Data Visualization Group
Northstar Middle School

Denny Lee

About Me

- Sr Staff Developer Advocate, Databricks
- Senior Director of Data Science Engineering at SAP Concur
- Principal Program Manager at Microsoft for Azure Cosmos DB, Project Isotope (Azure HDInsight), SQL Server

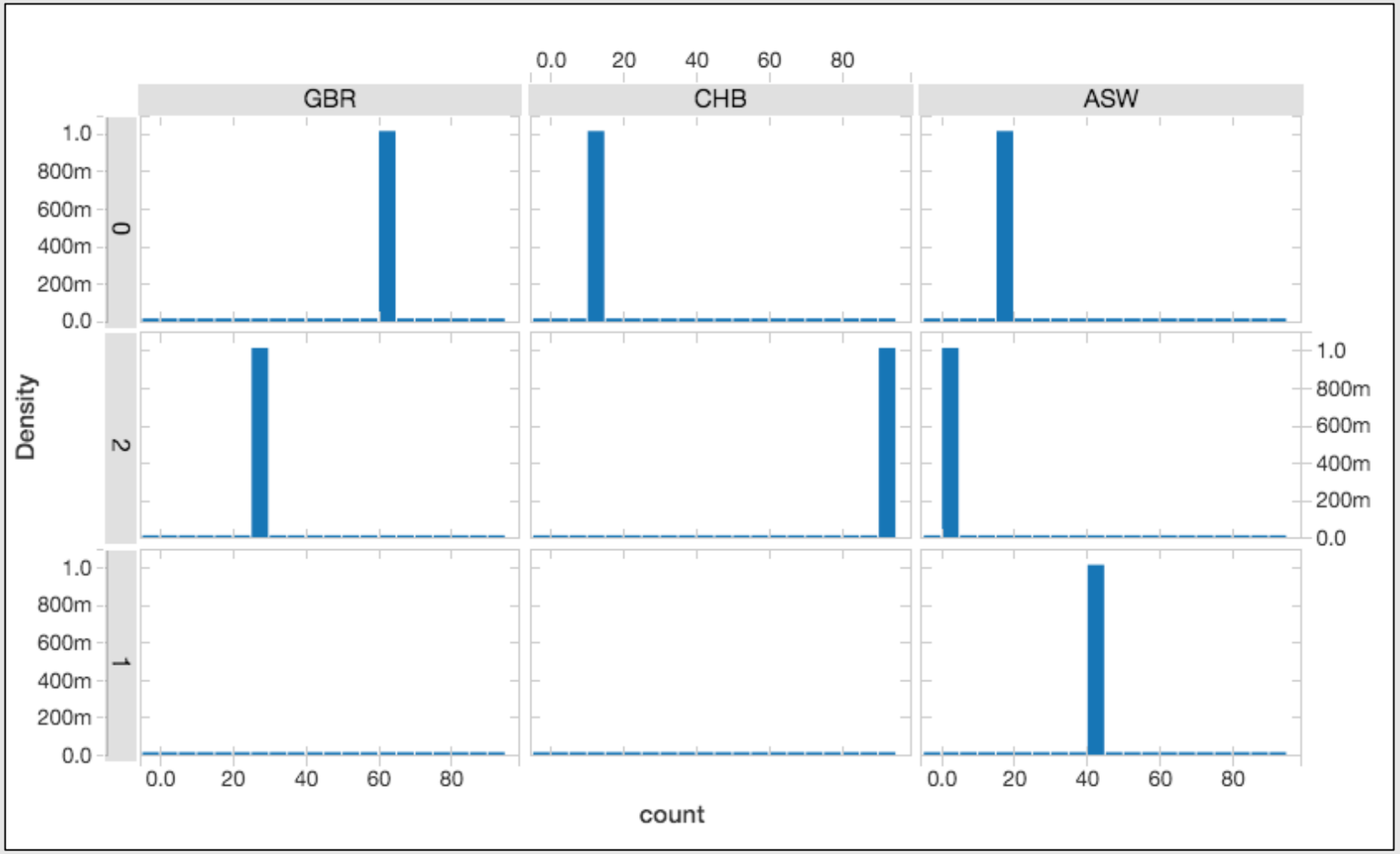
Denny surprised that he's still awake

Session Goals

- What is Deep Learning?
- Deep Learning Applications – including data visualization
- Biology vs scientific model
- Demos!
- Maths (completely optional)

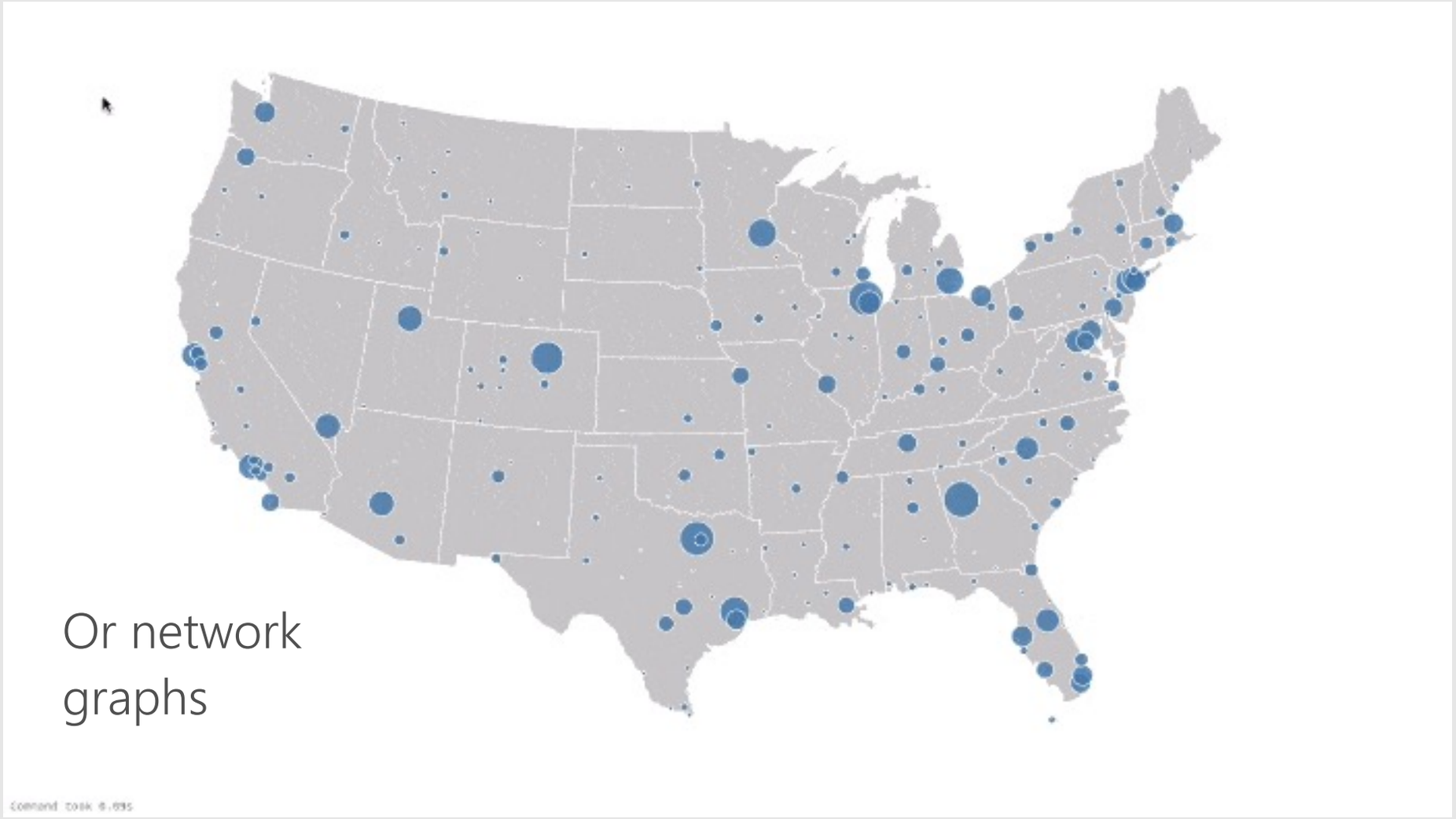
What is Deep Learning?


WAIT, ISN'T THIS
A VISUALIZATION SESSION?
imgflip.com



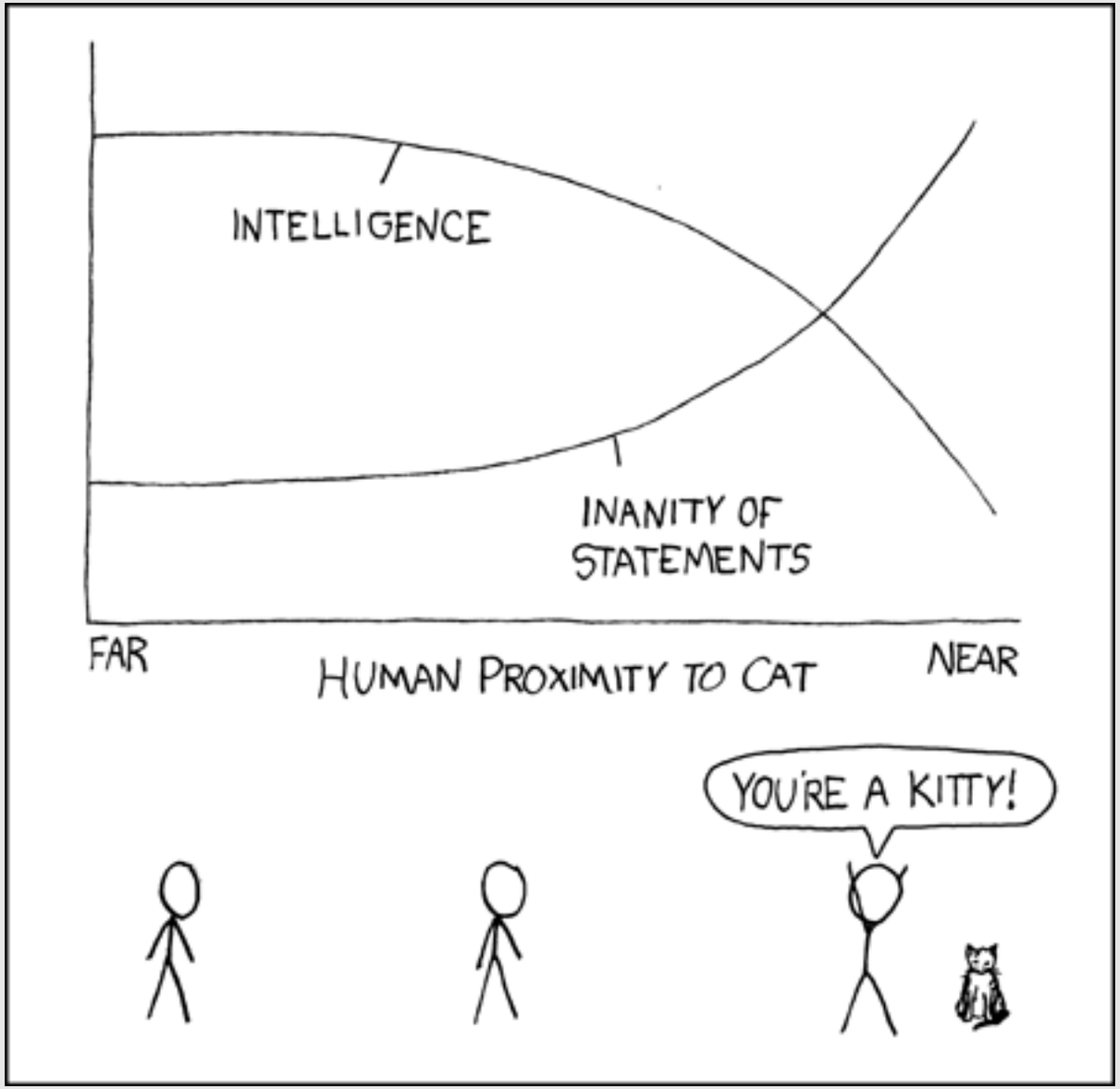
Data visualization can mean a lot of things

.. like graphs!



Or network graphs

Or even more charts …



xkcd comic 231

Or even worse …

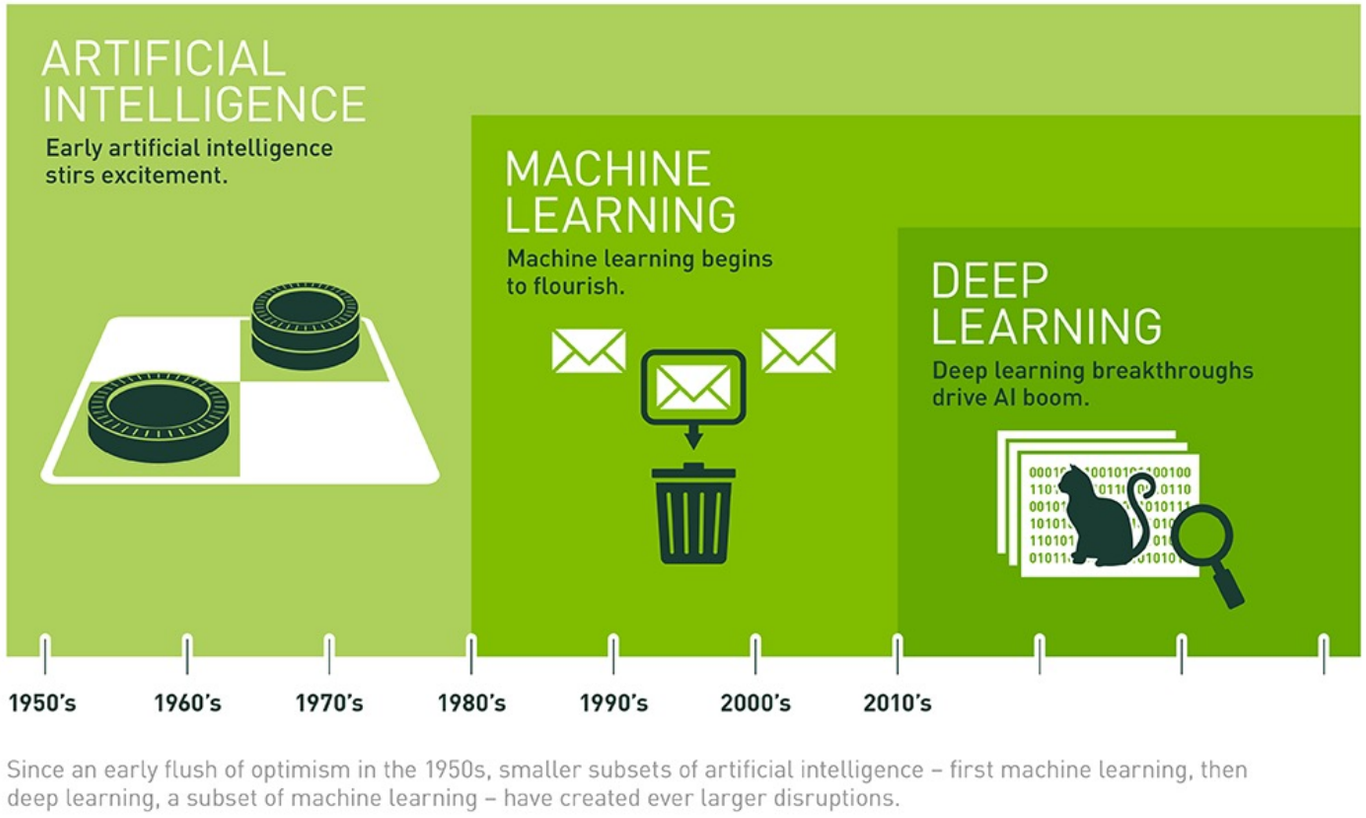
But today, we're talking about the ability to interpret visual data

source: http://bit.ly/2jcquh5

Deep Learning

The next step in AI

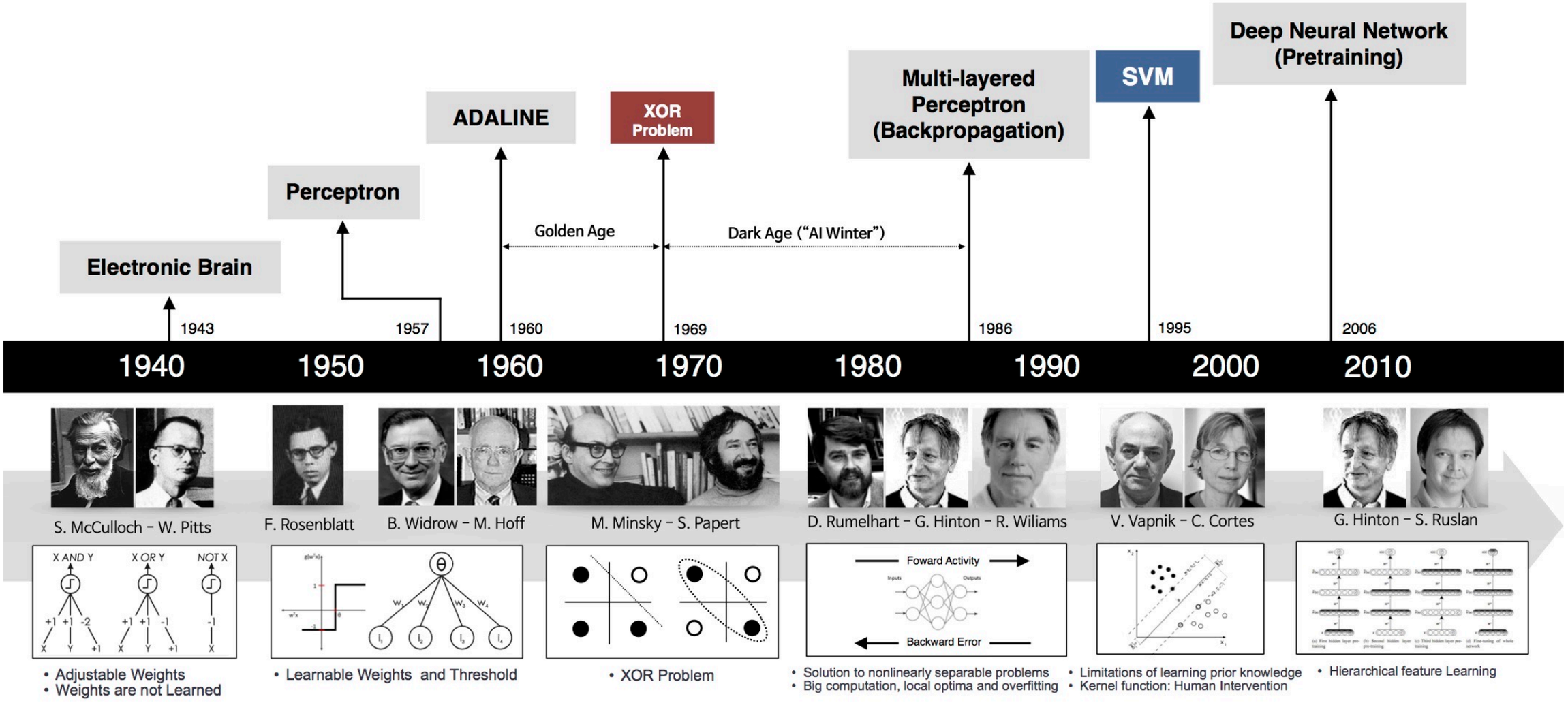
Learning… Lots of learning…



Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

Source: http://bit.ly/2suufGJ

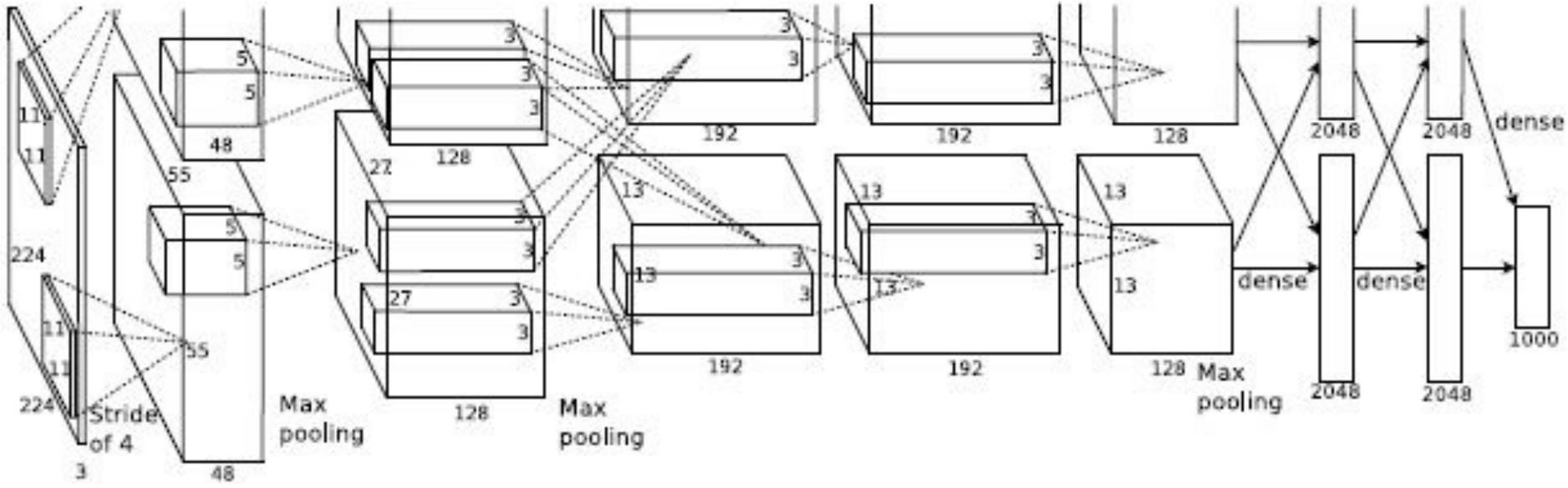
History of AI research



Source: http://bit.ly/2EILhpu

Deep learning

- Vast and sophisticated ANN structure
- Tens, hundreds, thousands… of hidden layers
- Ability to not only map the input to the output but recognize what inputs are needed for the task

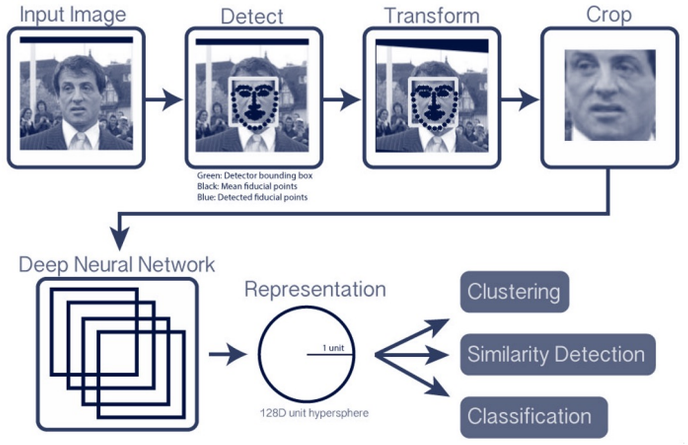


Example: AlexNet (ImageNet 2012 winner); Source: http://bit.ly/2tNa3Ps

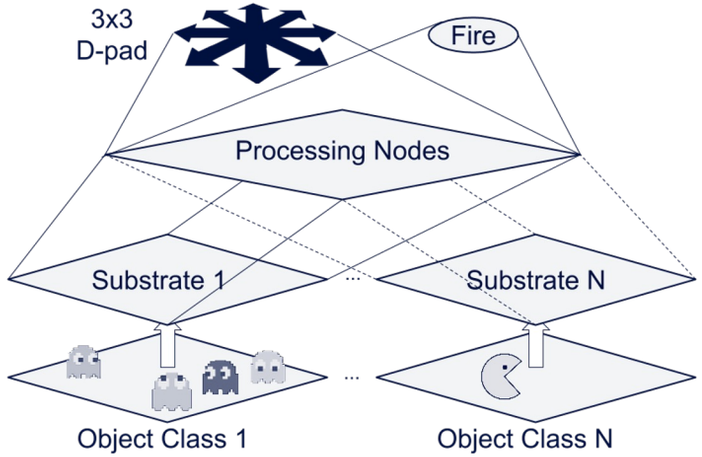
Deep Learning Applications

Applications of neural networks

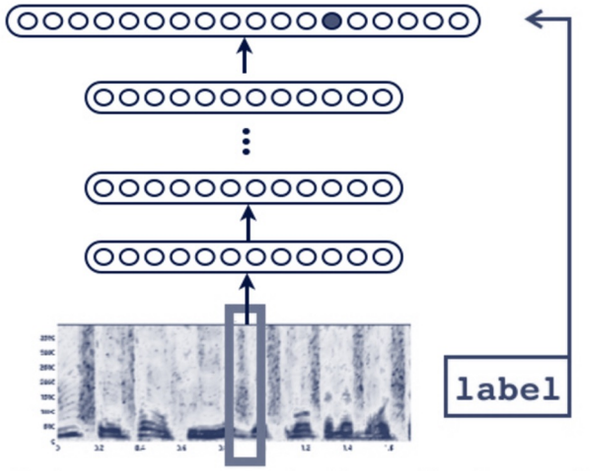
Object Recognition: Facial



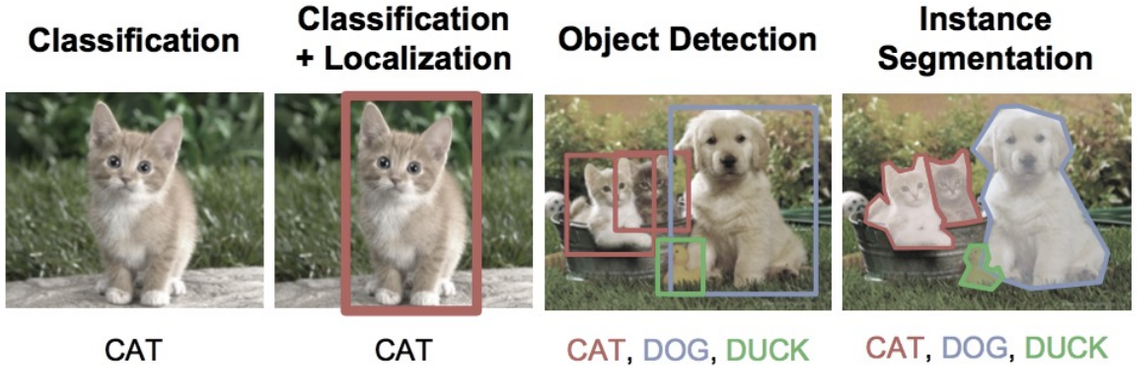
Game Playing



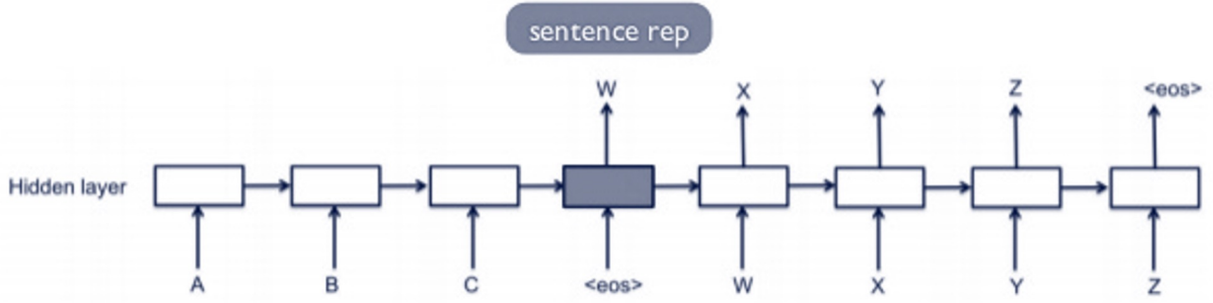
Object Recognition: Speech



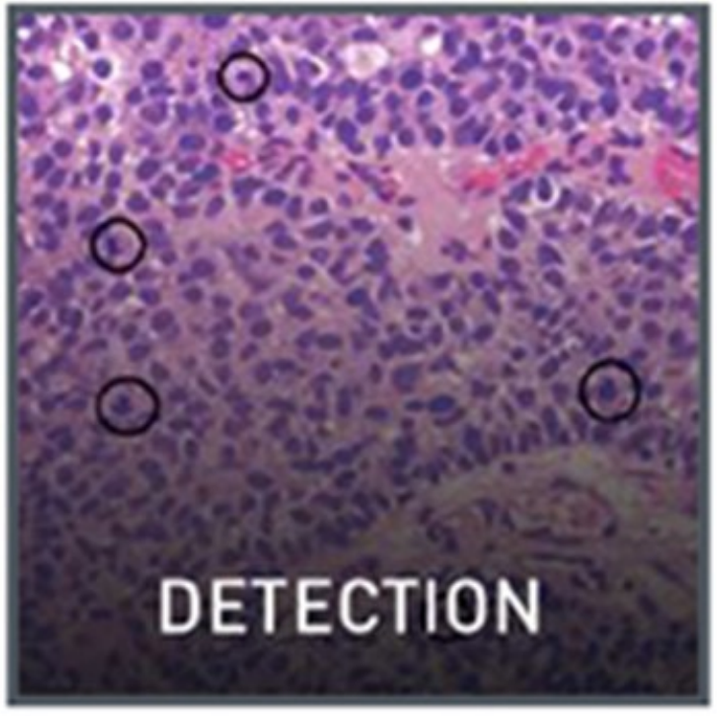
Object Classification

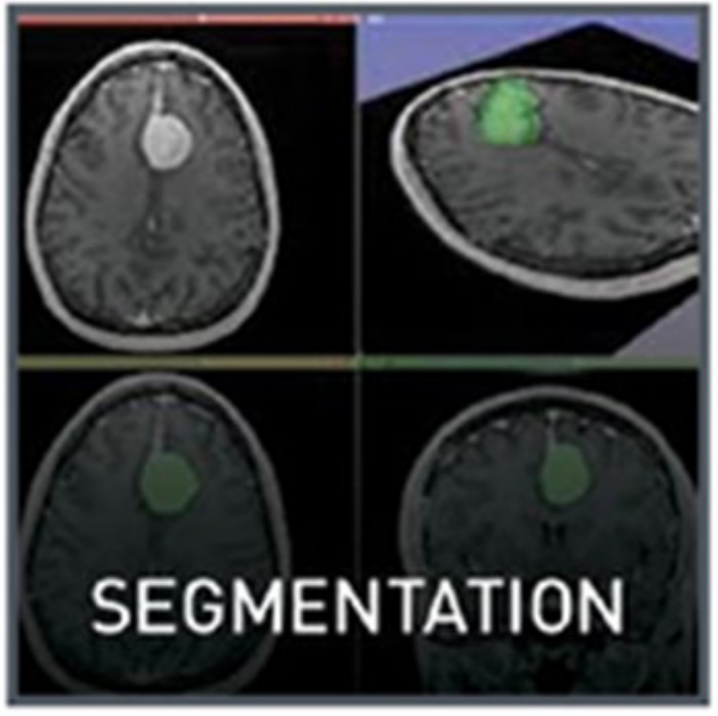


Language Translation



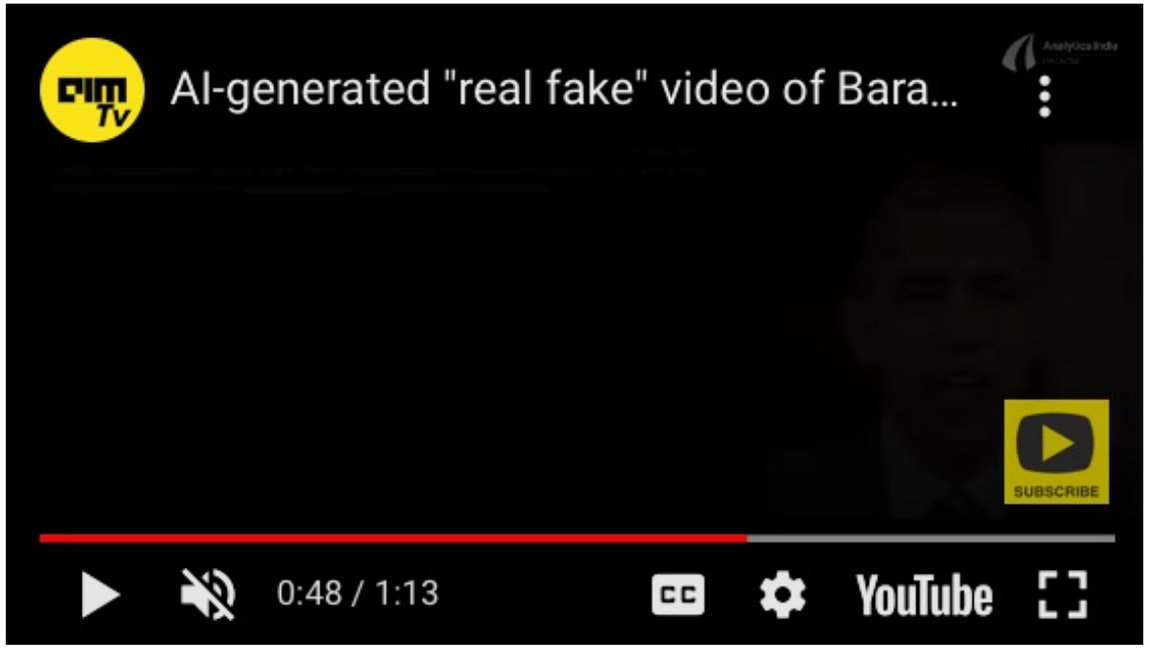
Healthcare





Source: http://bit.ly/2BXF5sR

Faking videos

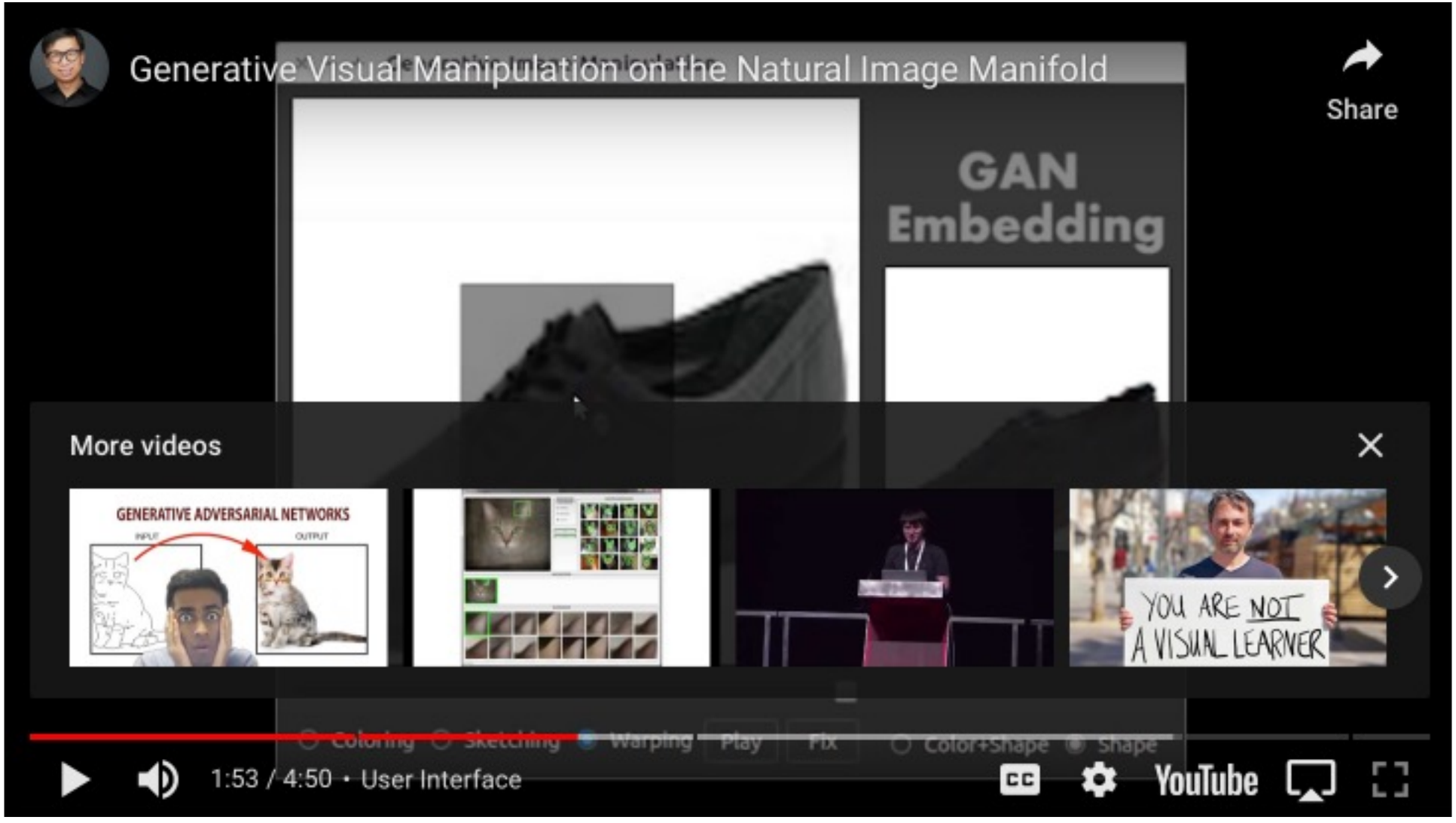


Source: https://youtu.be/dkoi7sZvWiU

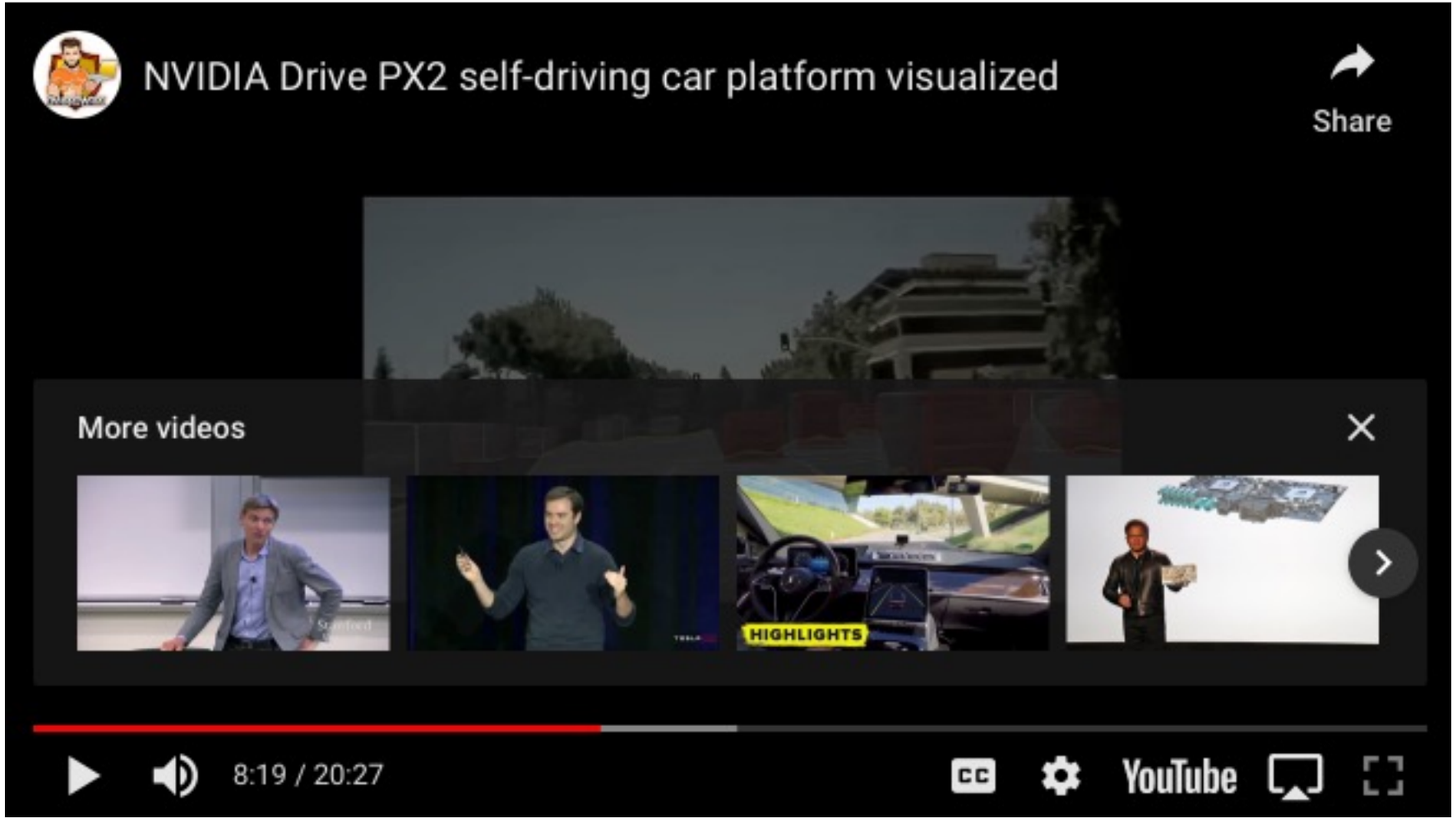
Source: https://youtu.be/JzgOfISLNjk

Drawing support

https://www.youtube.com/watch?v=9c4z6YsBGQ0

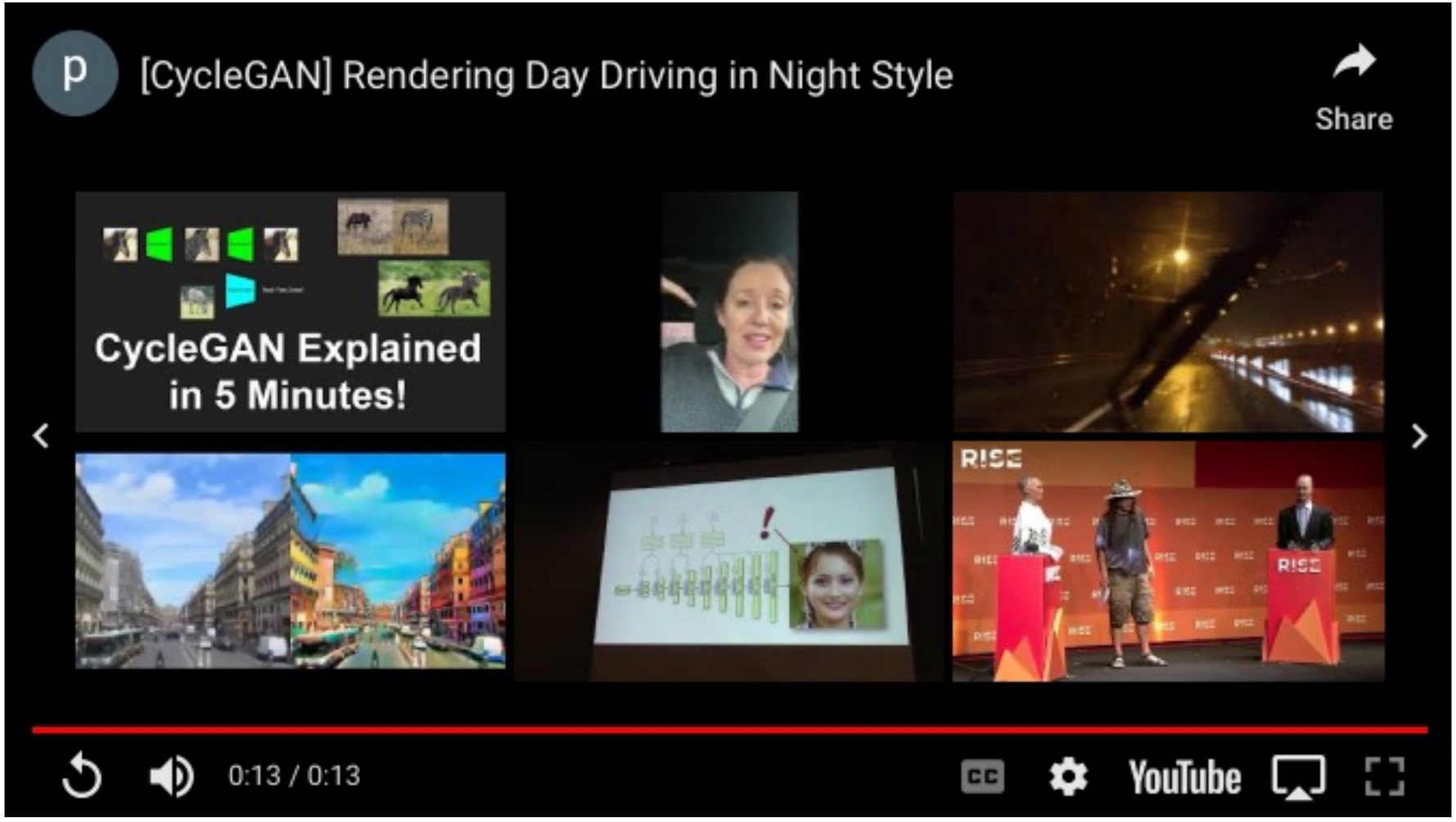


Self-driving cars



Source: https://youtu.be/URmxzxYlmtg?t=6m30s

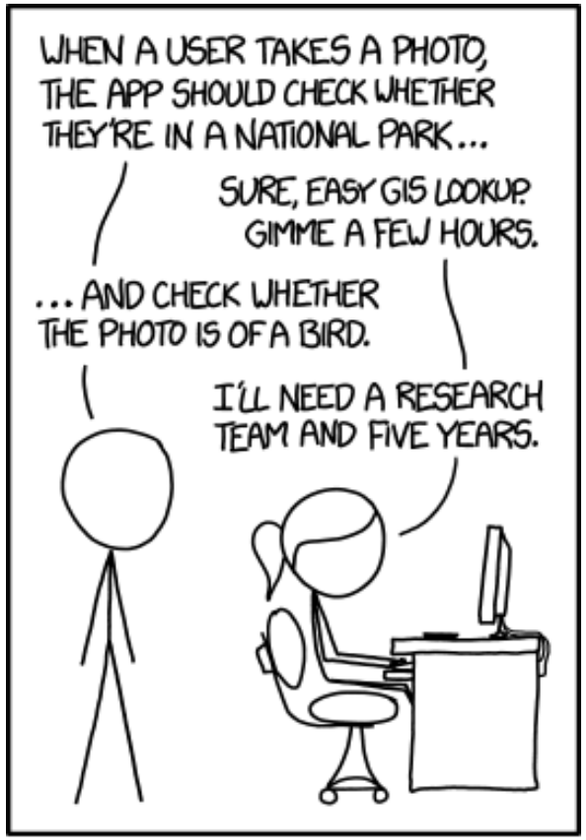
Turning the day into night



Source: https://youtu.be/N7KbfWodXJE

Recognizing Objects

xkcd #1425 (View original here)



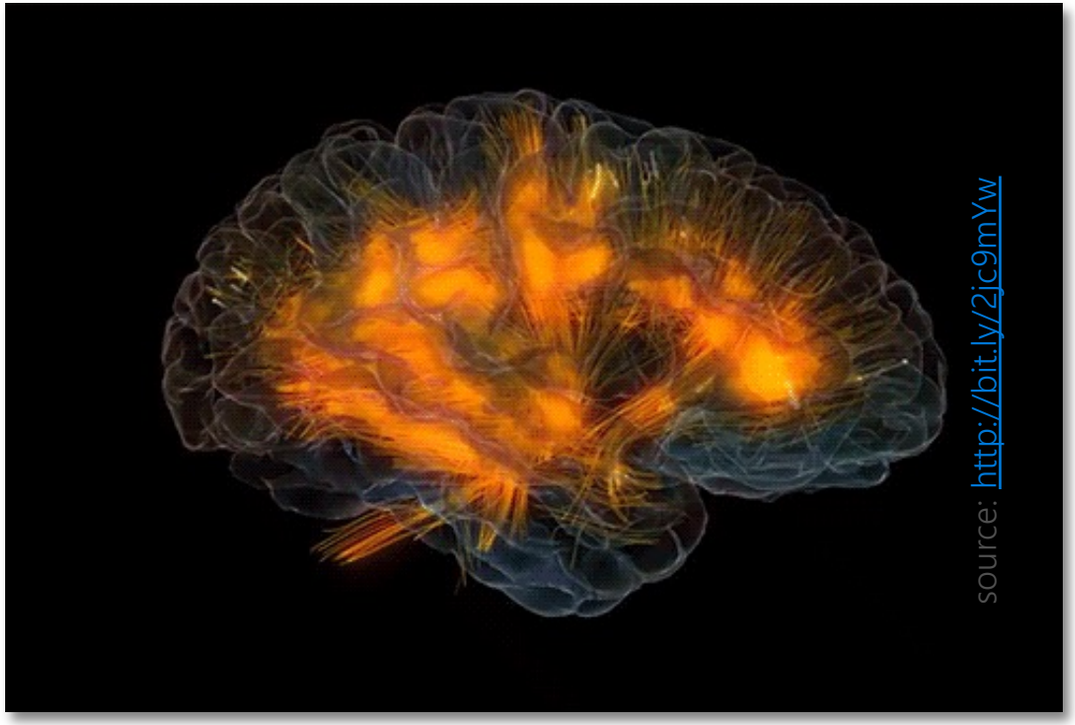
Really good explanation of convolution
http://bit.ly/2suZGkk

source: http://bit.ly/2jjzFyt

What are artificial neural networks?

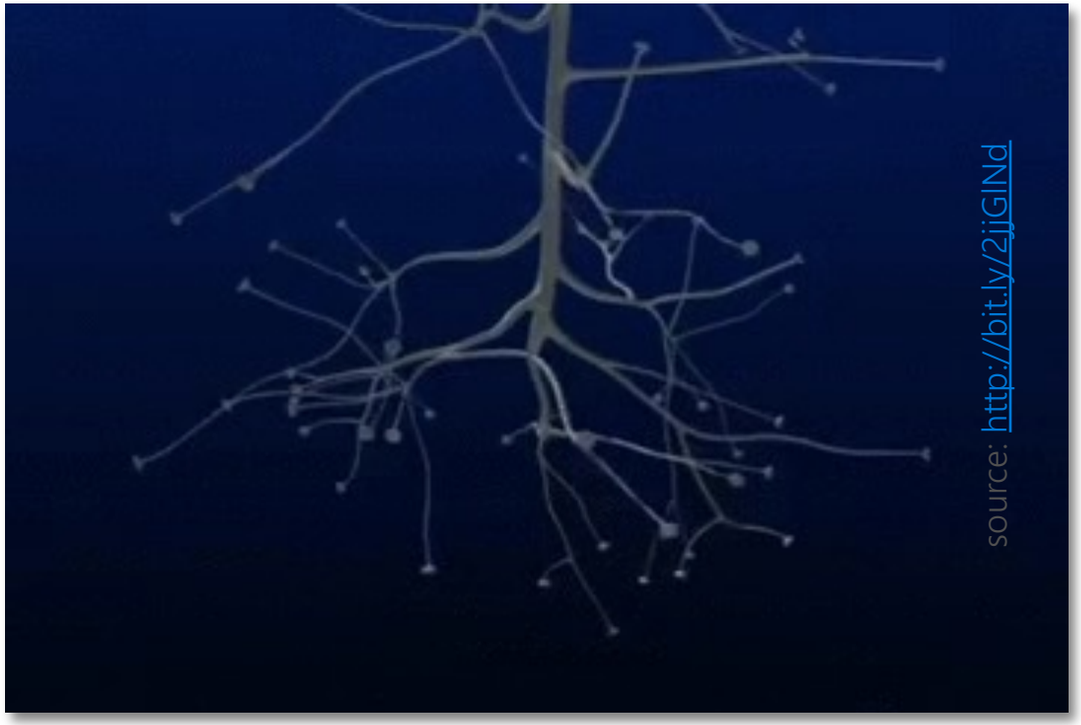
An imitation of human's brain

- Dense net of simple structures
- Around 100 billion neurons
- Each connected to ~10k other neurons
- 10^{15} synaptic connections



A neuron at work

- Receive signal
- Process it
- Propagate the signal (or not)

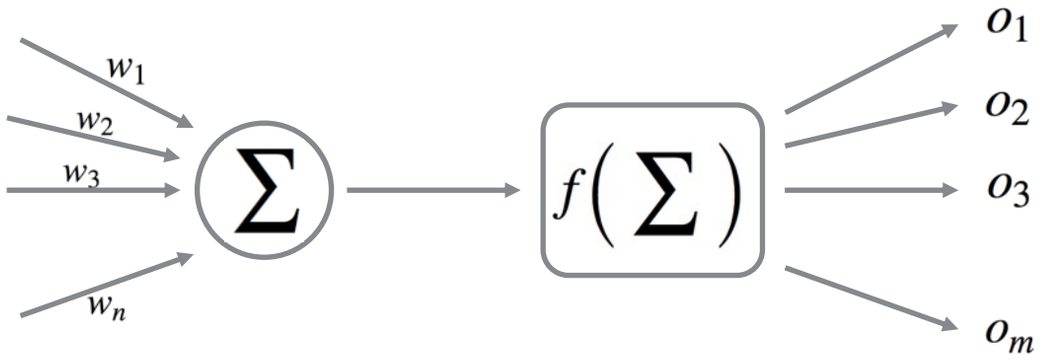


Conceptual mathematical model

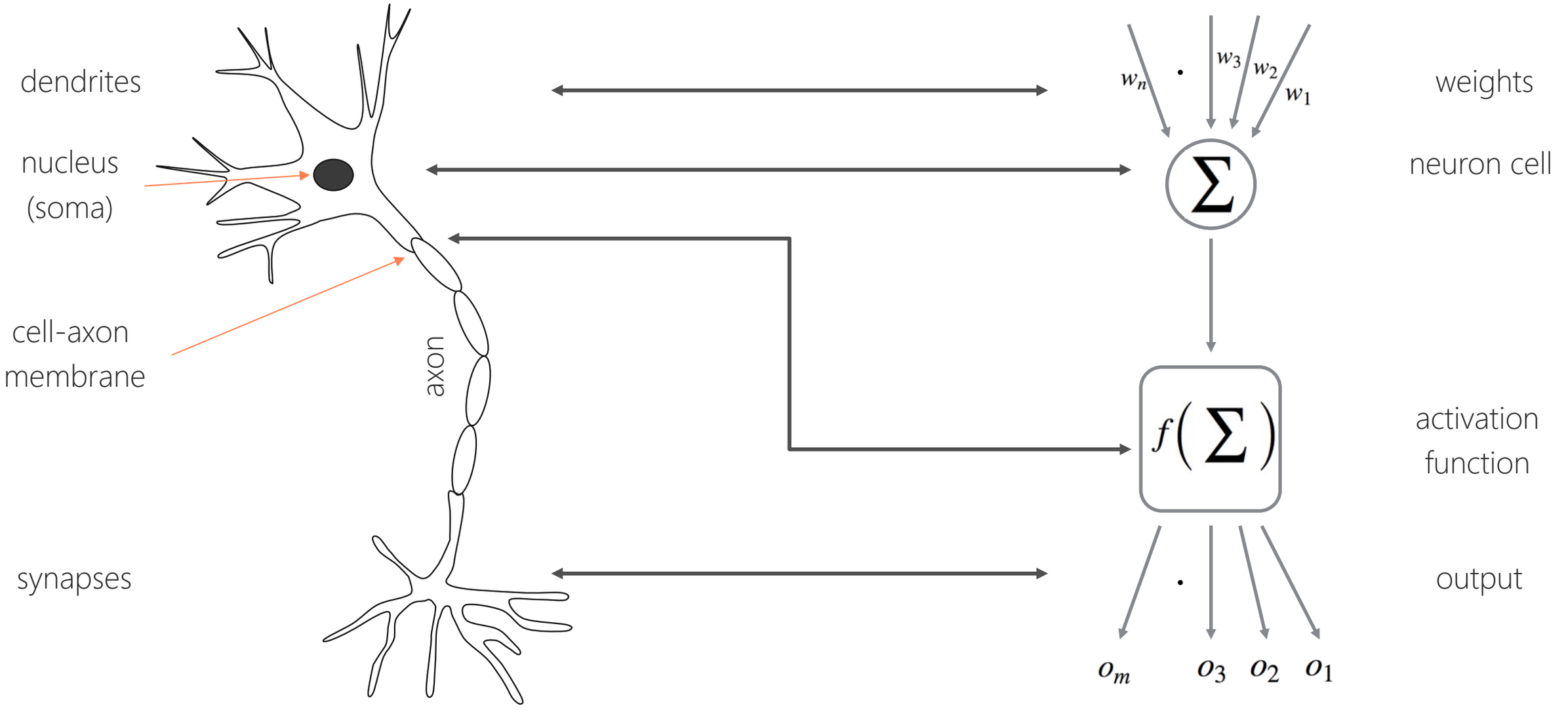
- Receives input from *n* sources
- Computes weighted sum

$$h_1 = x_1 w_1 + x_2 w_2 + \ldots + x_n w_n$$

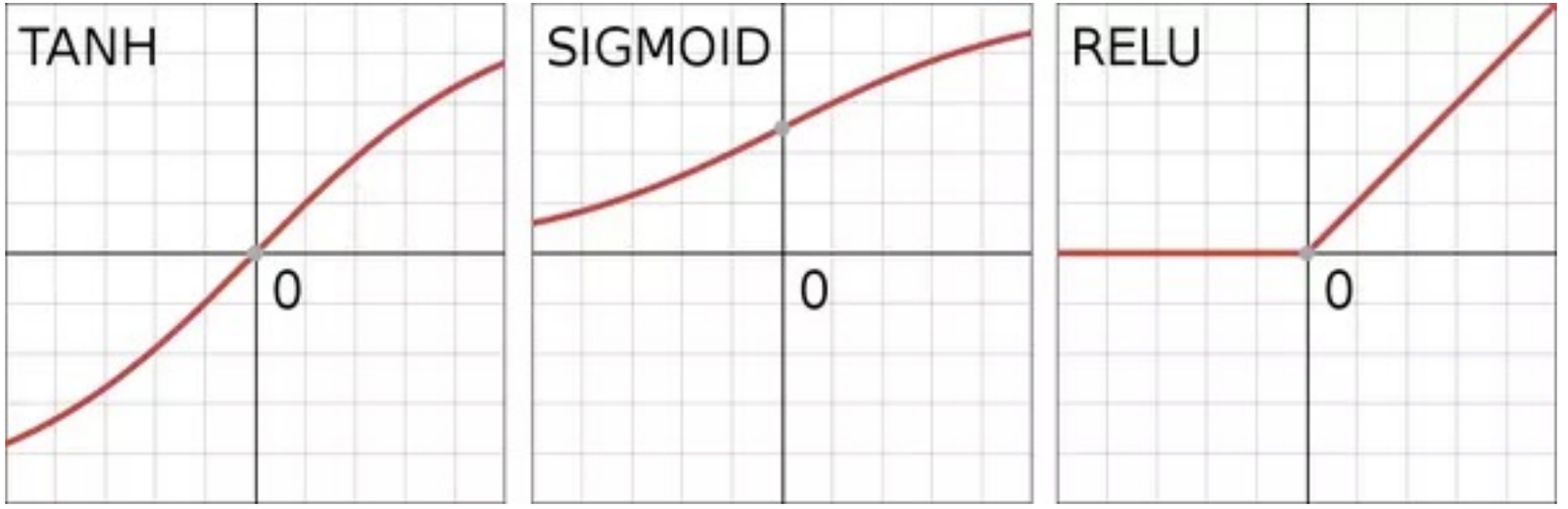
- Passes through an *activation function*
- Sends the signal to *m* succeeding neurons



Parallels

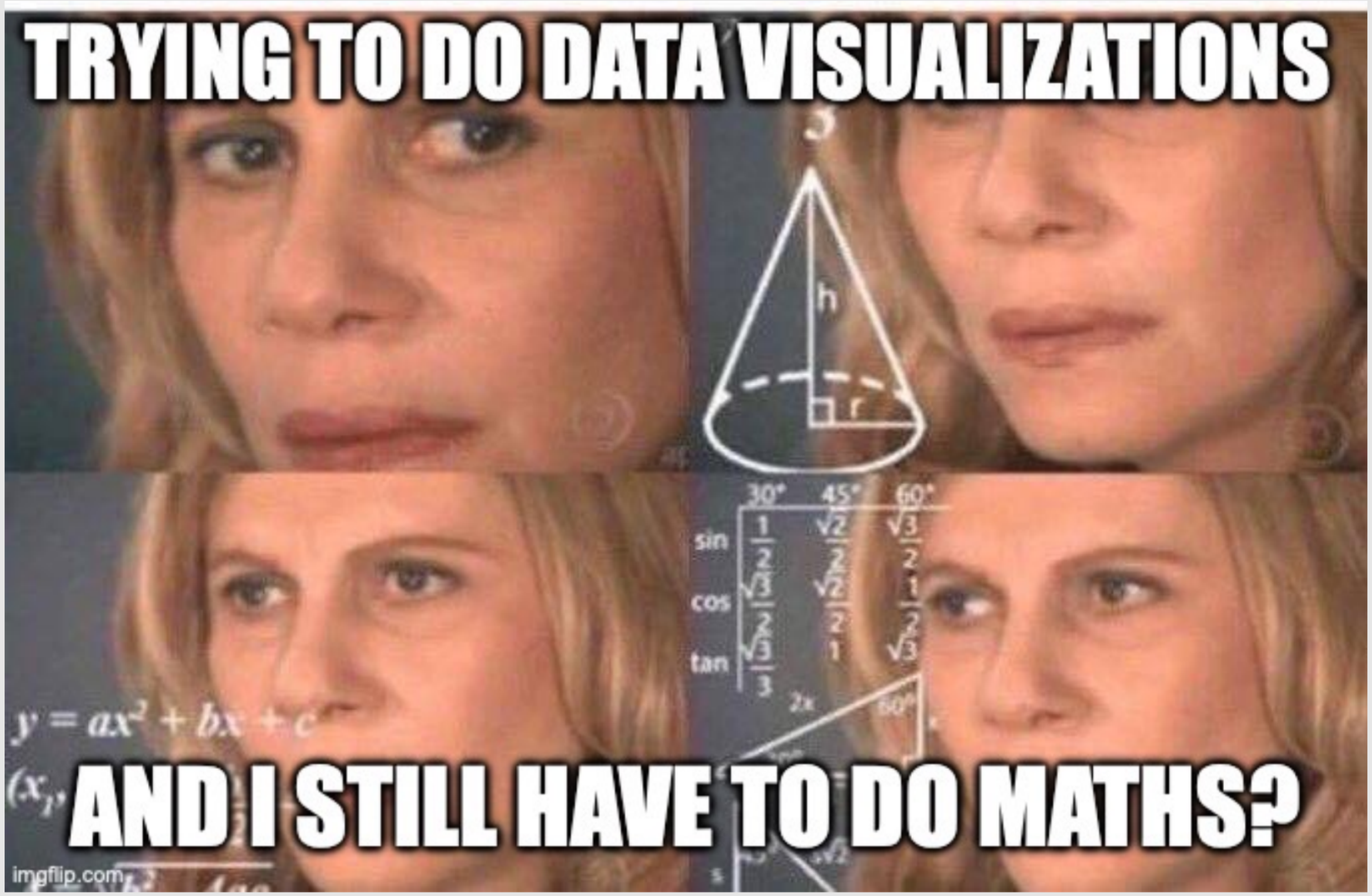

dendrites
nucleus
(soma)
cell-axon
membrane
axon
synapses
w_n
w_3
w_2
w_1
Σ
$f(\Sigma)$
o_m
o_3
o_2
o_1
weights
neuron cell
activation
function
output

Activation functions

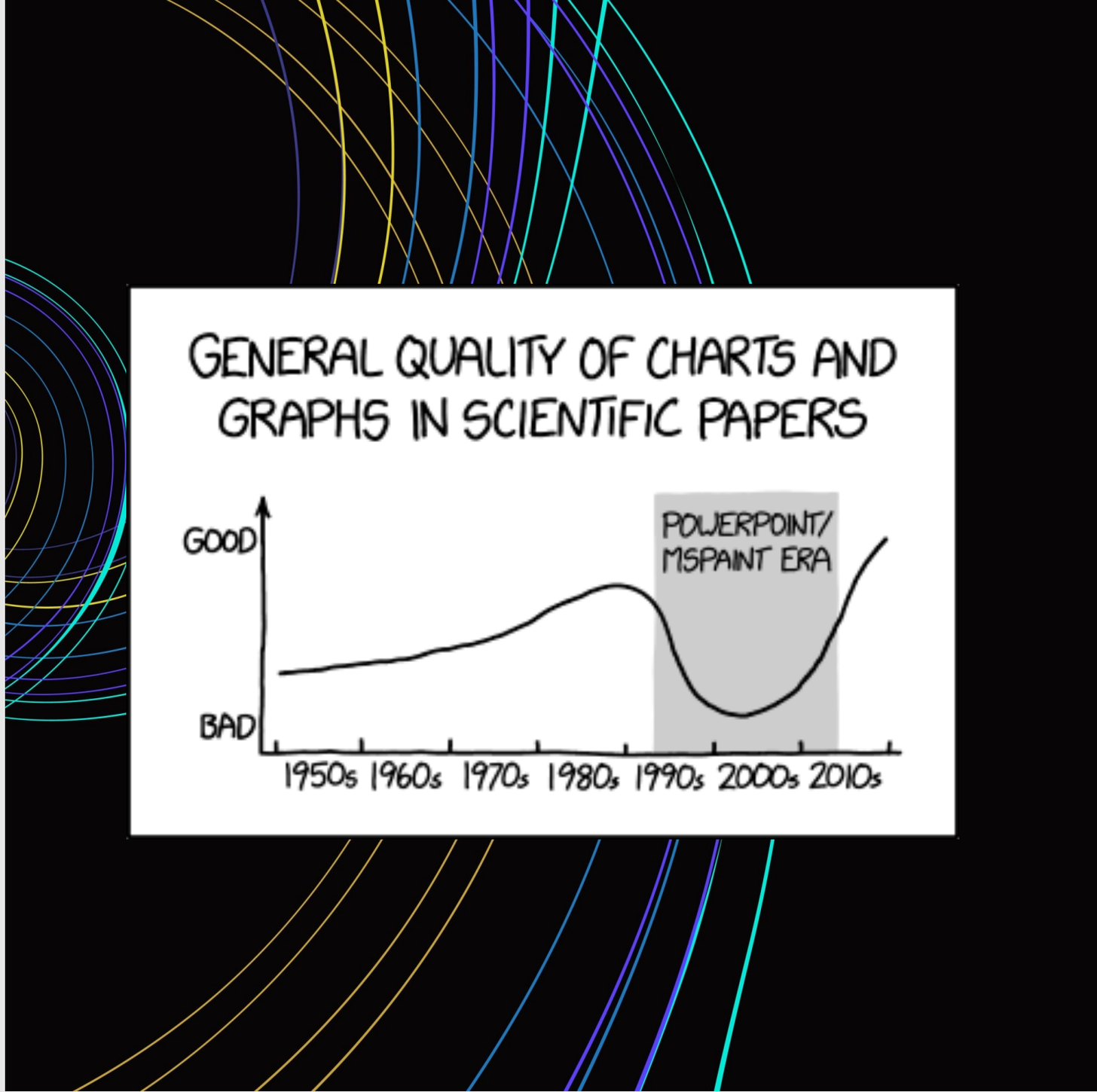


- Bias (threshold) activation function was proposed first
- Sigmoid and tanh introduce non-linearity with different codomains
- ReLu is the latest and greatest due to backprop (more later)

Source: http://bit.ly/2tKhbMS


TRYING TO DO DATA VISUALIZATIONS
h
r
30°
45°
60°
sin
cos
tan
$y = ax^2 + bx + c$
AND I STILL HAVE TO DO MATHS?
imgflip.com

Don’t worry, its demo time

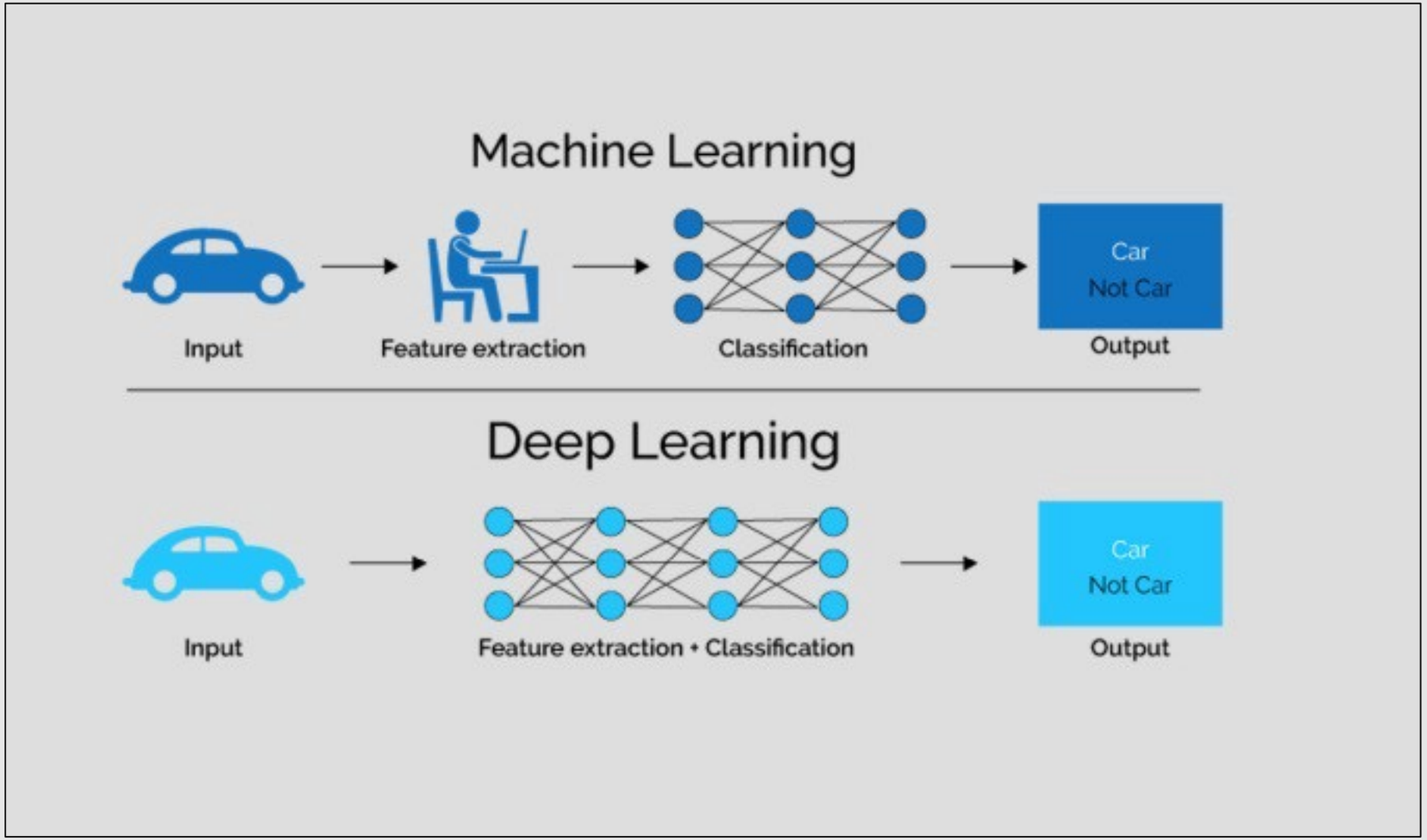


MNIST Keras Demo

Try it out at:

- Download the notebooks at Keras MNIST CNN notebooks: CPU | GPU
- The notebooks are for Databricks Community Edition (free) so work with your parents and teachers to get access

MNIST Keras Demo



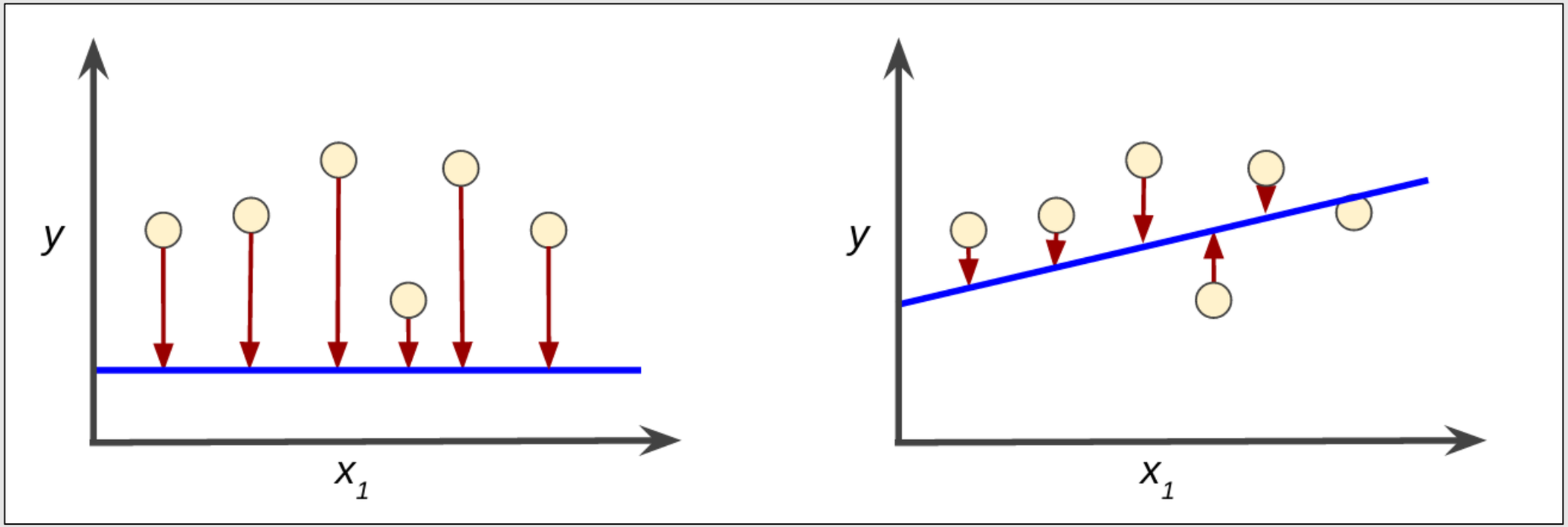
Source: [What is Training Data its types and why it is important?]

MNIST Keras Demo

More data so we can better train the model

Source: [ConvNetJS MNIST demo]

MNIST Keras Demo



High loss in the left model; low loss in the right model.
Source: Descending into ML: Training and Loss

MNIST Keras Demo

Test Accuracy: More green, less red

Source: [ConvNetJS MNIST demo]

ConvNetJS MNIST demo

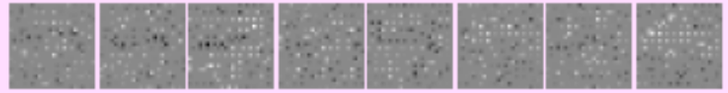
Weights:

Weight Gradients:

relu (24x24x8)
max activation: 4.22335, min: 0
max gradient: 0.00031, min: -0.00037

Activations:

Activation Gradients:



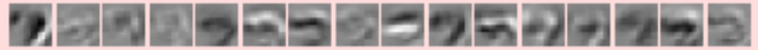
pool (12x12x8)
pooling size 2x2, stride 2
max activation: 4.22335, min: 0
max gradient: 0.00031, min: -0.00037

Activations:

Activation Gradients:

conv (12x12x16)
filter size 5x5x8, stride 1
max activation: 6.32598, min: -7.38596
max gradient: 0.00051, min: -0.00036
parameters: 16x5x5x8+16 = 3216

Activations:



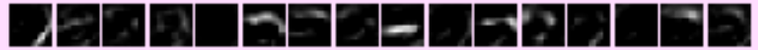
Activation Gradients:

Weights:

Weight Gradients:

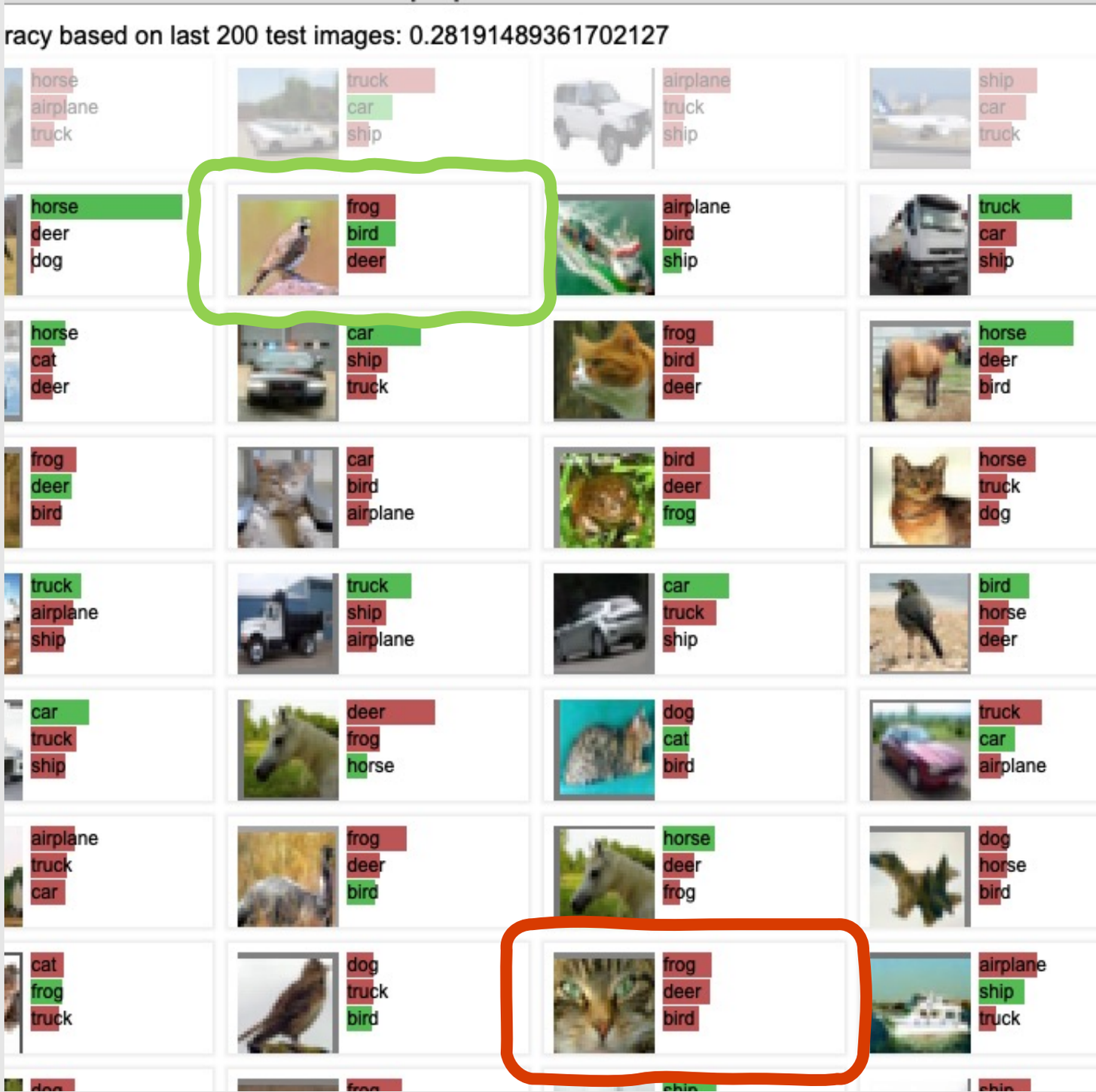
relu (12x12x16)
max activation: 6.32598, min: 0
max gradient: 0.00051, min: -0.00036

Activations:



Activation Gradients:

ConvNetJS CIFAR-10 demo



Deep Visualization Toolbox

Source: https://youtu.be/AgkfIQ4IGaM?t=118

Object Detection

Image AI: Video Object Detection, Tracking and Analysis utilizing YOLOv3 model

Source: Coffee Object Detection Demo

DALL·E 2

is a new AI system that can create realistic images and art from a description in natural language.

An astronaut
riding a horse in a
photorealistic style

https://openai.com/dall-e-2/

Want to know more about DALL·E 2?

How DALL·E 2 actually works?

- Link text and visual semantics via CLIP
  - *The insight that makes CLIP so powerful is the bright idea to train models to not just identify which category (of a pre-defined list of options) an image belongs to, but to identify the caption of each image from a list of random captions.*[1]

- Generating Images from Visual Semantics by doing the inverse with GLIDE via a diffusion model

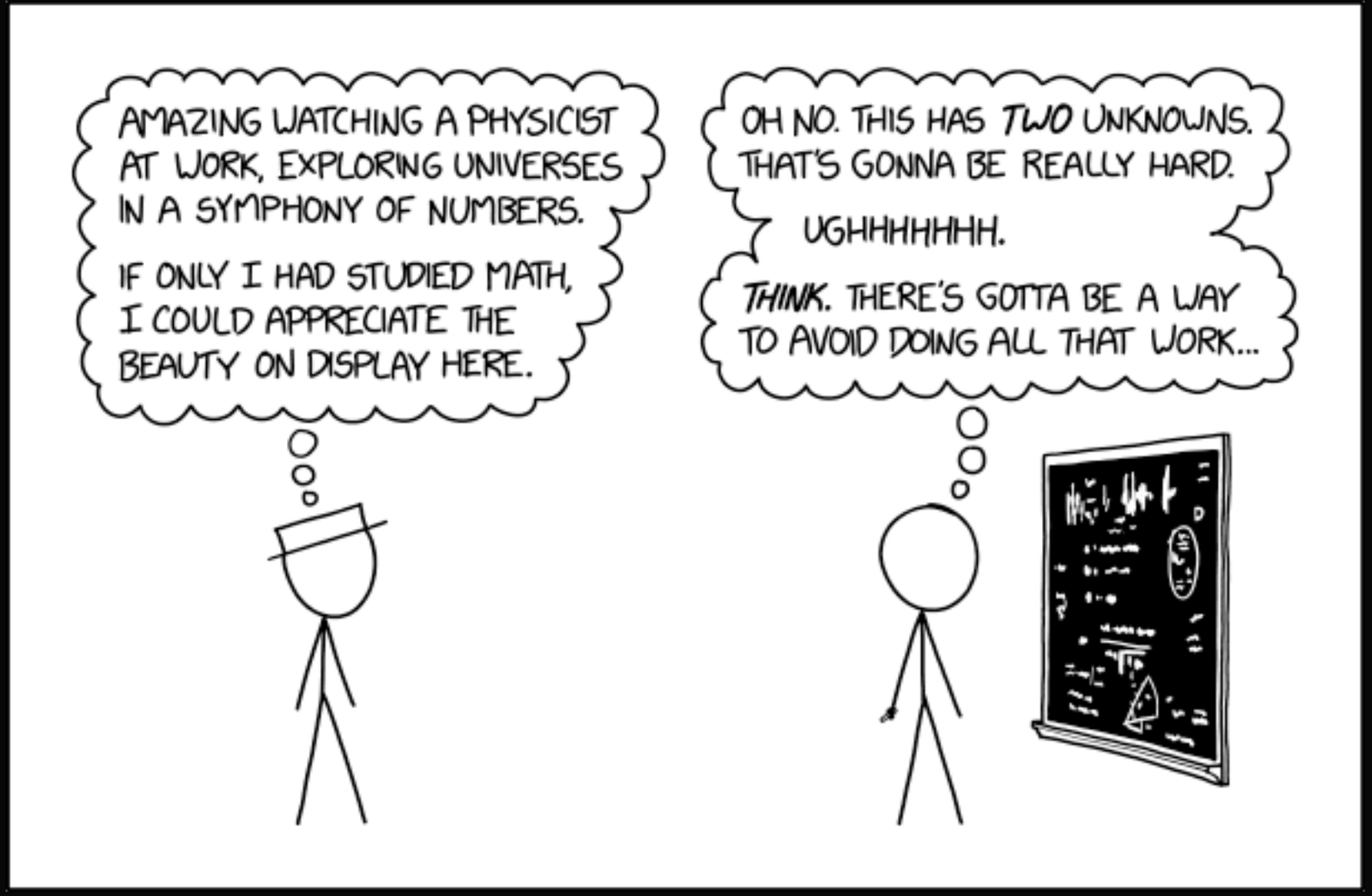
Want to know more about DALL·E 2?

What are diffusion models?

- *Diffusion Models learn to generate data by reversing a gradual noising process.*
- Think of this as unscrambling a Rubik's cube after scrambling it one step at at time (after forgetting about the steps) or
- *More practically, you could train a neural network to go from a state of disorder to a state of less disorder.*

[1] DALL·E 2.0, Explained

Want to do more math?



References

These slides: Data Visualization – Northstar Middle School
Keras MNIST Notebooks: GPU | CPU

Neural networks introduction

Artificial Neural Network

- Organized into layers of neurons
- Typically 3 or more: input, hidden and output
- A black-box model

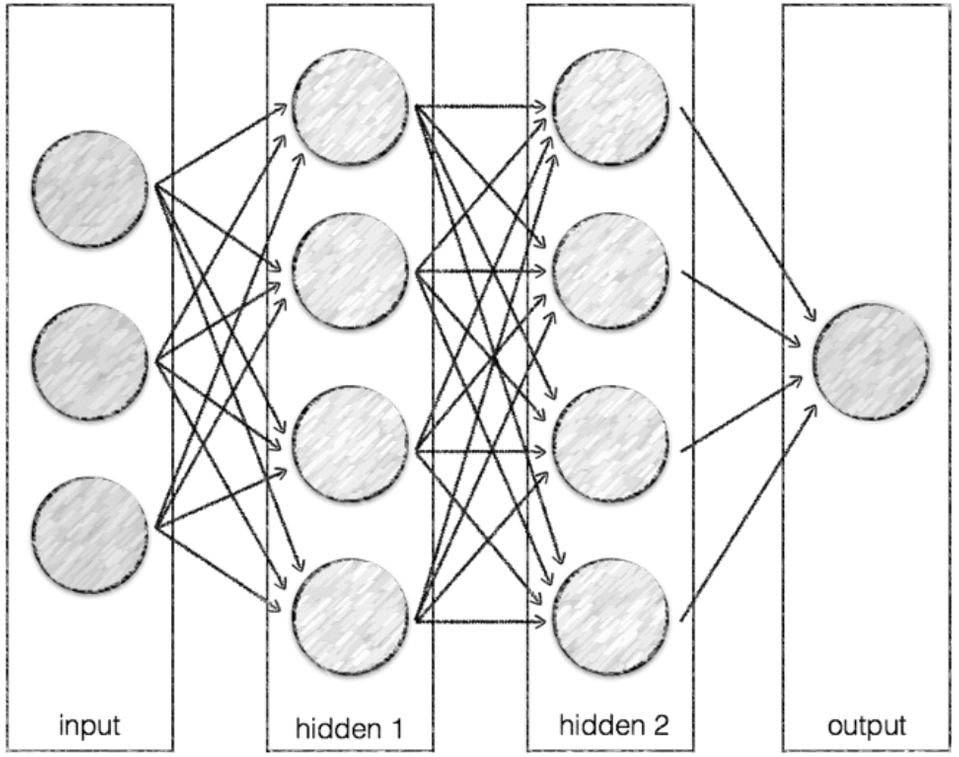
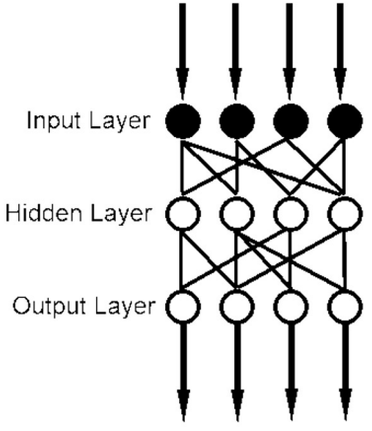


Image sources linked

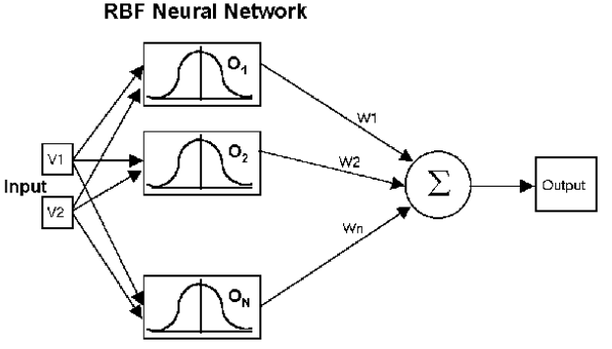
Types of neural networks

Some examples

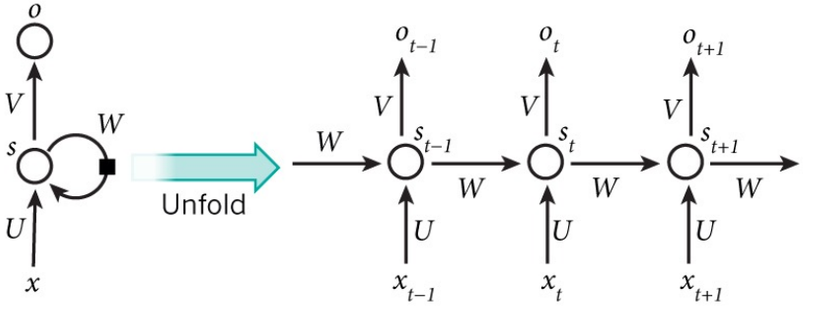
Single- or multi-layer
feedforward networks

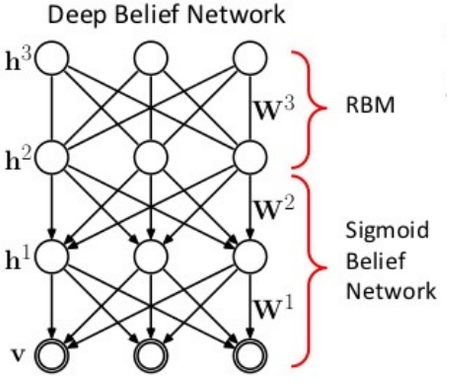


Radial Basis Function



Recurrent Neural Networks





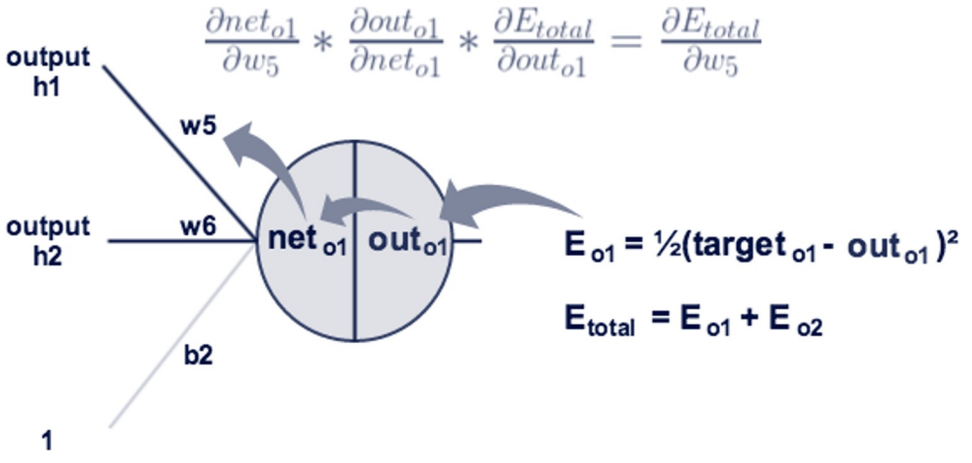
Deep belief networks

Image sources linked

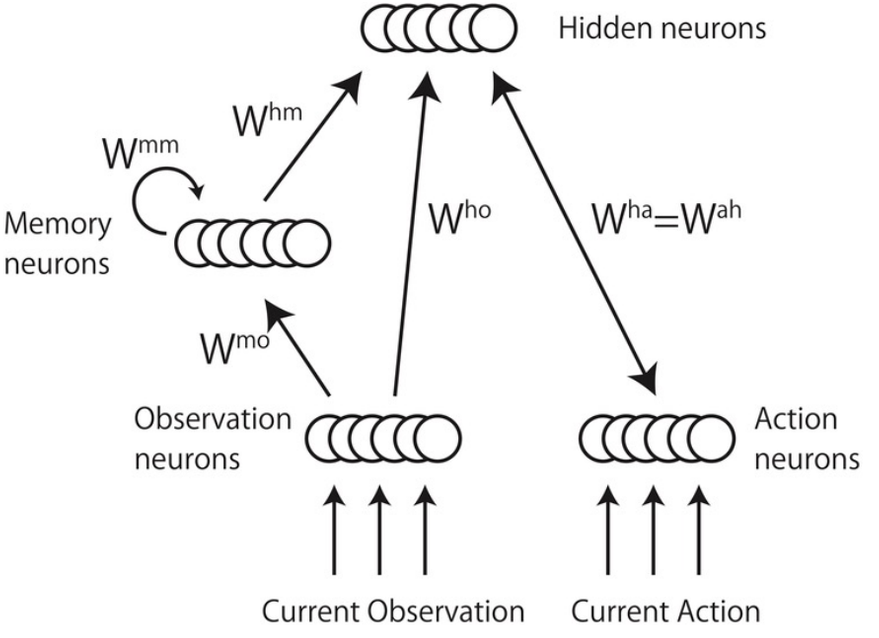
Learning

Some examples

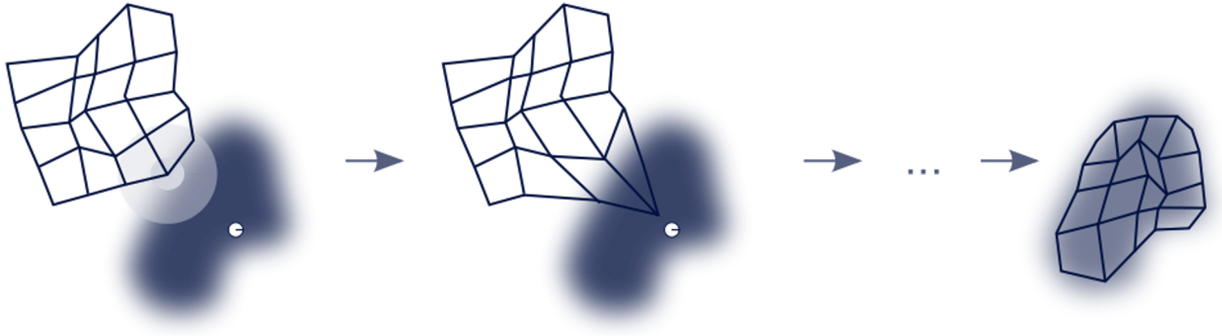
Backpropagation



Memory based learning



Self-organizing maps (competitive learning)



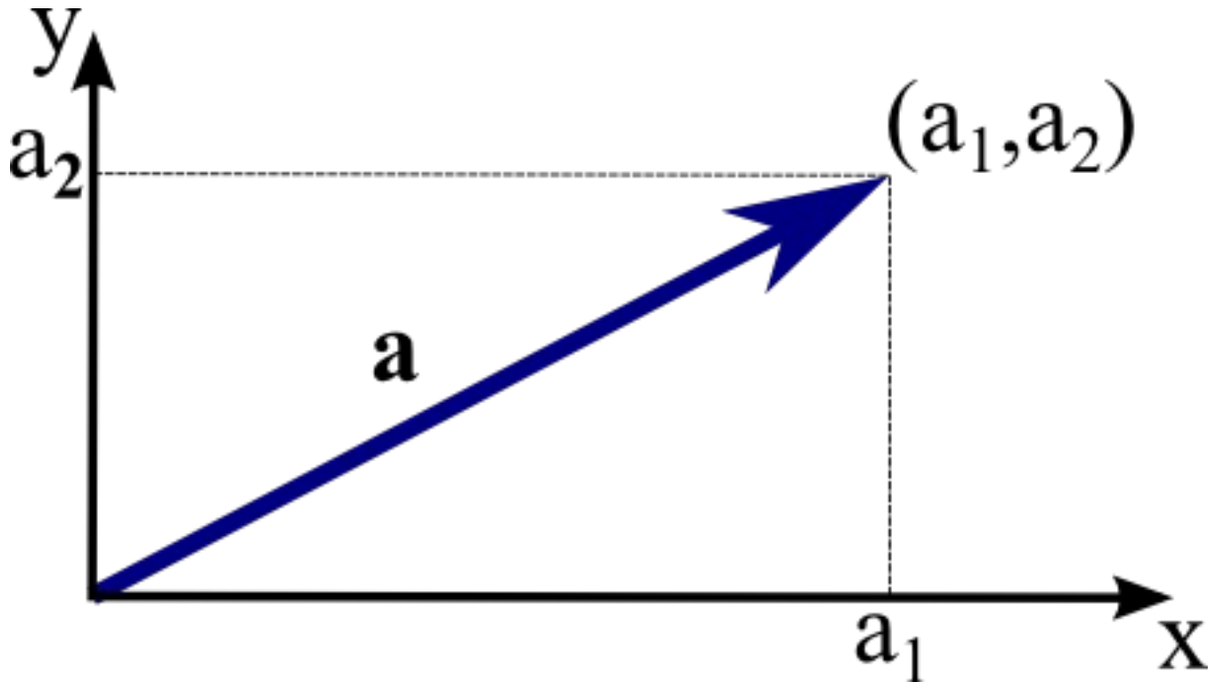
Introduction to tensors

Scalars, vectors, matrices and tensors

Scalar 2.01

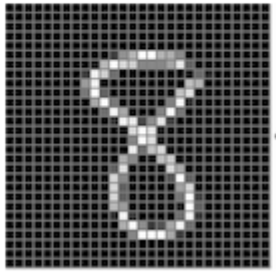
Scalars, vectors, matrices and tensors

Vector



Scalars, vectors, matrices and tensors

Matrix



28 x 28
784 pixels

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	4	62	146	182	254	254	181	176	139	15	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	34	186	253	217	208	136	136	136	166	232	99	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	61	242	208	111	3	0	0	0	0	0	18	32	107	43	0	0	0	0	0	0
0	0	0	0	0	0	0	0	156	242	23	0	0	0	0	0	0	0	13	191	181	6	0	0	0	0	0	0
0	0	0	0	0	0	0	0	121	255	98	3	0	0	0	0	0	8	194	225	12	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	169	253	120	3	0	0	0	0	128	247	51	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	3	111	244	169	19	0	14	131	249	117	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	59	241	235	72	142	229	66	0	0	0	0	0	0	0	0	0	0
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0	0	0	0	0	0	0	0	0	0	0	0	19	237	111	196	217	19	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	174	138	0	23	193	204	18	0	0	0	0	0	0	0	0	0
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0	0	0	0	0	0	0	0	0	0	0	215	138	0	0	0	0	86	253	99	0	0	0	0	0	0	0	0
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0	0	0	0	0	0	0	0	0	0	0	185	157	0	0	0	0	0	40	254	98	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	50	244	61	0	0	0	0	112	244	58	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	174	251	142	59	83	167	244	111	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	6	133	253	253	253	169	61	3	0	0	0	0	0	0	0	0
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0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Scalars, vectors, matrices and tensors

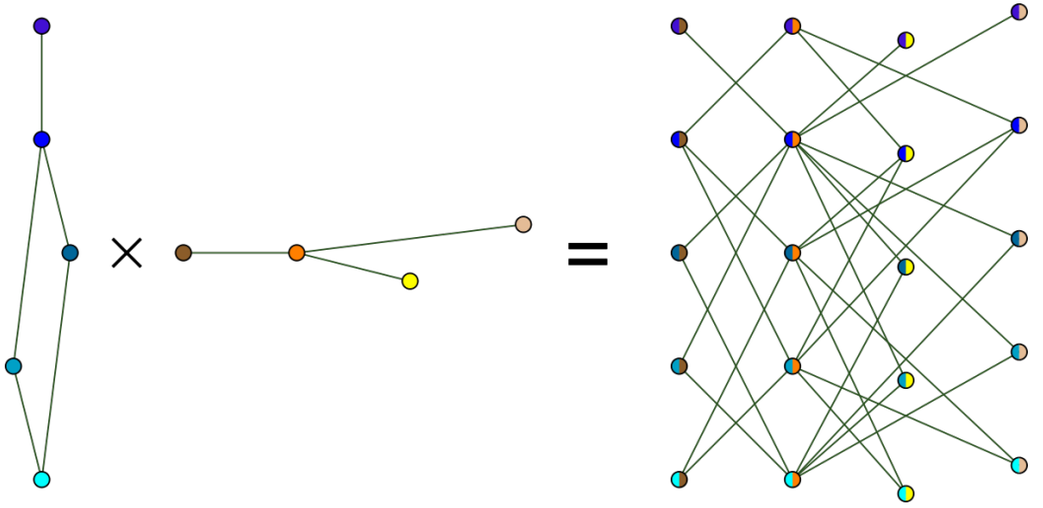
Tensor (3D)

Scalars, vectors, matrices and tensors

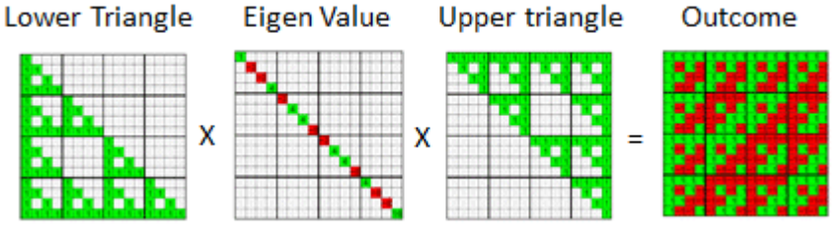
Tensor (4D)

Tensor operations

- Scaling
- Addition and subtraction
- Multiplication
- Contraction
- Tensor product
- Reshaping
- Transposition
- Eigenvectors and eigenvalues
- Cholesky decomposition
- …



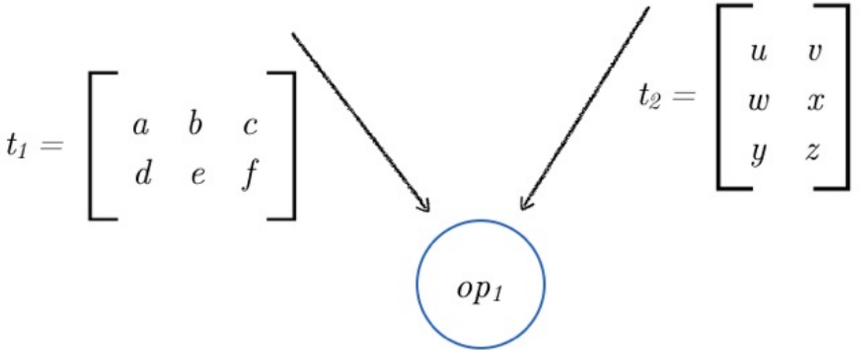
Source: http://bit.ly/2F7svG0



Source: http://bit.ly/2o8dyvy

Concept

- t_1 is a 2x3 matrix
- t_2 is a 3x2 matrix
- The op_1 is a multiplication operator

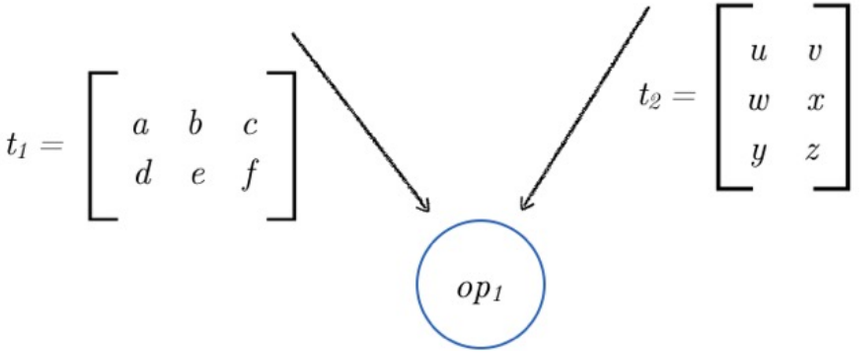


- The above can be represented in a matrix form

$$out = t_1 \underset{op\_1}{*} t_2 = \begin{bmatrix} au + bw + dy & av + bx + cz \\ du + ew + fy & dv + ex + fz \end{bmatrix}$$

Tensor product

- t_1 is a 2x3 matrix
- t_2 is a 3x2 matrix
- The op_1 is a tensor product operator



- The above can be represented in a matrix form

$$out = t_1 \underbrace{\otimes}_{op\_1} t_2 = \begin{bmatrix} at_2 & bt_2 & ct_2 \\ dt_2 & et_2 & ft_2 \end{bmatrix} = \begin{bmatrix} au & av & bu & bv & cu & cv \\ aw & ax & bw & bx & cw & cx \\ ay & az & by & bz & cy & cz \\ du & dv & eu & bv & fu & fv \\ dw & dx & ew & bx & fw & fx \\ dy & dz & qy & bz & fy & fz \end{bmatrix}$$

Neural network as a graph

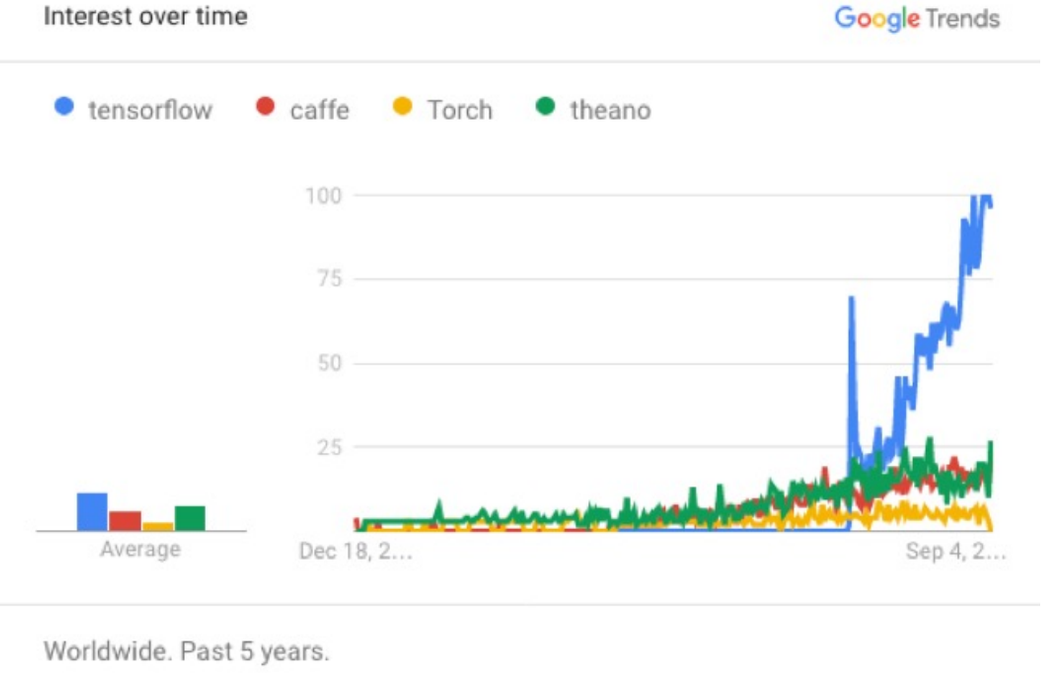
TensorFlow

Technology from Google

source: http://bit.ly/2itbqJT

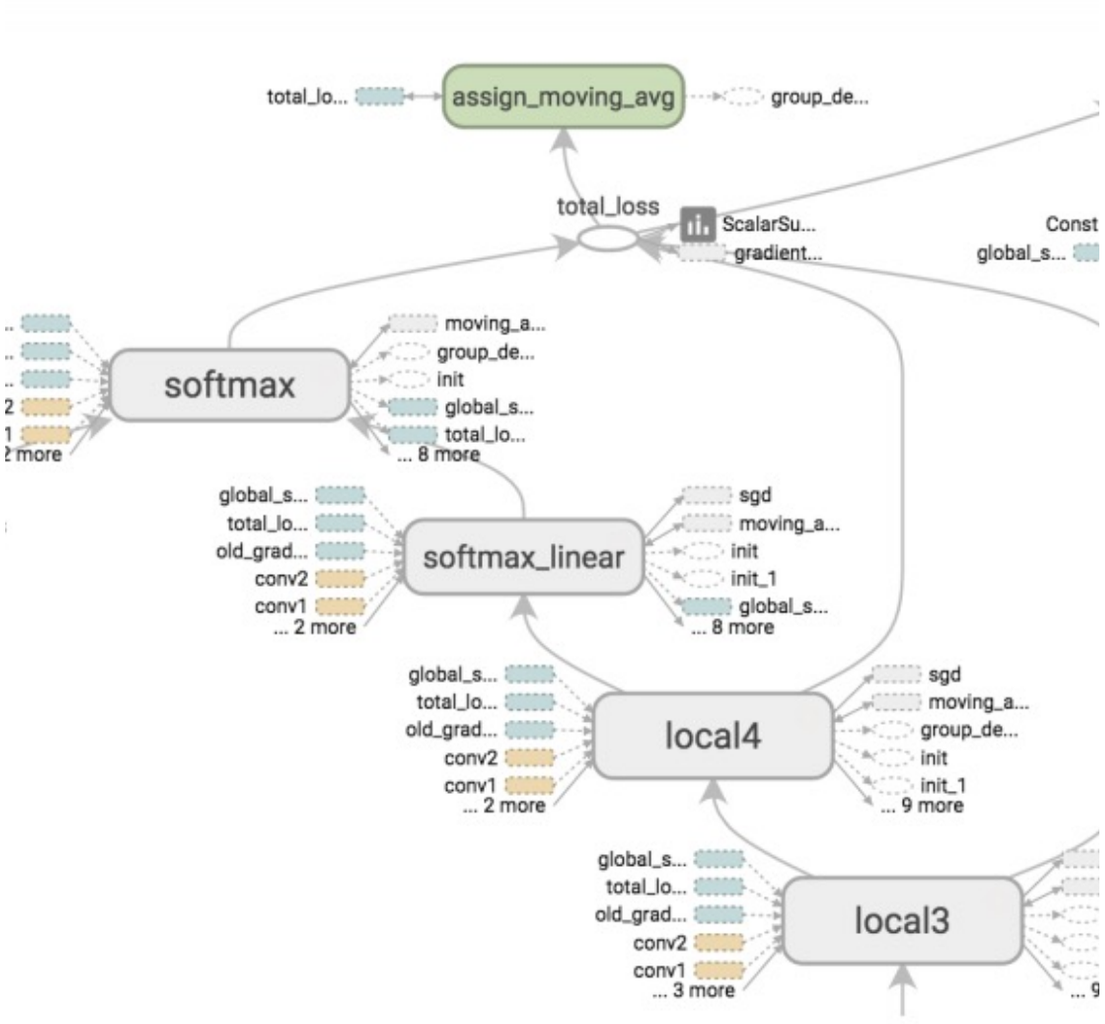
What is TensorFlow

- Open source software library for numerical computation using data flow graphs
- Based loosely on neural networks
- Built in C++ with a Python interface
- Quickly gained high popularity
- Supports GPU computations



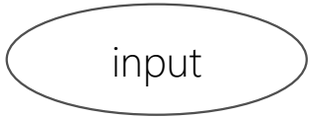
Data Flow Graph

- Nodes represent mathematical operations
- Edges are multidimensional arrays (tensors)
- Thus, TensorFlow is a flow of multidimensional arrays (tensors) between the mathematical operations (nodes)
- i.e. flow of *tensors*



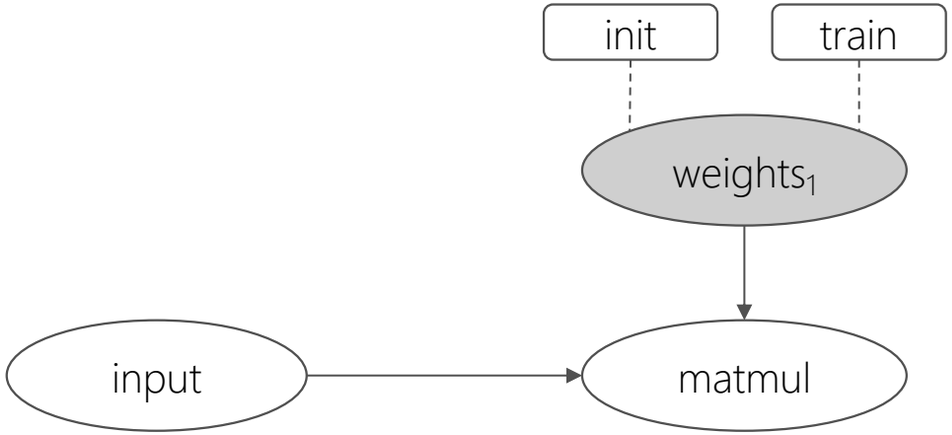
Step by step DAG: input

$$y = x$$



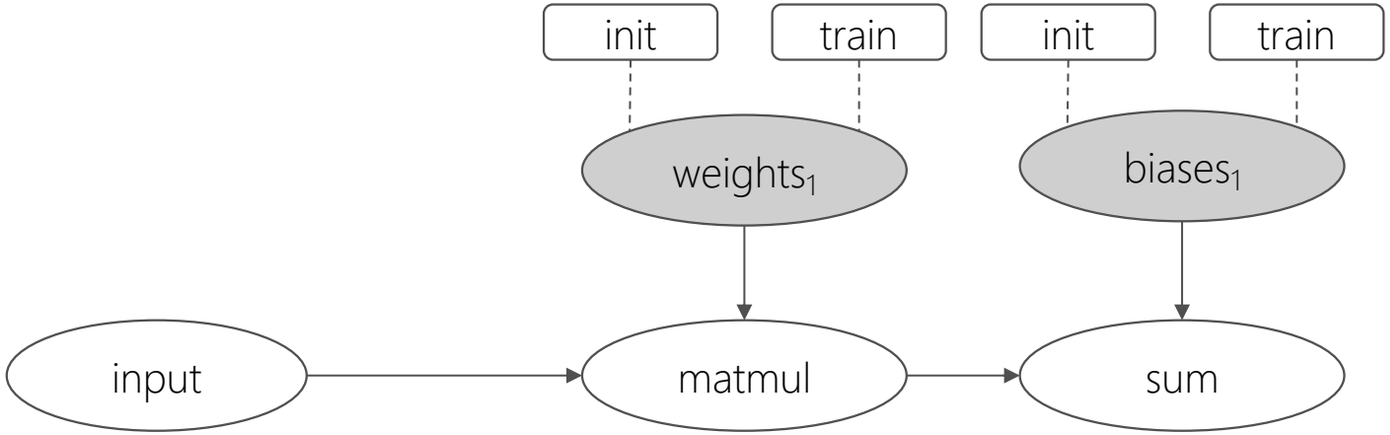
Step by step DAG: input

$$y = wx$$



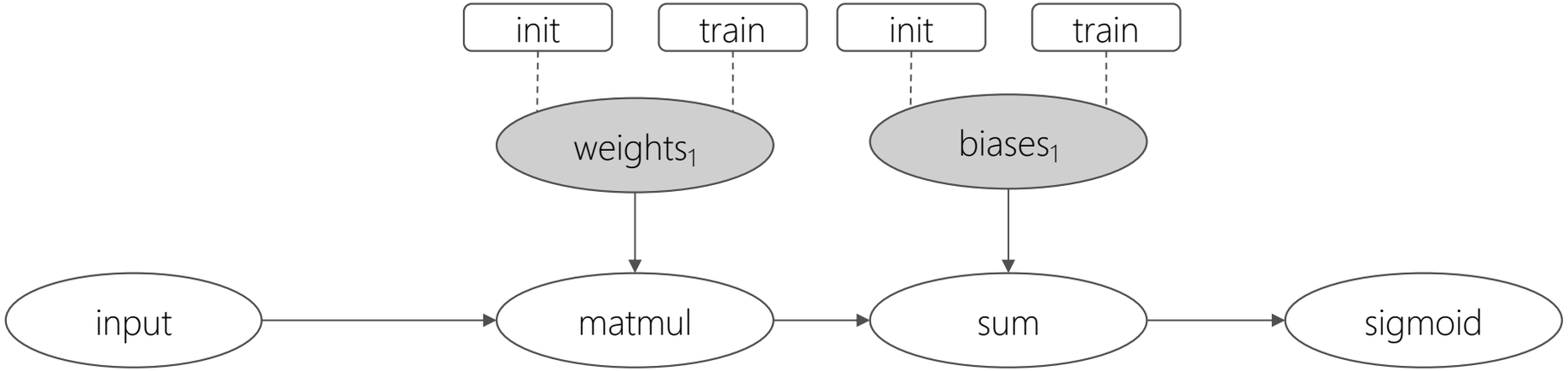
Step by step DAG: bias addition

$$y = wx + b$$



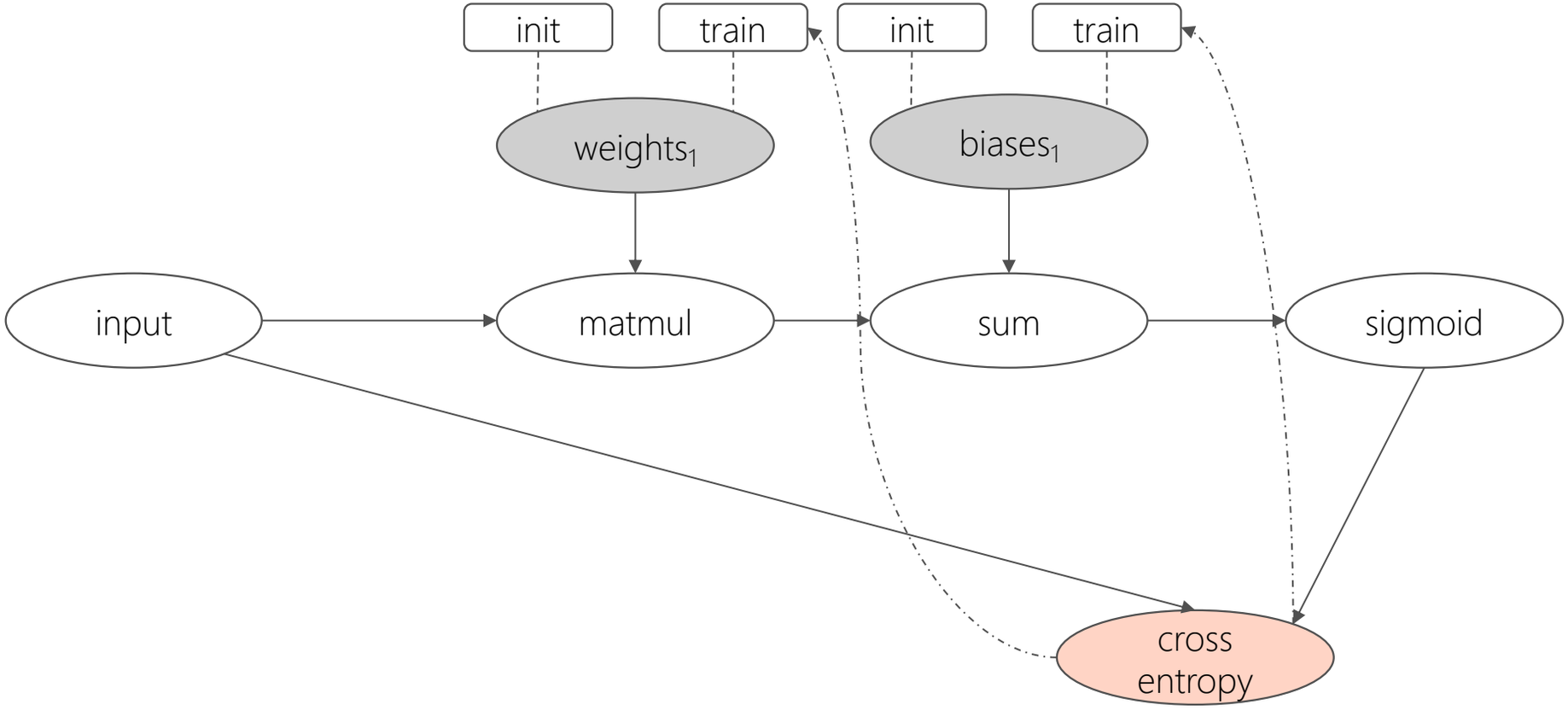
Step by step DAG: activation function

$$y = \frac{1}{1 + e^{-wx-b}}$$



Step by step DAG: cross entropy

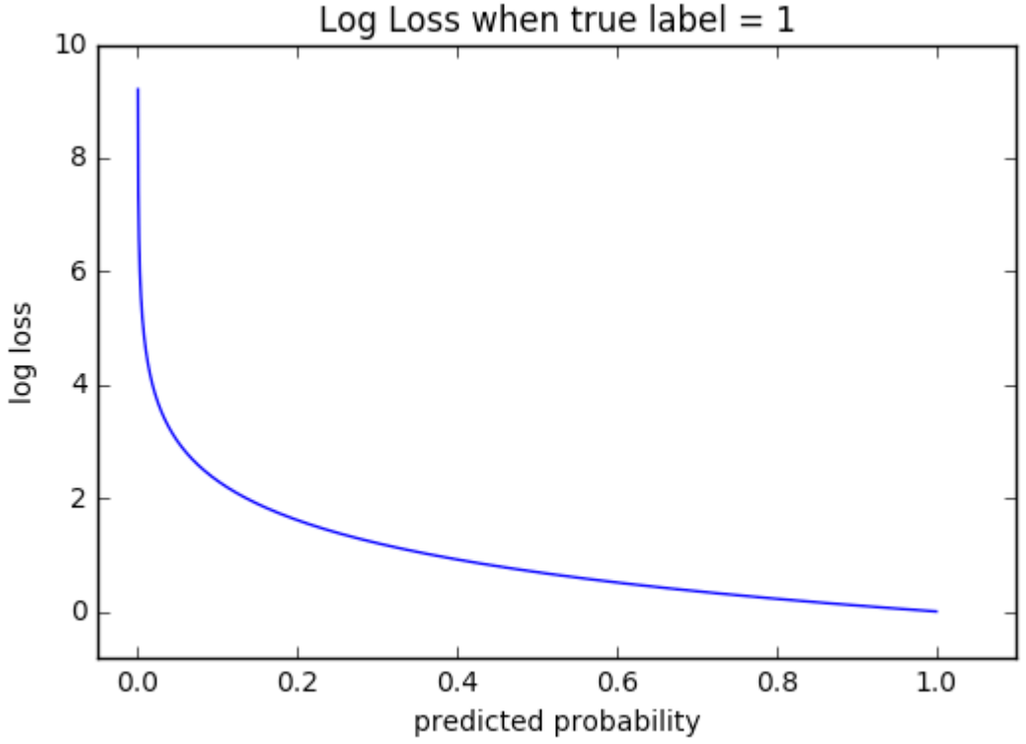
$$y = \frac{1}{1 + e^{-wx-b}}$$



$$loss = -(\check{y}\log(y) + (1-\check{y})\log(1-y))$$

Cross entropy

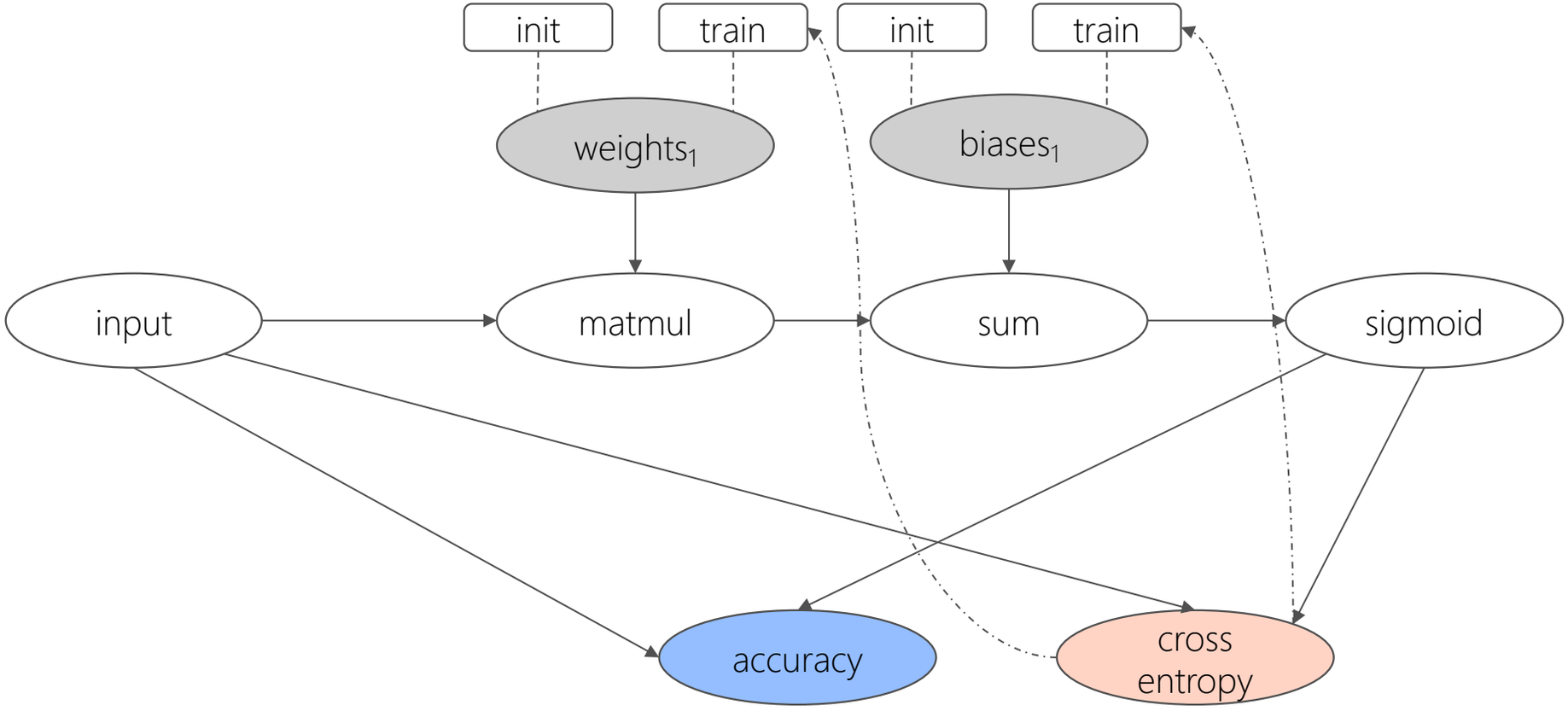
$$loss = -(\check{y}\log(y) + (1-\check{y})\log(1-y))$$



Source: http://bit.ly/2HhbJoG

Step by step DAG: accuracy

$$y = \frac{1}{1 + e^{-wx-b}}$$

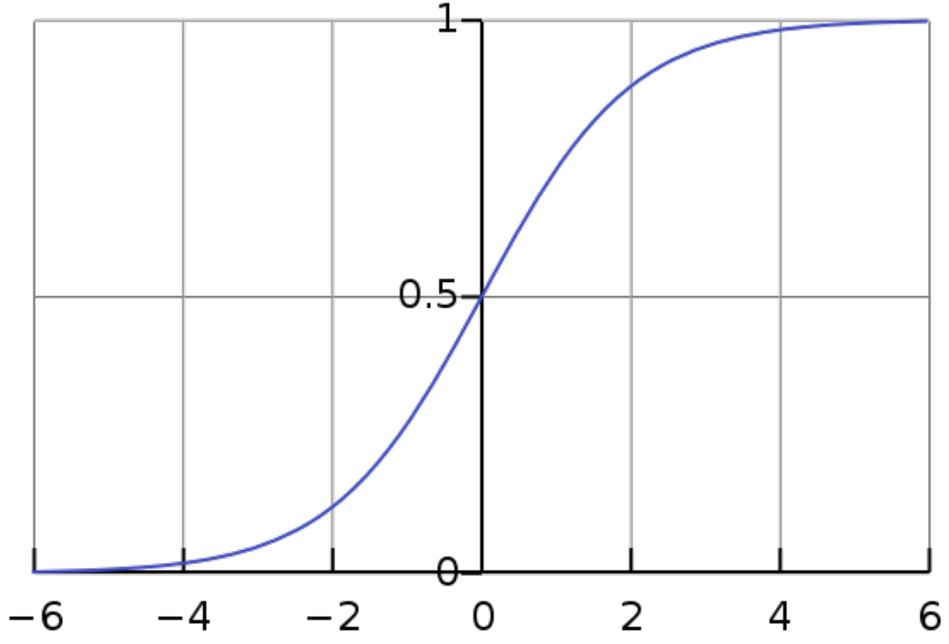


$$loss = -(\check{y}\log(y) + (1-\check{y})\log(1-y))$$

Activation functions

Sigmoid Function

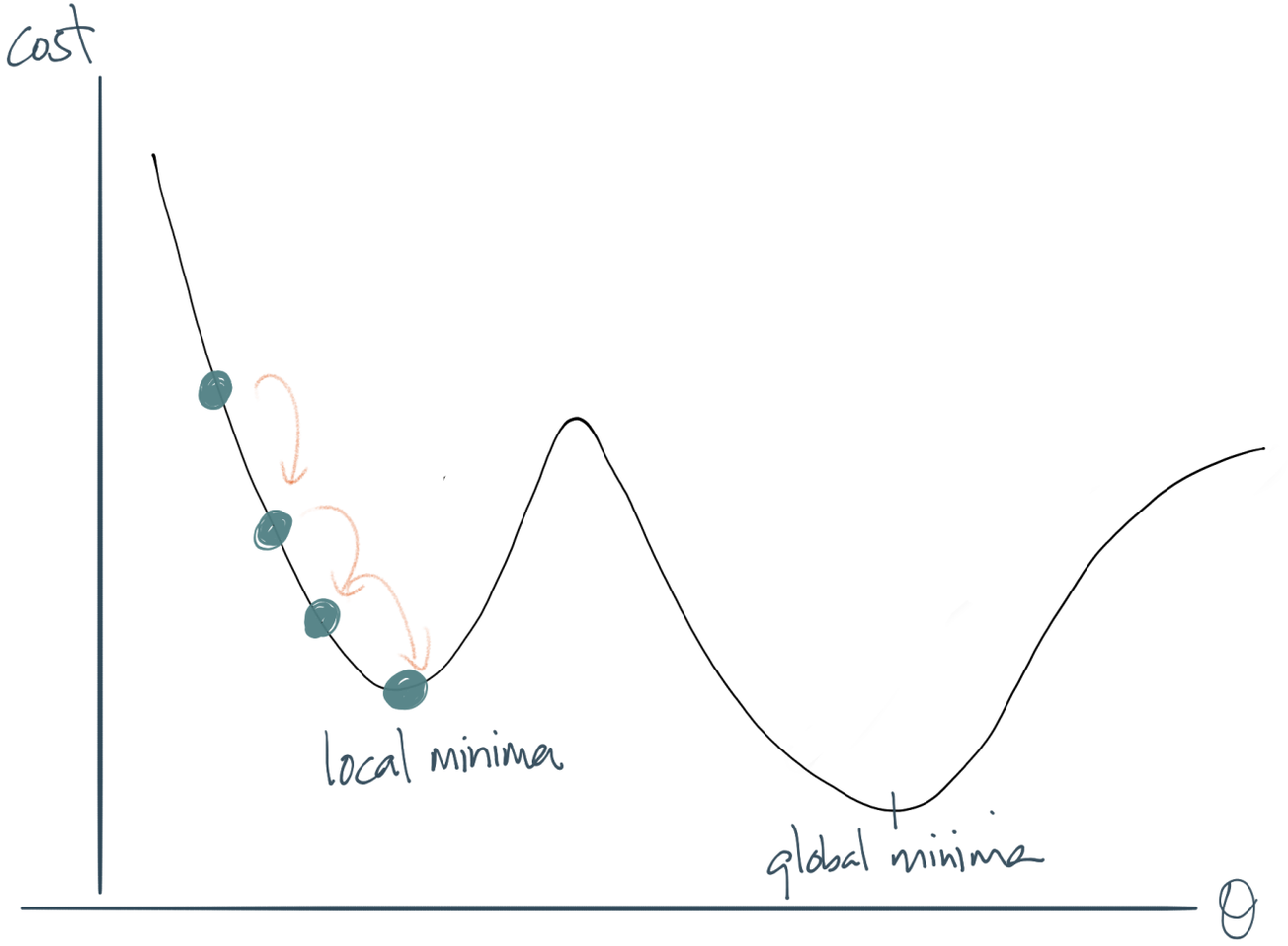
$$f(x) = \sigma(z) \equiv \frac{1}{1 + e^{-z}} = \frac{1}{1 + \exp(-\sum_j w_j x_j - b)}$$



Source: http://bit.ly/2GgMbGW

- Sigmoid non-linearity squashes real numbers between [0, 1]
- *Historically* nice interpretation of neuron firing rate (i.e. not firing at all (0) to fully-saturated firing (1)).

Gradient Descent

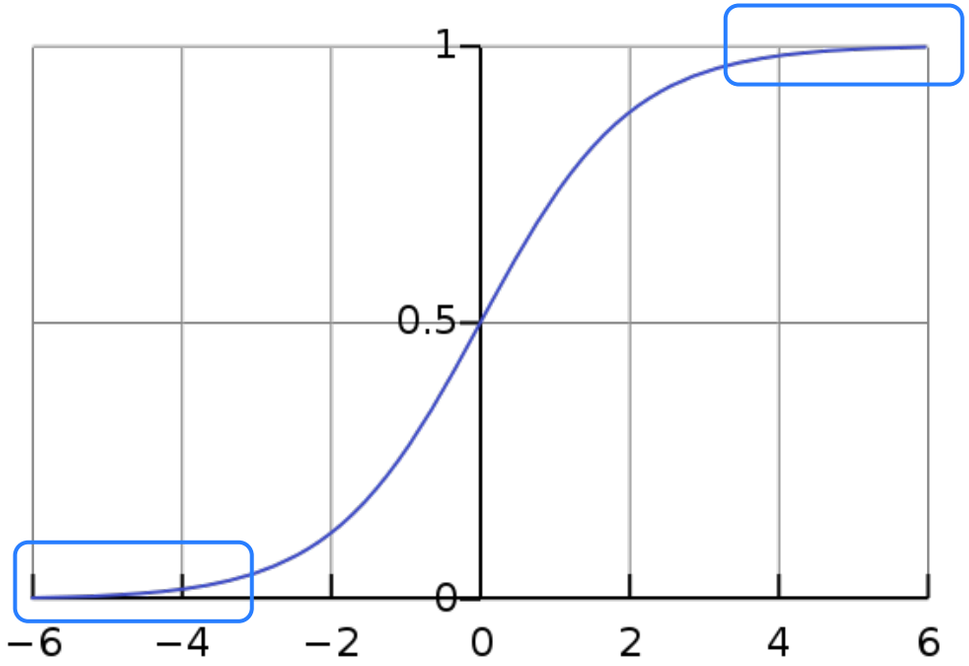


Cost function: what you want to minimize

Gradient descent: finding minimum of a function of multiple variables

Parameters like step size and learning rate are important to escape local minima

Sigmoid function (continued)



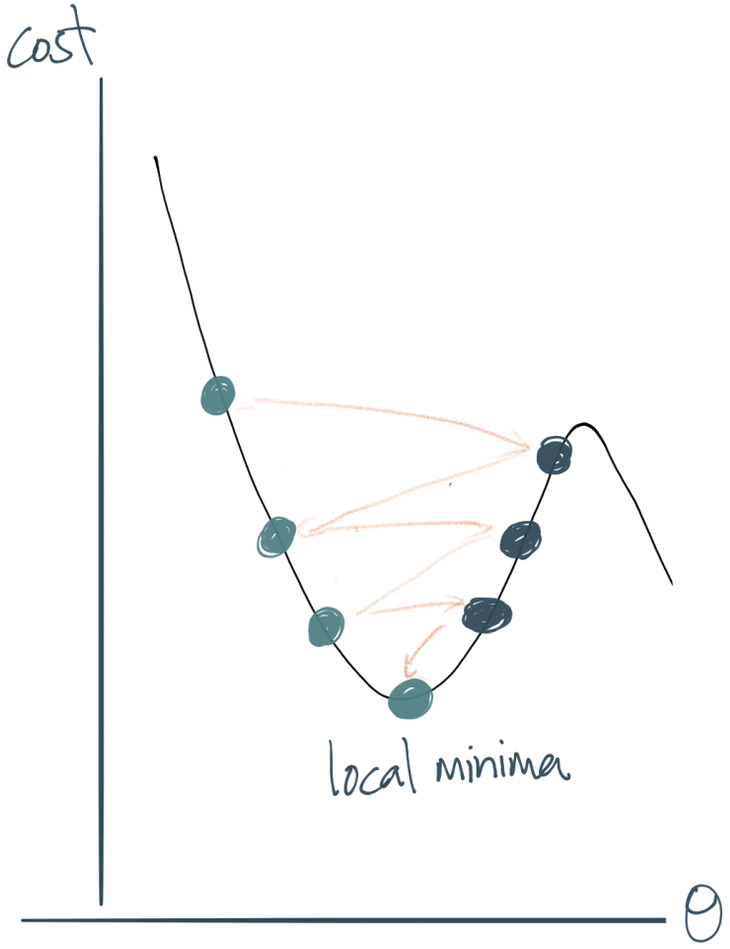
Source: http://bit.ly/2GgMbGW

Sigmoid function is not used as much b/c:

- Saturate and kill gradients: really large values are too close to 0 or 1, gradients are close to 0 (i.e. parallel to x-axis) thus stopping back propagation

- Output is not zero-centered: During gradient descent, if all values are positive then during back propagation the weights will become all positive or all negative creating zig zagging dynamics.

Sigmoid function (continued)



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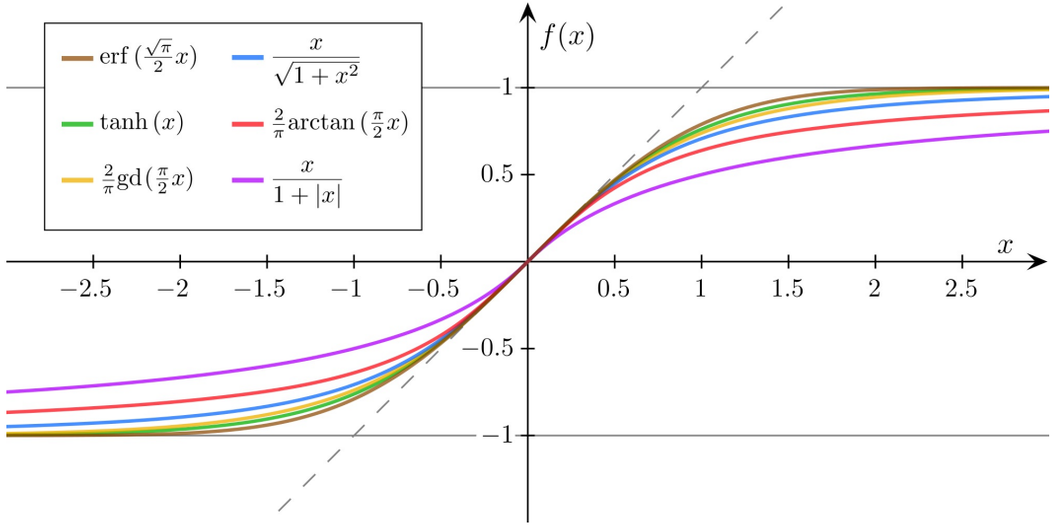
Tanh function

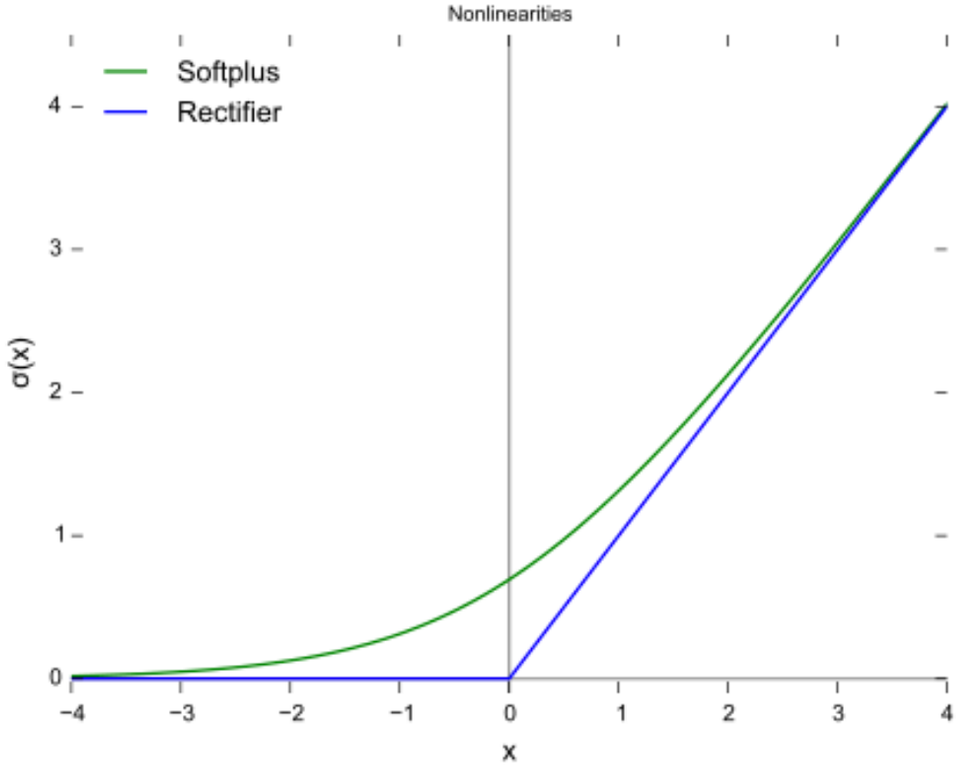


Source: http://bit.ly/2C4y89z

Tanh function squashes real numbers [-1, 1]

- Same problem as sigmoid that its activations saturate thus killing gradients.
- But it is zero-centered minimizing the zig zagging dynamics during gradient descent.
- Currently preferred *sigmoid nonlinearity*

ReLU: Rectifier Linear Unit



CC0, http://bit.ly/2EwRnds

ReLU's activation is thresholded at zero

$$f(z) = \max(0, u)$$

- Quite popular over the last few years
- Speeds up SGD convergence
- It is easier to implement due to simpler mathematical functions
- Sensitive to high learning rate during training resulting in "dead" neurons (i.e. neurons that will not activate across the entire dataset).

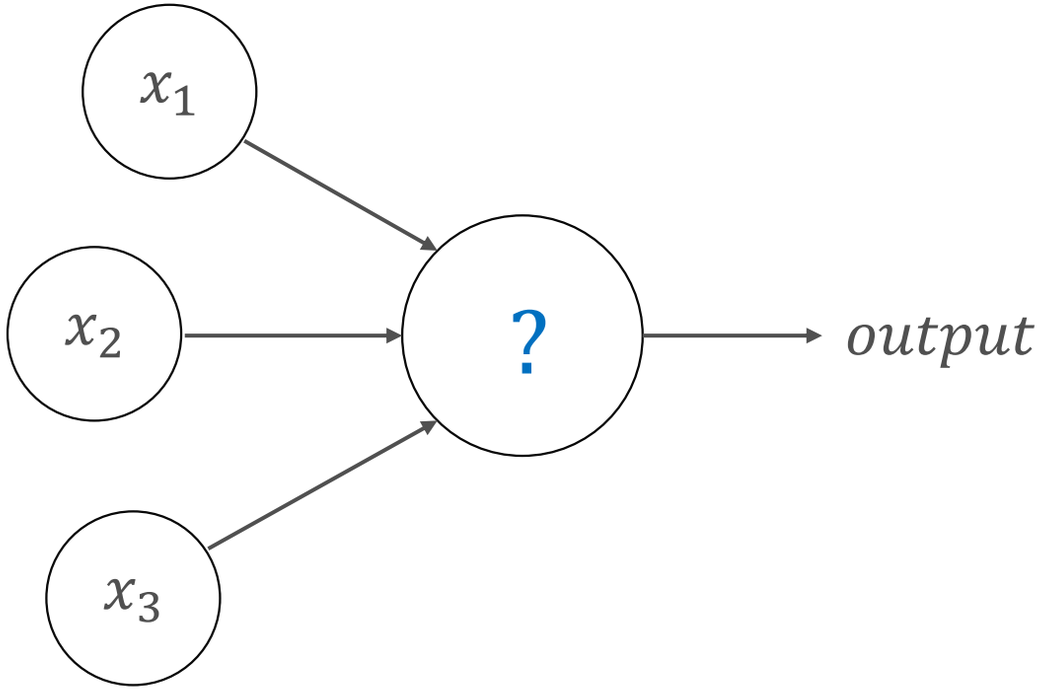
The Immense Power of Simple Structures

Resources:

- Andrej Karpathy's CS231N Neural Networks
- Steve Miller's How to build a neural network
- Michael Nielsen's Neural Networks and Deep Learning, Chapter 1

Perceptron

Simplified (binary) artificial neuron



$Do\ I\ snowboard\ at\ Whistler\ this\ weekend?$

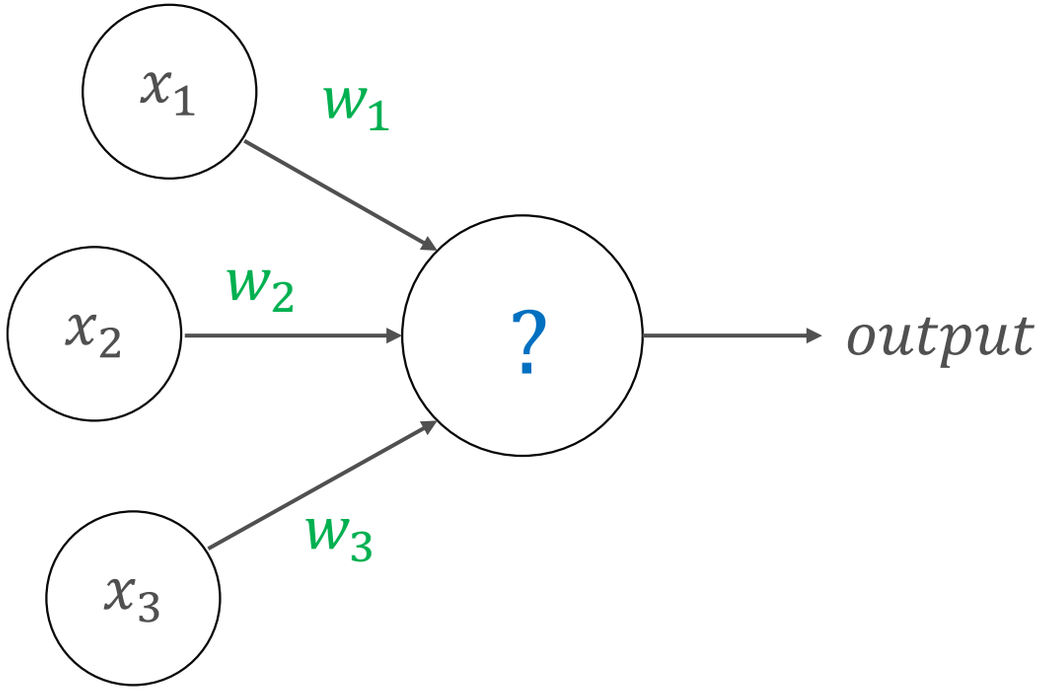
$x_1 \rightarrow Is\ the\ weather\ good?$

$x_2 \rightarrow Is\ the\ powder\ good?$

$x_3 \rightarrow Am\ I\ in\ the\ mood\ to\ drive?$

Perceptron

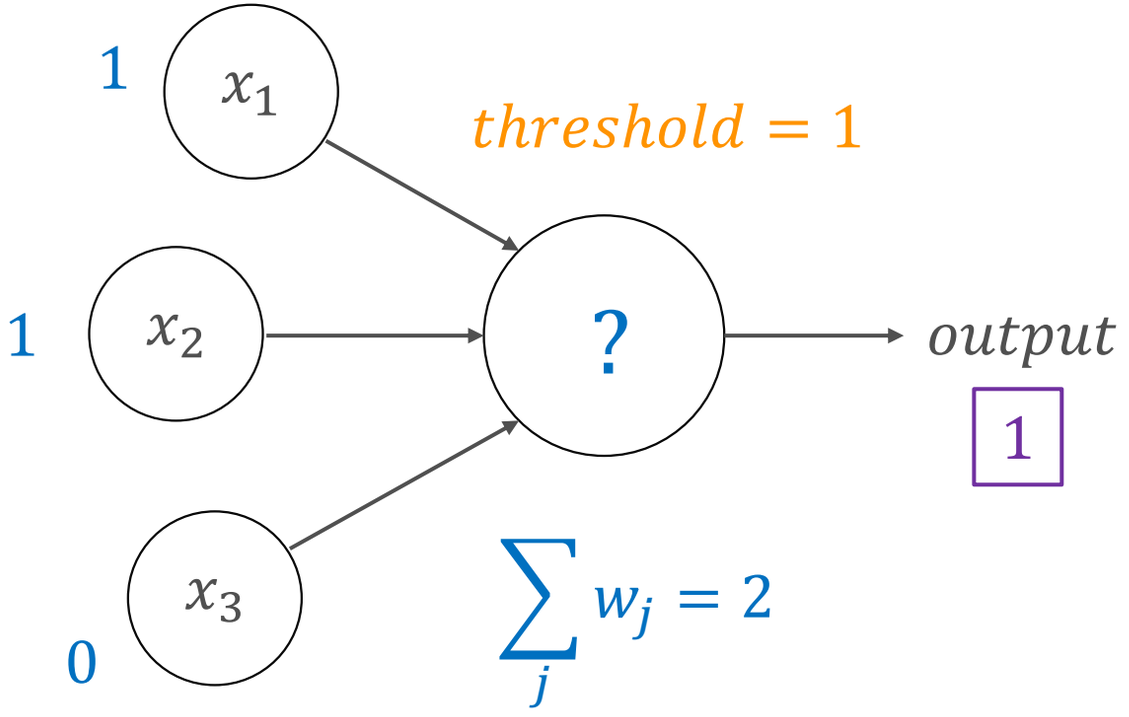
Simplified (binary) artificial neuron with weights



$$output = \begin{cases} 0, & \sum_{j=0}^{n} w_j x_j \leq threshold \\ 1, & \sum_{j=0}^{n} w_j x_j > threshold \end{cases}$$

Perceptron

Simplified (binary) artificial neuron; *no weights*



$Do\ I\ snowboard\ at\ Whistler\ this\ weekend?$

$x_1 = 1\ (good\ weather)$

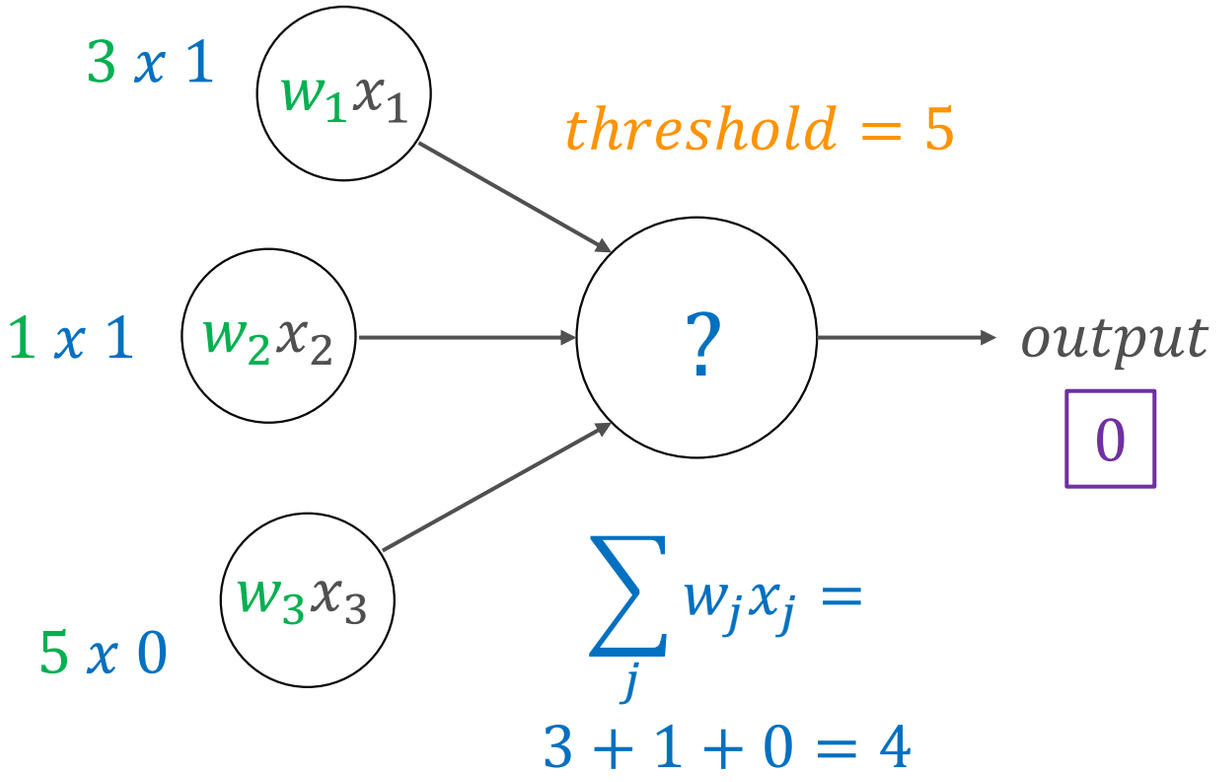
$x_2 = 1\ (a\ lot\ of\ powder)$

$x_3 = 0\ (driving\ sucks)$

Perceptron

Simplified (binary) artificial neuron; *add weights*

Persona: Après-ski'er



Do I snowboard at Whistler this weekend?

$x_1 = 1$ (*good weather*)
$w_1 = 3$

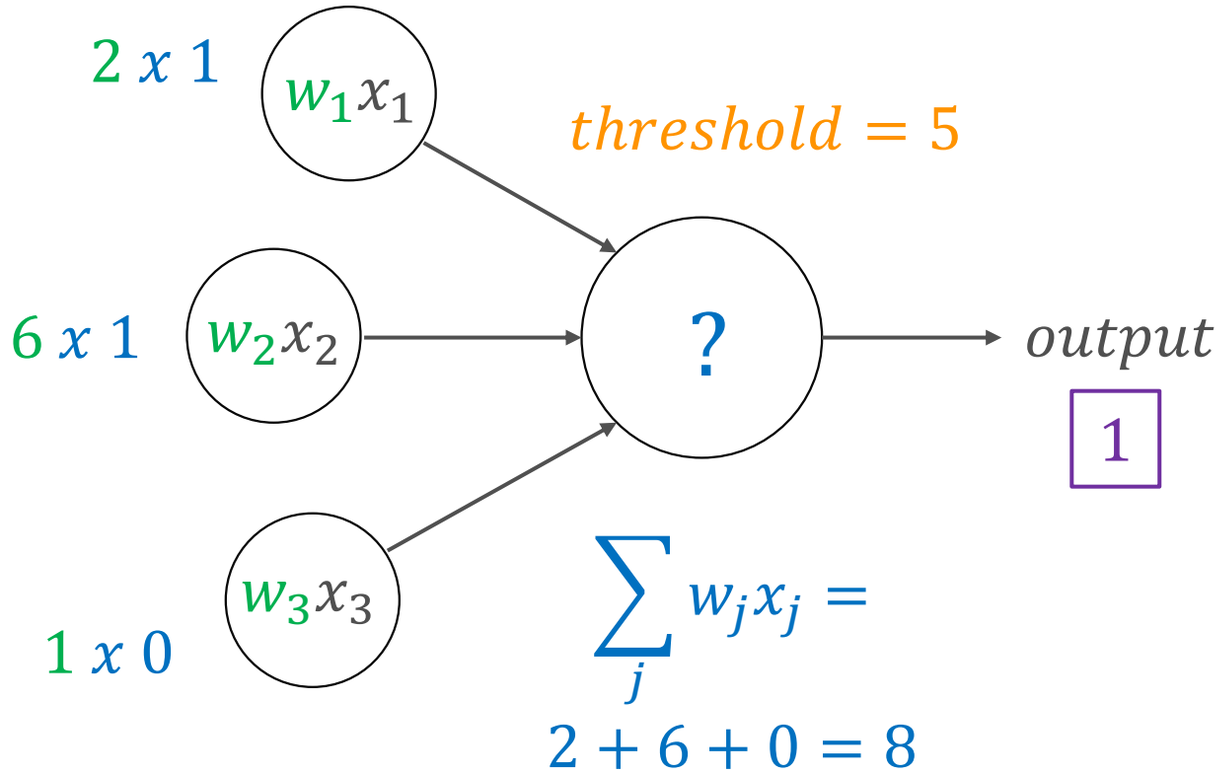
$x_2 = 1$ (*a lot of powder*)
$w_2 = 1$

$x_3 = 0$ (*driving sucks*)
$w_3 = 5$

Perceptron

Simplified (binary) artificial neuron; *add weights*

Persona: Shredder



Do I snowboard at Whistler this weekend?

$x_1 = 1$ (*good weather*)
$w_1 = 2$

$x_2 = 1$ (*a lot of powder*)
$w_2 = 6$

$x_3 = 0$ (*driving sucks*)
$w_3 = 1$

Introducing Bias

Perceptron needs to take into account of bias

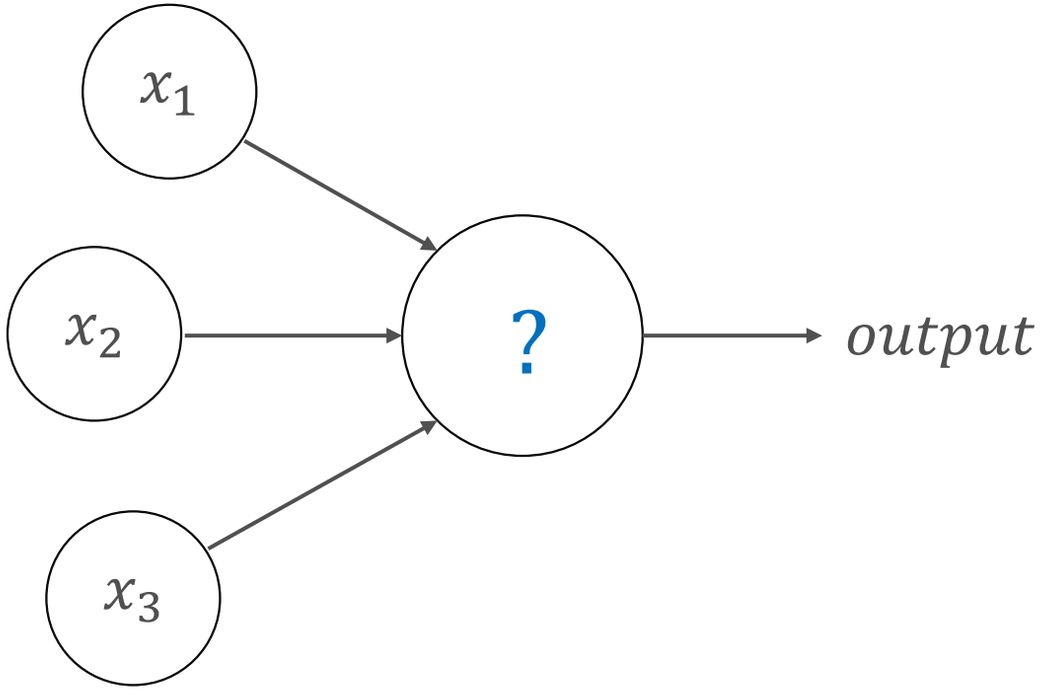
$$output = \begin{cases} 0, & wx + b \leq 0 \\ 1, & wx + b > 0 \end{cases}$$

where b is how easy it is to get the perceptron to fire

e.g. Shredder has a strong positive bias to go to Whistler
while Après-Ski'er bias is not as strong

Sigmoid Neuron

The more common artificial neuron

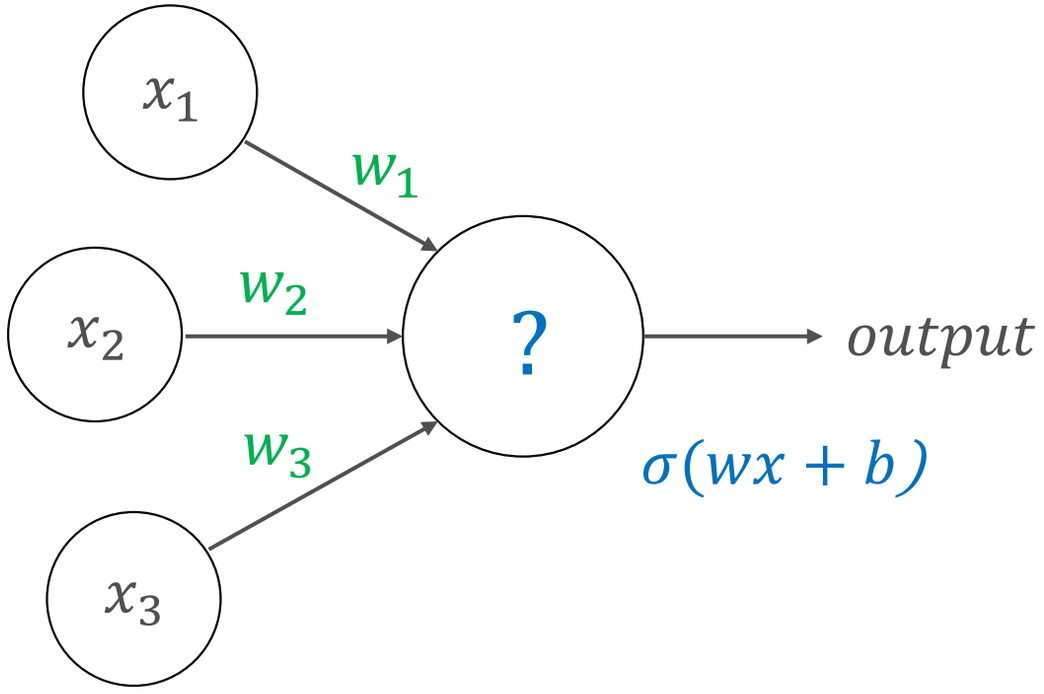


Instead of [0, 1], now (0…1)

Where output is defined by $\sigma(wx + b)$

Sigmoid Neuron

The more common artificial neuron

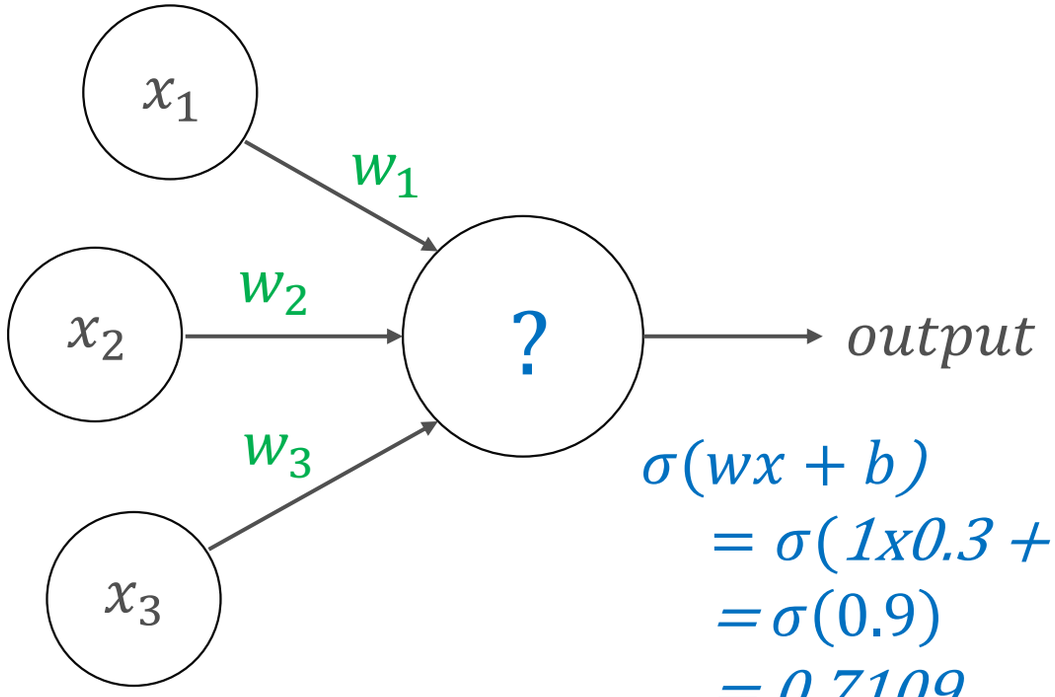


Instead of [0, 1], now (0…1)

Where output is defined by $\sigma(wx + b)$

Sigmoid Neuron

Persona: Shredder



$\sigma(wx + b)$
$= \sigma(1x0.3 + 1x0.6 + 0x\ 0.1)$
$= \sigma(0.9)$
$= 0.7109$

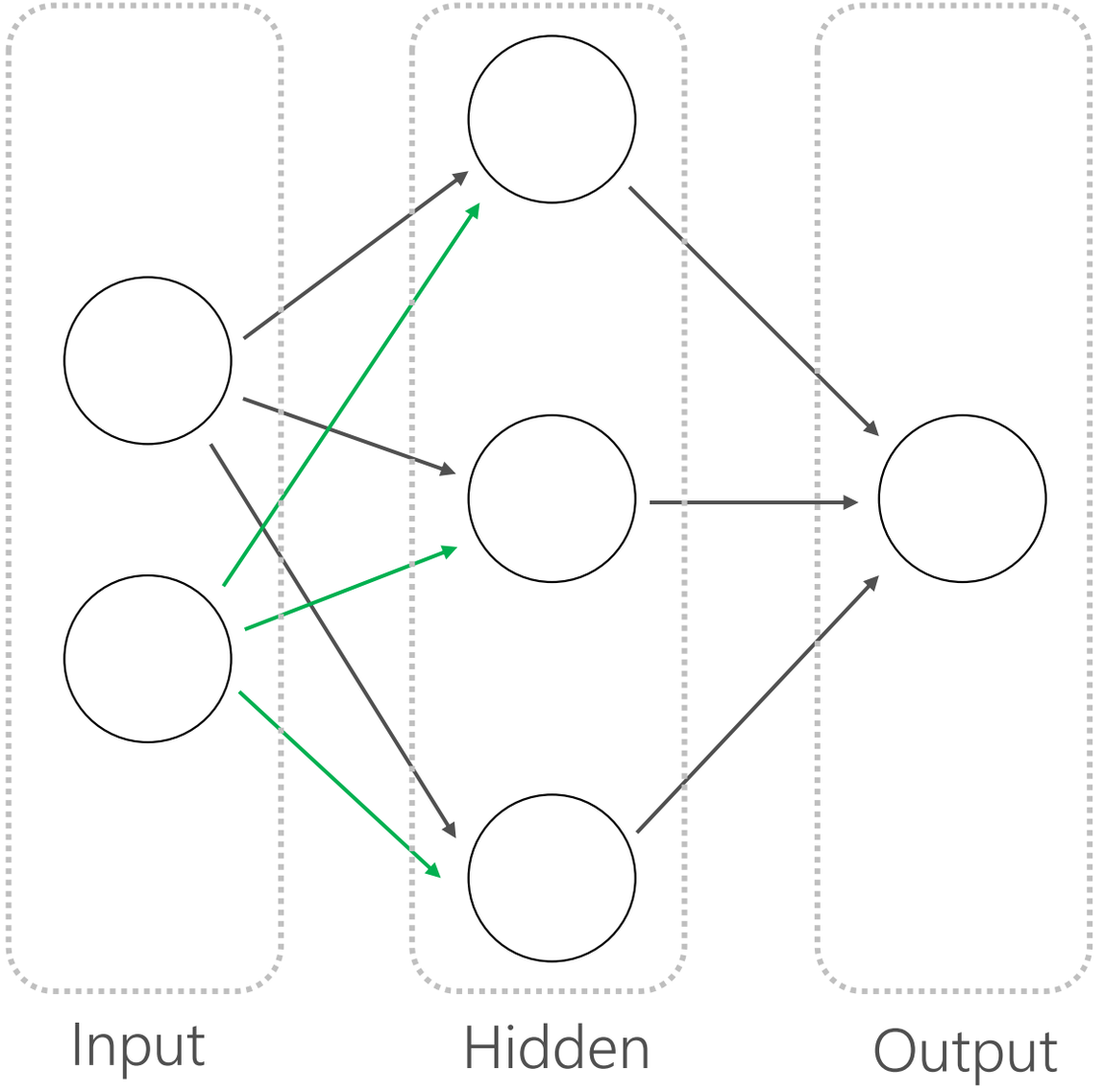
Do I snowboard at Whistler this weekend?

$x_1 = 1$ $(good\ weather)$
$w_1 = 0.3$

$x_2 = 1$ $(a\ lot\ of\ powder)$
$w_2 = 0.6$

$x_3 = 0$ $(driving\ sucks)$
$w_3 = 0.1$

Simplified Two-Layer ANN

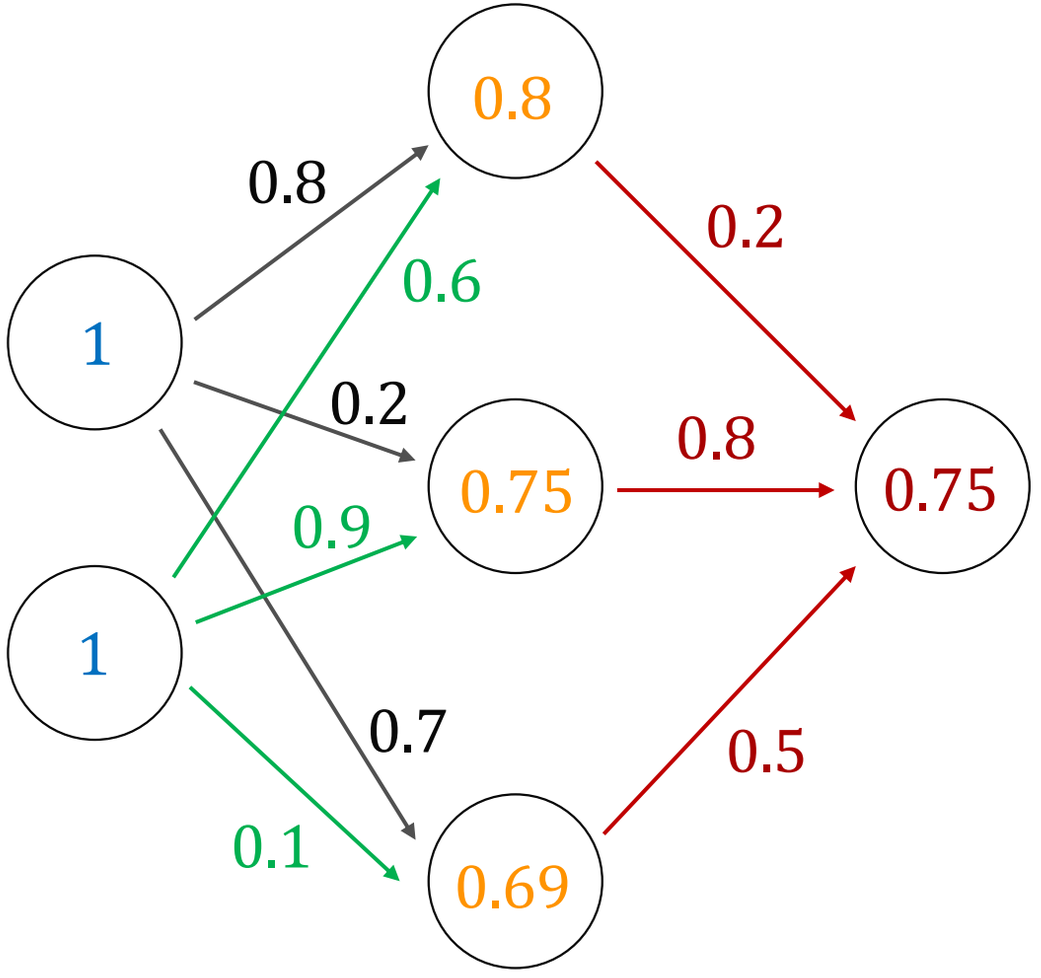


$Do\ I\ snowboard\ at\ Whistler\ this\ weekend?$

$x_1 = Après\ Ski'er$
$x_2 = Shredder$

$h_1 = weather$
$h_2 = powder$
$h_3 = driving$

Simplified Two-Layer ANN



$h_1 = \sigma(1x0.8 + 1x0.6) = 0.80$
$h_2 = \sigma(1x0.2 + 1x0.9) = 0.75$
$h_3 = \sigma(1x0.7 + 1x0.1) = 0.69$

$output$
$= \sigma(0.2x0.8 +$
$0.8x0.75 +$
$0.5x0.69)$
$= \sigma(1.105) = 0.75$

Great References

Andrej Karparthy's ConvNetJS MNIST Demo

What is back propagation in neural networks?

CS231n: Convolutional Neural Networks for Visual Recognition
Syllabus and Slides | Course Notes | YouTube

- With particular focus on CS231n: Lecture 7: Convolution Neural Networks

Neural Networks and Deep Learning

TensorFlow

Great References

Deep Visualization Toolbox

Back Propagation with TensorFlow

TensorFrames: Google TensorFlow with Apache Spark

Integrating deep learning libraries with Apache Spark

Upcoming webinar: Build, Scale, and Deploy Deep Learning Pipelines with Ease

Microsoft

Q&A