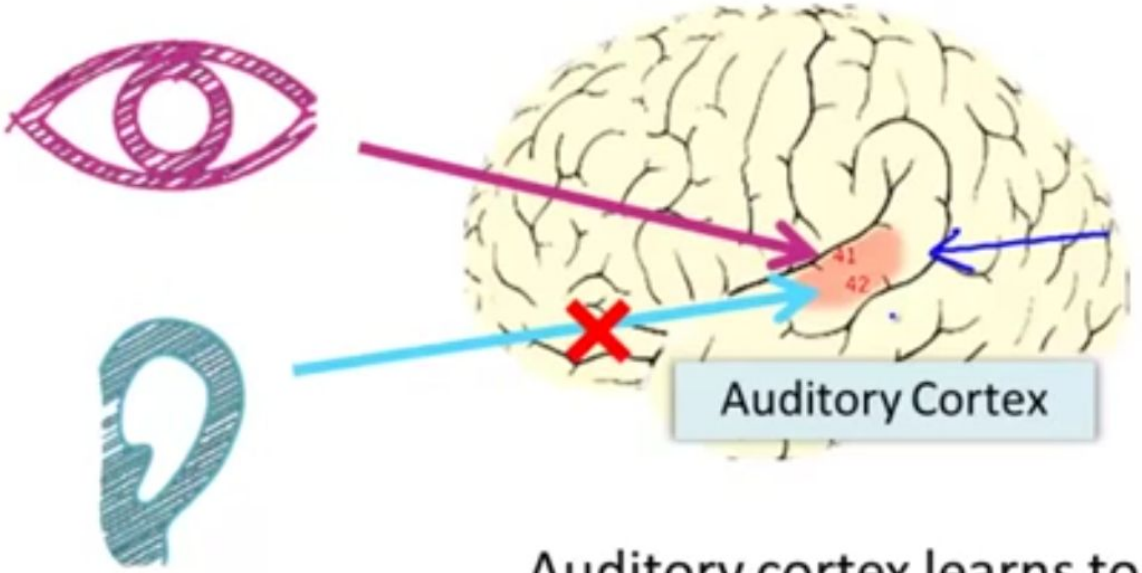
The “one learning algorithm” hypothesis



Auditory cortex learns to see

[Roe et al., 1992]

The “one learning algorithm” hypothesis



Auditory cortex learns to see

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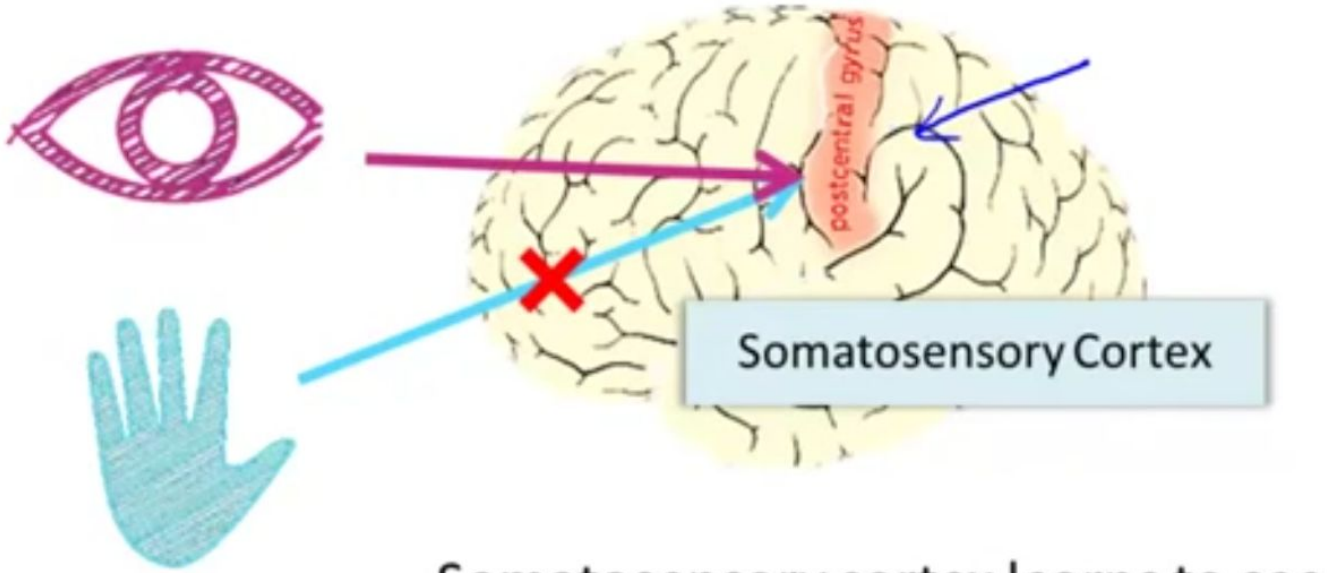
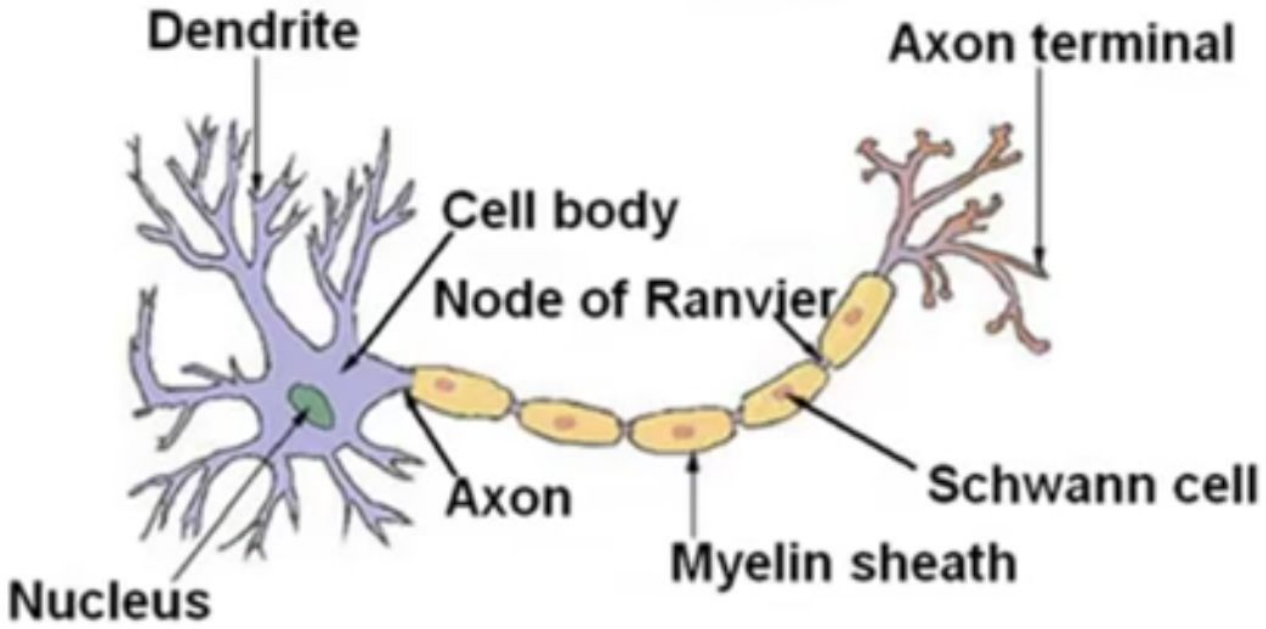
The “one learning algorithm” hypothesis



Somatosensory cortex learns to see

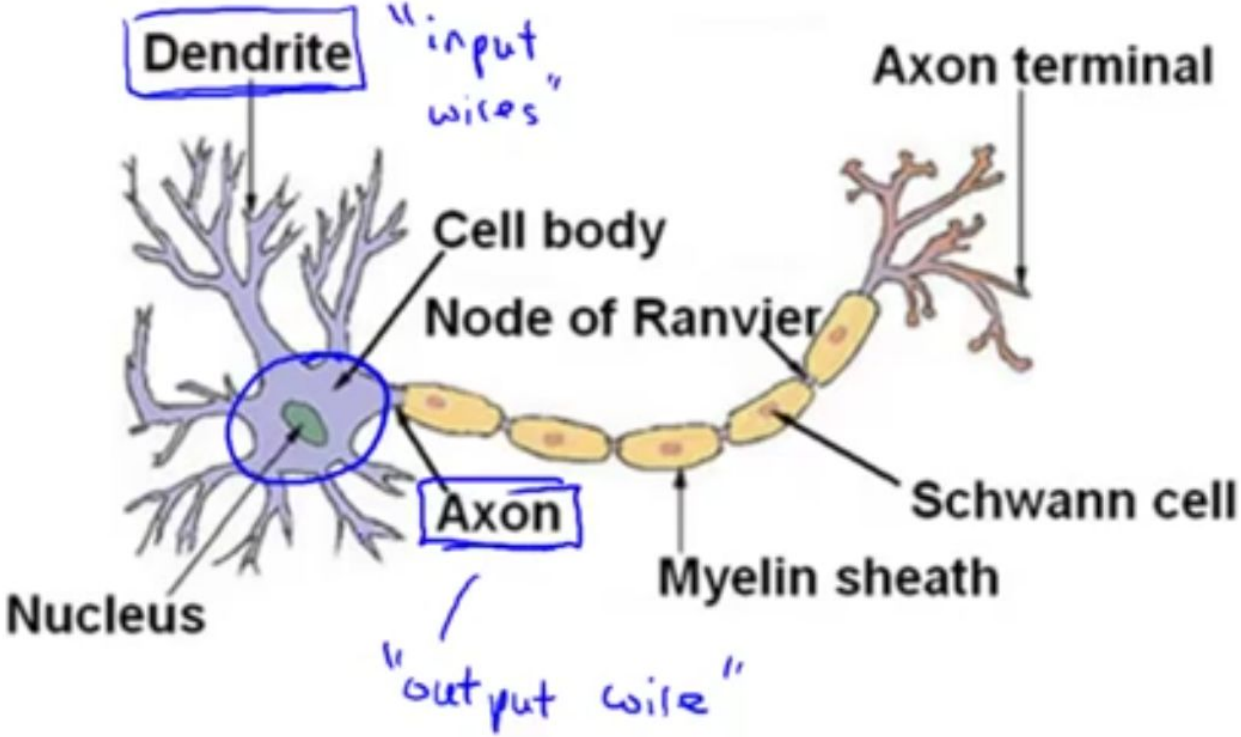
[Metin & Frost, 1989]

Neuron in the brain

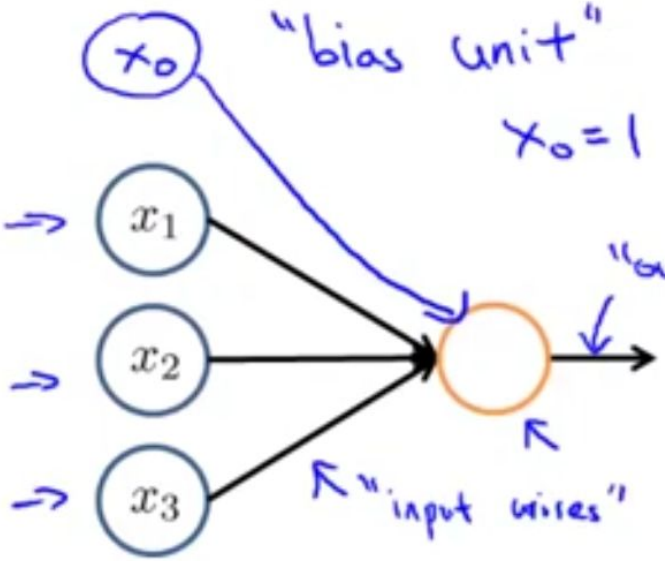


Neural Network Representation- Model Representation

Neuron in the brain



Neuron model: Logistic unit



$$x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} \qquad \theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix}$$

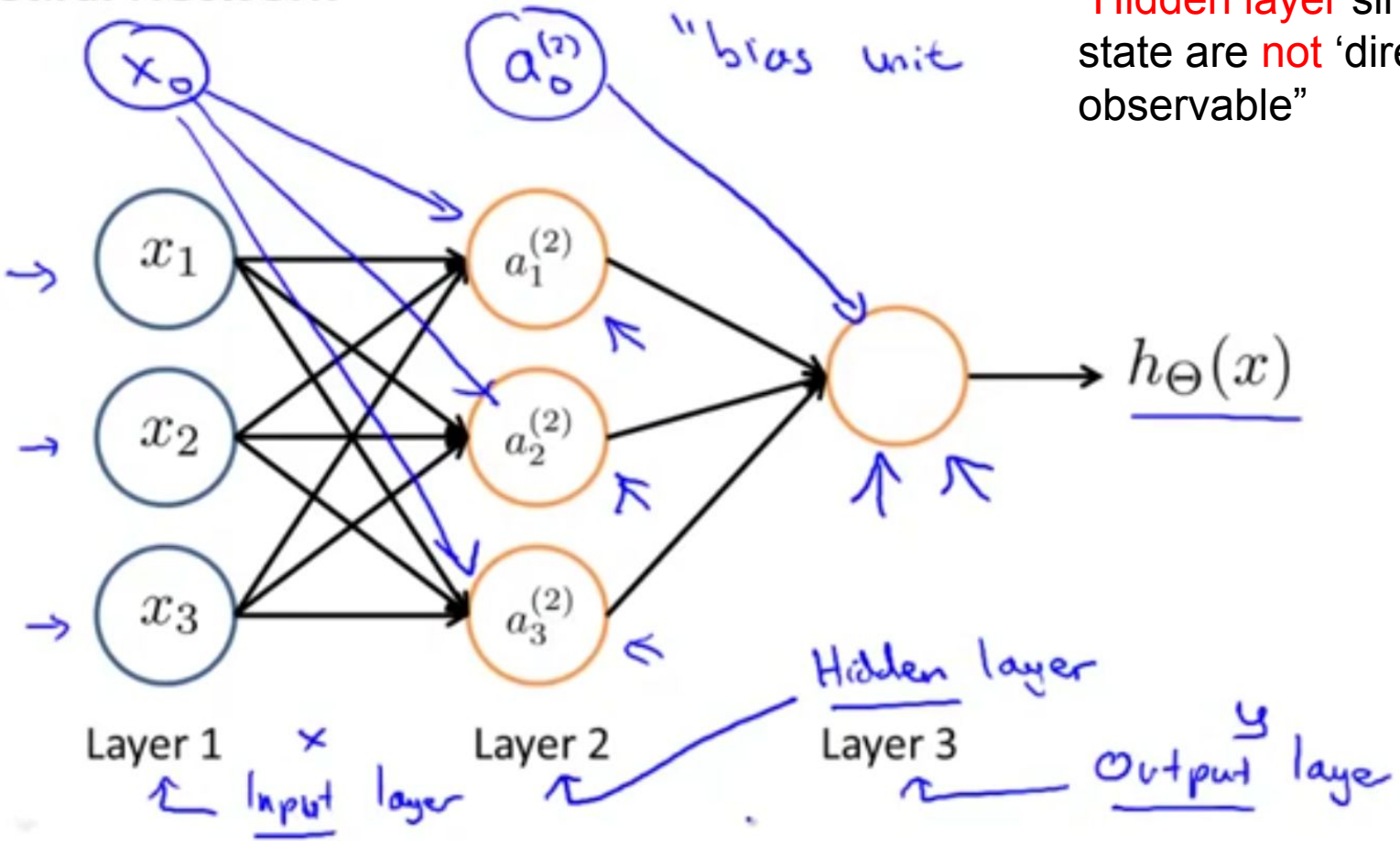
"weights" ← (parameters ↙)

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$

Sigmoid (logistic) activation function.

$$g(z) = \frac{1}{1 + e^{-z}}$$

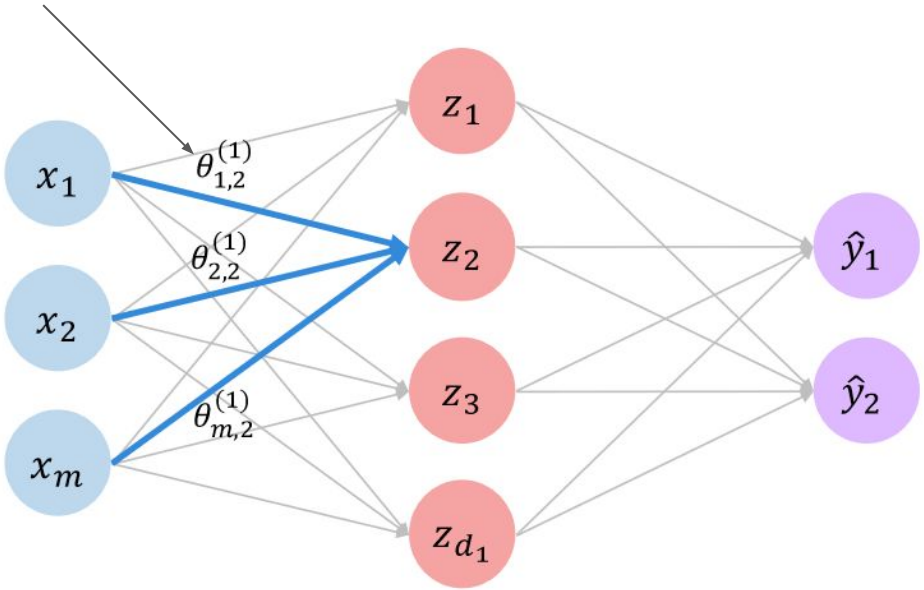
Neural Network



"Hidden layer since its state are not 'directly observable"

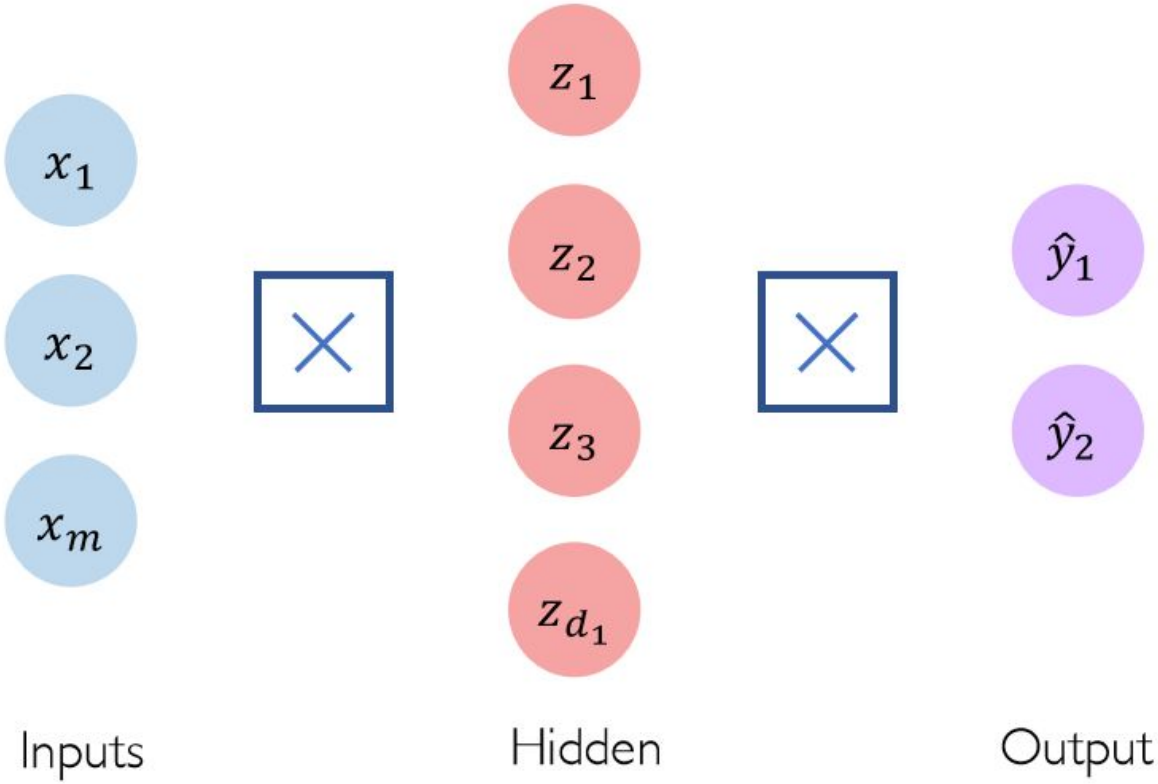
Single Layer Neural Network

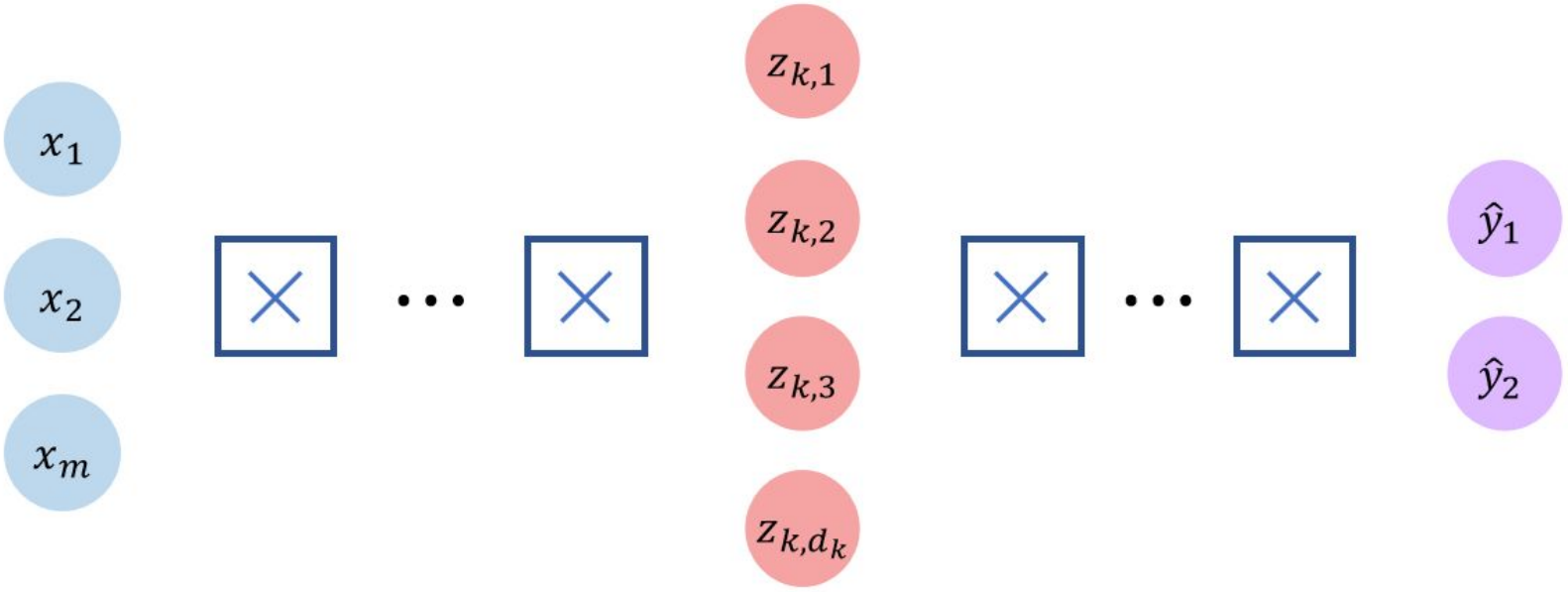
(Input => hidden)



$$z_2 = \theta_{0,2}^{(1)} + \sum_{j=1}^{m} x_j \, \theta_{j,2}^{(1)}$$

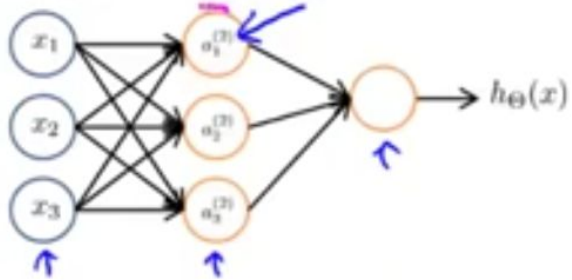
$$= \theta_{0,2}^{(1)} + x_1 \, \theta_{1,2}^{(1)} + x_2 \, \theta_{2,2}^{(1)} + x_m \, \theta_{m,2}^{(1)}$$


x_1
x_2
x_m
z_1
z_2
z_3
z_{d_1}
$\hat{y}_1$
$\hat{y}_2$
Inputs
Hidden
Output



$$z_{k,i} = \theta_{0,i}^{(k)} + \sum_{j=1}^{d_{k-1}} g(z_{k-1,j})\, \theta_{j,i}^{(k)}$$

Neural Network



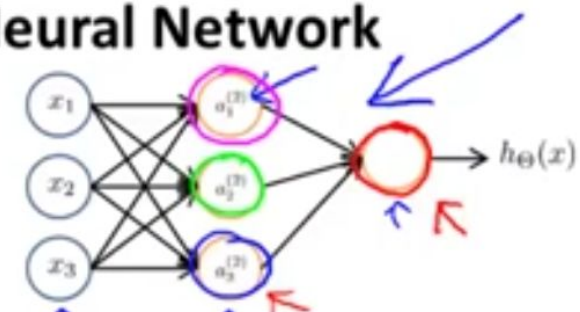
→ $a_i^{(j)}$ = "activation" of unit i in layer j

→ $\Theta^{(j)}$ = matrix of weights controlling function mapping from layer j to layer $j+1$

$$a_1^{(2)} = g(\Theta_{10}^{(1)}x_0 + \Theta_{11}^{(1)}x_1 + \Theta_{12}^{(1)}x_2 + \Theta_{13}^{(1)}x_3)$$
$$a_2^{(2)} = g(\Theta_{20}^{(1)}x_0 + \Theta_{21}^{(1)}x_1 + \Theta_{22}^{(1)}x_2 + \Theta_{23}^{(1)}x_3)$$
$$a_3^{(2)} = g(\Theta_{30}^{(1)}x_0 + \Theta_{31}^{(1)}x_1 + \Theta_{32}^{(1)}x_2 + \Theta_{33}^{(1)}x_3)$$
$$h_\Theta(x) = a_1^{(3)} = g(\Theta_{10}^{(2)}a_0^{(2)} + \Theta_{11}^{(2)}a_1^{(2)} + \Theta_{12}^{(2)}a_2^{(2)} + \Theta_{13}^{(2)}a_3^{(2)})$$

If network has s_j units in layer j, s_{j+1} units in layer $j+1$, then $\Theta^{(j)}$ will be of dimension $s_{j+1} \times (s_j + 1)$.

Neural Network



→ $a_i^{(j)}$ = "activation" of unit i in layer j

→ $\Theta^{(j)}$ = matrix of weights controlling function mapping from layer j to layer $j+1$

$\Theta^{(1)} \in \mathbb{R}^{3\times 4}$

$h_\Theta(x)$

$$\rightarrow a_1^{(2)} = g(\Theta_{10}^{(1)}x_0 + \Theta_{11}^{(1)}x_1 + \Theta_{12}^{(1)}x_2 + \Theta_{13}^{(1)}x_3)$$

$$\rightarrow a_2^{(2)} = g(\Theta_{20}^{(1)}x_0 + \Theta_{21}^{(1)}x_1 + \Theta_{22}^{(1)}x_2 + \Theta_{23}^{(1)}x_3)$$

$$\rightarrow a_3^{(2)} = g(\Theta_{30}^{(1)}x_0 + \Theta_{31}^{(1)}x_1 + \Theta_{32}^{(1)}x_2 + \Theta_{33}^{(1)}x_3)$$

$\Theta^{(2)}$

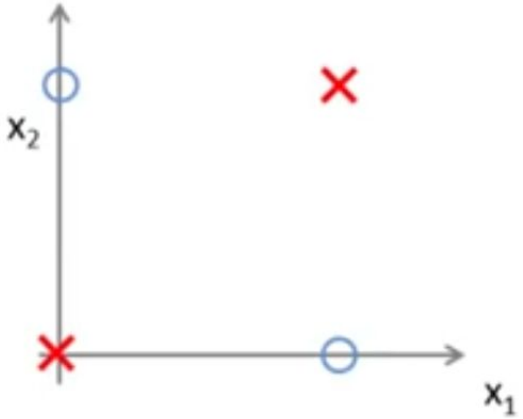
$$\rightarrow h_\Theta(x) = a_1^{(3)} = g(\Theta_{10}^{(2)}a_0^{(2)} + \Theta_{11}^{(2)}a_1^{(2)} + \Theta_{12}^{(2)}a_2^{(2)} + \Theta_{13}^{(2)}a_3^{(2)})$$

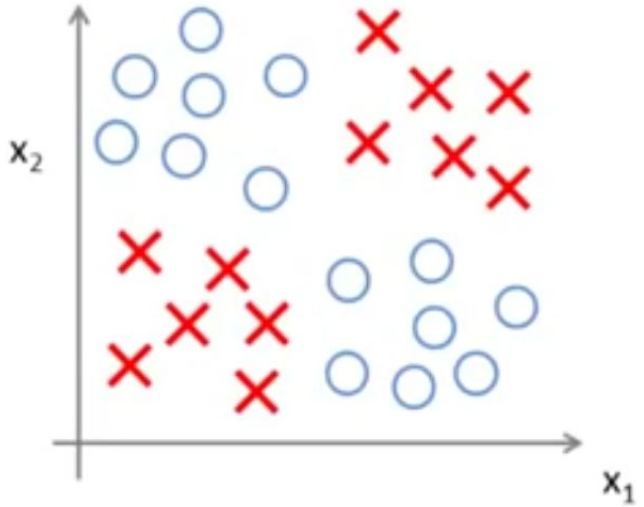
↳ If network has s_j units in layer j, s_{j+1} units in layer $j+1$, then $\Theta^{(j)}$ will be of dimension $s_{j+1} \times (s_j + 1)$.

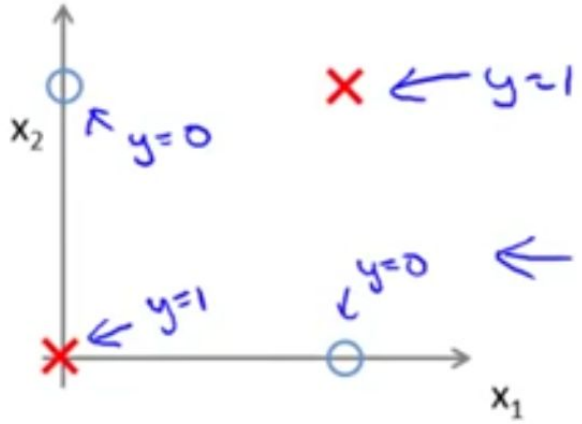
$s_{j+1} \times (s_j + 1)$

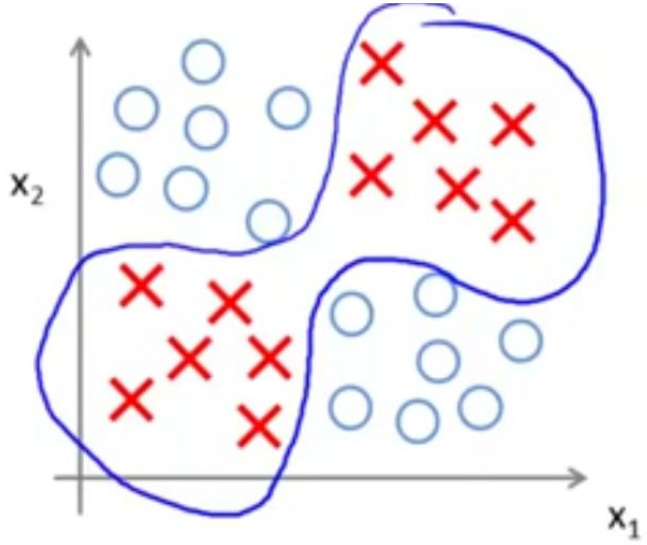
Non-linear classification example: XOR/XNOR

→ x_1, x_2 are binary (0 or 1).









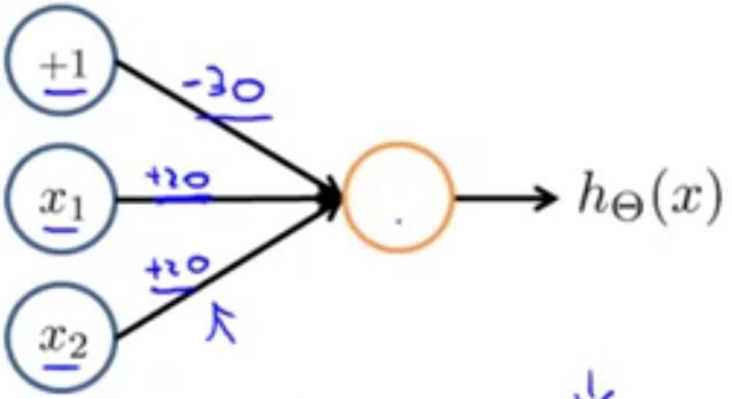
$y = x_1 \text{ XOR } x_2$

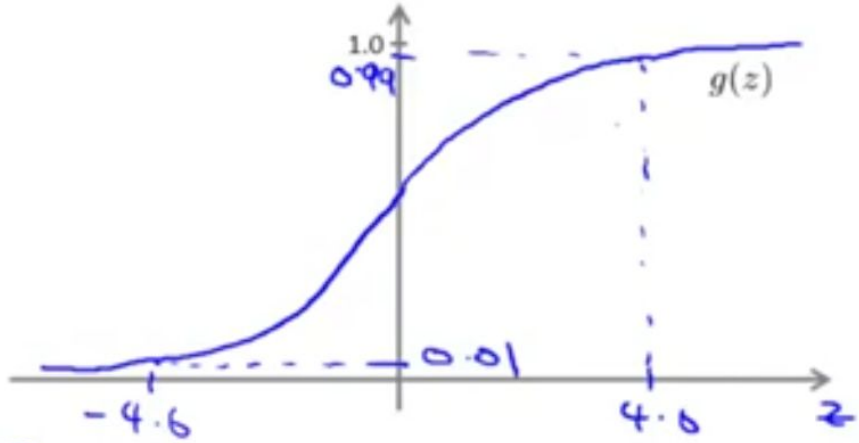
$x_1 \text{ XNOR } x_2$

$\text{NOT } (x_1 \text{ XOR } x_2)$

Simple example: AND

- $x_1, x_2 \in \{0, 1\}$
- $y = x_1$ AND x_2





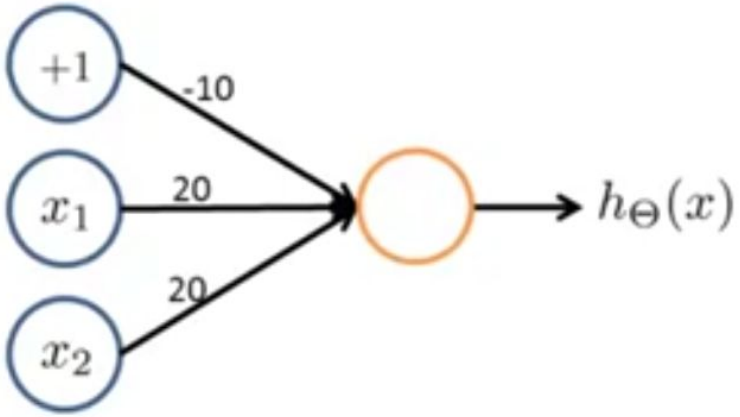
$h_\Theta(x) = g(-30 + 20x_1 + 20x_2)$

$\Theta^{(1)}_{10}$ $\Theta^{(1)}_{11}$ $\Theta^{(1)}_{12}$

x_1	x_2	$h_\Theta(x)$
0	0	$g(-30) \approx 0$
0	1	$g(-10) \approx 0$
1	0	$g(-10) \approx 0$
1	1	$g(10) \approx 1$

$h_\Theta(x) \approx x_1$ AND x_2

Example: OR function

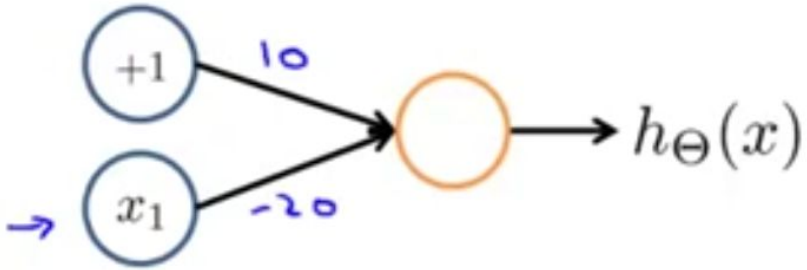


$g(-10 + 20x_1 + 20x_2)$

x_1	x_2	$h_\Theta(x)$
0	0	$g(-10) \approx 0$
0	1	$g(10) \approx 1$
1	0	≈ 1
1	1	≈ 1

Negation:

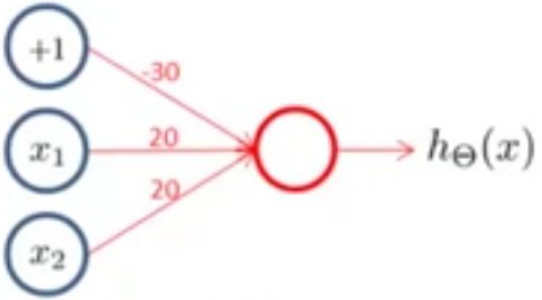
NOT x_1



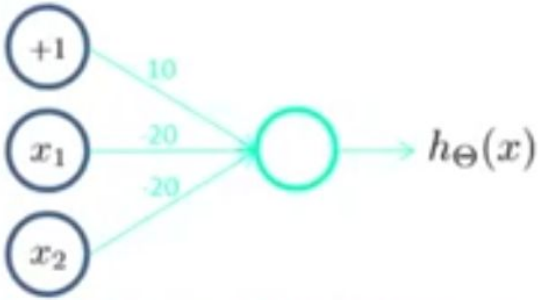
x_1	$h_\Theta(x)$
0	$g(10) \approx 1$
1	$g(-10) \approx 0$

$$h_\Theta(x) = g(10 - 20x_1)$$

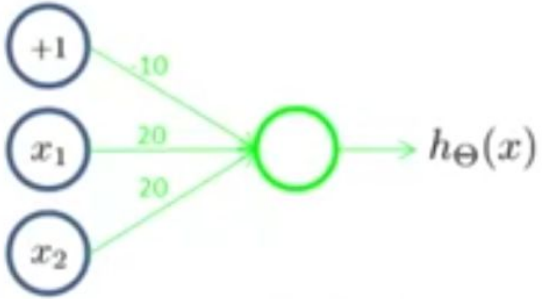
Putting it together: x_1 XNOR x_2



x_1 AND x_2



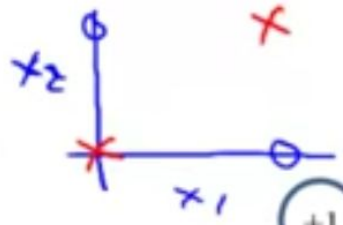
(NOT x_1) AND (NOT x_2)

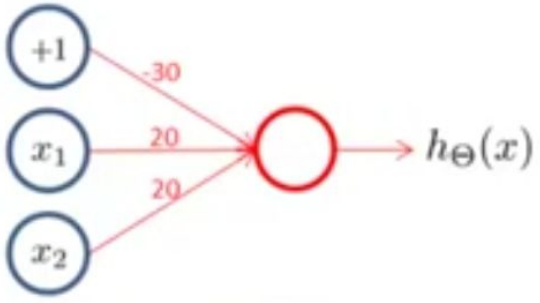


x_1 OR x_2

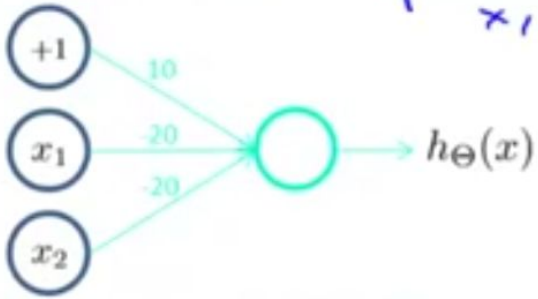
x_1	x_2	$a_1^{(2)}$	$a_2^{(2)}$	$h_\Theta(x)$
0	0			
0	1			
1	0			
1	1			

Putting it together: x_1 XNOR x_2

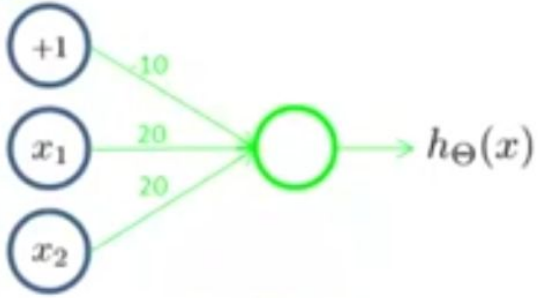




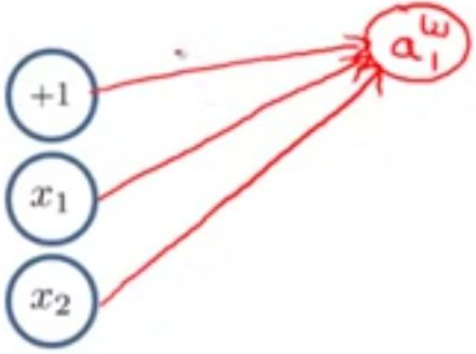
→ x_1 AND x_2



→ (NOT x_1) AND (NOT x_2)

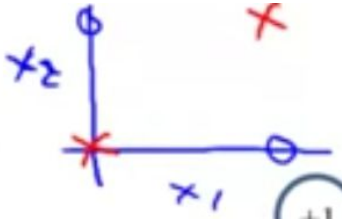


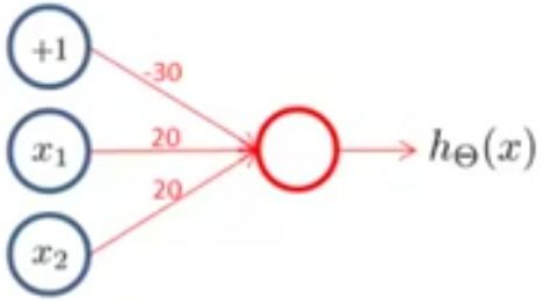
→ x_1 OR x_2



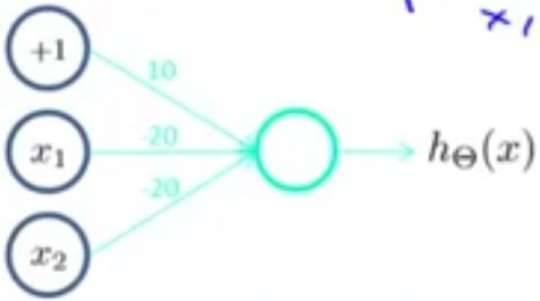
x_1	x_2	$a_1^{(2)}$	$a_2^{(2)}$	$h_\Theta(x)$
0	0			
0	1			
1	0			
1	1			

Putting it together: x_1 XNOR x_2

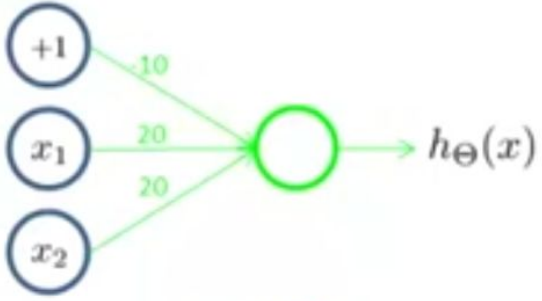




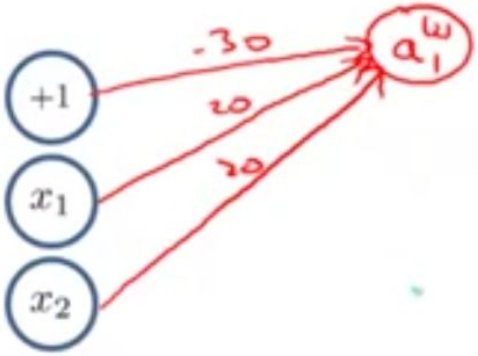
→ x_1 AND x_2



→ (NOT x_1) AND (NOT x_2)

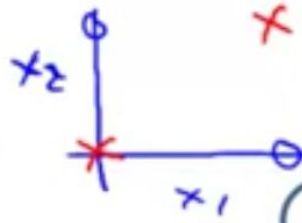


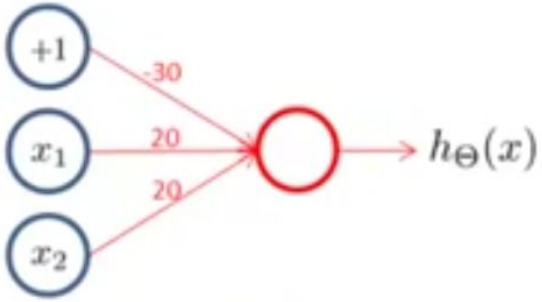
→ x_1 OR x_2



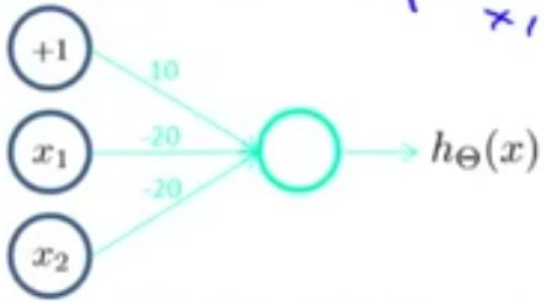
x_1	x_2	$a_1^{(2)}$	$a_2^{(2)}$	$h_\Theta(x)$
0	0			
0	1			
1	0			
1	1			

Putting it together: x_1 XNOR x_2

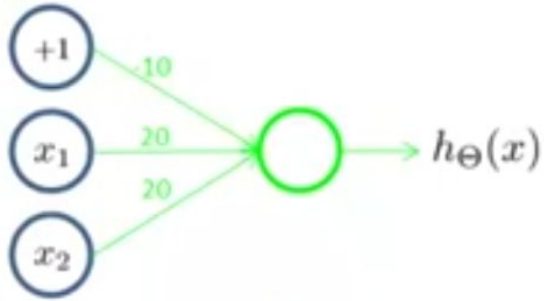




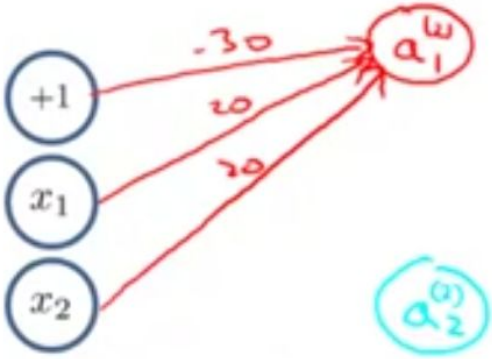
→ x_1 AND x_2



→ (NOT x_1) AND (NOT x_2)

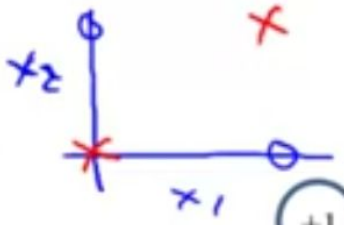


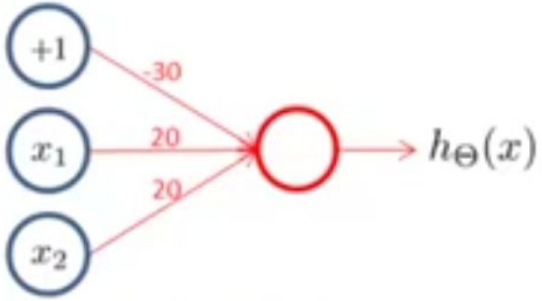
→ x_1 OR x_2



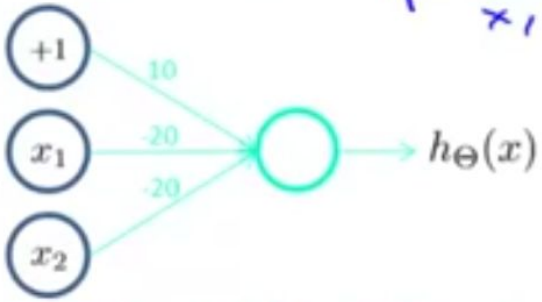
x_1	x_2	$a_1^{(2)}$	$a_2^{(2)}$	$h_\Theta(x)$
0	0			
0	1			
1	0			
1	1			

Putting it together: x_1 XNOR x_2

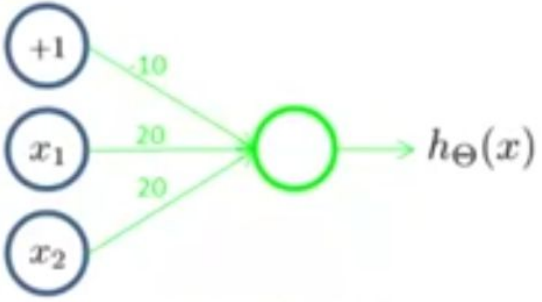




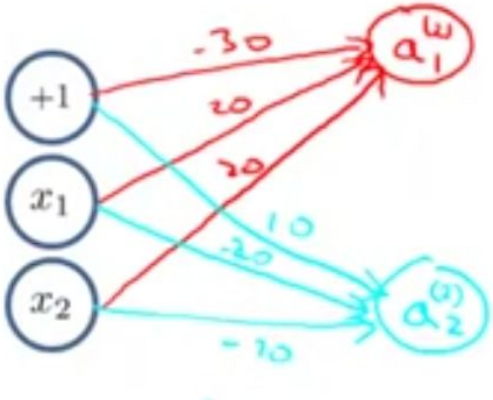
$\rightarrow x_1$ AND x_2



$\rightarrow$ (NOT x_1) AND (NOT x_2)

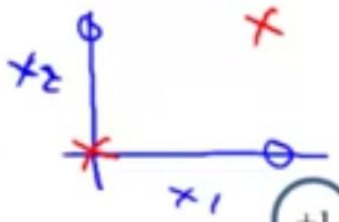


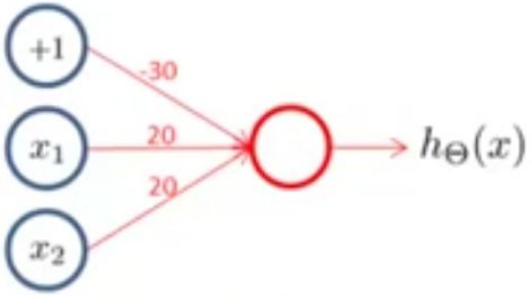
$\rightarrow x_1$ OR x_2



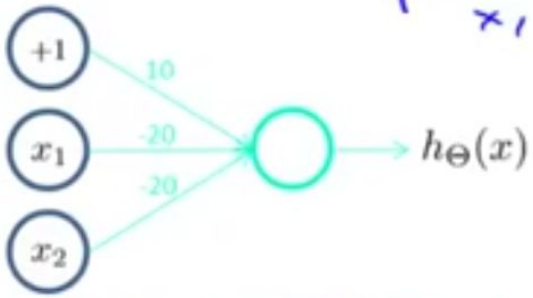
x_1	x_2	$a_1^{(2)}$	$a_2^{(2)}$	$h_\Theta(x)$
0	0			
0	1			
1	0			
1	1			

Putting it together: x_1 XNOR x_2

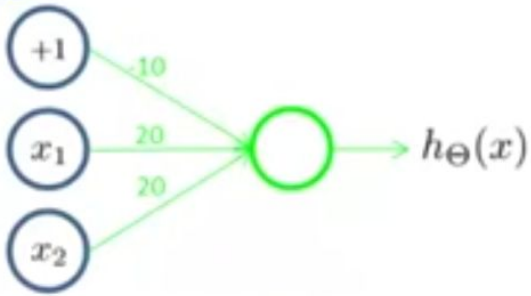




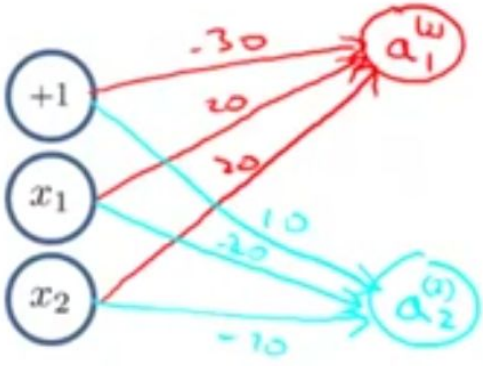
→ x_1 AND x_2



→ (NOT x_1) AND (NOT x_2)



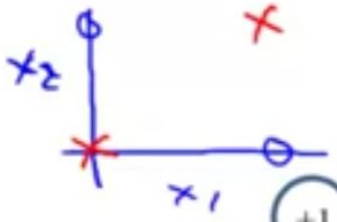
→ x_1 OR x_2

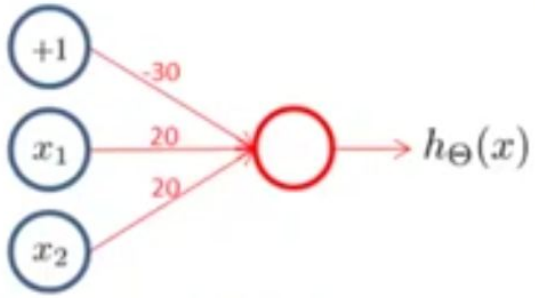


$a^{(2)}$

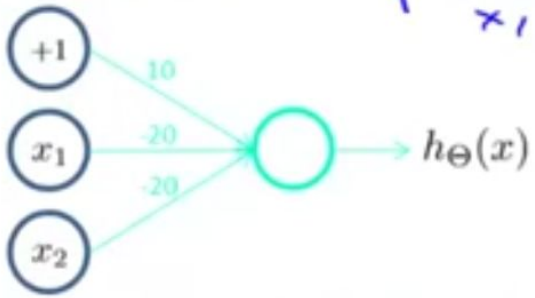
x_1	x_2	$a_1^{(2)}$	$a_2^{(2)}$	$h_\Theta(x)$
0	0	0	1	
0	1	0	0	
1	0	0	0	
1	1	1	0	

Putting it together: x_1 XNOR x_2

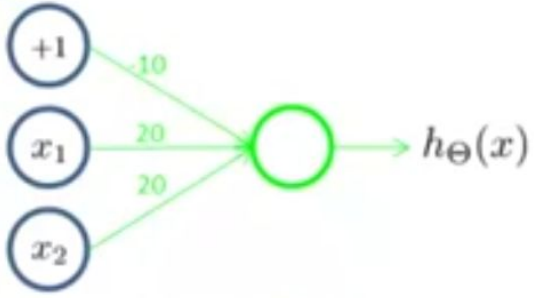




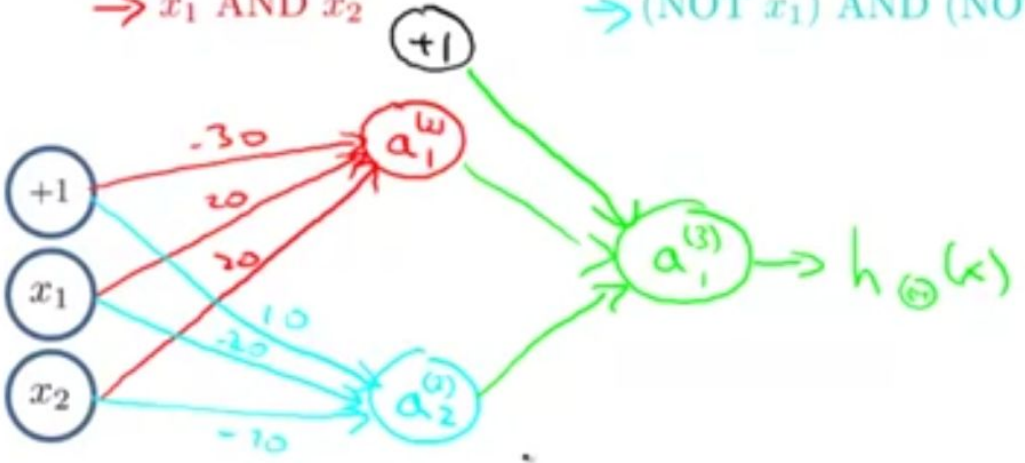
→ x_1 AND x_2



→ (NOT x_1) AND (NOT x_2)

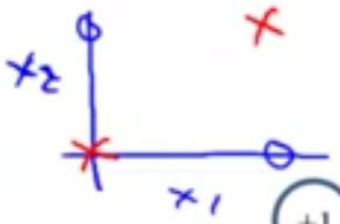


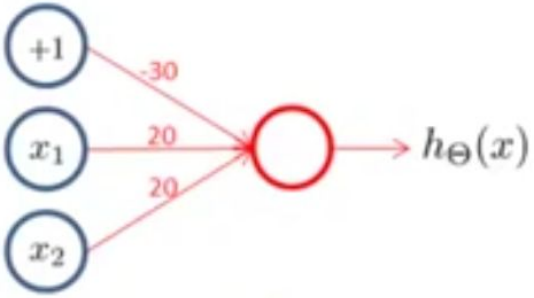
→ x_1 OR x_2



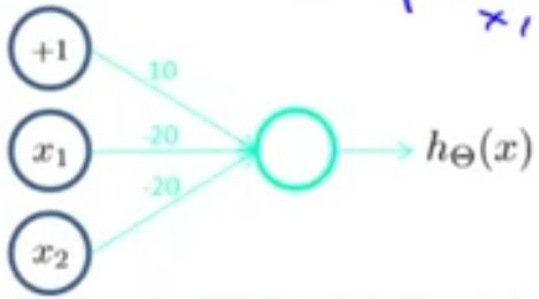
x_1	x_2	$a_1^{(2)}$	$a_2^{(2)}$	$h_\Theta(x)$
0	0	0	1	
0	1	0	0	
1	0	0	0	
1	1	1	0	

Putting it together: x_1 XNOR x_2

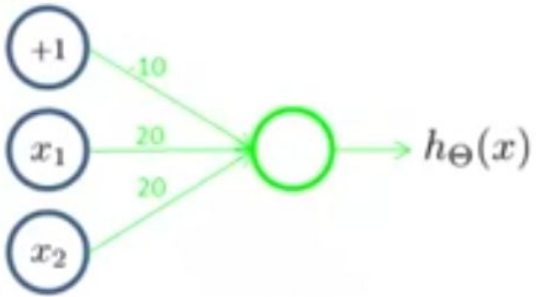




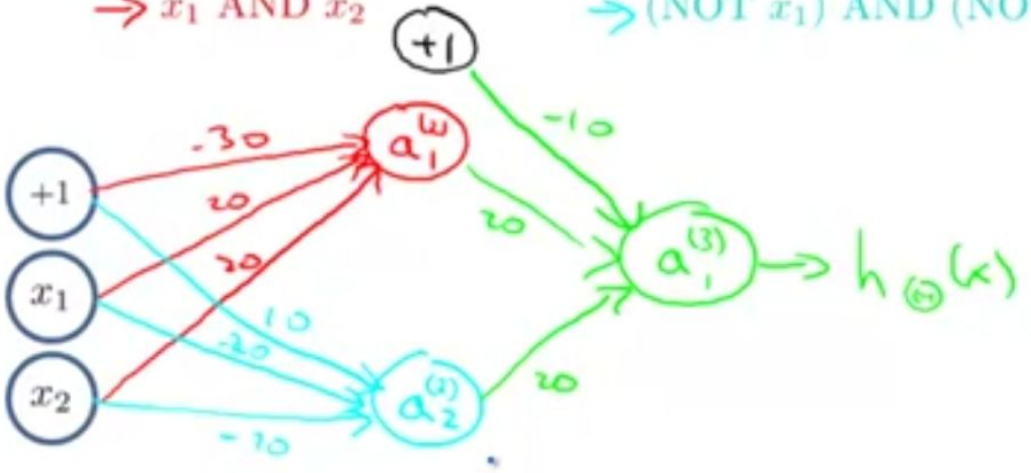
→ x_1 AND x_2



→ (NOT x_1) AND (NOT x_2)



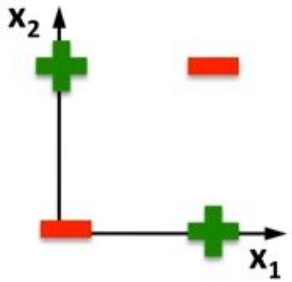
→ x_1 OR x_2

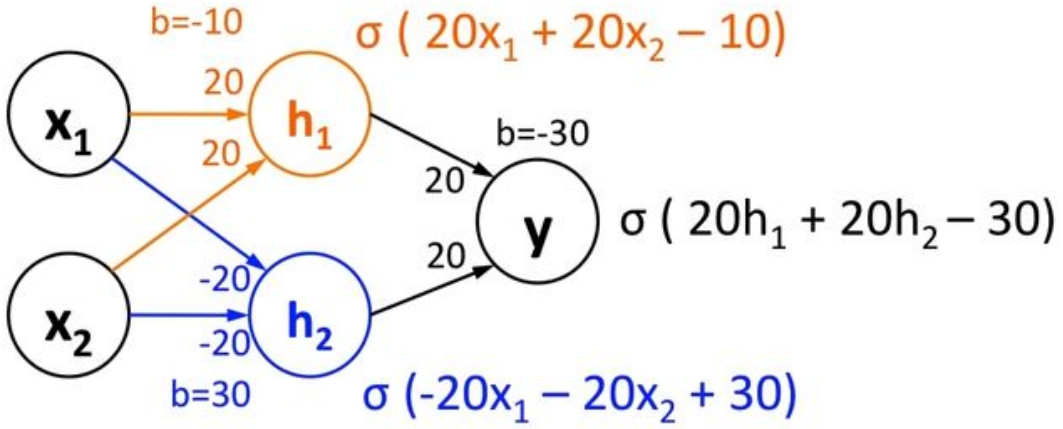


x_1	x_2	$a_1^{(2)}$	$a_2^{(2)}$	$h_\Theta(x)$
0	0	0	1	
0	1	0	0	
1	0	0	0	
1	1	1	0	

Solving XOR with a Neural Net

Linear classifiers cannot solve this

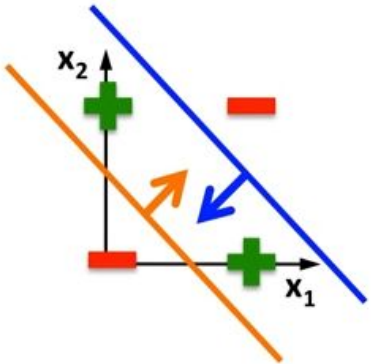


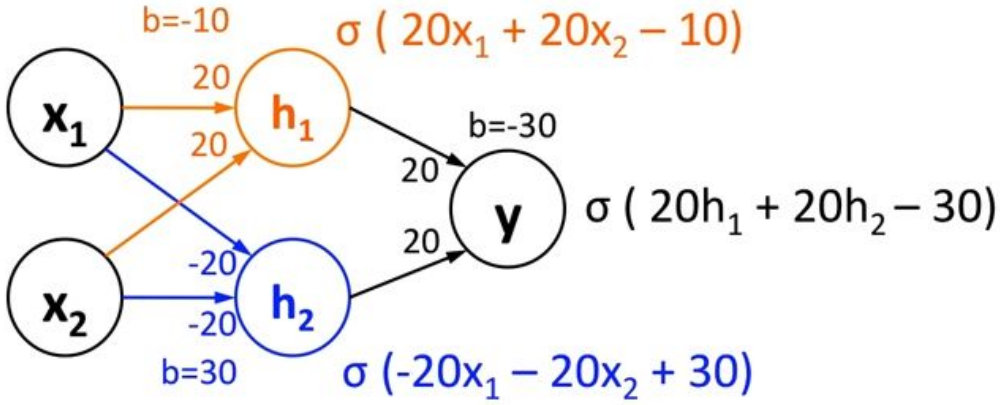


$\sigma(20*0 + 20*0 - 10) \approx 0$	$\sigma(-20*0 - 20*0 + 30) \approx 1$	$\sigma(20*0 + 20*1 - 30) \approx 0$
$\sigma(20*1 + 20*1 - 10) \approx 1$	$\sigma(-20*1 - 20*1 + 30) \approx 0$	$\sigma(20*1 + 20*0 - 30) \approx 0$
$\sigma(20*0 + 20*1 - 10) \approx 1$	$\sigma(-20*0 - 20*1 + 30) \approx 1$	$\sigma(20*1 + 20*1 - 30) \approx 1$
$\sigma(20*1 + 20*0 - 10) \approx 1$	$\sigma(-20*1 - 20*0 + 30) \approx 1$	$\sigma(20*1 + 20*1 - 30) \approx 1$
OR	OR	OR

Solving XOR with a Neural Net

Linear classifiers cannot solve this



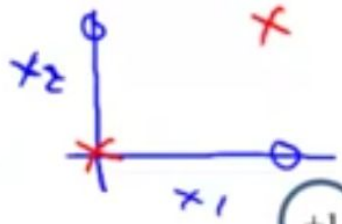


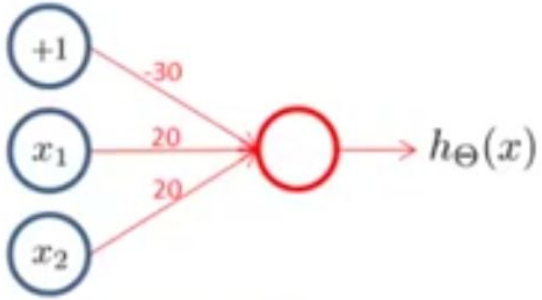
σ(20*0 + 20*0 – 10) ≈ 0
σ(20*1 + 20*1 – 10) ≈ 1
σ(20*0 + 20*1 – 10) ≈ 1
σ(20*1 + 20*0 – 10) ≈ 1

σ (-20*0 – 20*0 + 30) ≈ 1
σ (-20*1 – 20*1 + 30) ≈ 0
σ (-20*0 – 20*1 + 30) ≈ 1
σ (-20*1 – 20*0 + 30) ≈ 1

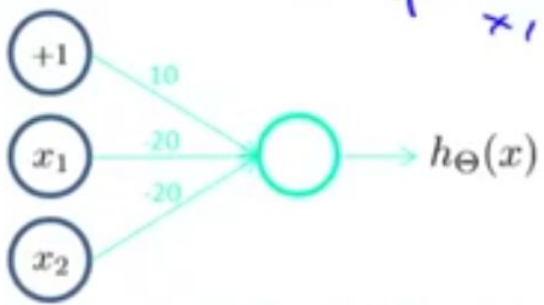
σ (20*0 + 20*1 – 30) ≈ 0
σ (20*1 + 20*0 – 30) ≈ 0
σ (20*1 + 20*1 – 30) ≈ 1
σ (20*1 + 20*1 – 30) ≈ 1

Putting it together: x_1 XNOR x_2

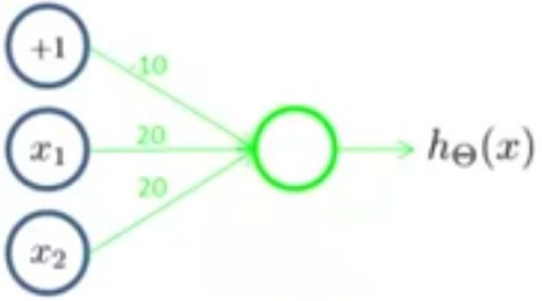




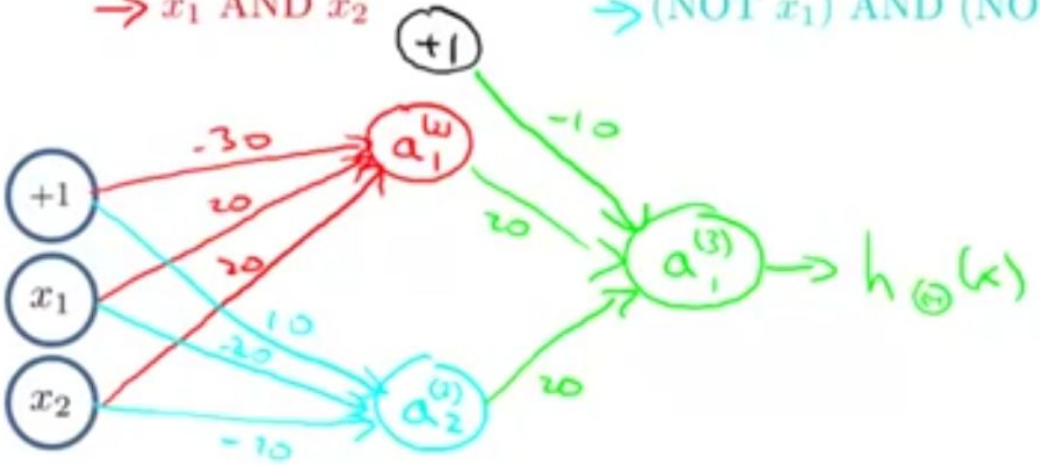
x_1 AND x_2



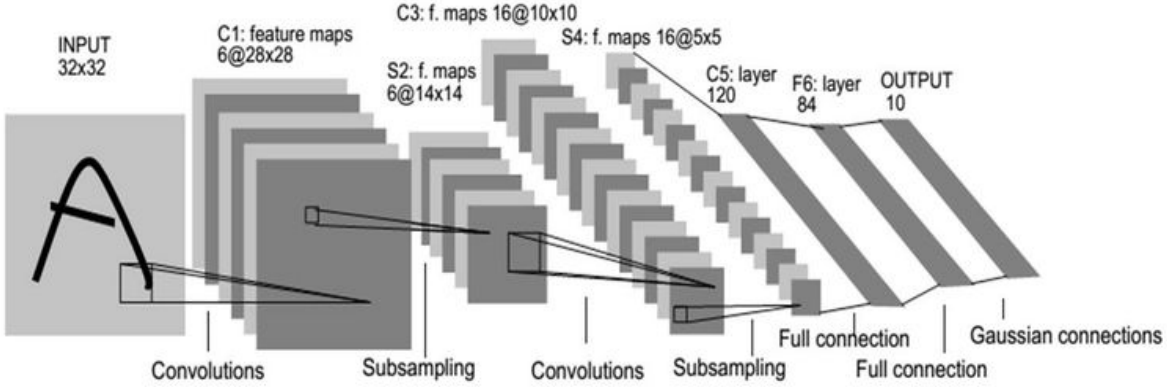
(NOT x_1) AND (NOT x_2)

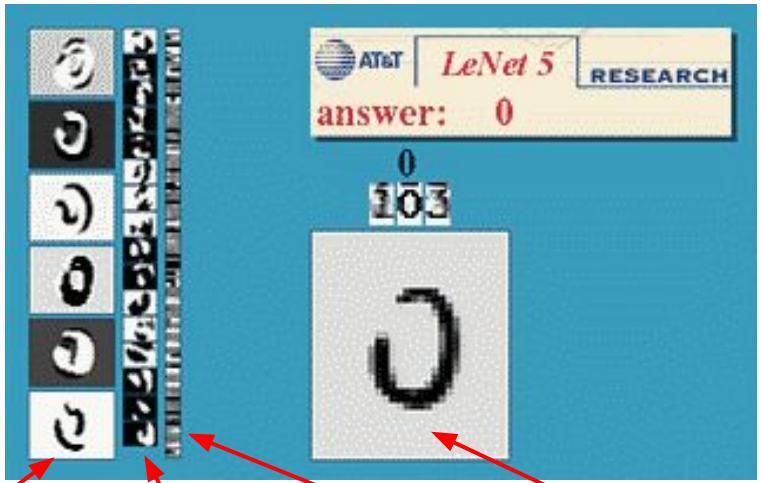


x_1 OR x_2



x_1	x_2	$a_1^{(2)}$	$a_2^{(2)}$	$h_\Theta(x)$
0	0	0	1	1
0	1	0	0	0
1	0	0	0	0
1	1	1	0	1





Layer - 1 Layer - 3 Layer - 5 Input

Yann LeCun

Director of AI Research

facebook

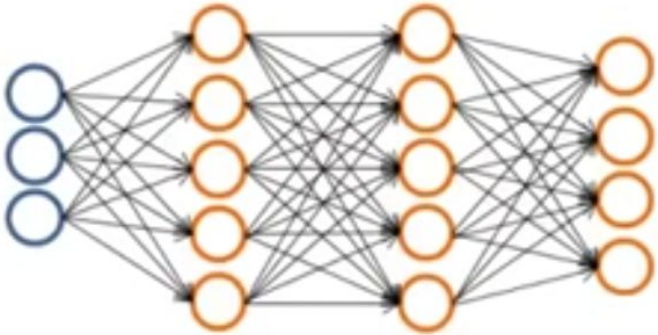
Multiple output units: One-vs-all.

Pedestrian

Car

Motorcycle

Truck

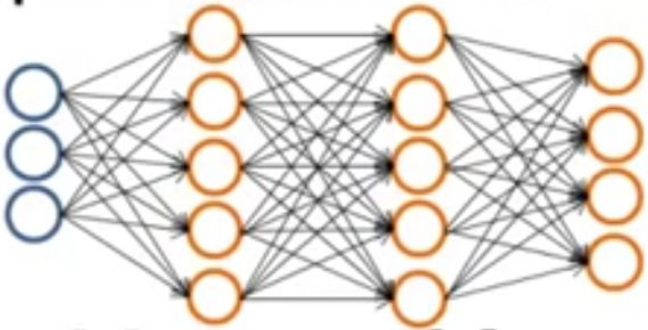


$h_\Theta(x) \in \mathbb{R}^4$

Want $h_\Theta(x) \approx \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$, $h_\Theta(x) \approx \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$, $h_\Theta(x) \approx \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$, etc.

when pedestrian when car when motorcycle

Multiple output units: One-vs-all.



$h_\Theta(x) \in \mathbb{R}^4$

Want $h_\Theta(x) \approx \begin{bmatrix}1\\0\\0\\0\end{bmatrix}$, $h_\Theta(x) \approx \begin{bmatrix}0\\1\\0\\0\end{bmatrix}$, $h_\Theta(x) \approx \begin{bmatrix}0\\0\\1\\0\end{bmatrix}$, etc.

when pedestrian when car when motorcycle

Training set: $(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \ldots, (x^{(m)}, y^{(m)})$

$y^{(i)}$ one of $\begin{bmatrix}1\\0\\0\\0\end{bmatrix}, \begin{bmatrix}0\\1\\0\\0\end{bmatrix}, \begin{bmatrix}0\\0\\1\\0\end{bmatrix}, \begin{bmatrix}0\\0\\0\\1\end{bmatrix}$

pedestrian car motorcycle truck

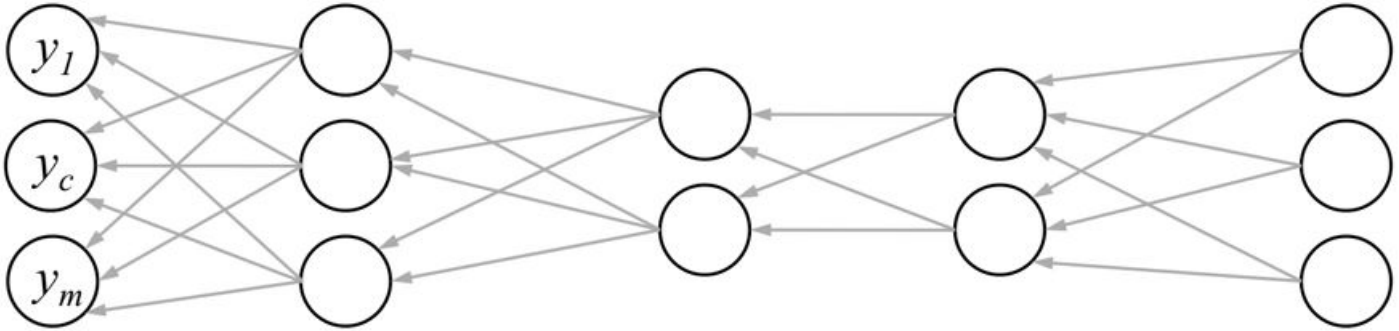
$(x^{(i)}, y^{(i)})$

Previously: $y \in \{1, 2, 3, 4\}$

$h_\Theta(x^{(i)}) \approx y^{(i)}$

$\mathbb{R}^4$

Multi-class Neural Networks



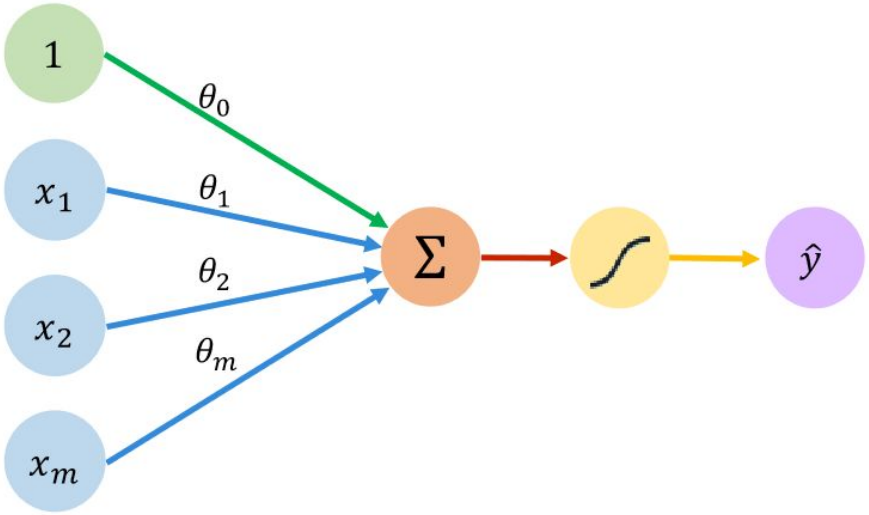
- Default NN predicts a single class (or number)
- Add separate output y_c unit for each class c
  - example $(\mathbf{x},c)$: set $y_c = 1$, and $y_i = 0$ for all $i \neq c$
- Predict class c with the highest y_c
- Can compute confidence in c: $P(c \mid y) = \frac{e^{y_c}}{\sum_c e^{y_c}}$
  - soft-max rule, same as in logistic

PERCEPTRON

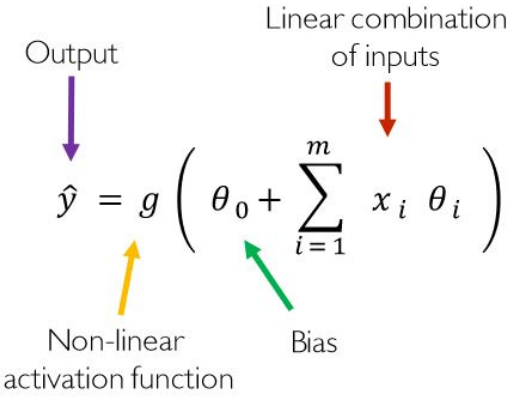
The fundamental building block of Deep Learning.

PLAYGROUND

Review



Inputs Weights Sum Non-Linearity Output

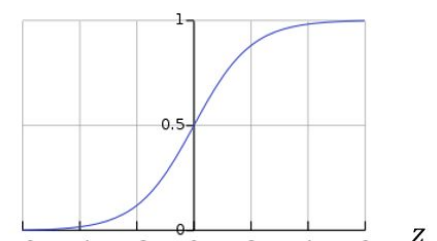


Activation Functions

$$\hat{y} = g(\theta_0 + \boldsymbol{X}^T \boldsymbol{\theta})$$

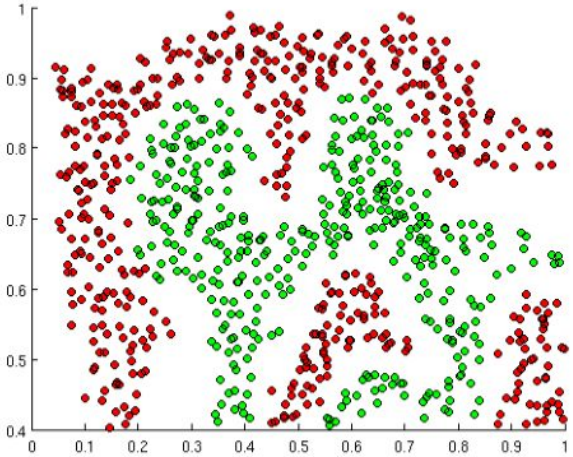
- Example: sigmoid function

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

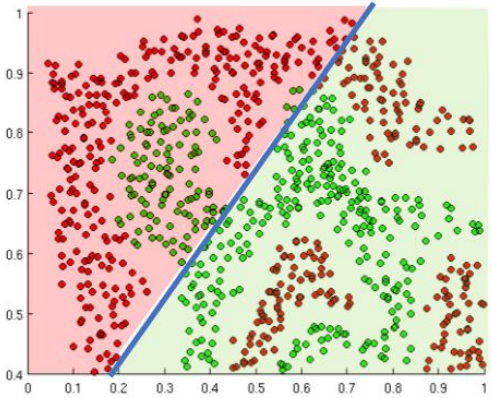


where: $\boldsymbol{X} = \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix}$ and $\boldsymbol{\theta} = \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_m \end{bmatrix}$

The purpose of activation functions is to introduce non-linearities into the network.



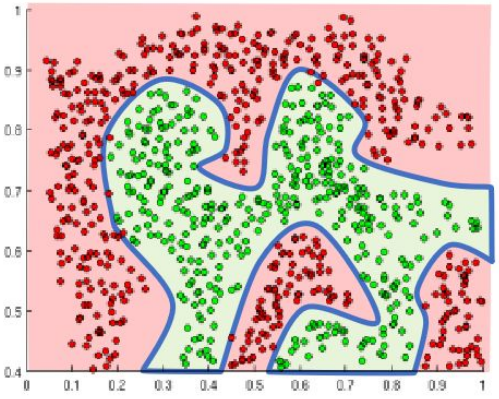
What you can doing..



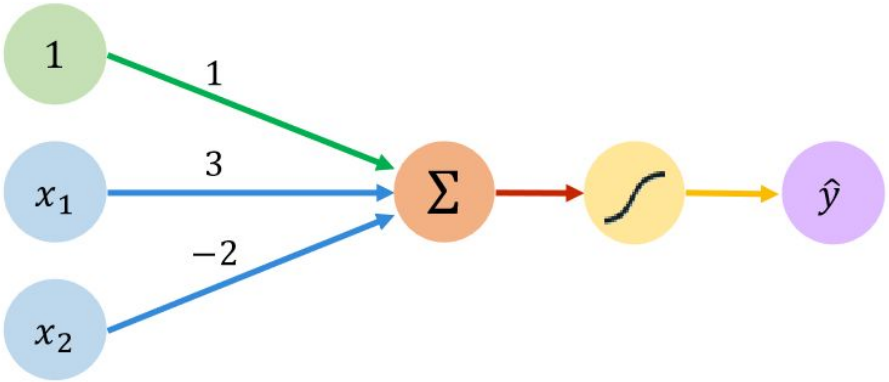
Linear Activation functions produce linear decisions no matter the network size

Reality is complex i.e non-linear..

What you want to do..



Non-linearities allow us to approximate arbitrarily complex functions



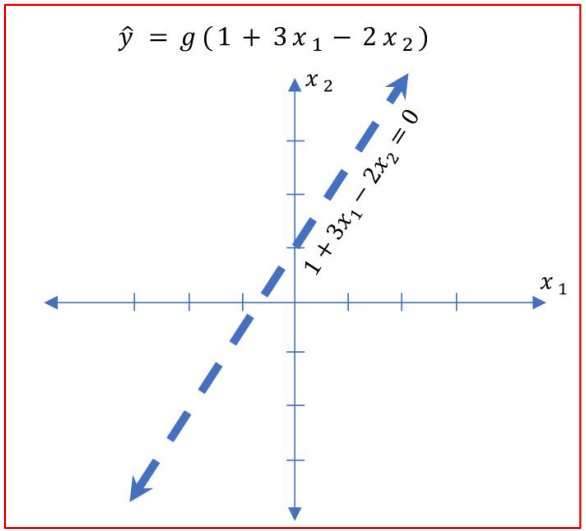
We have: $\theta_0 = 1$ and $\boldsymbol{\theta} = \begin{bmatrix} 3 \\ -2 \end{bmatrix}$

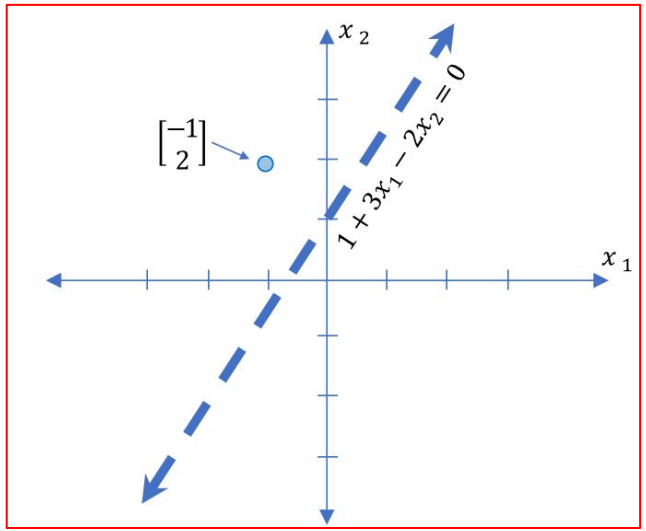
$$\hat{y} = g(\theta_0 + \boldsymbol{X}^T \boldsymbol{\theta})$$

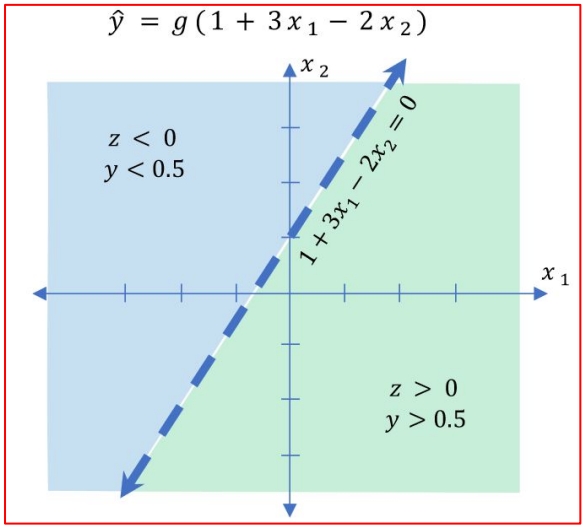
$$= g\left(1 + \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}^T \begin{bmatrix} 3 \\ -2 \end{bmatrix}\right)$$

$$\hat{y} = g(\underbrace{1 + 3x_1 - 2x_2}_{})$$

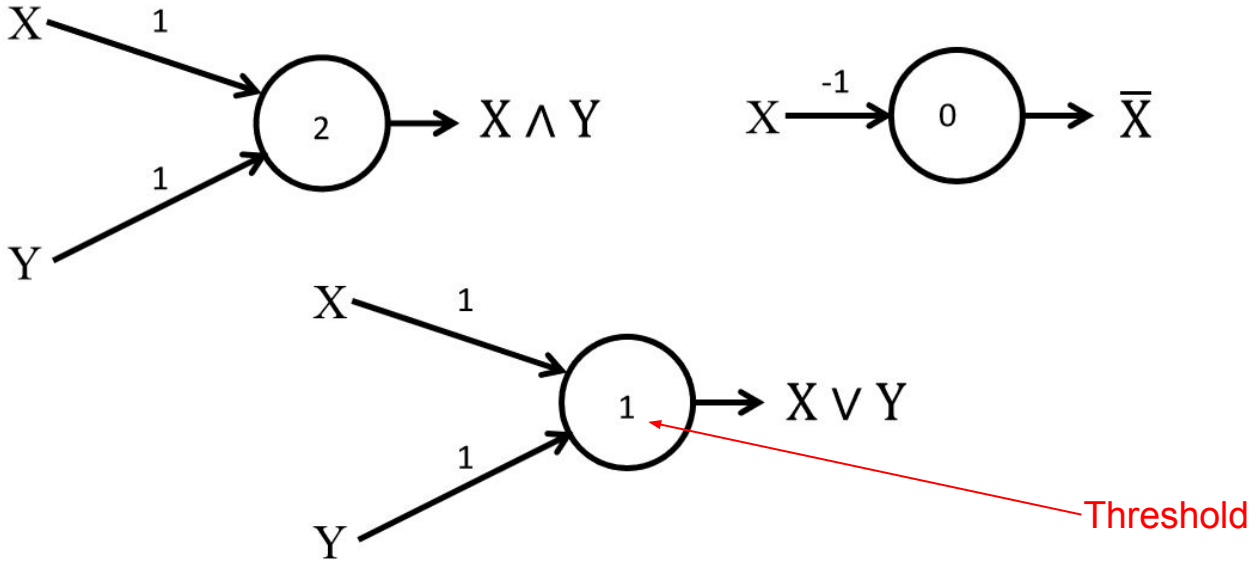
This is just a line in 2D!





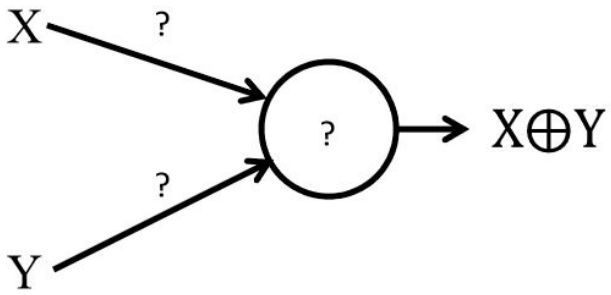


The perceptron as a Boolean gate



- A perceptron can model any simple binary Boolean gate

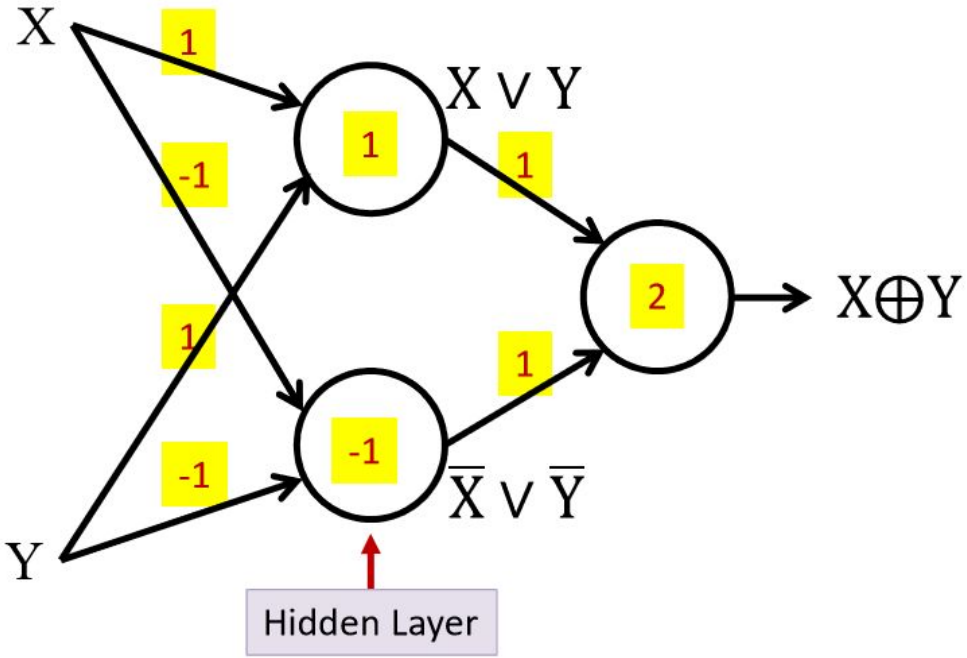
The perceptron is not enough



No solution for XOR, therefore Not universal!

- Cannot compute an XOR

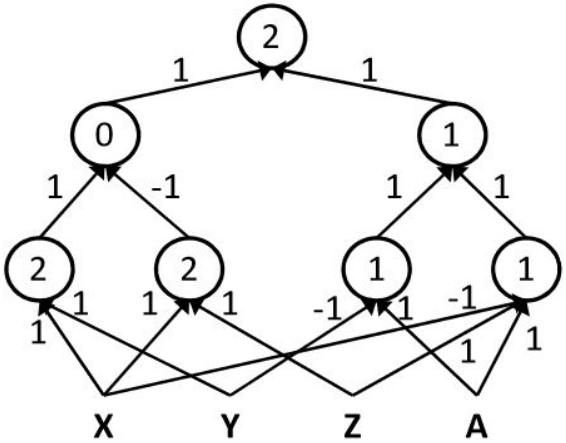
Multi-layer perceptron



- MLPs can compute the XOR

Multi-layer perceptron

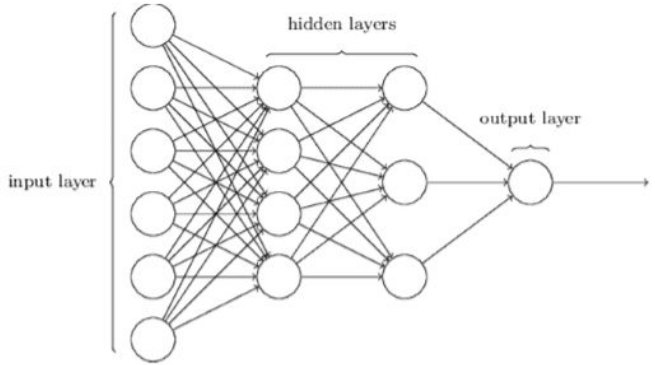
$$((A\&\bar{X}\&Z)|(A\&\bar{Y}))\&((X\ \&\ Y)|\overline{(X\&Z)})$$

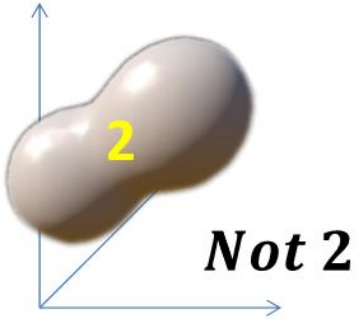


- MLPs can compute more complex Boolean functions
- MLPs can compute *any* Boolean function
  - Since they can emulate individual gates
- **MLPs are *universal Boolean functions***

The MLP as a classifier

784 dimensions
(MNIST)

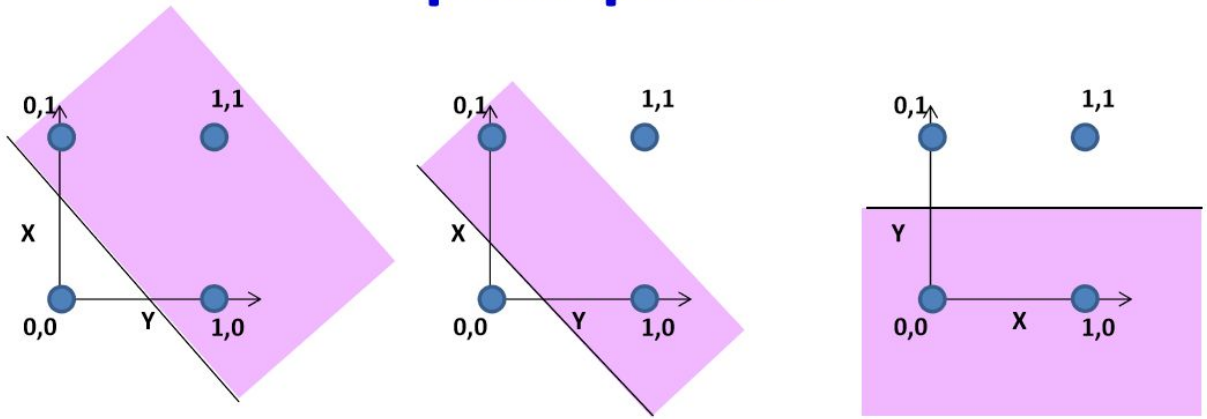




784 dimensions

- MLP as a function over real inputs
- MLP as a function that finds a complex “decision boundary” over a space of *reals*

Boolean functions with a real perceptron



- Boolean perceptrons are also linear classifiers
  - Purple regions are 1

Hinton's Closing Prayer

Our father who art in n-dimensions

hallowed by the backprop,

thy loss be minimized,

thy gradients unvarnished,

on earth as it is in Euclidean space.

Give us this day our daily hyperparameters,

and forgive us our large learning rates,

as we forgive those whose parameters diverge,

and lead us not into discrete optimization,

but deliver us from local optima.

For thine are dimensions,

and the GPUs, and the glory,

forever and ever. Dropout.

From buZZrobot

Q&A SESSION