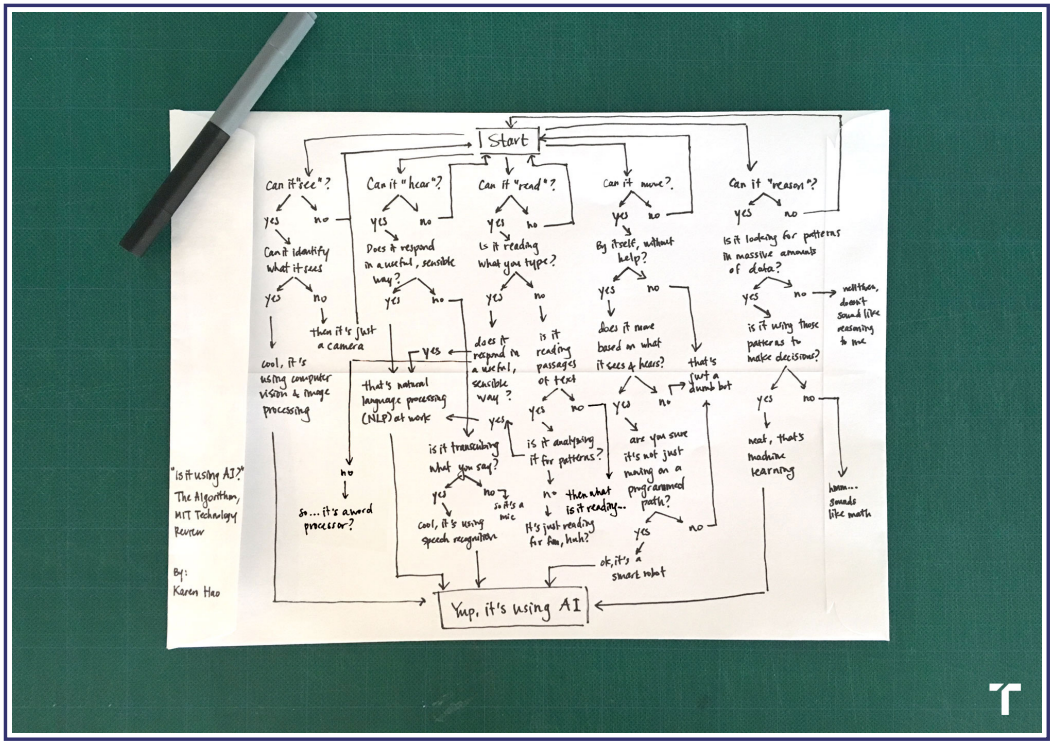
Machine learning

A gentle introduction



ML: BFD!!

Our 'menu' for today

We humans (not other animals!) have been to outer space, invented agriculture, found cures for diseases, invented countless things, create and use STEM, have radically altered the environment... But, these pale in comparison, when it comes to the promise/potential/dream of machine intelligence.

Our specific topic today - a DATA-DRIVEN approach to AI.

But, let's step way back (or go up to a steep perch!), and survey "everything"! We'll be looking at:

- ————————————————————————————
- warmup 'trailers'
- types of AI
- ML: oversimplified
- neurons
- neural networks ('NN's)
- 'AI winter'
- ————————————————————————————
- 'deep learning' - the new revolution
- convolutional NNs, ie. CNNs
- RNN, LSTM
- CapsNet

- NN architectures
- ————————————————————————————
- GANs!
- players
- hardware acceleration
- NN on the cloud
- NN on the edge
- ————————————————————————————
- the big prize
- current directions
- the 'race' for AI
- dangers!
- learning more
- a smorgasbord! [collage, cornucopia, EBTKS, boatload…] [of applications]
- ————————————————————————————

We will necessarily leave out the underlying math - courses related to ML (CS566, CS567…) will provide you that [almost all the math falls into these three categories: **statistics, probability** - for data sampling, experiment design, simulation, model building; **linear algebra** - for data description and analysis (eg. in NNs), geometric operations on data; **calculus** - for function optimization (eg error reduction, reward maximization)]

A couple of clips...

Knosis.ai: https://www.youtube.com/watch?v=3RJ_YPh-1t8 - glimpses of how ML is FUELED by data!!

A fascinating documentary on (data-driven) ML: https://www.pbs.org/wgbh/frontline/film/in-the-age-of-ai - ~2 hours, every second of which is worth watching (because this is how our future is being shaped). Set aside 2 hours, watch it; or, as my friend Lurong would exclaim, "just-tu do it!!" :) **For now, we simply want a TL;DR - so, let's watch just till 1:15.**

Types of AI, Machine Learning ("ML"), types of ML

Here is a good way [after Arend Hintze] to **classify AI types** (not just techniques!)..

Type I: Reactive machines - make optimal moves - no memory, no past 'experience'. Ex: game trees.

Type II: Limited memory - human-compiled/provided , one-shot 'past' 'experiences' are stored for lookup. Ex: expert systems, neural networks.

Type III: Theory of Mind - "the understanding that people, creatures and objects in the world can have thoughts and emotions that affect the AI programs' own behavior".

Type IV: Self-awareness - machines that have consciousness, that can form representations about themselves (and others).

Type I AI is simply, application of rules/logic (eg. chess-playing machines).

Type II AI is where we are, today - specifically, this is what we call 'machine learning' - it is **"data-driven AI"**! Within the last decade or so, spectacular progress has been made in this area, ending what was called the 'AI Winter'.

As of now, types III and IV are in the realm of speculation and science-fiction, but in the general public's mind, they appear to be certainty in the near term :)

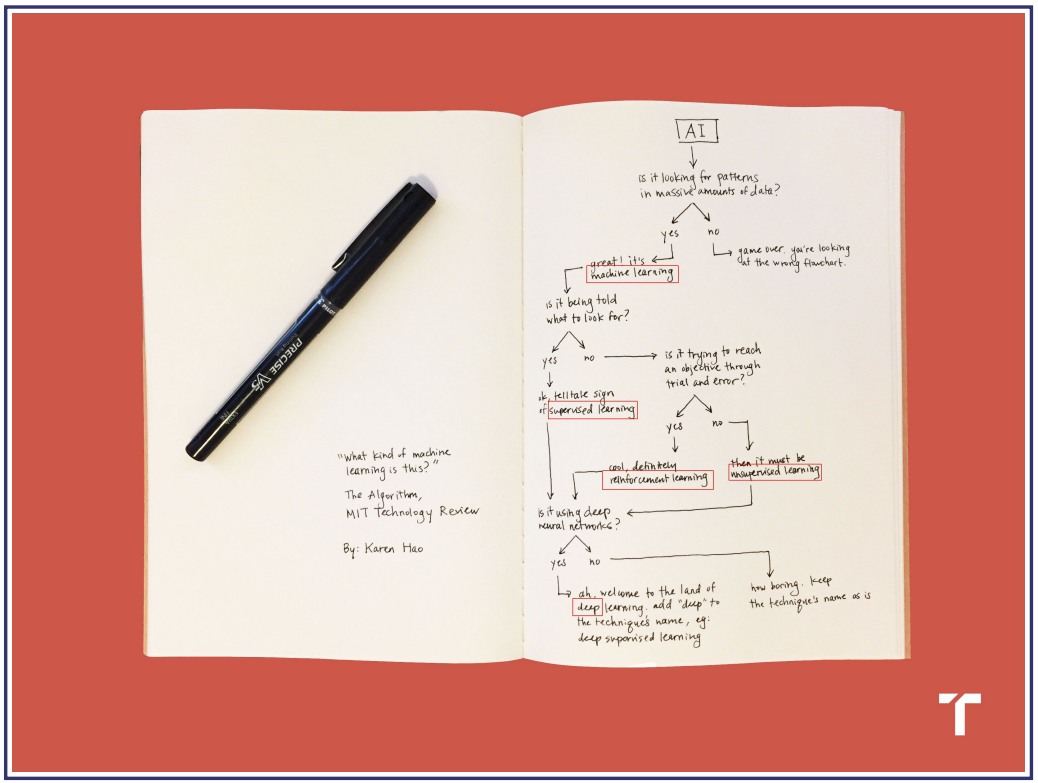
ML is the ONE subset of AI that is revolutionizing the world.

"Machine learning focuses on the construction and study of systems that can learn from data to optimize a performance function, such as optimizing the expected reward or minimizing loss functions. The goal is to develop deep insights from data assets faster, extract knowledge from data with greater precision, improve the bottom line and reduce risk."
- Wayne Thompson, SAS

ML comes in several flavors - the key types of machine learning include:

- Supervised learning
- Unsupervised learning
- Semisupervised learning
- Reinforcement learning

Here is a classification:



Supervised learning algorithms are "trained" using examples (**DATA!**] where in addition to features [inputs], the desired output [label, aka target] is known. The goal is to LEARN the patterns inherent in the training dataset, and use the knowledge to PREDICT the labels for new data.

Unsupervised learning is a type of machine learning where the system operates on unlabeled examples. In this case, the system is not told the "right answer." The algorithm tries to find a hidden structure or manifold in unlabeled data. The goal of unsupervised

learning is to explore the data to find intrinsic structures within it using methods like clustering or dimension reduction.

For Euclidian space data: k-means clustering, Gaussian mixtures and principal component analysis (PCA)

For non-Euclidian space data: ISOMAP, local linear embedding (LLE), Laplacian eigenmaps, kernel PCA.

Use matrix factorization, topic models/graphs for social media data.

Here is a WIRED mag writeup on unsupervised learning:

Let's say, for example, that you're a researcher who wants to learn more about human personality types. You're awarded an extremely generous grant that allows you to give 200,000 people a 500-question personality test, with answers that vary on a scale from one to 10. Eventually you find yourself with 200,000 data points in 500 virtual "dimensions" - one dimension for each of the original questions on the personality quiz. These points, taken together, form a lower-dimensional "surface" in the 500-dimensional space in the same way that a simple plot of elevation across a mountain range creates a two-dimensional surface in three-dimensional space.

What you would like to do, as a researcher, is identify this lower-dimensional surface, thereby reducing the personality portraits of the 200,000 subjects to their essential properties - a task that is similar to finding that two variables suffice to identify any point in the mountain-range surface. Perhaps the personality-test surface can also be described with a simple function, a connection between a number of variables that is significantly smaller than 500. This function is likely to reflect a hidden structure in the data.

In the last 15 years or so, researchers have created a number of tools to probe the geometry of these hidden structures. For example, you might build a model of the surface by first zooming in at many different points. At each point, you would place a drop of virtual ink on the surface and watch how it spread out. Depending on how the surface is curved at each point, the ink would diffuse in some directions but not in others. If you were to connect all the drops of ink, you would get a pretty good picture of what the surface looks like as a whole. And with this information in hand, you would no longer have just a collection of data points. Now you would start to see the connections on the surface, the interesting loops, folds and kinks. This would give you a map.

Here is a practical use for unsupervised learning.

Semisupervised learning is used for the same applications as supervised learning. But this technique uses both labeled and unlabeled data for training - typically, a small amount of labeled data with a large amount of unlabeled data. The primary goal is unsupervised learning (clustering, for example), and labels are viewed as side information (cluster

indicators in the case of clustering) to help the algorithm find the right intrinsic data structure.

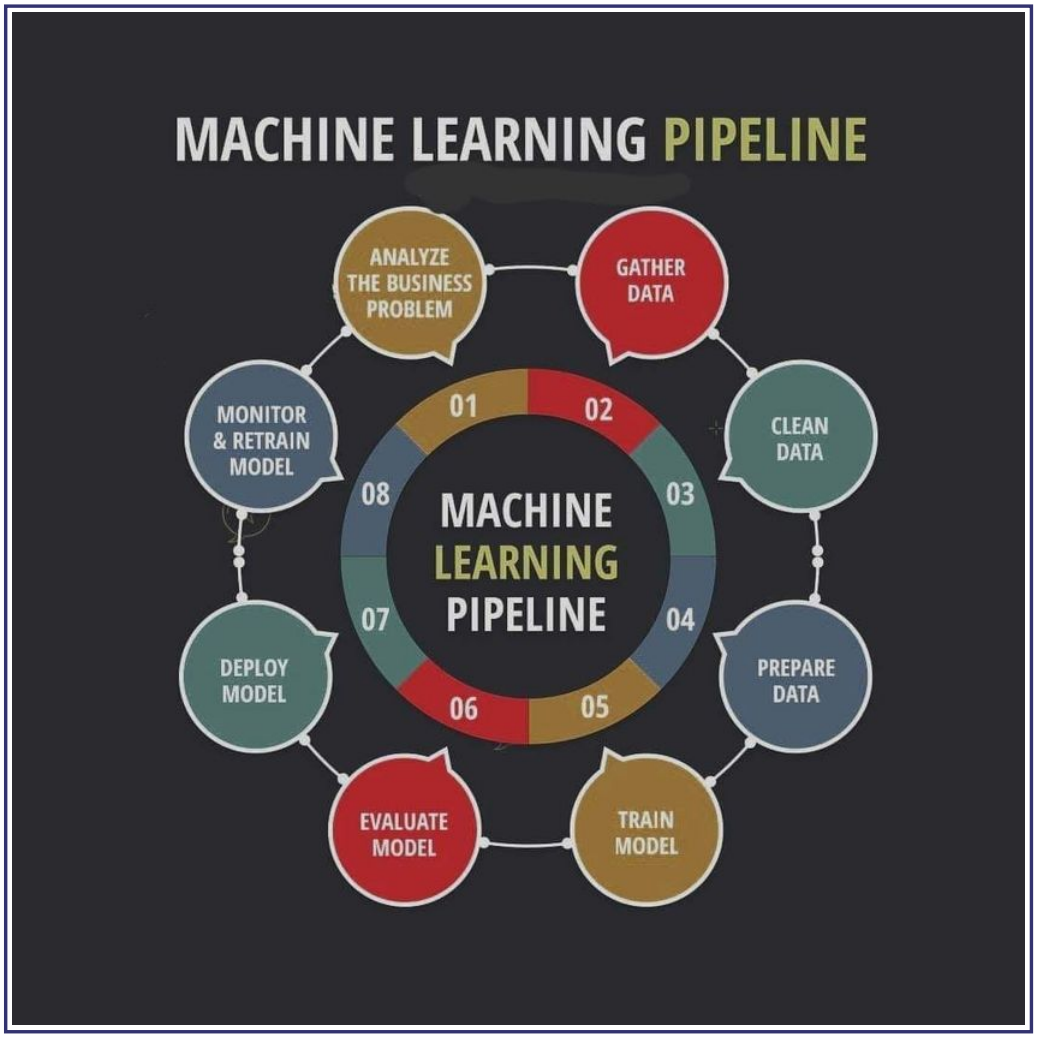
With **reinforcement learning** 'RL'), the algorithm discovers for itself which actions yield the greatest rewards through trial and error. Reinforcement learning has three primary components:
1. agent - the learner or decision maker
2. environment - everything the agent interacts with
3. actions - what the agent can do

The objective is for the agent to choose actions that maximize the expected reward over a given period of time. The agent will reach the goal much quicker by following a good policy, so the goal in reinforcement learning is to learn the best policy. Reinforcement learning is often used for robotics and navigation.

Markov decision processes (MDPs) are popular models used in reinforcement learning. MDPs assume the state of the environment is perfectly observed by the agent. When this is not the case, we can use a more general model called partially observable MDPs (or POMDPs).

And there's also, hierarchical RL: https://sites.google.com/view/hrl-ep3

ML pipeline



What we do in (supervised) ML is IDENTICAL to what we do in BI, DM!

It's ALL about **calculating quantities derived from patterns in existing data**.

ML - the 'big picture'

EVERY neural network (which is really (supervised) ML is) is simply, a giant, deterministic, non-linear EQUATION!!!

$$y = F(x0, x1, x2...)$$

$$f(x0, x1, x2...) \longrightarrow y$$

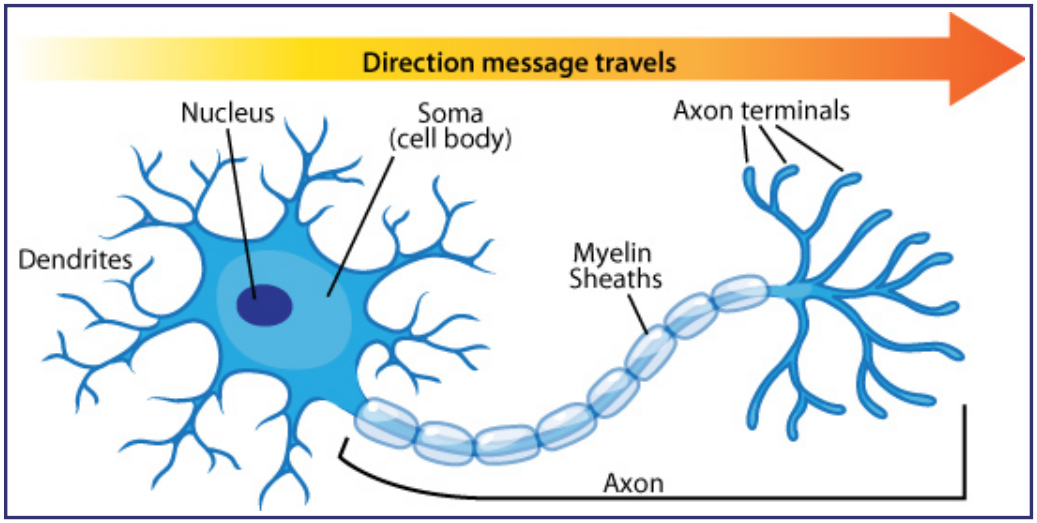
(x0,x1,x2...) is a single piece (row) of data. Given it, WHAT IS 'y'? In other words, **WHAT IS f()? [wtf, lol]**

How can we calculate f()?

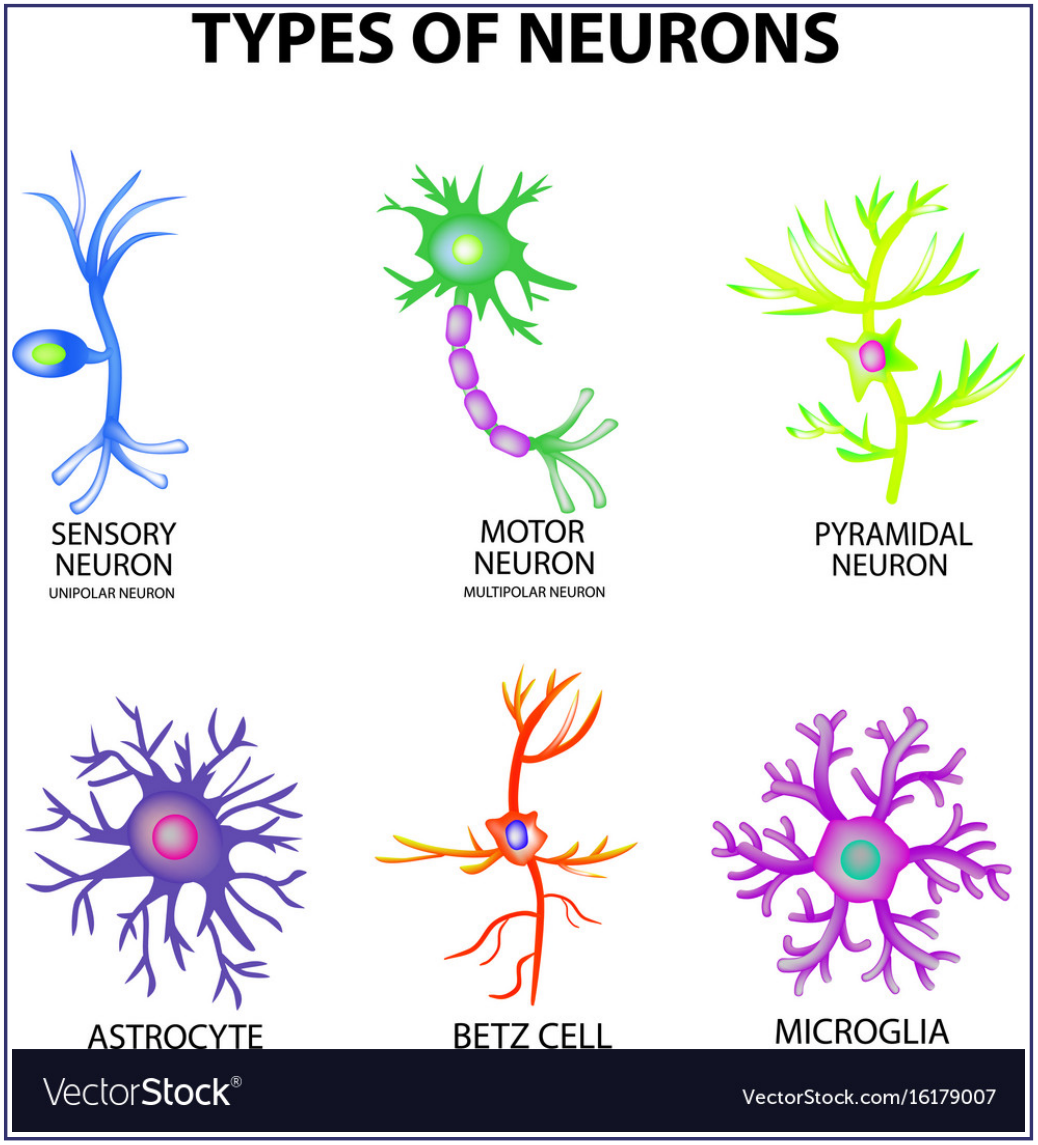
- using LOTS of data
- by iteration - via 'hyper params' such as architecture, learning rate, momentum; by optimizing our solving; by computing and using error between computed and expected outputs
- using nonlinearity
- using LOTS of small, simple 'neuron' subfunctions (out of which our f() is COMPOSED) [connected using specific *architectures*]

Neurons

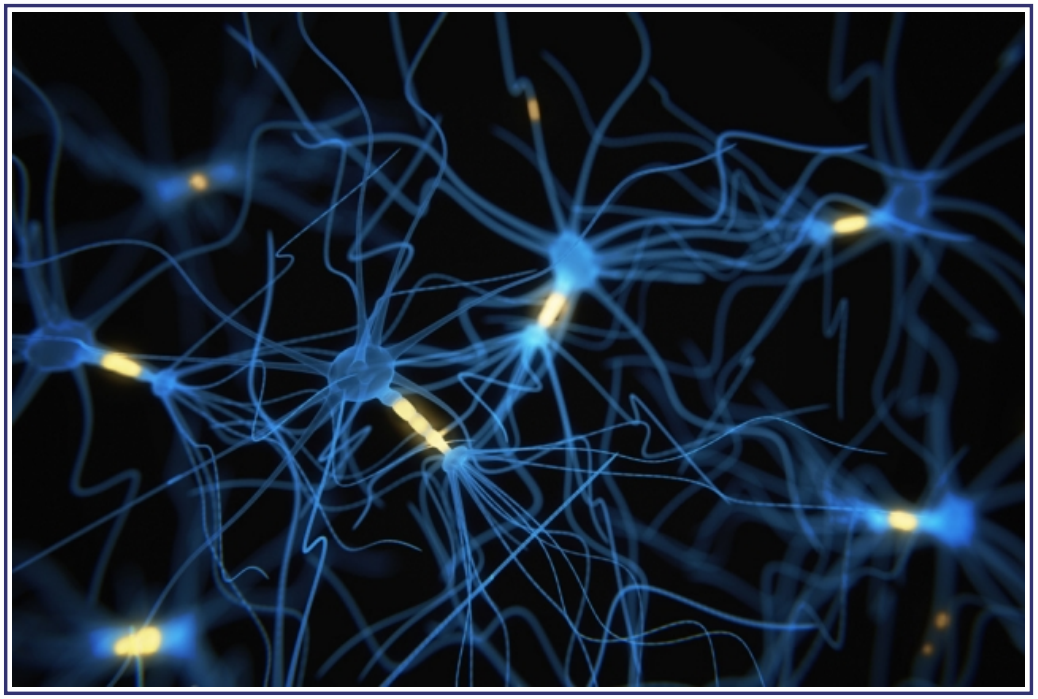
Our brains contain about 100 billion of them - each neuron is like a function, with inputs ("dendrites"), and an output ("axon"):



Neurons ENCODE memory, learning... There are many types of neurons:



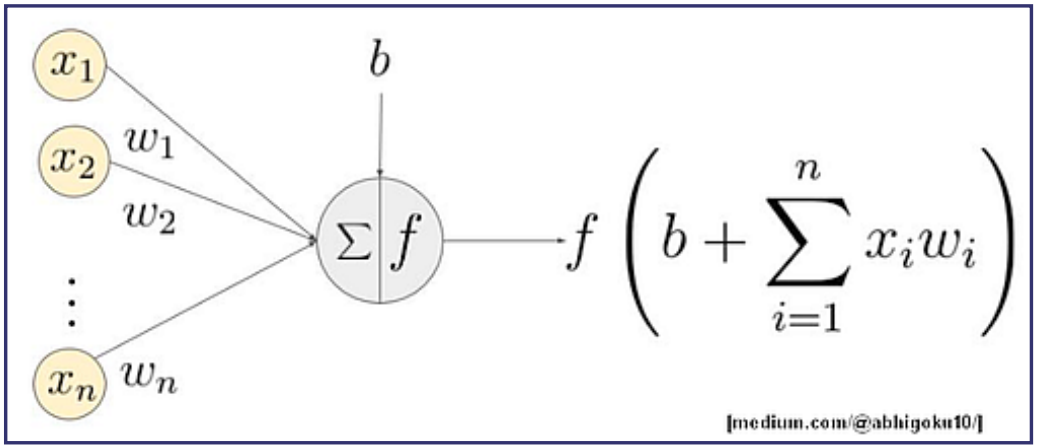
A neurons CONNECTS, via dendrites (inputs) and axon (output), to other neurons:



NN basics - it's all about 'backprop'

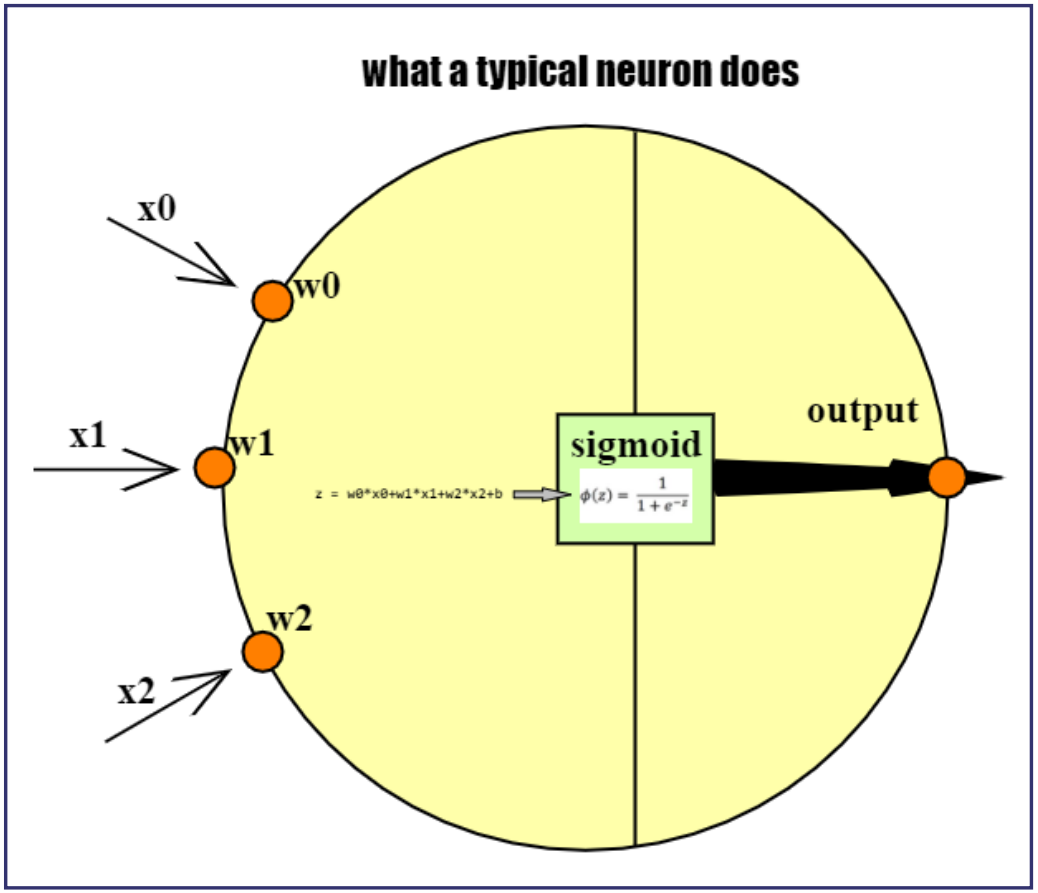
A neural network is a form of 'AI' - uses neuron-like connected units to **learn patterns** in training (existing) data that has known outcomes, and uses the learning to be able to gracefully respond to new (non-training, 'live') data.

Definition: a neural net(work) is **an interconnected set of weighted, nonlinear functions** [this compact definition will become clear[(er), soon]:

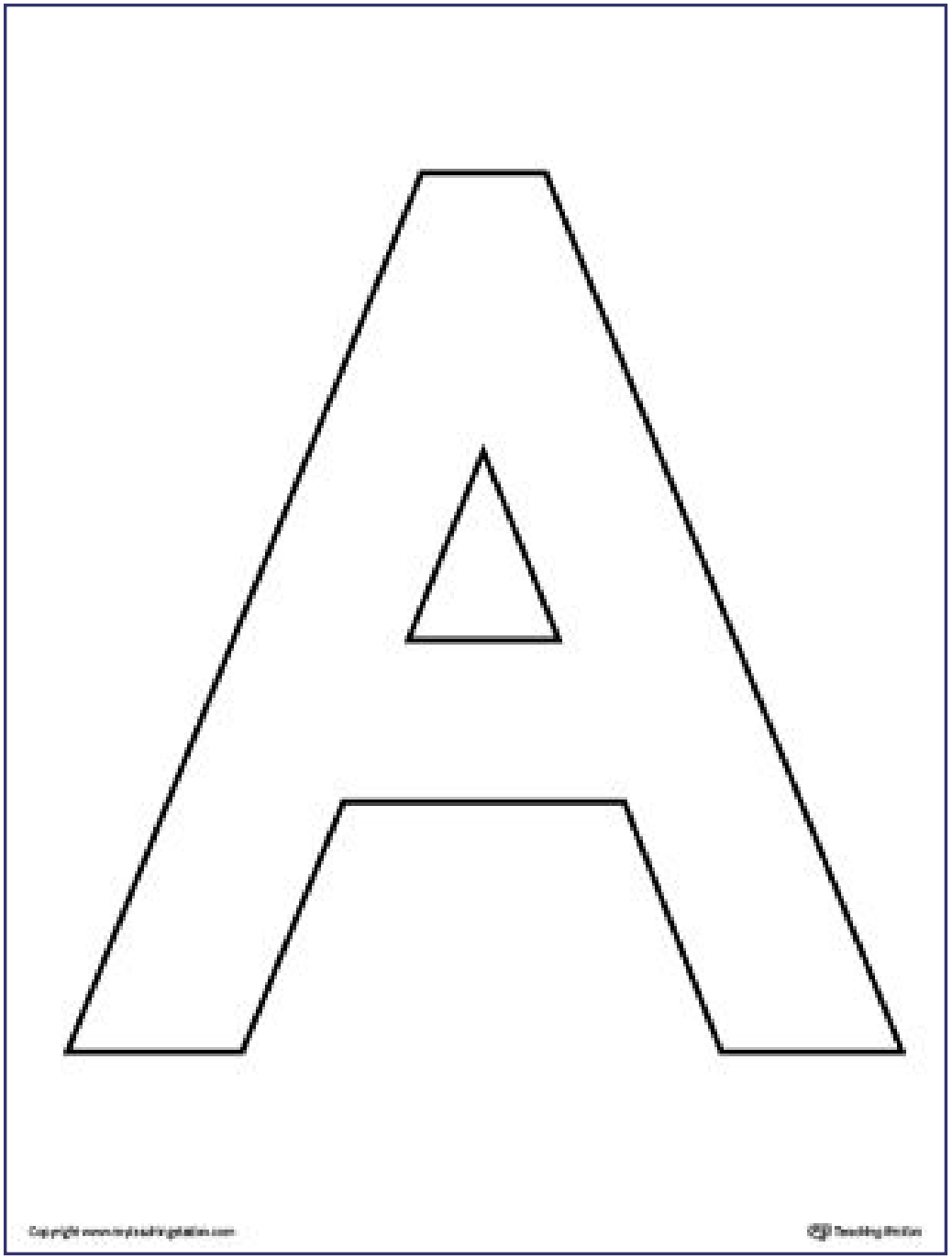


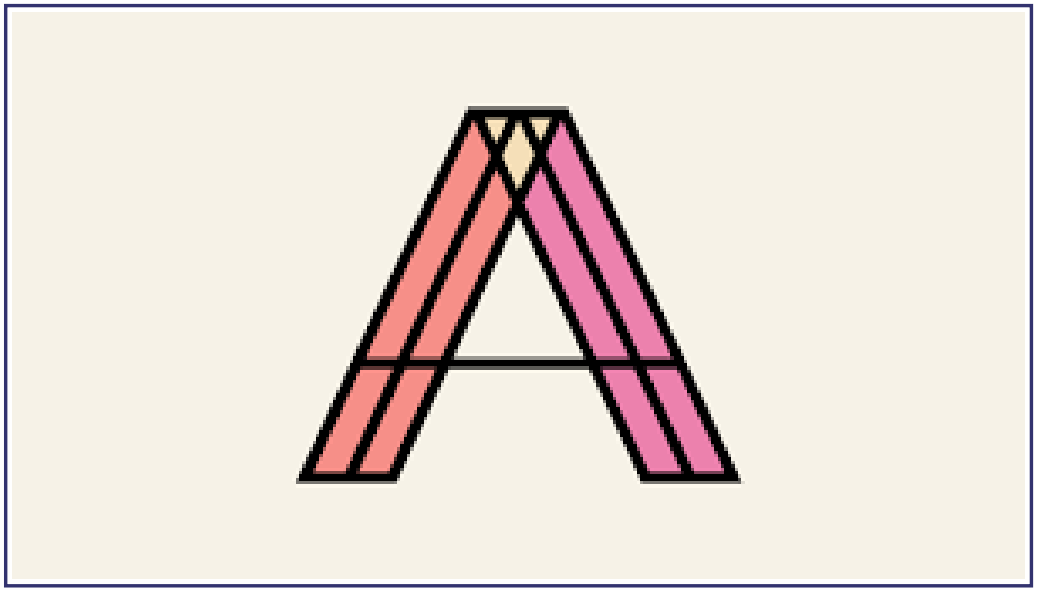
The overall idea is this:

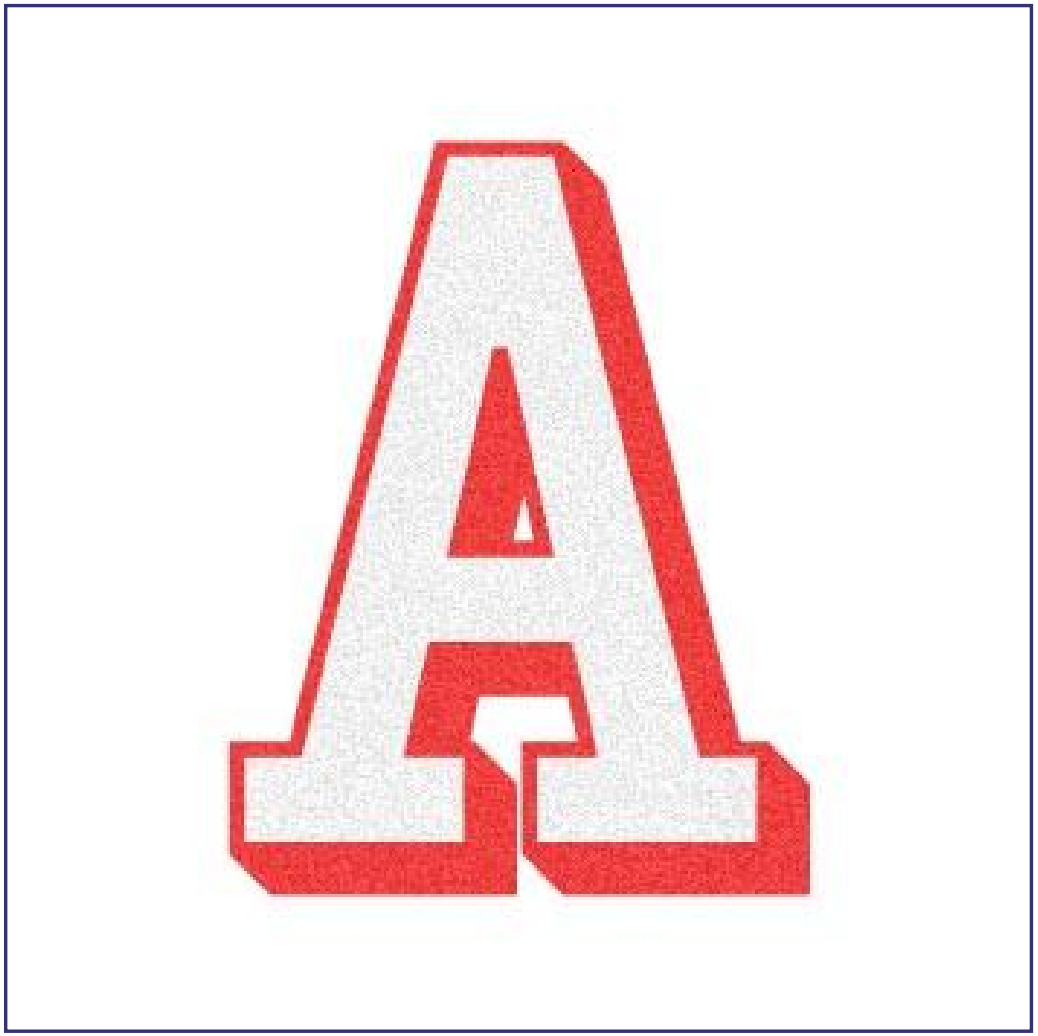
- existing data is used to TRAIN a neural network - the network 'learns' patterns in the data, by adapting weights in each interconnected unit ('neuron')
- the network can now go 'live', ie. be deployed
- new data can be processed on the DEPLOYED network, which would make predictions about it based on the patterns learned

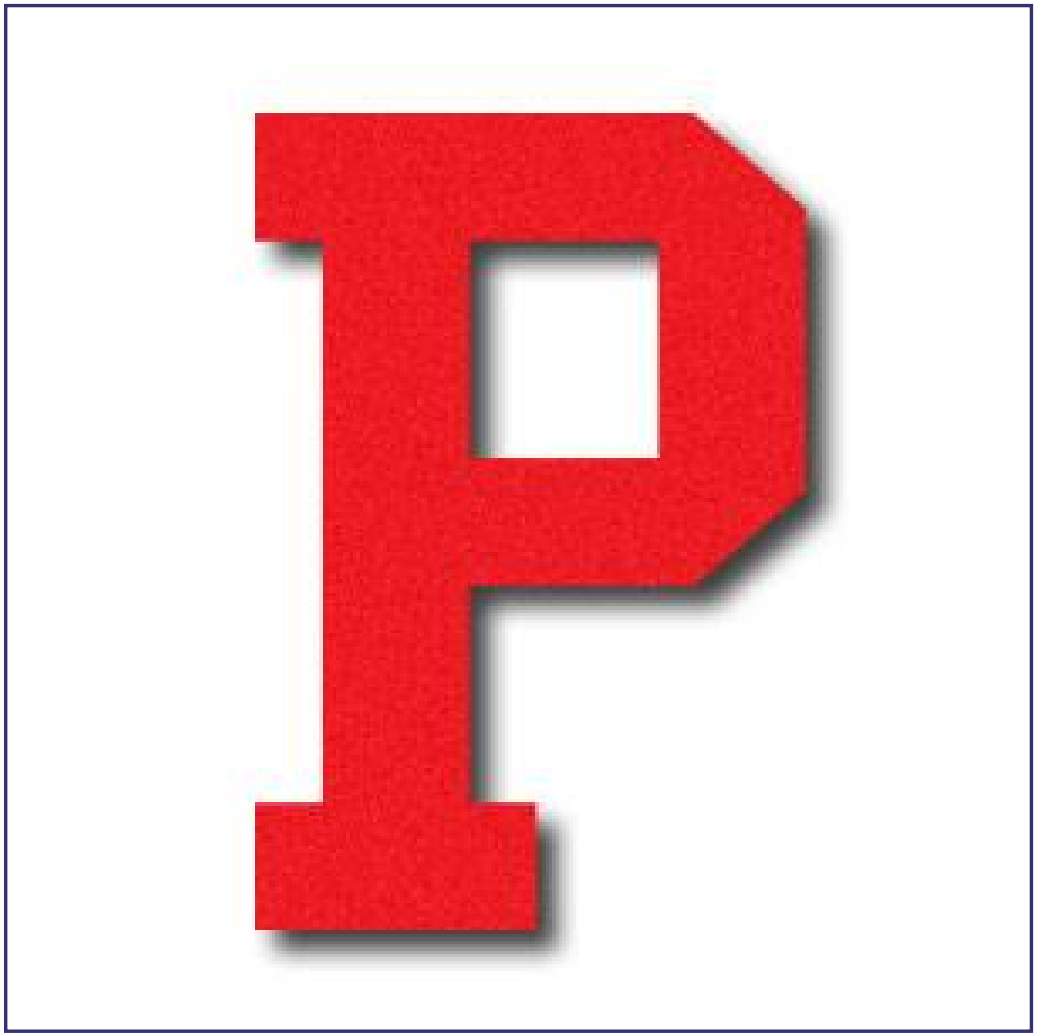


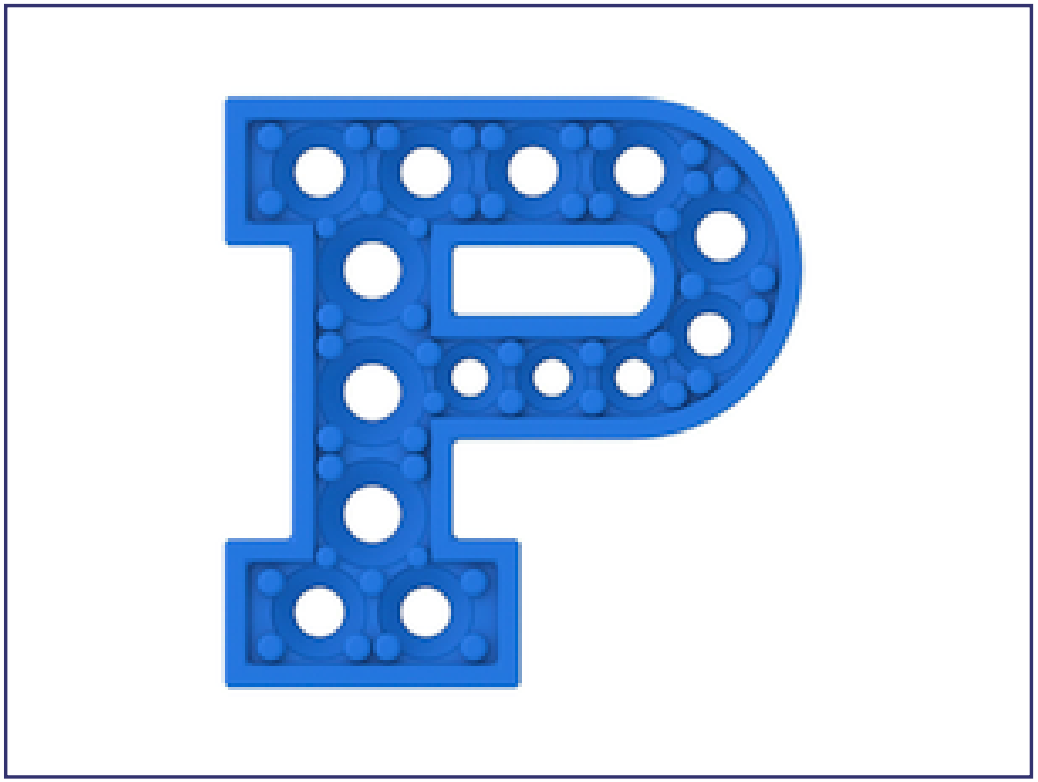
Guess why you are able to recognize these?











Neural networks (NNs) can be used to:

- recognize/classify features - traffic, terrorists, expressions, plants, words..
- detect anomalies - unusual CC activity, unusual machine states, gene sequences, brain waves..
- predict exchange rates, 'likes'..
- calculate numerical values (eg. home prices)
- ... [HUNDREDS, if not THOUSANDS, of uses - ANY form of data, that has ANY pattern in it, can be learned!!]

Here is some early NN work.

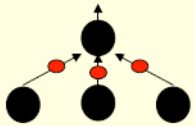
As you can imagine, 'Big Data' can help in all of the above! The bigger the training set, the better the learning, and therefore, better the result.

Below is an overview of how NNs work..

The brain (specifically, learning/training) is modeled after strengthening relevant neuron connections - neurons communicate (through axons and dendrites) dataflow-style (neurons send output signals to other neurons):

How the brain works on one slide!

- Each neuron receives inputs from other neurons
  - A few neurons also connect to receptors.
  - Cortical neurons use spikes to communicate.
- The effect of each input line on the neuron is controlled by a synaptic weight
  - The weights can be positive or negative.
- The synaptic weights adapt so that the whole network learns to perform useful computations
  - Recognizing objects, understanding language, making plans, controlling the body.
- You have about 10^{11} neurons each with about 10^{4} weights.
  - A huge number of weights can affect the computation in a very short time. Much better bandwidth than a workstation.

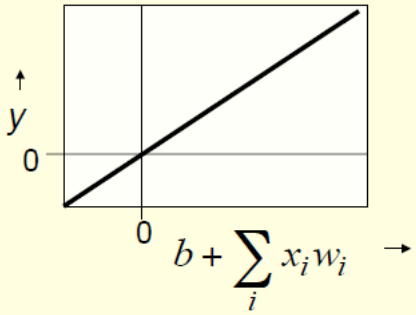


Linear (identity), 'leaky' output: input values get passed through 'verbatim' (not very useful to us, does not happen in real brains!):

Linear neurons

- These are simple but computationally limited
  - If we can make them learn we may get insight into more complicated neurons.

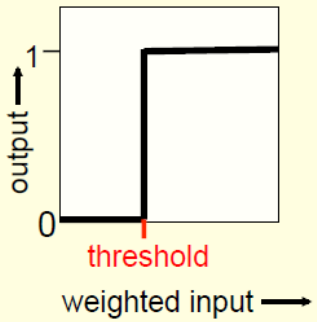
$$y = b + \sum_i x_i w_i$$



A better model is when a neuron outputs a 1 (stays 0 to start with) ("fires") if and when its combined inputs exceed a threshold value:

Binary threshold neurons

- McCulloch-Pitts (1943): influenced Von Neumann.
  - First compute a weighted sum of the inputs.
  - Then send out a fixed size spike of activity if the weighted sum exceeds a threshold.
  - McCulloch and Pitts thought that each spike is like the truth value of a proposition and each neuron combines truth values to compute the truth value of another proposition!



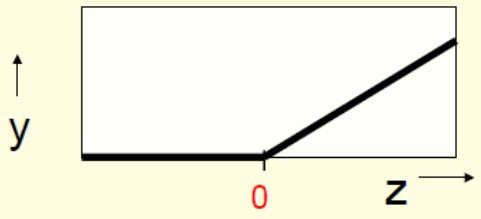
Another option is to convert the 'step' pulse to a ramp:

Rectified Linear Neurons
(sometimes called linear threshold neurons)

They compute a linear weighted sum of their inputs.
The output is a non-linear function of the total input.

$$z = b + \sum_i x_i w_i$$

$$y = \begin{cases} z & \text{if } z > 0 \\ 0 & \text{otherwise} \end{cases}$$

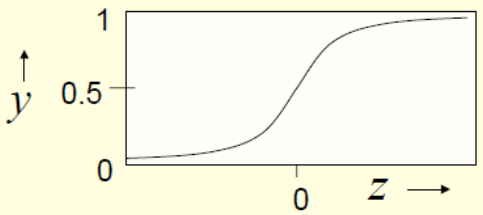


Even better - use a smoother buildup of output:

Sigmoid neurons

- These give a real-valued output that is a smooth and bounded function of their total input.
  - Typically they use the logistic function
  - They have nice derivatives which make learning easy (see lecture 3).

$$z = b + \sum_i x_i w_i \qquad y = \frac{1}{1 + e^{-z}}$$

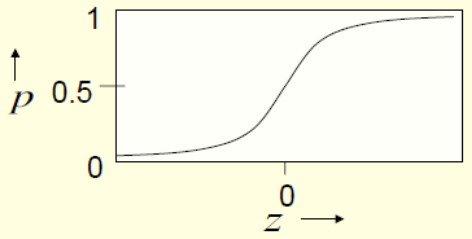


Even better - use a sigmoidal probability distribution for the output:

Stochastic binary neurons

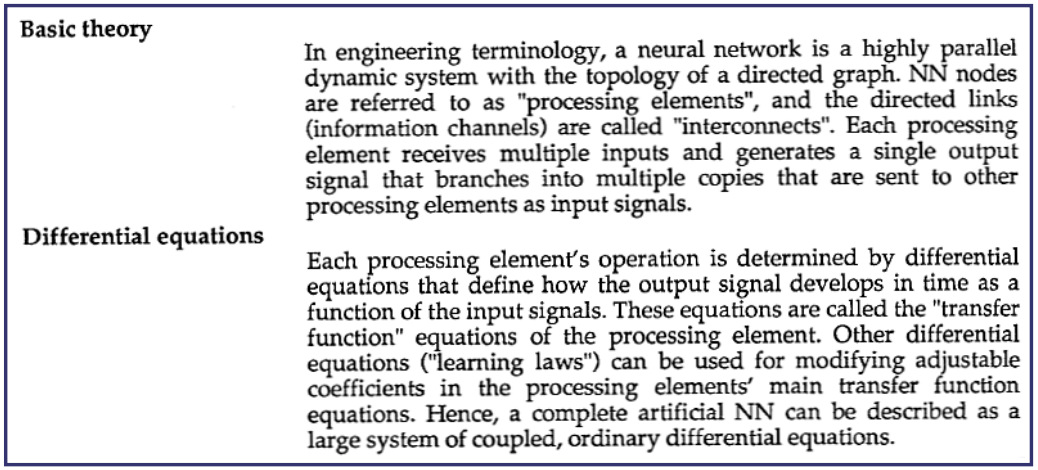
- These use the same equations as logistic units.
  - But they treat the output of the logistic as the probability of producing a spike in a short time window.
- We can do a similar trick for rectified linear units:
  - The output is treated as the Poisson rate for spikes.

$$z = b + \sum_i x_i w_i \qquad p(s=1) = \frac{1}{1+e^{-z}}$$



The functions we use to generate the output, are called activation functions - the ones we looked at are identity, binary threshold, rectifier and sigmoid. The gradients of these functions are used during backprop. There are more (look these up later) - symmetrical sigmoid, ie. hyperbolic tangent (tanh), soft rectifier, polynomial kernels...

This is from an early ('87) newsletter - today's NNs are not viewed as systems of coupled ODEs - instead we use 'training' to make processing element 'learn' how to respond to its inputs:



Basic theory

In engineering terminology, a neural network is a highly parallel dynamic system with the topology of a directed graph. NN nodes are referred to as "processing elements", and the directed links (information channels) are called "interconnects". Each processing element receives multiple inputs and generates a single output signal that branches into multiple copies that are sent to other processing elements as input signals.

Differential equations

Each processing element's operation is determined by differential equations that define how the output signal develops in time as a function of the input signals. These equations are called the "transfer function" equations of the processing element. Other differential equations ("learning laws") can be used for modifying adjustable coefficients in the processing elements' main transfer function equations. Hence, a complete artificial NN can be described as a large system of coupled, ordinary differential equations.

With the above info, we can start to build our neural networks!

* we create LAYER upon LAYER of neurons - each layer is a set (eg. column) of neurons, which feed their (stochastic) outputs downstream, to neurons in the next (eg. column to the right) layer, and so on

* each layer is responsible for 'learning' some aspect of our target - usually the layers operate in a hierarchical (eg. raw pixels to curves to regions to shapes to FEATURES) fashion

* a layer 'learns' like so: its input weights are adjusted (modified iteratively) so that the weights make the neurons fire when they are given only 'good' inputs.

Here is how to visualize the layers.

The above steps can be summarized this way:

- We start by choosing a model-class: $y = f(\mathbf{x}; \mathbf{W})$
  - A model-class, *f*, is a way of using some numerical parameters, **W**, to map each input vector, **x**, into a predicted output y.
- Learning usually means adjusting the parameters to reduce the discrepancy between the target output, t, on each training case and the actual output, y, produced by the model.
  - For regression, $\frac{1}{2}(y-t)^2$ is often a sensible measure of the discrepancy.
  - For classification there are other measures that are generally more sensible (they also work better).

Learning (ie. iterative weights modification/adjustment) works via 'backpropagation', with iterative weight adjustments starting from the last hidden layer (closest to the output layer) to the first hidden layer (closest to the input layer). Backpropagation aims to reduce the ERROR between the expected and the actual output [by finding the minimum of the [quadratic] loss function], for a given training input. Two hyper/meta parameters guide convergence: learning rate [scale factor for the error], momentum [scale factor for error from the previous step]. To know more (mathematical details), look at this page, and this.

Here is backprop again, in equation and code form:

For each input/target pair $(\mathbf{x}^{(n)}, t^{(n)})$ $(n = 1, \ldots, N)$, compute $y^{(n)} = y(\mathbf{x}^{(n)}; \mathbf{w})$, where

$$y(\mathbf{x}; \mathbf{w}) = \frac{1}{1 + \exp(-\sum_i w_i x_i)}, \tag{39.18}$$

define $e^{(n)} = t^{(n)} - y^{(n)}$, and compute for each weight w_i

$$g_i^{(n)} = -e^{(n)} x_i^{(n)}. \tag{39.19}$$

Then let

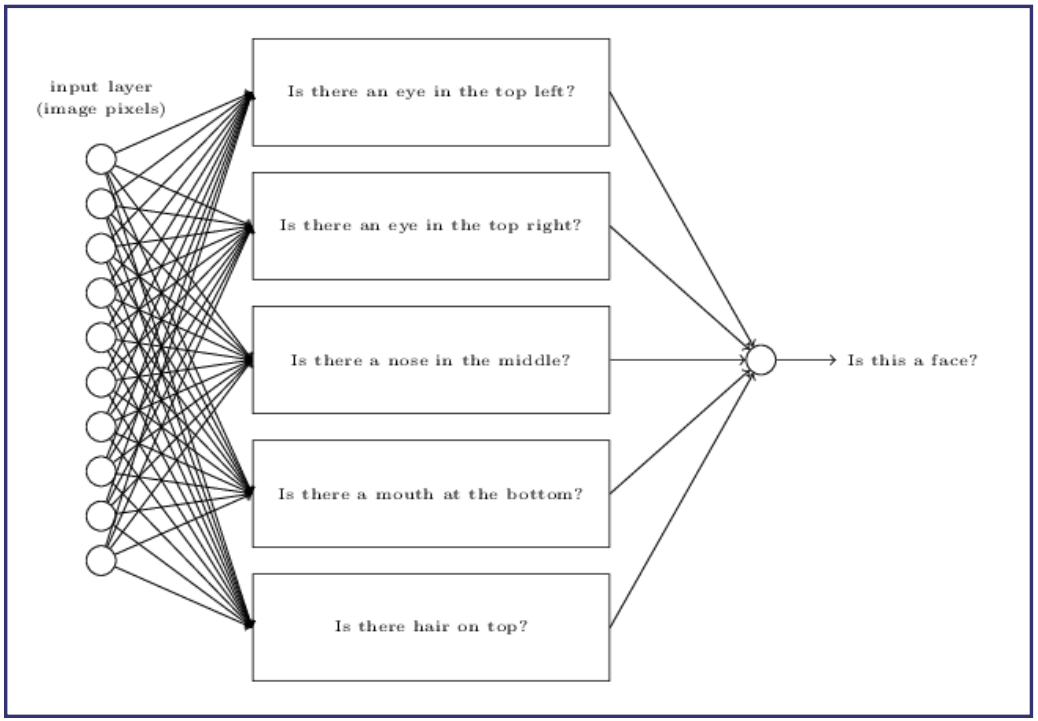
$$\Delta w_i = -\eta \sum_n g_i^{(n)}. \tag{39.20}$$

```
global x ;        # x is an N * I matrix containing all the input vectors
global t ;        # t is a vector of length N containing all the targets

for l = 1:L       # loop L times

   a = x * w  ;                          # compute all activations
   y = sigmoid(a) ;                      # compute outputs
   e = t - y   ;                         # compute errors
   g = - x' * e ;                        # compute the gradient vector
   w = w - eta * ( g + alpha * w )  ;    # make step, using learning rate eta
                                         #    and weight decay alpha
endfor

function f = sigmoid ( v )
   f = 1.0 ./ ( 1.0 .+ exp ( - v ) ) ;
endfunction
```

To quote MIT's Alex "Sandy" Pentland: "The good magic is that it has something called the credit assignment function. What that lets you do is take stupid neurons, these little linear

functions, and figure out, in a big network, which ones are doing the work and encourage them more. It's a way of taking a random bunch of things that are all hooked together in a network and making them smart by giving them feedback about what works and what doesn't. It sounds pretty simple, but it's got some complicated math around it. That's the magic that makes AI work."

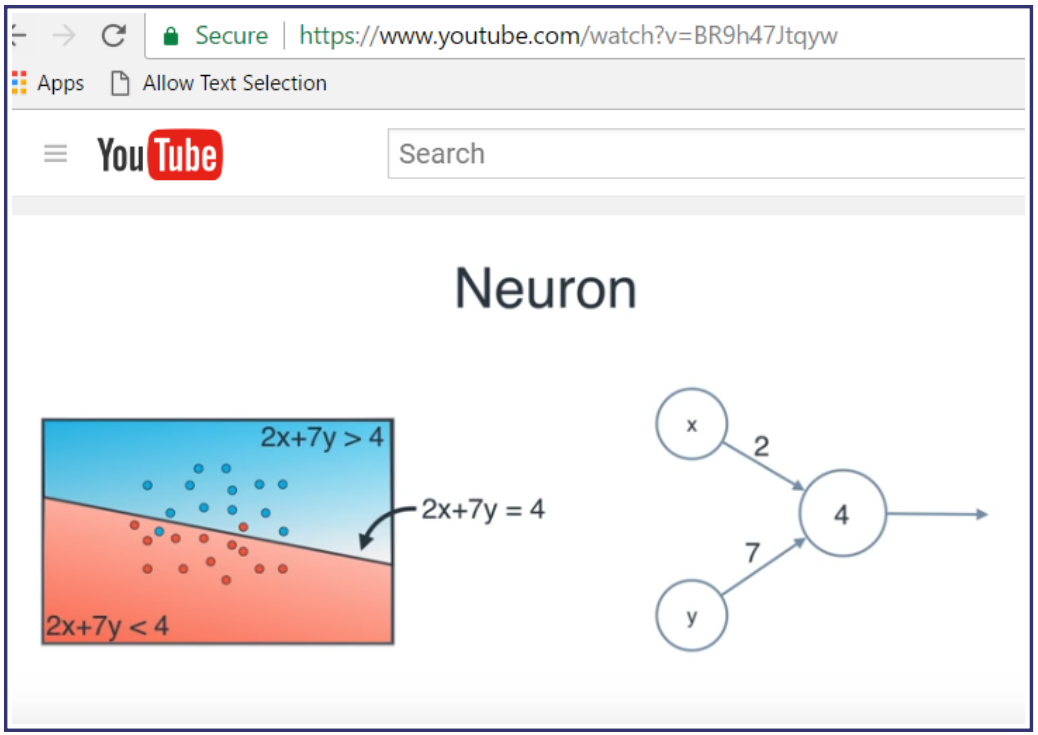
As per the above, here is a schematic showing how we could look for a face:



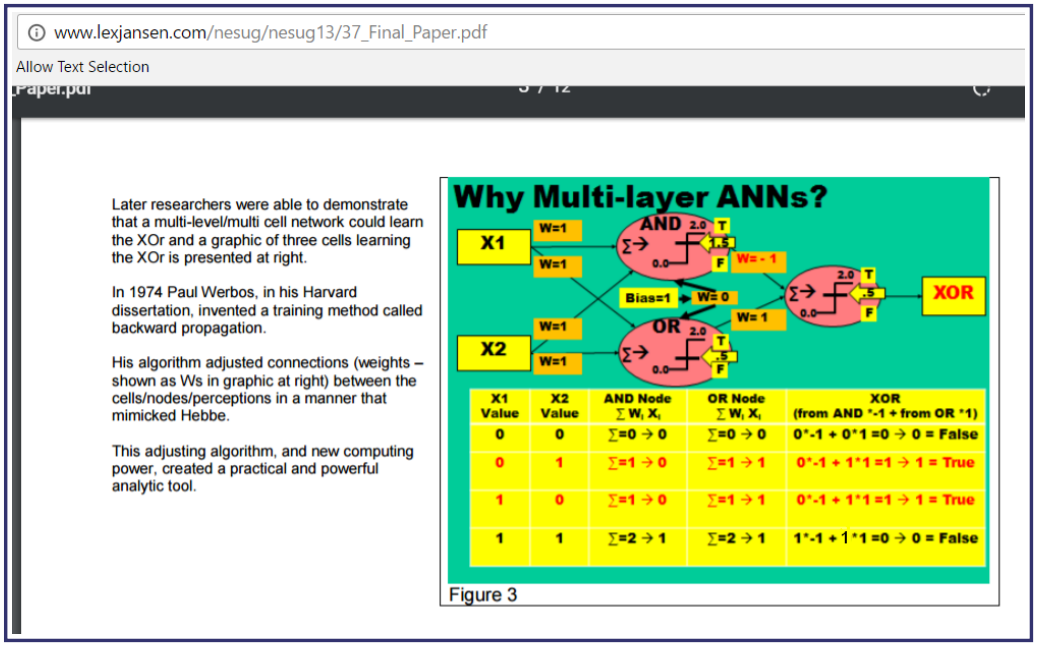
Note that a single neuron's learning/training (backprop-based calculation of weights and bias) can be considered to be equivalent to multi-linear regression - the neuron's inputs are features (x_0, x_1..), the learned weights are corresponding coefficients (w_0,w_1..) and the bias 'b' is the y intercept! We then take this result ('y') and non-linearize it for output, via an

activation function. So overall, this is equivalent to applying logistic regression to the inputs. When we have multiple neurons in multiple layers (all hidden, except for inputs and outputs), we are chaining multiple sigmoids, which can approximate ANY continuous function! THIS is the true magic of ANNs. Such 'approximation by summation' occurs elsewhere as well - the Stone-Weierstrass theorem, Fourier/wavelet analysis, power series for trig functions...

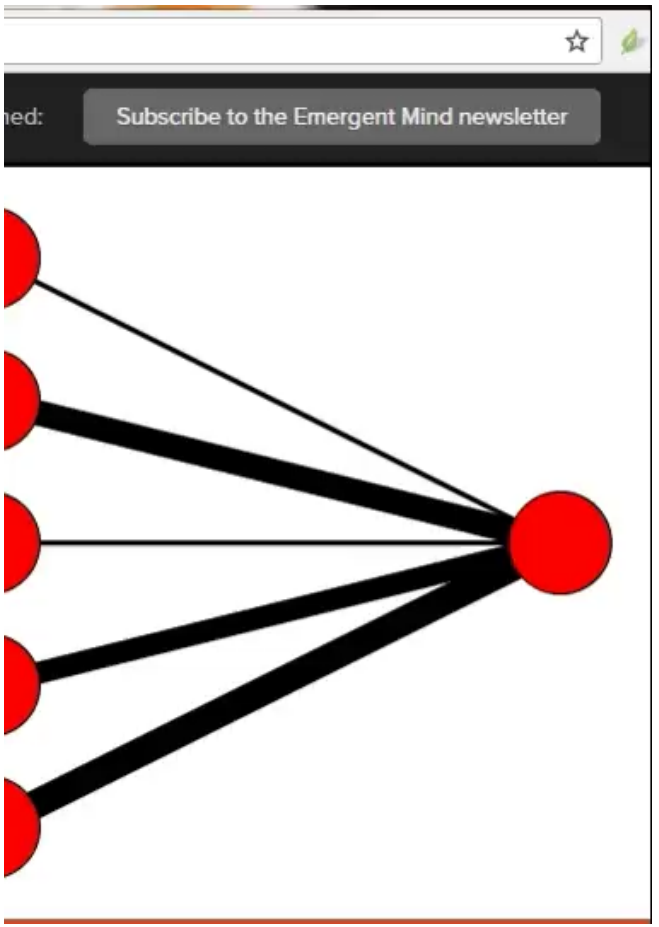
A simpler example - a red or blue classifier can trained, by feeding it a large set of (x,y) values and corresponding blueness values - the learned weights in this case are the coefficients a and b, in the line equation ax+by=c [equivalently, m and c, in y=mx+c]:



Here is a simple network to learn XOR(A,B) - here all the 6 weights (1,1,1,1,-1,1) are learned:



The following clip shows how a different NN (with one middle ('hidden') layer with 5 neurons) learns XOR - as the 5 neurons' weights (not pictured) are repeatedly modified, the 4 inputs ((0,0), (0,1), (1,0), (1,1)) progressively lead to the corresponding expected XOR values of 0,1,1,0 [in other words, the NN learns to predict XOR-like outputs when given binary inputs, just by being provided the inputs as well as expected outputs]:



0:00 / 0:59

This page has clear, detailed steps on weights updating.

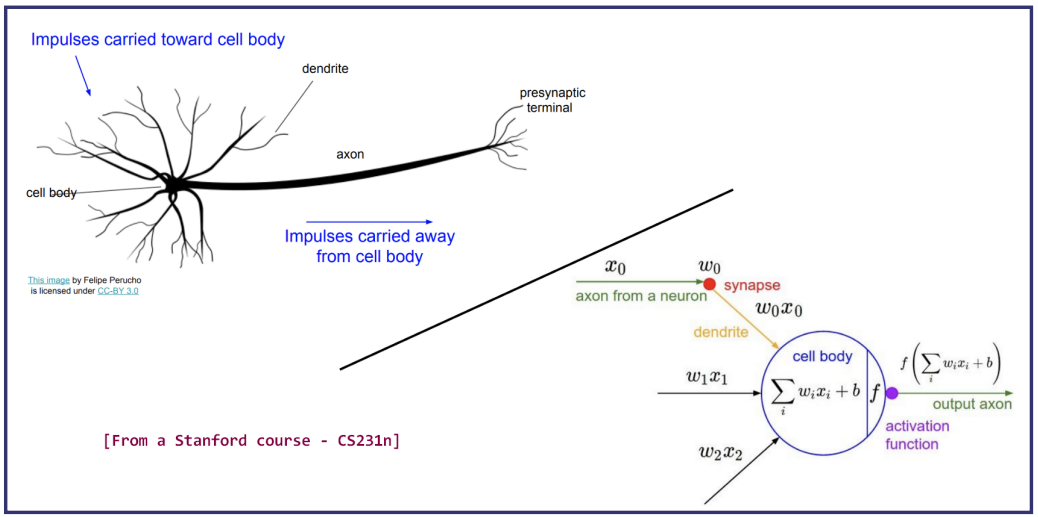
In the above examples, there was a single neuron at the output layer, with a single 0 to 1 probability value as its output; if we had multiple neurons (one for each class we want to identify), we'd like their probabilities to sum up to 1.0 - we'd then use a 'Softmax' classifier [a generalization of the sigmoid classifier shown above]. A Softmax classifier takes an array of 'k' real-valued inputs, and returns an array of 'k' 0..1 outputs that sum up to 1.

NN-based learning has started to REVOLUTIONIZE AI, thanks to three advances:

- Big Data (BILLIONS of images, tens of thousands of hours of video/audio, terabytes of text, billions of tweets..), to use for training: more training predictably leads to better learning
- better algorithms - fruits of decades' worth of academic research in ML; more recently, 'industry' (Google, Facebook, Microsoft, IBM) seems to be taking the lead
- faster cloud computing platforms and libraries

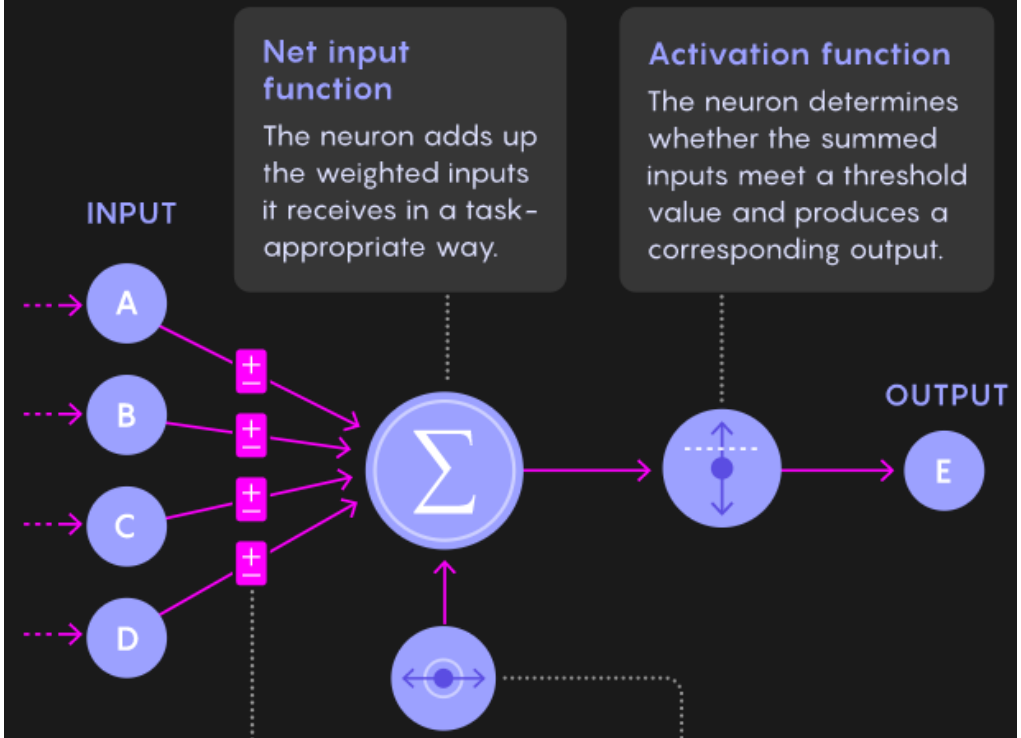
Here is a (Jupyter) notebook with an NN implementation, if you want to play with it [you can simply look at the rendered/static version on GitHub, or interact with it].

'Summary':



Simulating a Neuron

The interconnected devices in artificial neural networks conceptually resemble living neurons: Inputs from their "synapses" are weighted, tallied and translated into an output value.



And, REMEMBER:

Imagine God's voice, BOOMING DOWN this answer:
THE SIGMOID IS THE *LINCHPIN* THAT HOLDS THE TRILLION DOLLAR AI ECONOMY TOGETHER!!!!!!!!!!
I cannot say this any louder, climbing on any taller mountain, lol.

IF we omit the sigmoid, what we'll have is a GIANT **LINEAR** equation (agree?) THAT WILL NOT CONVERGE, ie WON'T LEARN, even after trillions of backprop iterations!!! It's THAT important - **NO SIGMOID, NO ML!!!!!!!!!! Period.**

Again: if you remove the sigmoid, the network cannot learn the patterns in input data.

'AI winter' [more accurately, 'NN winter']

Throughout the late 80s, all of 90s, and early 2000s, NN research had come to a standstill, instead, attention was on other approaches (such as Cyc).

In the 2000s leading up to now, these things came to be: SDCs, GPUs, cloud computing, Siri/Alexa... so AI, specifically NN, specifically DL [including CNNs] started to take off.

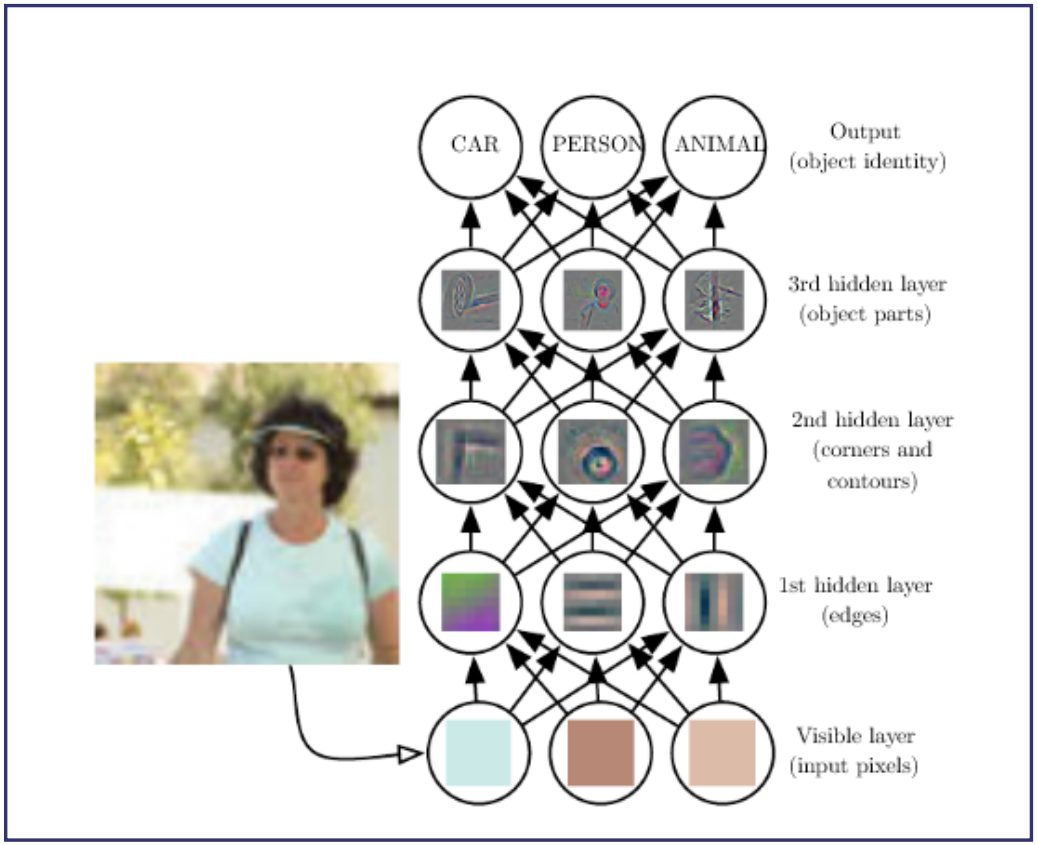
What is old is new again :)

Deep learning (NN++)

Deep Learning is starting to yield spectacular results, to what were once considered intractable problems..

Why now? Massive amounts of learnable data, massive storage, massive computing power, advances in ML.. Here is NVIDIA's response (to 'why now')..

In Deep Learning, we have large numbers (even 1000!) of hidden layers, each of which learns/processes a single feature. Eg. here is a (non-so-deep) NN:



"Deep learning is currently one of the best providers of solutions regarding problems in image recognition, speech recognition, object recognition, and natural language with its increasing number of libraries that are available in Python. The aim of deep learning is to develop deep neural networks by increasing and improving the number of training layers for each network, so that a machine learns more about the data until it's as accurate as possible. Developers can avail the techniques provided by deep learning to accomplish complex machine learning tasks, and train AI networks to develop deep levels of perceptual recognition."

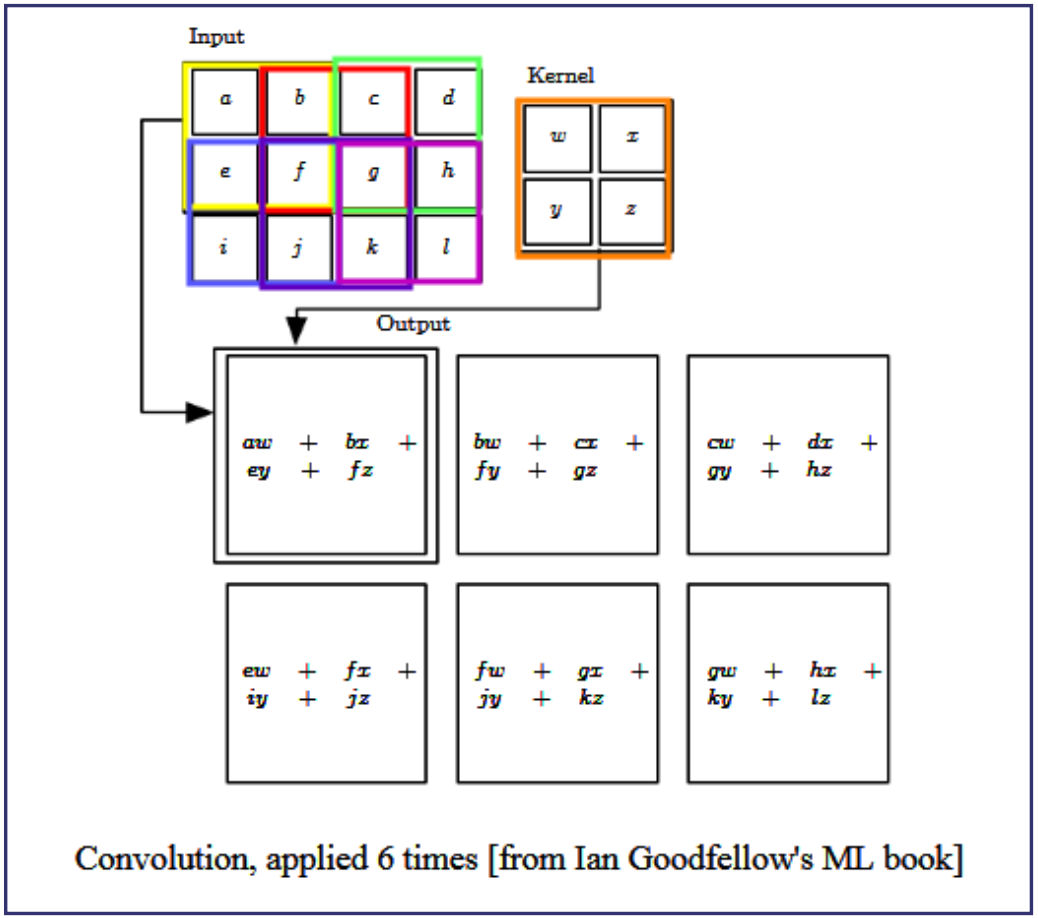
Q: so what makes it 'deep'? A: the number of intermediate layers of neurons.

Deep learning is a "game changer"..

CNN [Convolutional Neural Network]

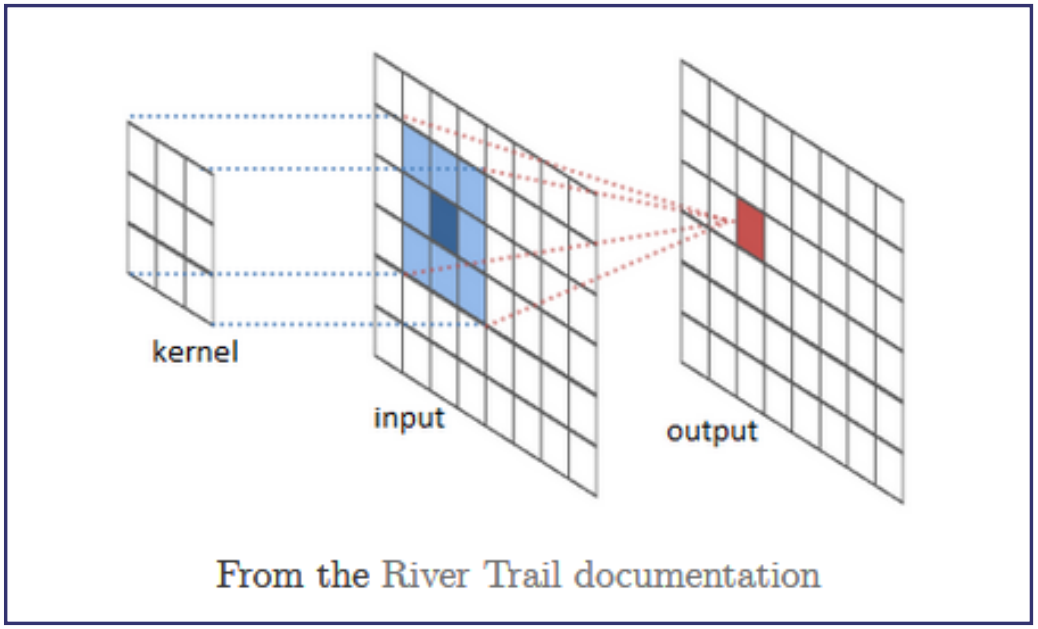
In signal processing, a convolution is a blending (or integrating) operation between two functions (or signals or numerical arrays) - one function is convolved (pointwise-multiplied) with another, and the results summed.

Here is an example of convolution - the 'Input' function [with discrete array-like values] is convolved with a 'Kernel' function [also with a discrete set of values] to produce a result; here this is done six times:



Convolution, applied 6 times [from Ian Goodfellow's ML book]

Convolution is used heavily in creating image-processing filters for blurring, sharpening, edge-detection, etc. The to-be-processed image represents the convolved function, and a 'sliding' "mask" (grid of weights), the convolving function (aka convolution kernel):



Here is [the result of] a blurring operation:

0	0	0	0	0
0	1/9	1/9	1/9	0
0	1/9	1/9	1/9	0
0	1/9	1/9	1/9	0
0	0	0	0	0

Derived from the Gimp documentation

Here you can fill in your own weights for a kernel, and examine the resulting convolution.

So - how does this relate to neural nets? In other words, what are CNNs?

CNNs are biologically inspired - (convo) filters are used across a whole layer, to enable the entire layer as a whole to detect a feature. Detection regions are overlapped, like with cells in the eye.

Here is an*excellent* talk on CNNs/DNNs, by Facebook's LeCun.

Here is a *great* page, with plenty of posts on NNs - with lots of explanatory diagrams.

In essence, a CNN is where we represent a neuron's weights as a matrix (kernel), and slide it (IP-style) over an input (an image, a piece of speech, text, etc.) to produce a convolved

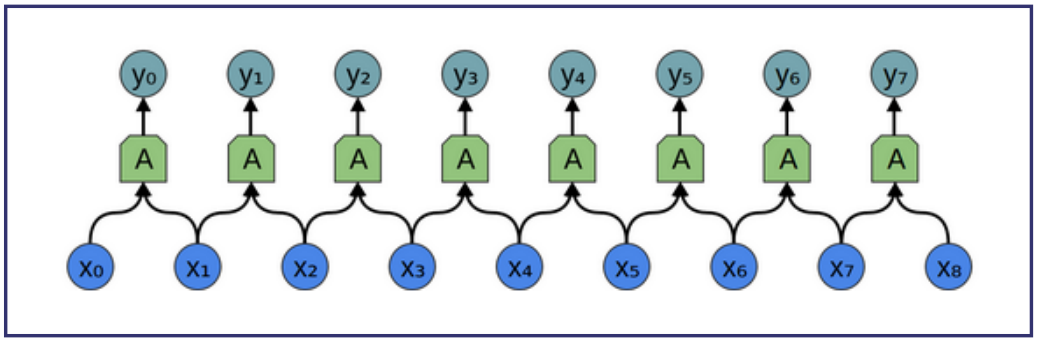
output.

In what sense is a neuron's weights, a convolution kernel?

We know that for an individual neuron, its output y is expressed by

$y=x0\cdot w0+w1\cdot x1+....+wn\cdot xn+b$, where the wis represent the neuron's weights, and the xis, the incoming signals [b is the neuron's activation bias]. The multiplications and summations resemble a convolution! The incoming 'function' is [x0,x1,x2,....xn], and the neuron's kernel 'function', [w0,w1,w2,....wn].

Eg. if the kernel function is [0,0,0...w0,w1,0,0...] [where we only process our two nearest inputs], the equivalent network would look like so [fig from Chris Olah]:



The above could be considered one 'layer' of neurons, in a multi-layered network. The convolution (each neuron's application of w0 and w1 to its inputs) would produce the following:

$y0=x0\cdot w0+x1\cdot w1+b0$

$y1=x1\cdot w0+x2\cdot w1+b1$

$y2 = x2 \cdot w0 + x3 \cdot w1 + b2$

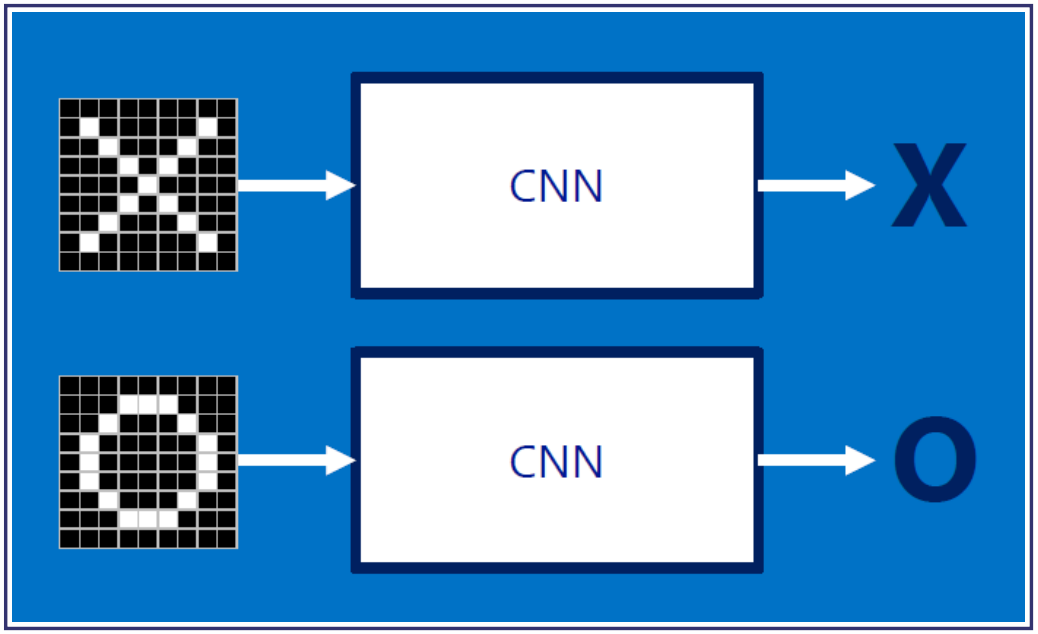
....

Pretty cool, right? Treating the neuron as a kernel function provides a convenient way to represent its weights as an array. For 2D inputs such as images, speech and text, the kernels would be 2D arrays that are coded to detect specific features (such as a vertical edge, color..).

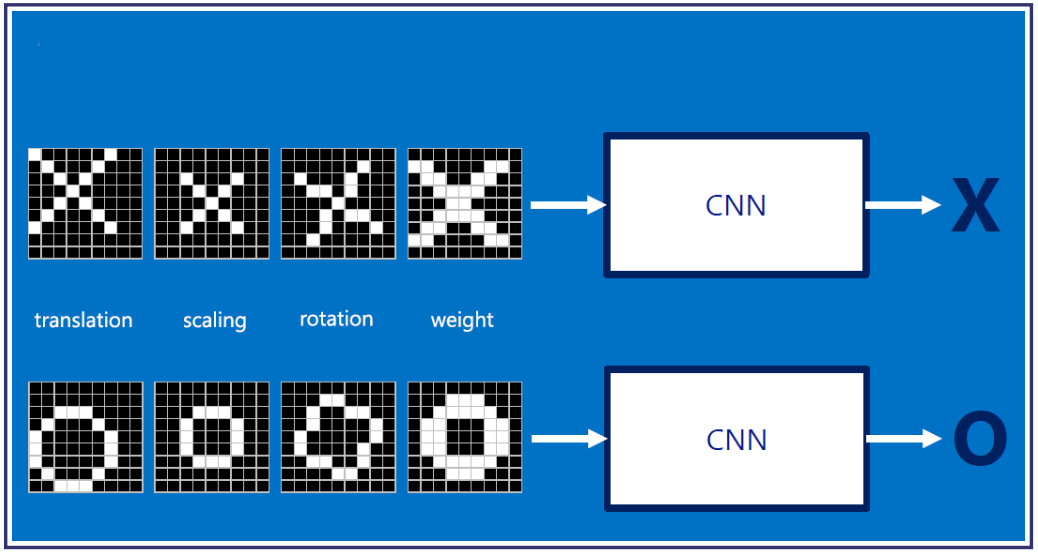
EACH NEURON IS CONVOLVED OVER THE ENTIRE INPUT (again, IP-style), AND AN OUTPUT IS GENERATED FROM ALL THE CONVOLUTIONS. The output gets 'normalized' (eg. clamped), and 'collapsed' (reduced in size, aka 'pooling'), and the process repeats down several layers of neurons: input -> convolve -> normalize -> reduce/pool -> convolve -> normalize -> reduce/pool -> ... -> output.

The following pics are from a talk by Brandon Rohrer (Microsoft). You DON'T need to know the details of the steps - just understand that PIXELs are input, classification is the output.

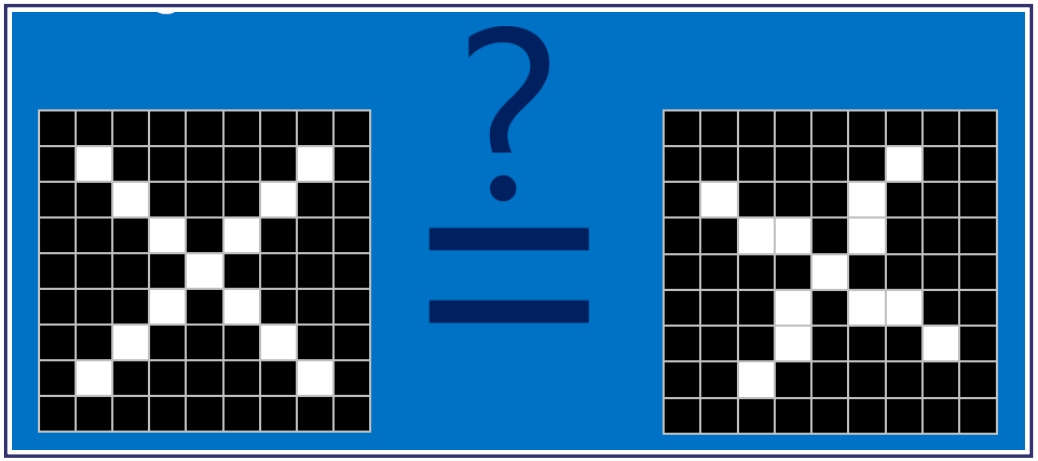
What we want:



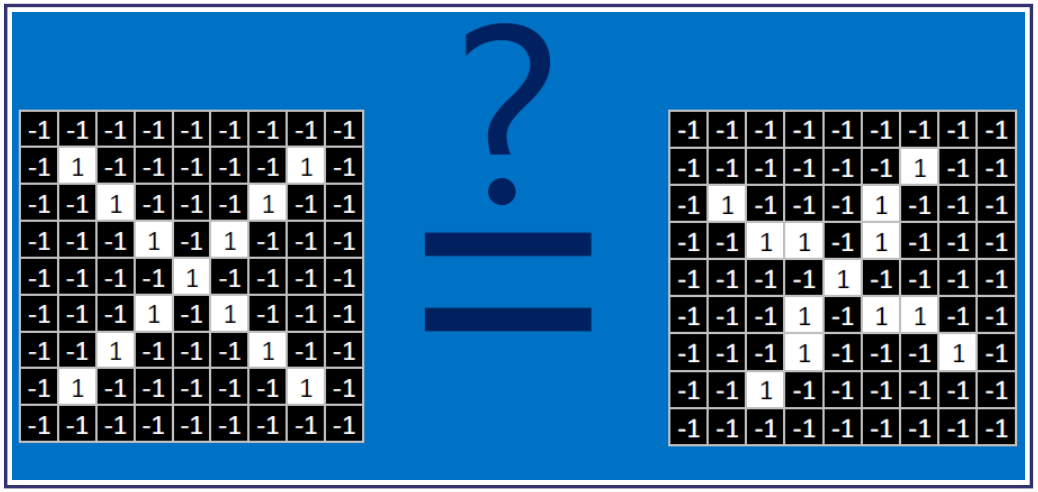
The input can be RST (rotation, scale, translation) of the original:

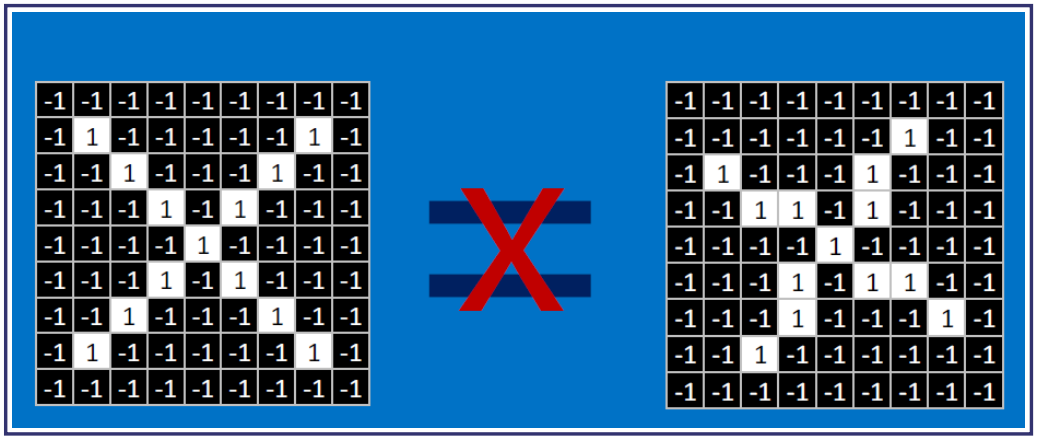


How can we compute similarity, but not LITERALLY (ie without pixel by pixel comparison)?

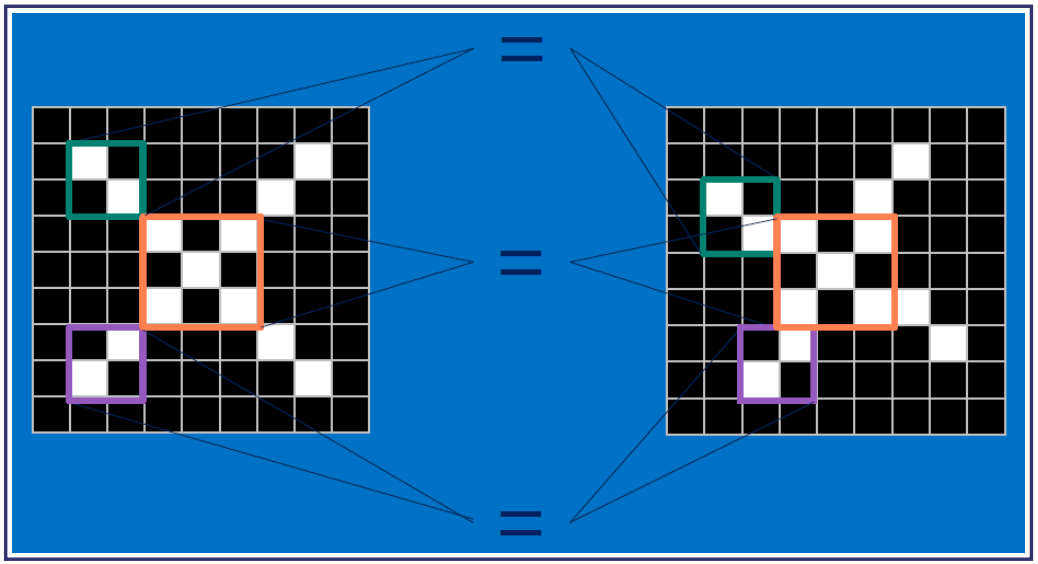


Useful pixels are 1, background pixels are -1:

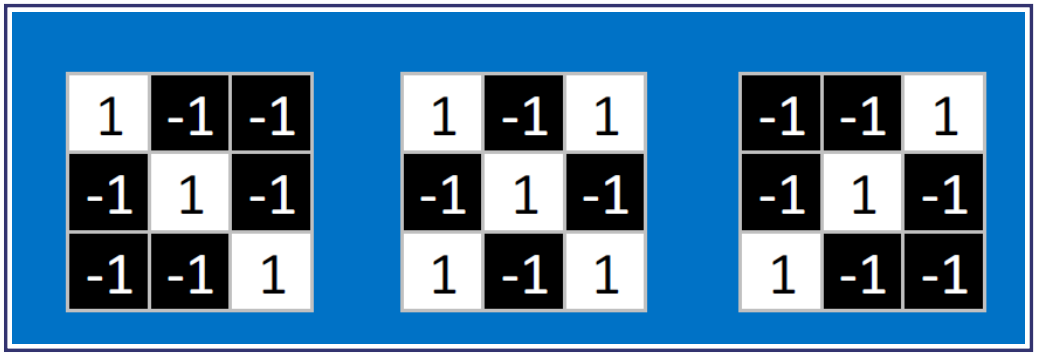


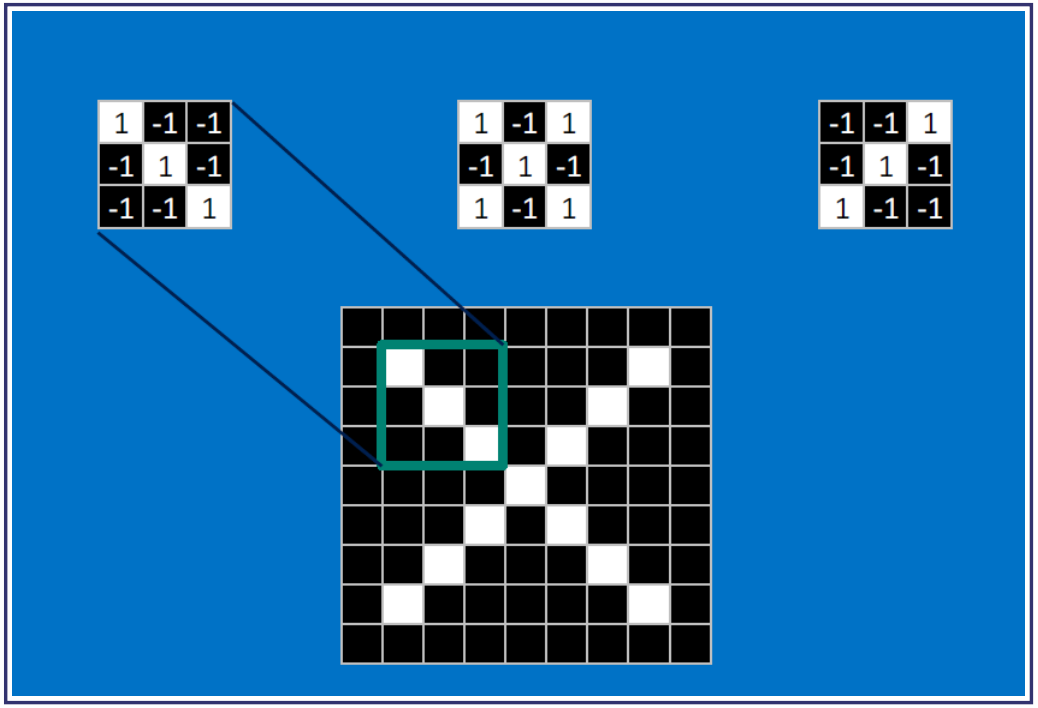


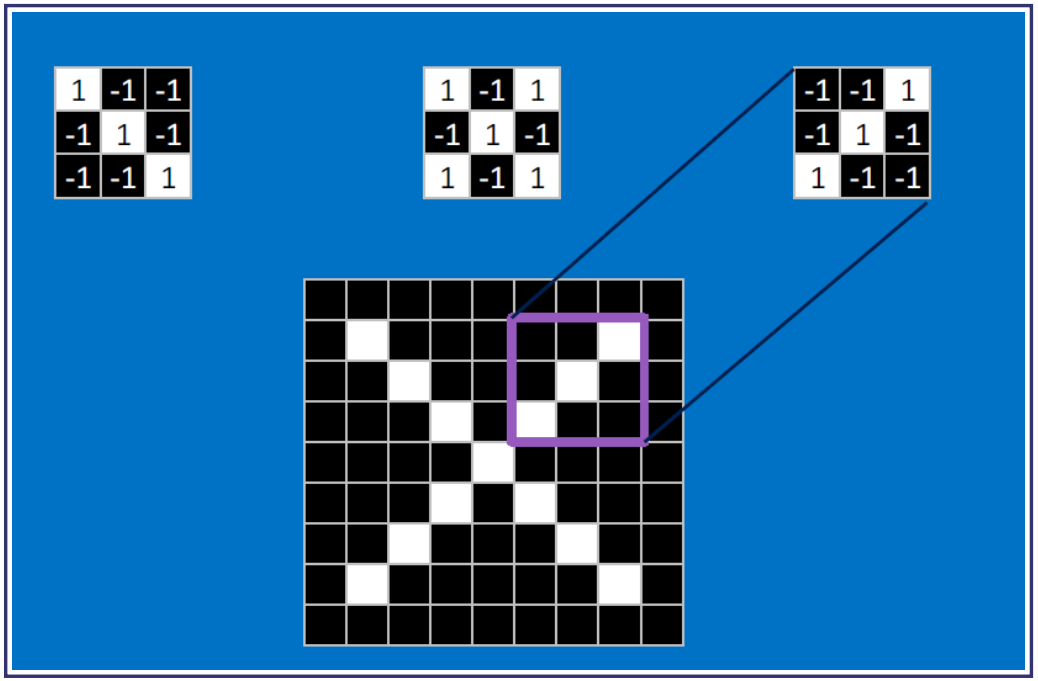
We match SUBREGIONS:

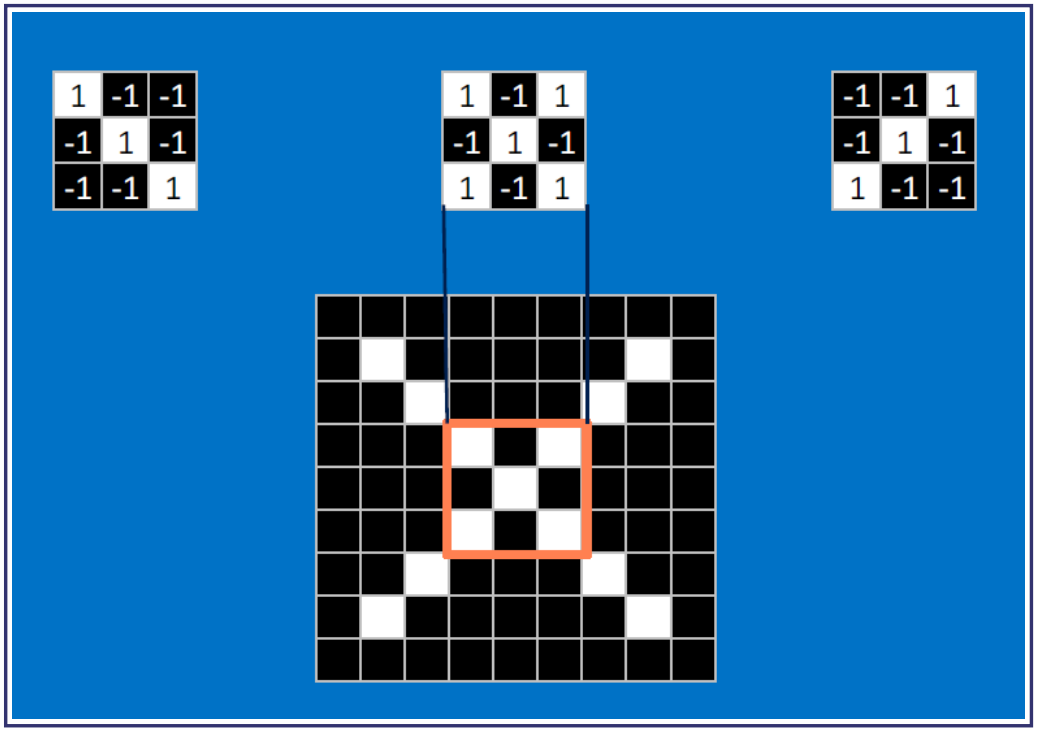


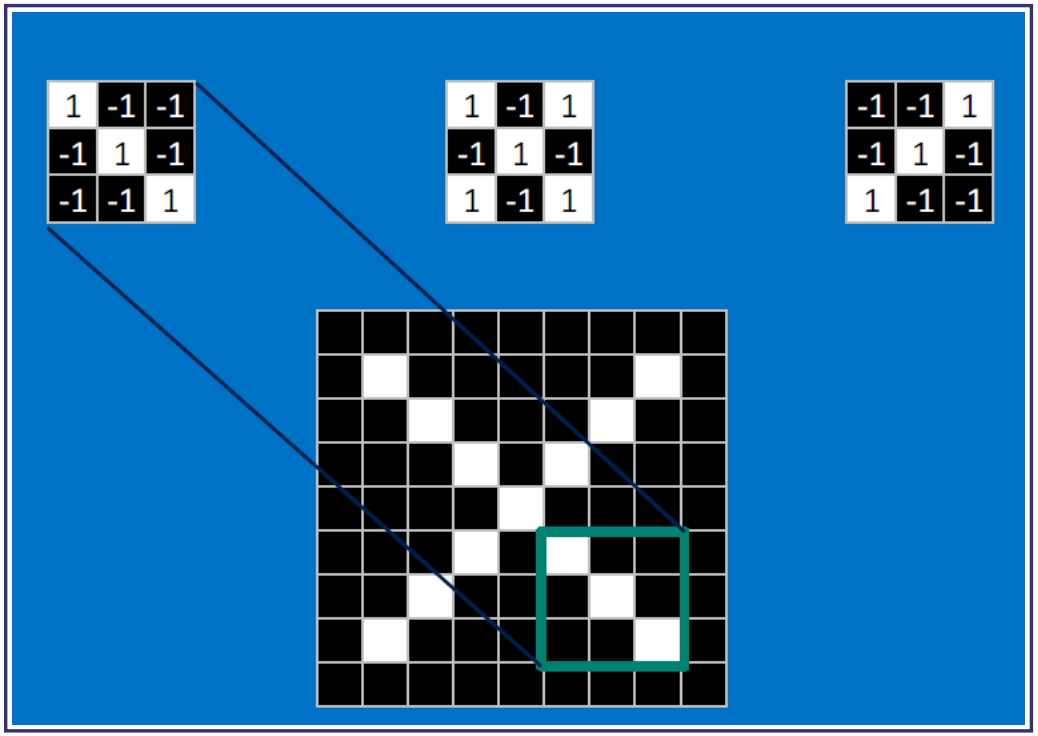
Convolutional neurons that check for these three features:

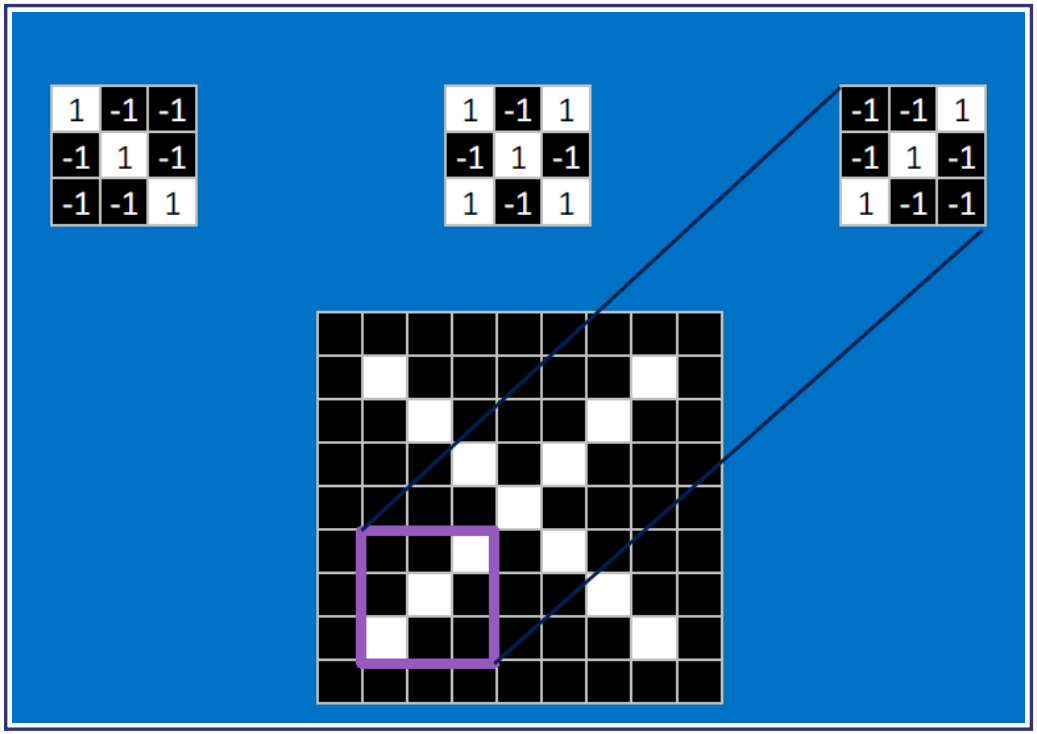

1 -1 -1
-1 1 -1
-1 -1 1
1 -1 1
-1 1 -1
1 -1 1
-1 -1 1
-1 1 -1
1 -1 -1


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

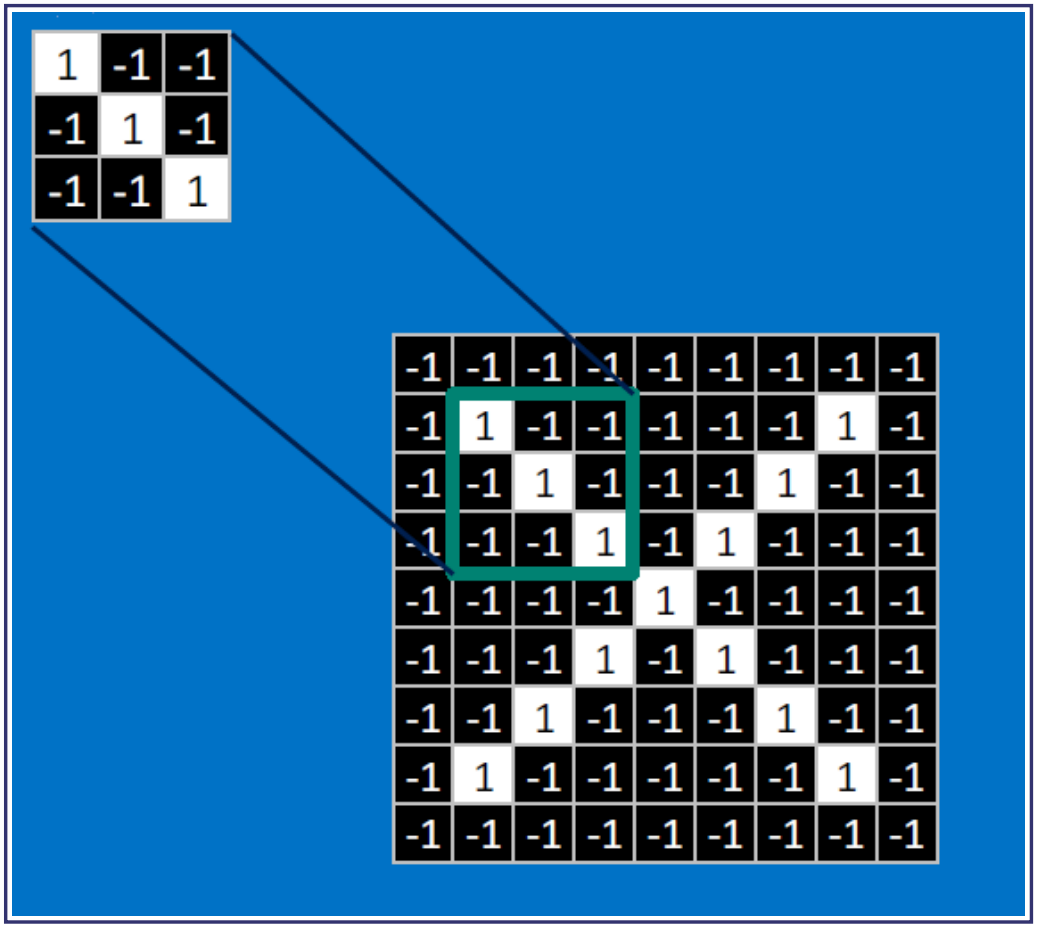

1 -1 -1
-1 1 -1
-1 -1 1
1 -1 1
-1 1 -1
1 -1 1
-1 -1 1
-1 1 -1
1 -1 -1


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


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



CONVOLVE, ie. do xi·wi, then average, output a value:


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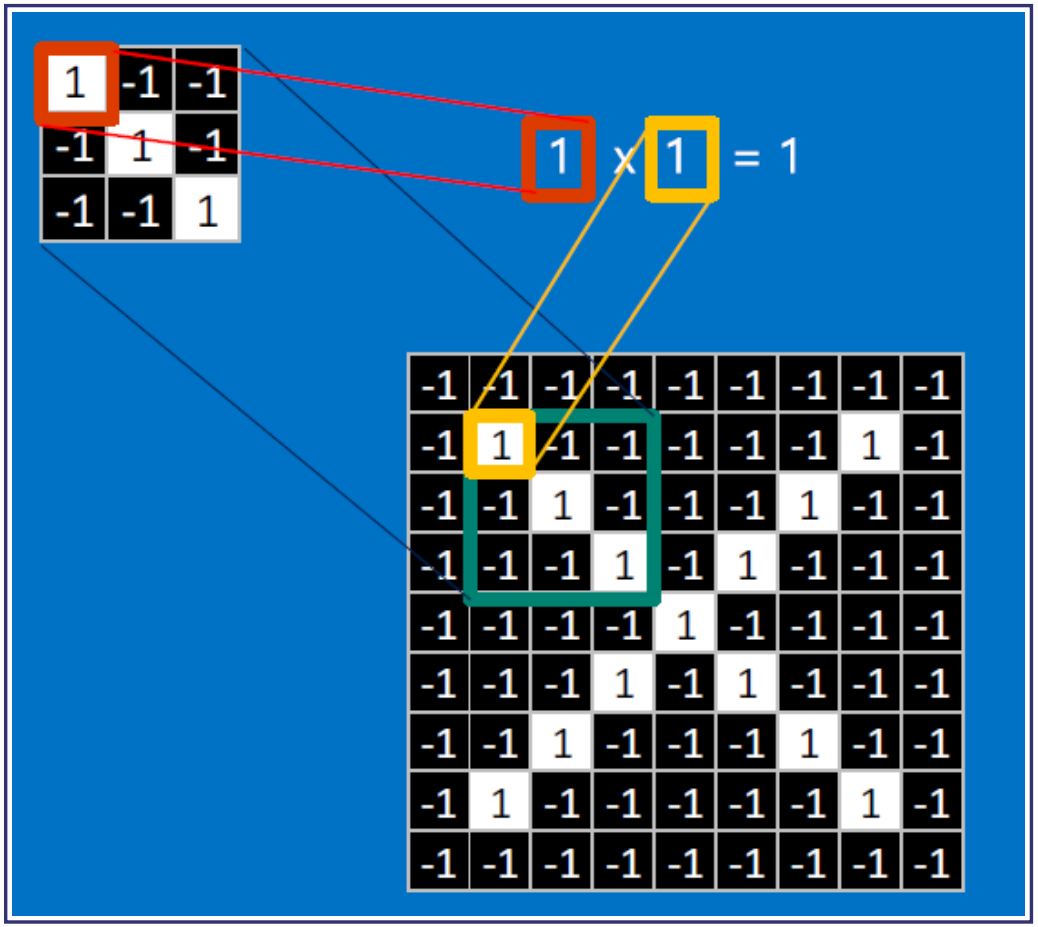
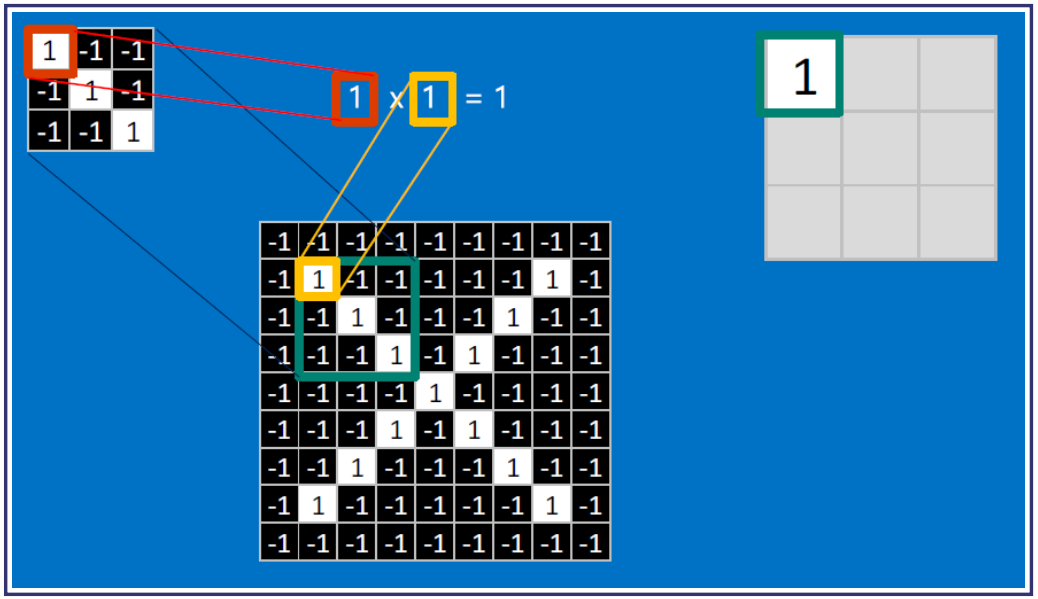
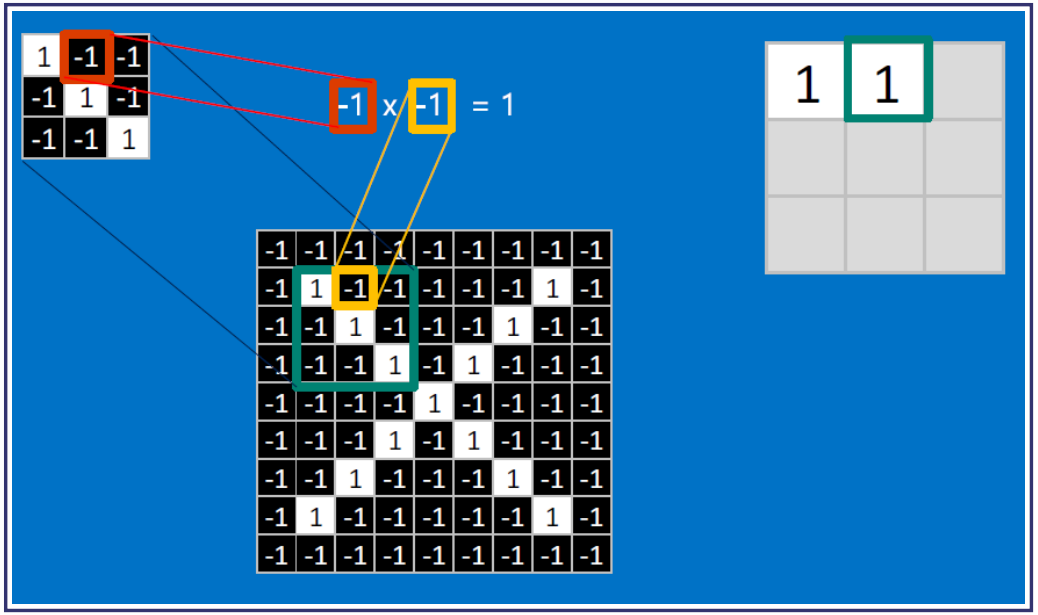
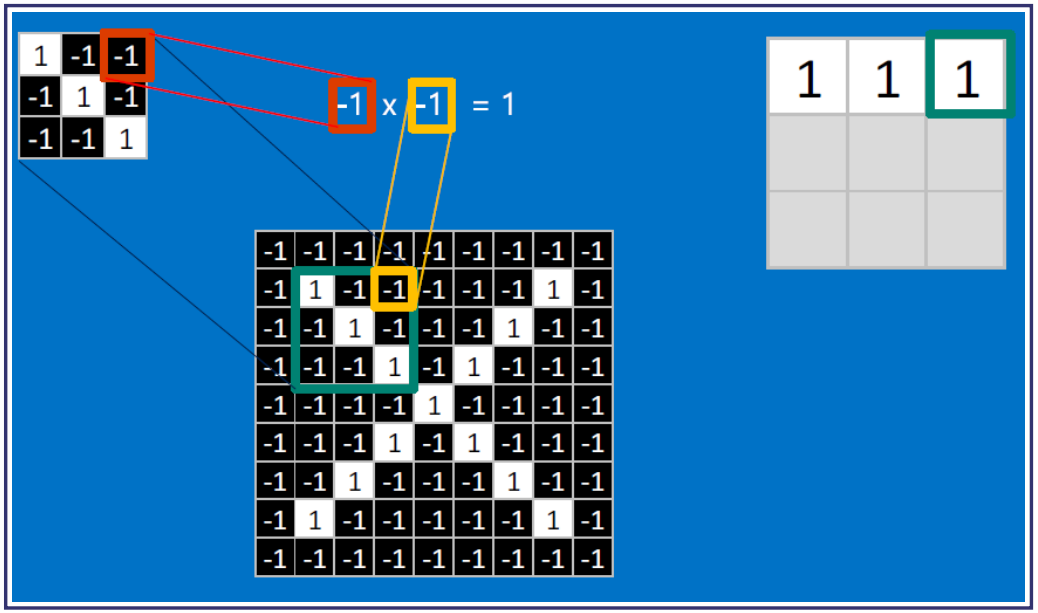
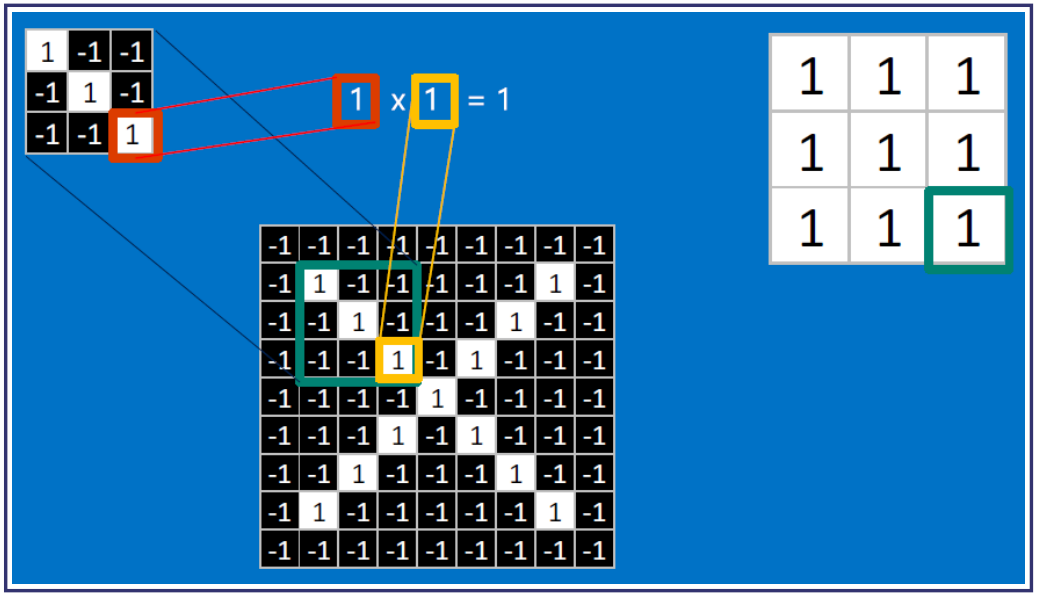
-1 1 -1 -1 -1 -1 -1 1 -1
-1 -1 -1 -1 -1 -1 -1 -1 -1

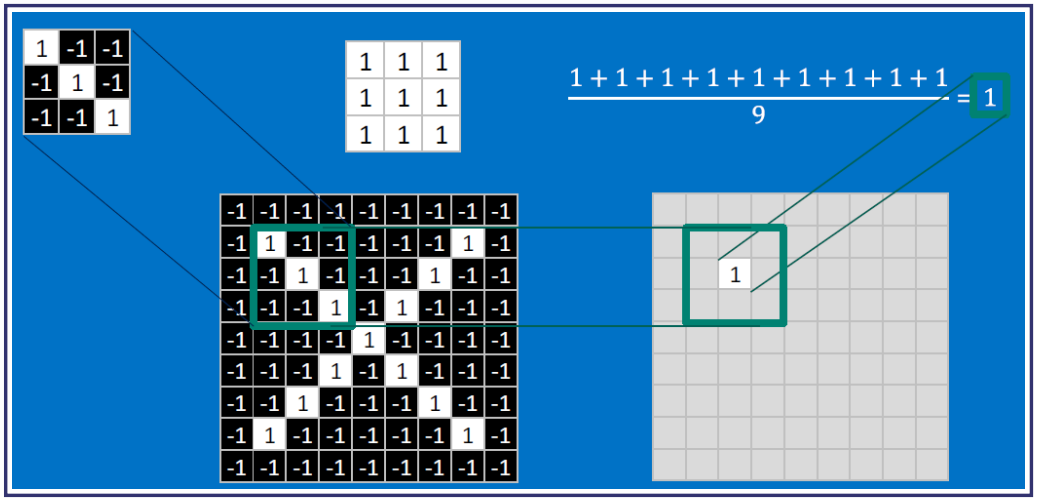

1 -1 -1
-1 1 -1
-1 -1 1
1 x 1 = 1
-1 -1 -1 -1 -1 -1 -1 -1 -1
-1 1 -1 -1 -1 -1 -1 1 -1
-1 -1 1 -1 -1 -1 1 -1 -1
-1 -1 -1 1 -1 1 -1 -1 -1
-1 -1 -1 -1 1 -1 -1 -1 -1
-1 -1 -1 1 -1 1 -1 -1 -1
-1 -1 1 -1 -1 -1 1 -1 -1
-1 1 -1 -1 -1 -1 -1 1 -1
-1 -1 -1 -1 -1 -1 -1 -1 -1


1 -1 -1
-1 1 -1
-1 -1 1
1 x 1 = 1
1

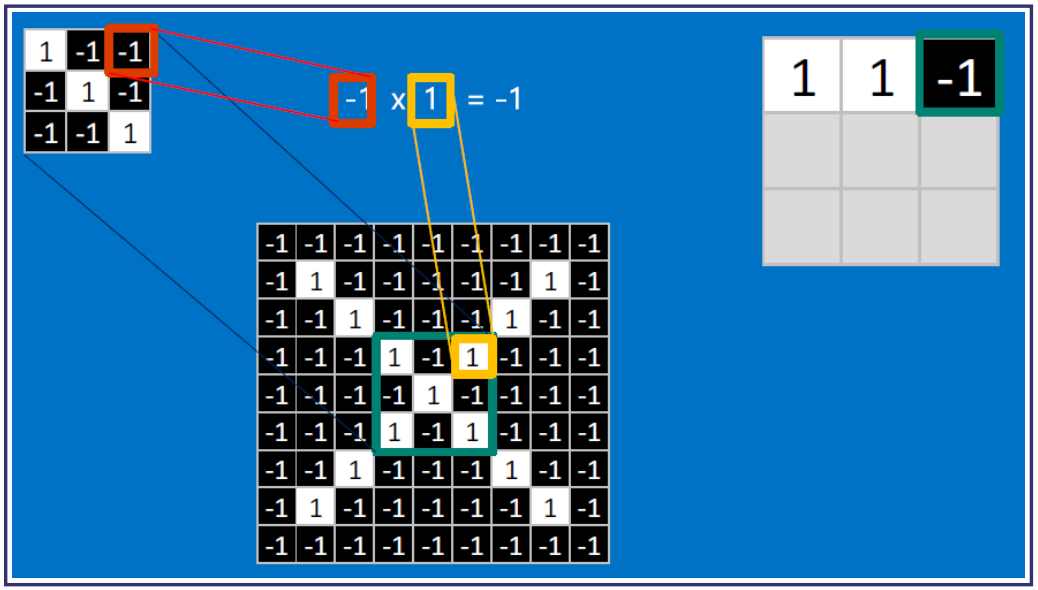

1 -1 -1
-1 1 -1
-1 -1 1
-1 x -1 = 1
1 1

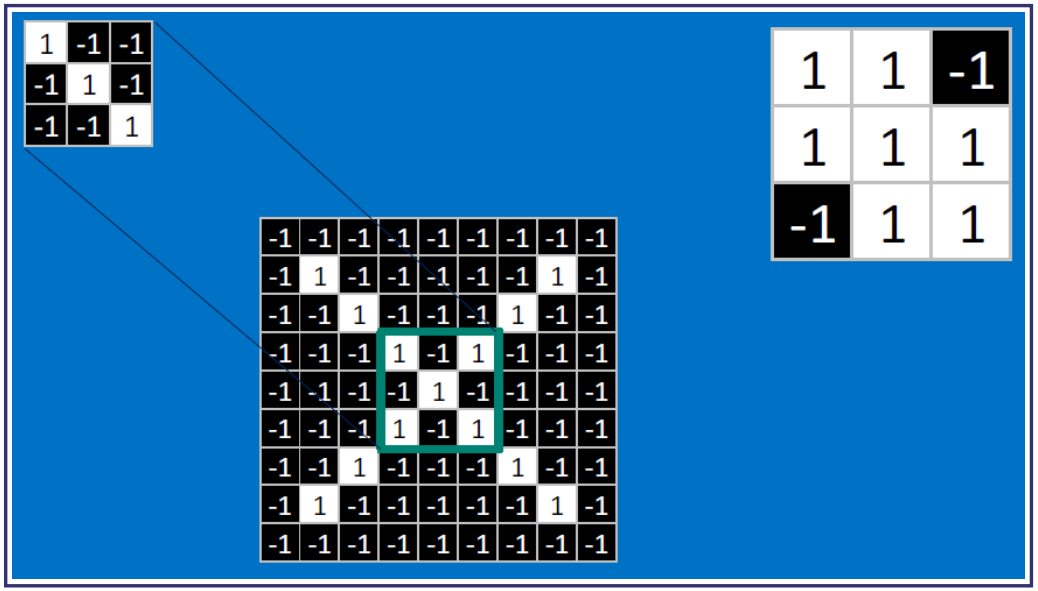

1 -1 -1
-1 1 -1
-1 -1 1
-1 x -1 = 1
1 1 1

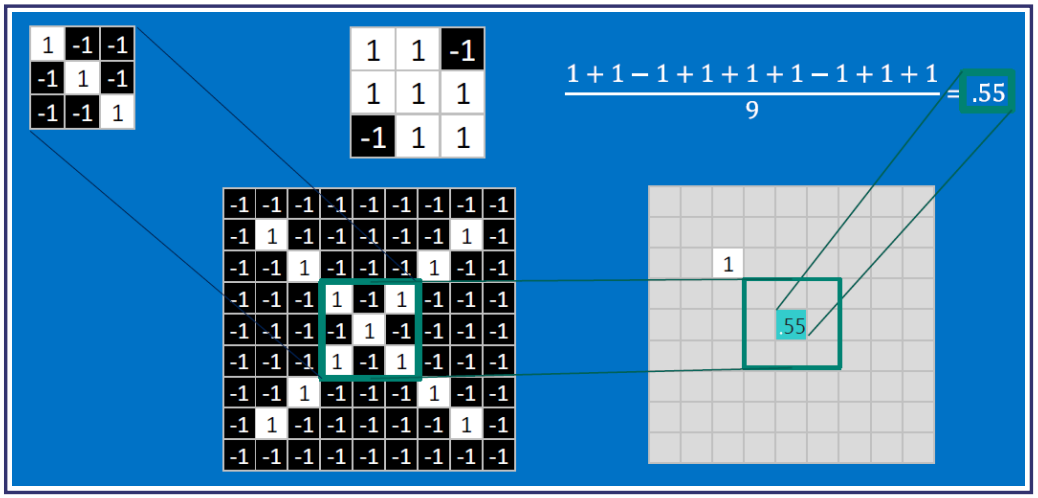

1 -1 -1
-1 1 -1
-1 -1 1
1 x 1 = 1
1 1 1
1 1 1
1 1 1



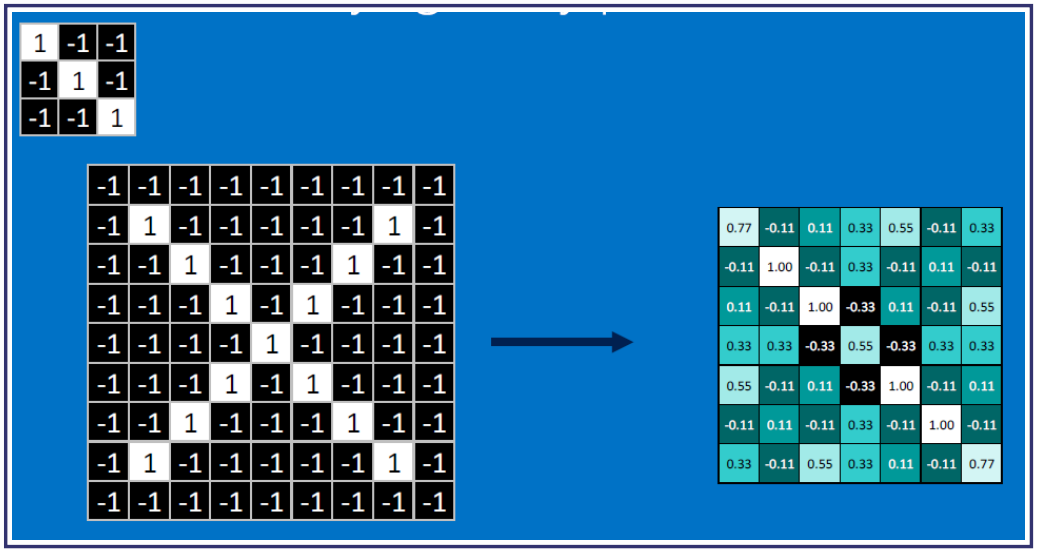
Need to center the kernel at EVERY pixel (except at the edges) and compute a value for that pixel!

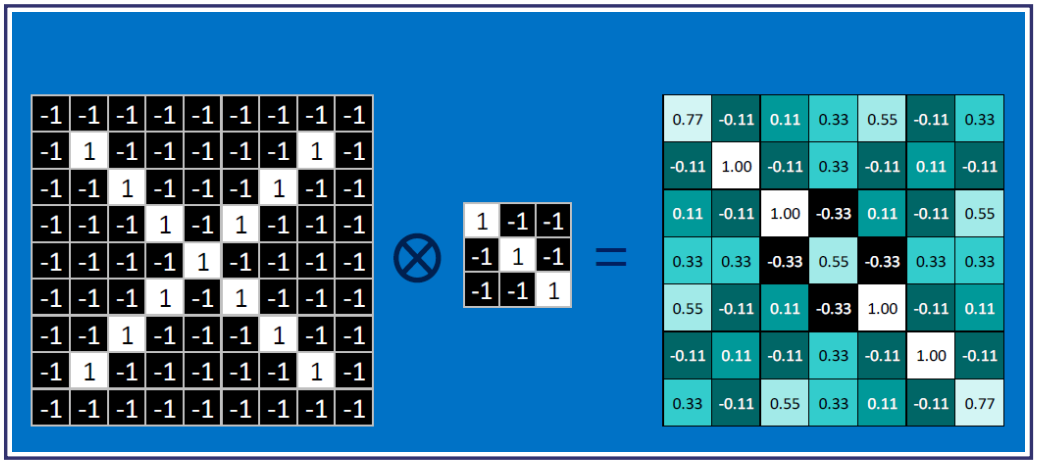




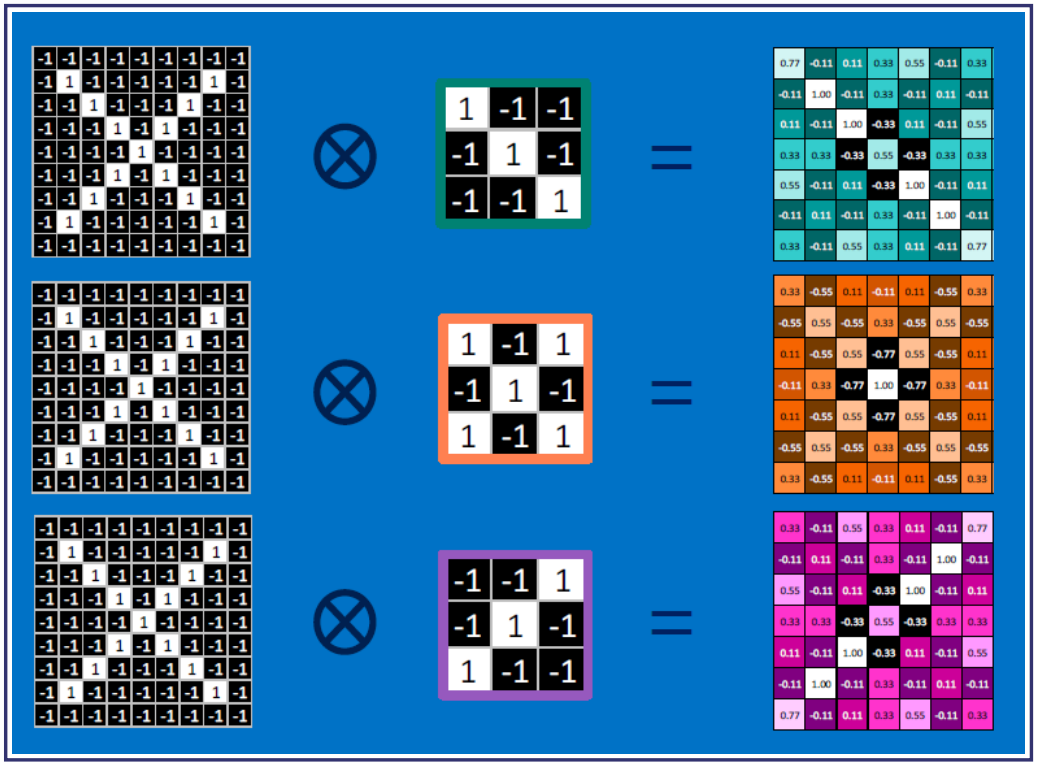


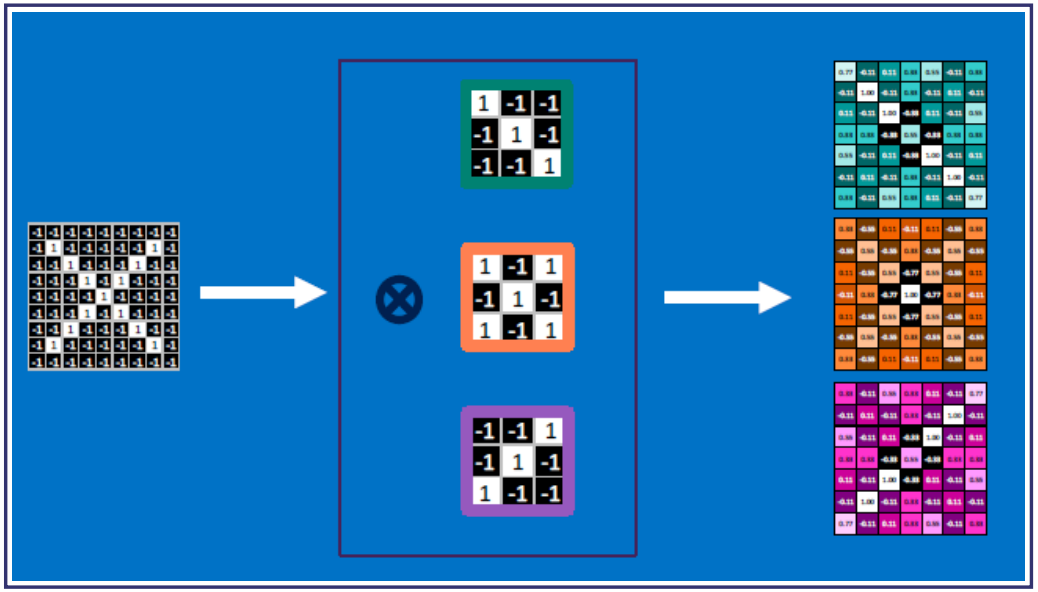
We end up with a 7x7 output grid, just for this (negative slope diagonal) feature:



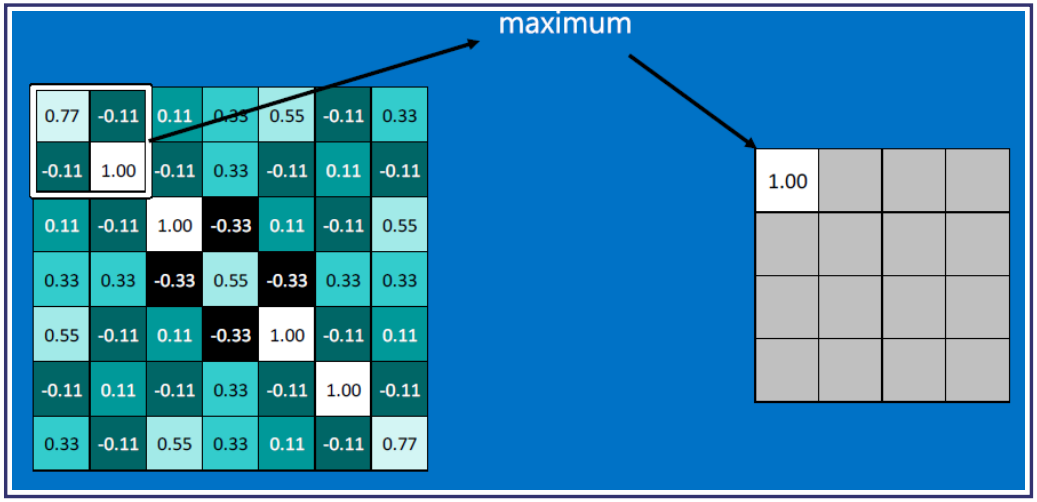


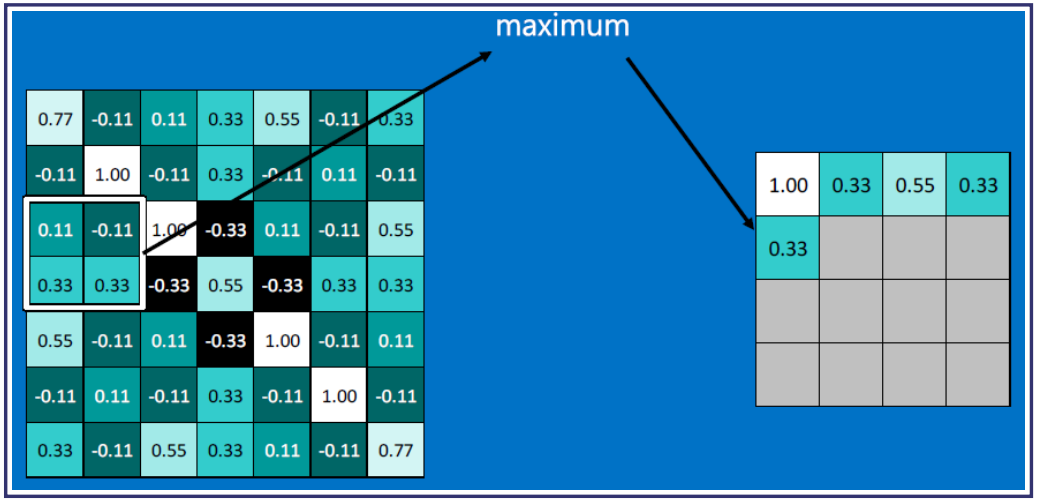
Each neuron (feature detector) produces an output - so a single input image produces a STACK of output images [three in our case, one from each feature detector]:

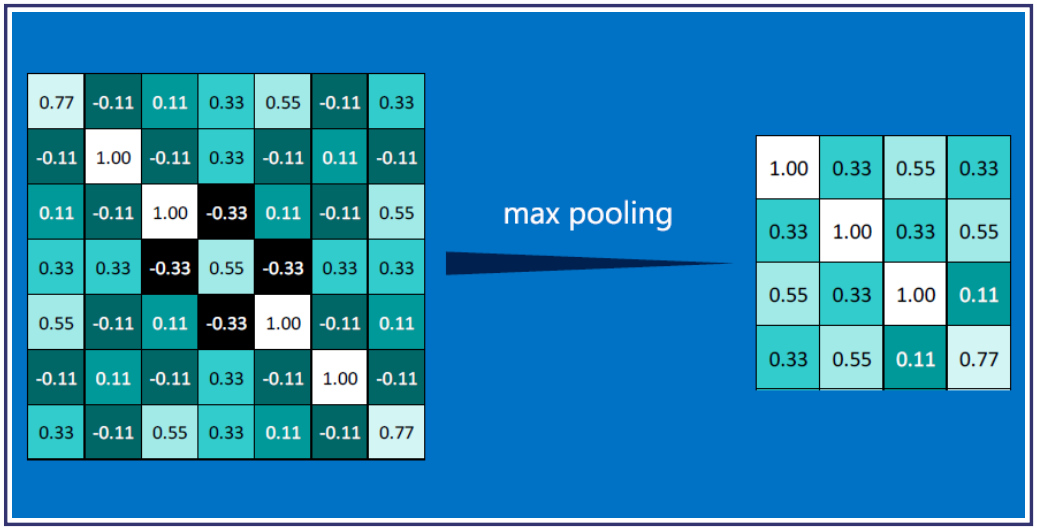




To collapse the outputs, we do 'max pooling' - replace an mxn (eg. 2x2) neighborhood of pixels with a single value, the max of all the m*n pixels.



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max pooling
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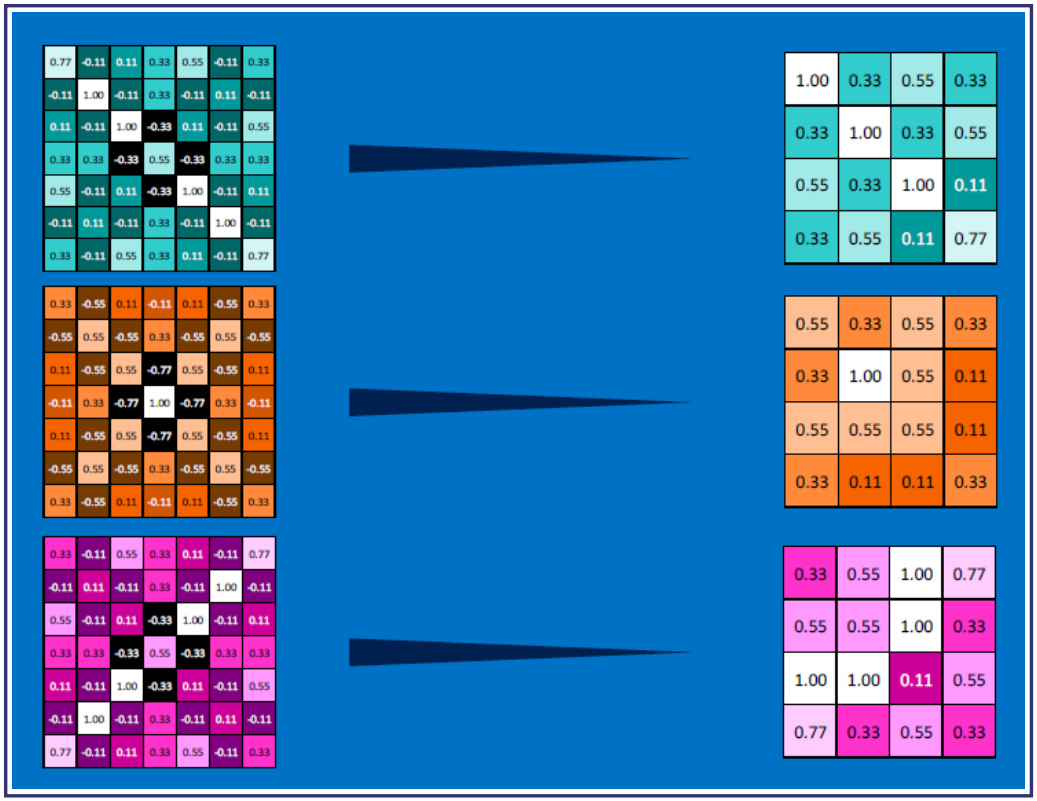
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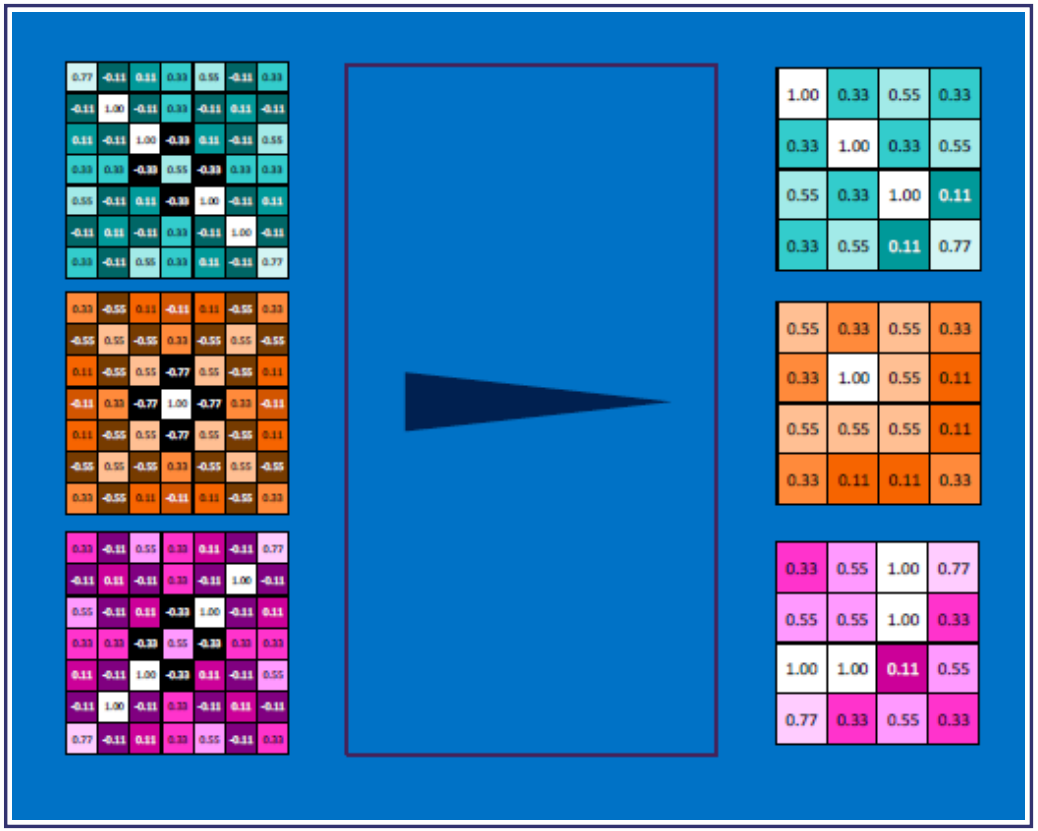
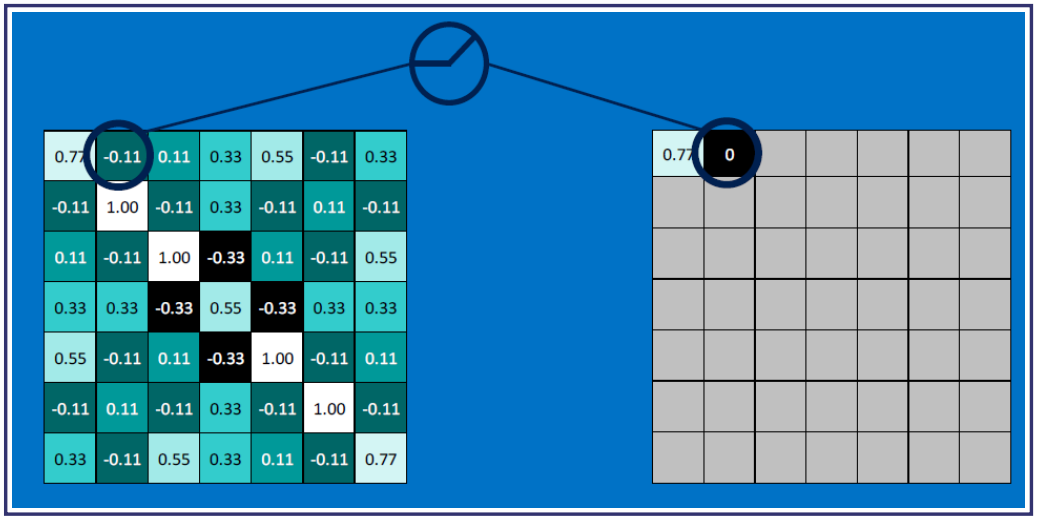


Next, create a ReLU - rectified linear unit - replace negative values with 0s: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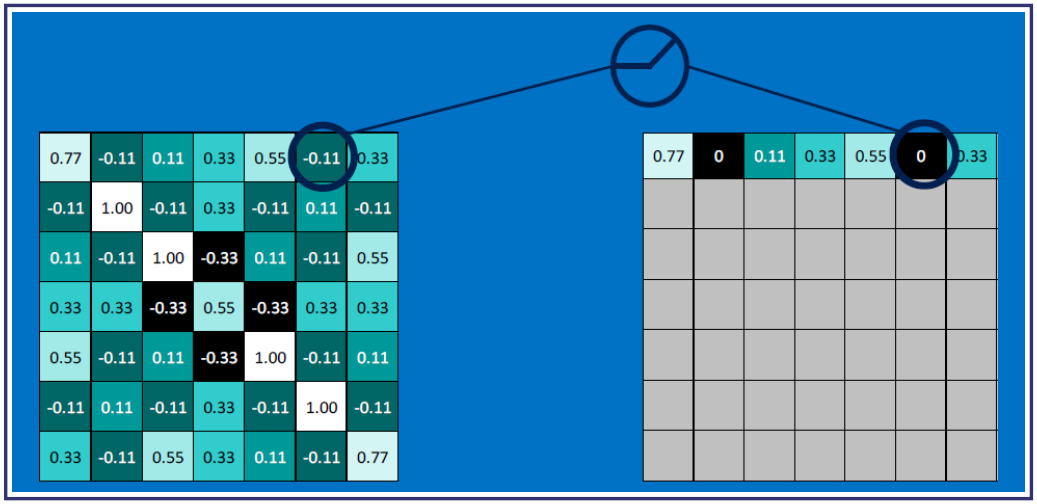
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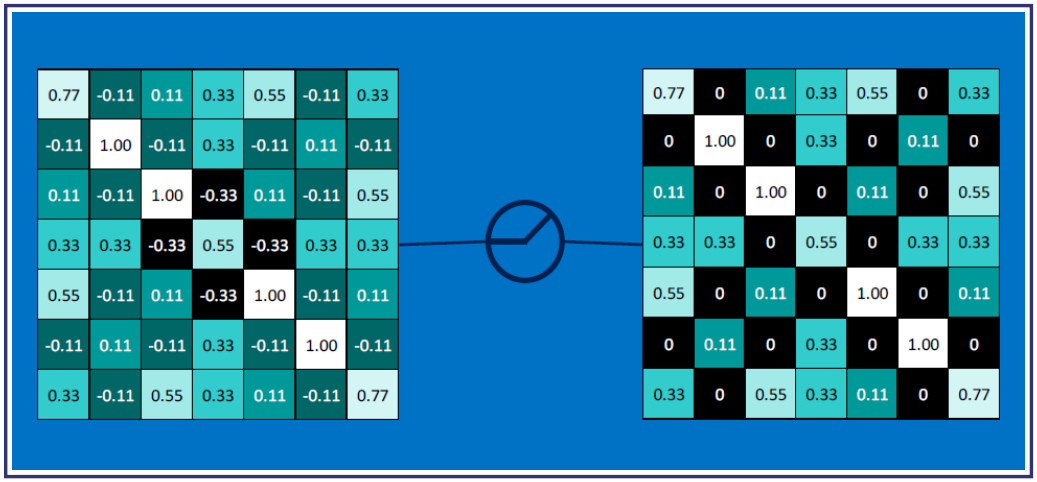
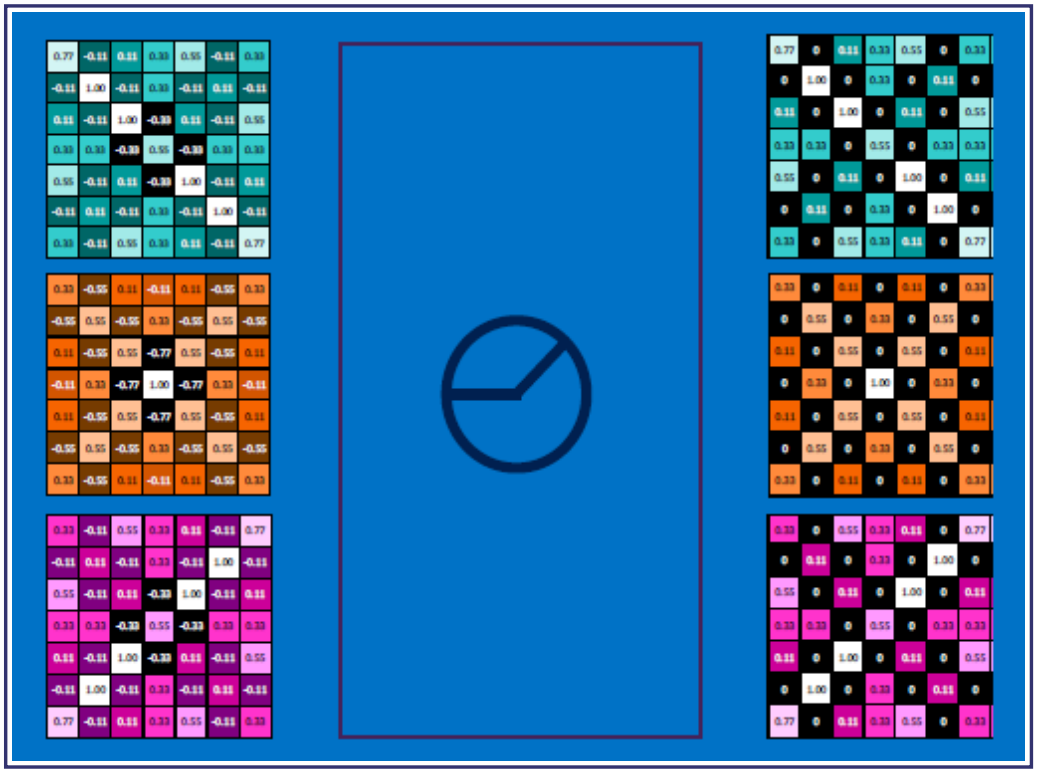
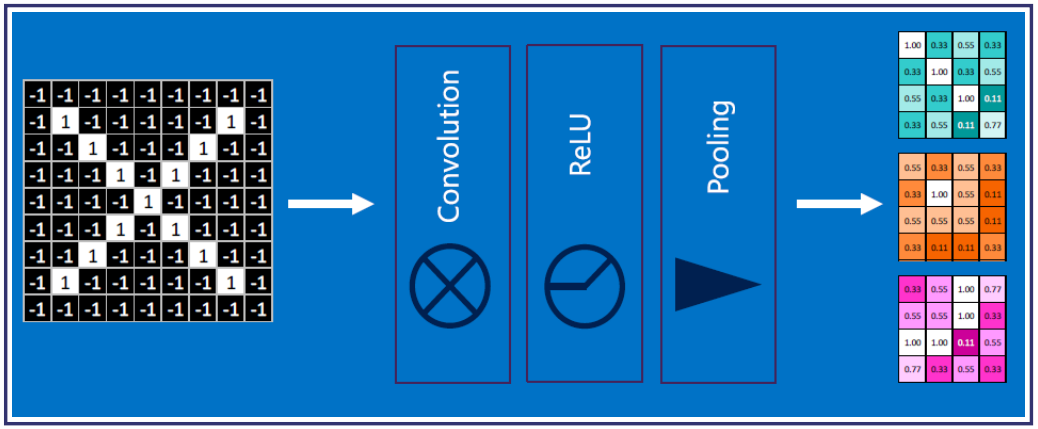
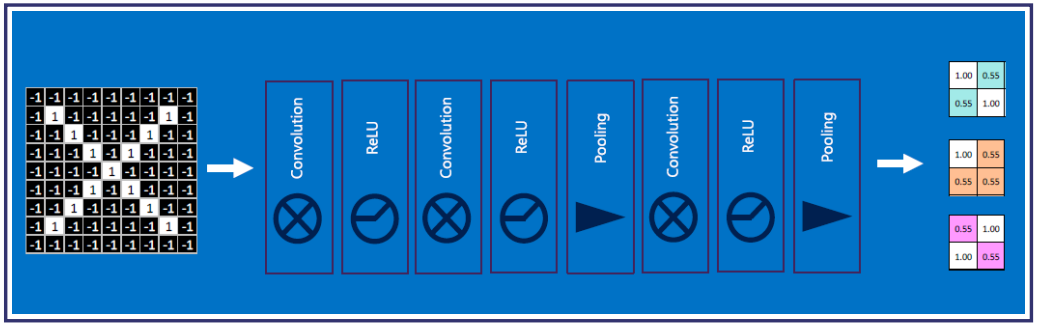




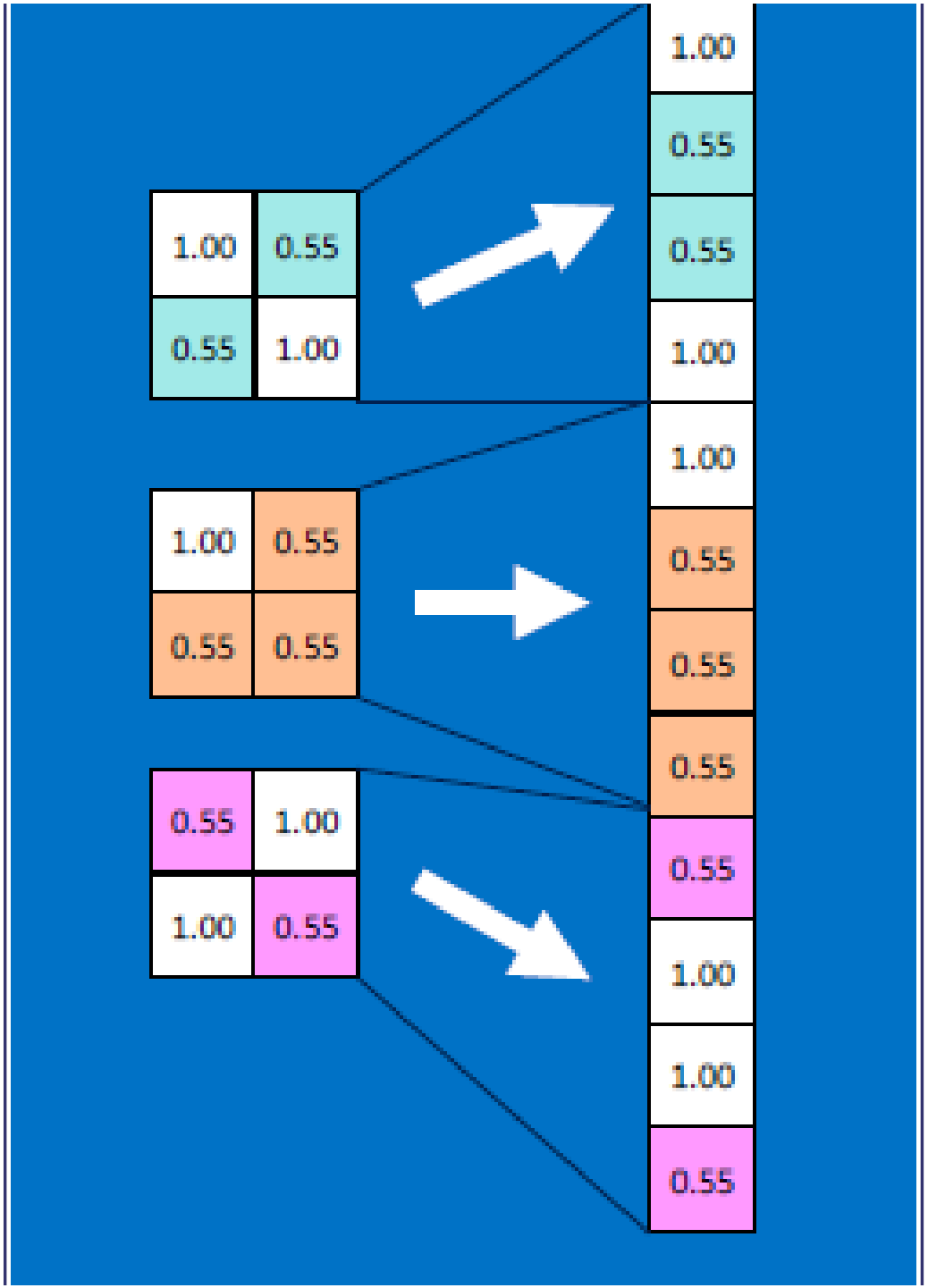
After a single stage of convolution, ReLU, pooling (or eqvt'ly, convolution, pooling, ReLU):



Usually there are multiple stages:



The resulting output values (12 in our case) are equivalent to VOTES: values at #0, #3, #4, #9, #10 contribute to voting for an 'X'; by repeated training with X-like images, which produce high-valued outputs for exactly those values at #0,#3,#4,#9,#10, the RECEIVER of all the 12 values, ie . the 'X' detector, learns to adjust its weights so that those inputs at #0,#3,#4,#9,#10 matter more (get assigned higher weight multipliers) compared to the other inputs such as #1,#2..: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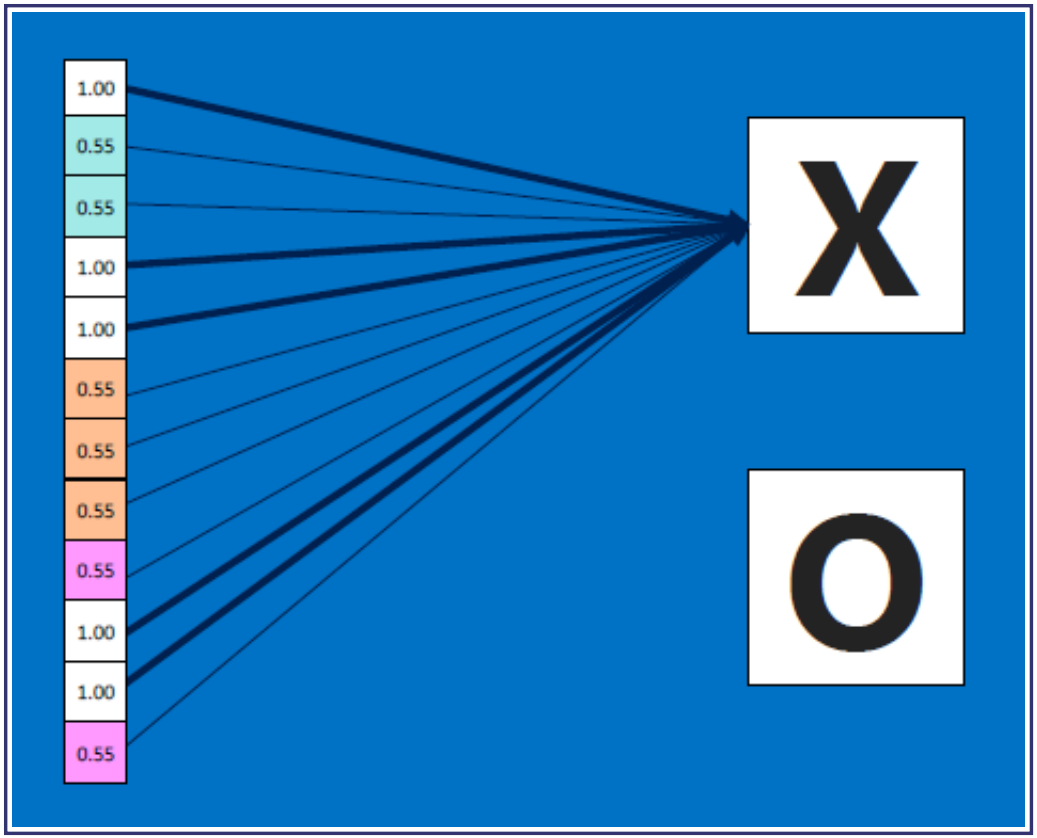
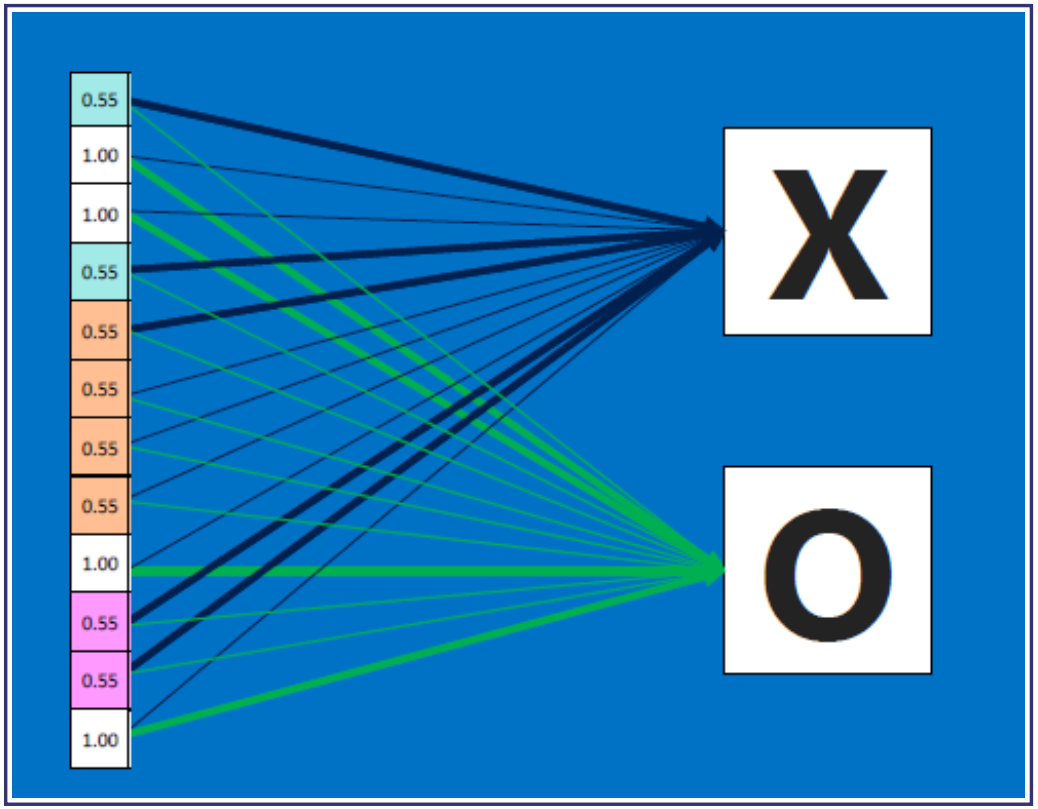
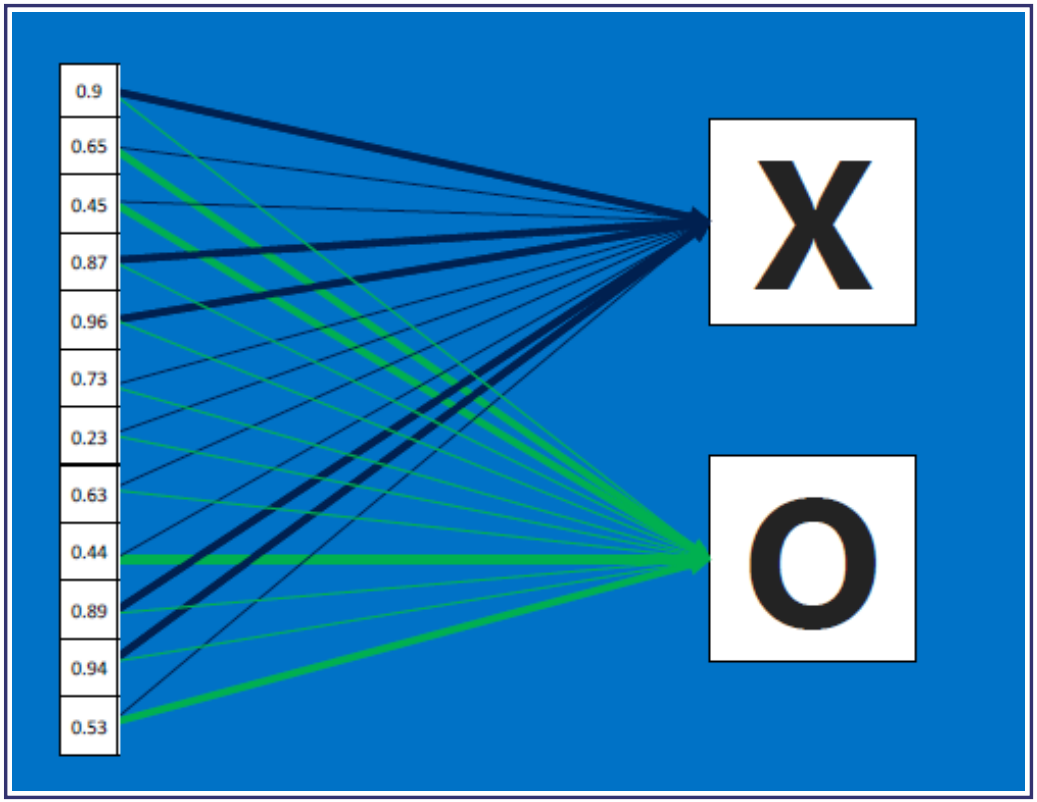


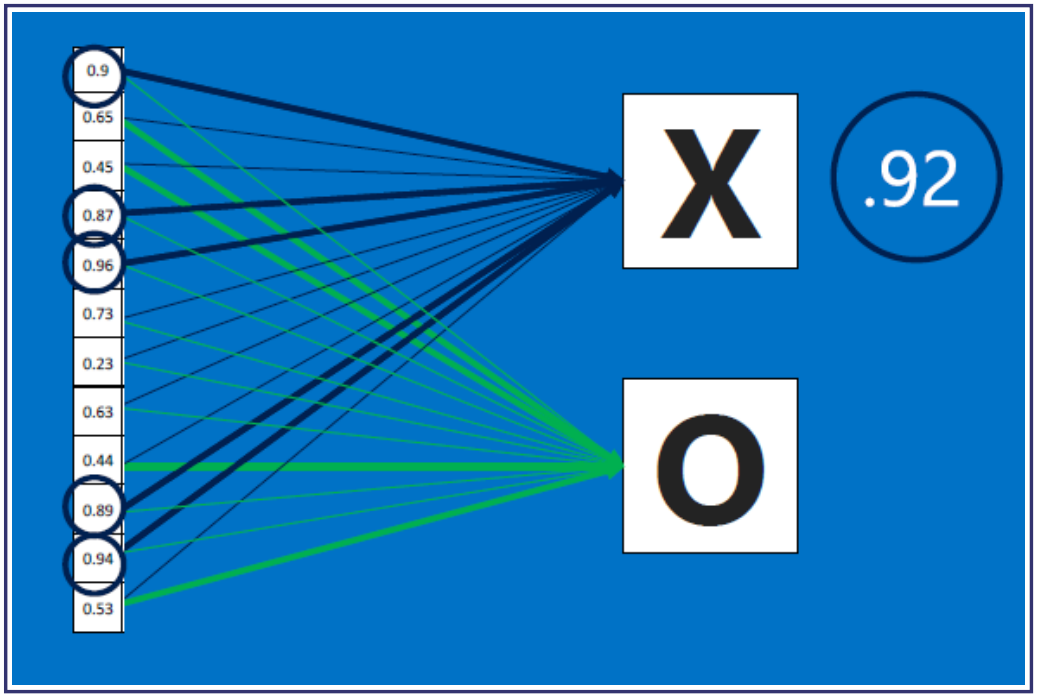
Likewise, if we fed O image detectors kernels' results (also an array of 12 values) to the O receiver, the O receiver would classify it as an O - because the O detector has been separately trained, using several O-like images and O-feature detector neurons!!

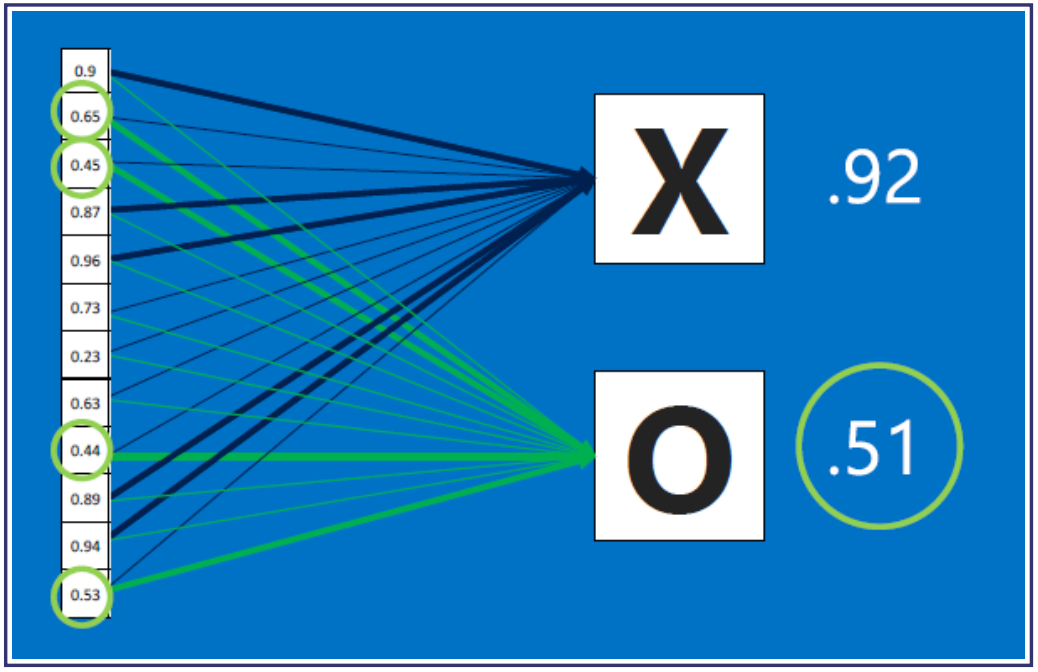


After training, a new ('test') image is fed to BOTH the X feature detector neurons AND to the O feature detector neurons, who outputs are all combined to produce a 12-element array as before. Now we feed that array to both the X-decider neuron and the O-decider neuron:



Here's the output for X and O - the results average to 0.91 for X, and 0.52 for O - the NN would therefore classify this as an X:


0.9
0.65
0.45
0.87
0.96
0.73
0.23
0.63
0.44
0.89
0.94
0.53
X
O
.92

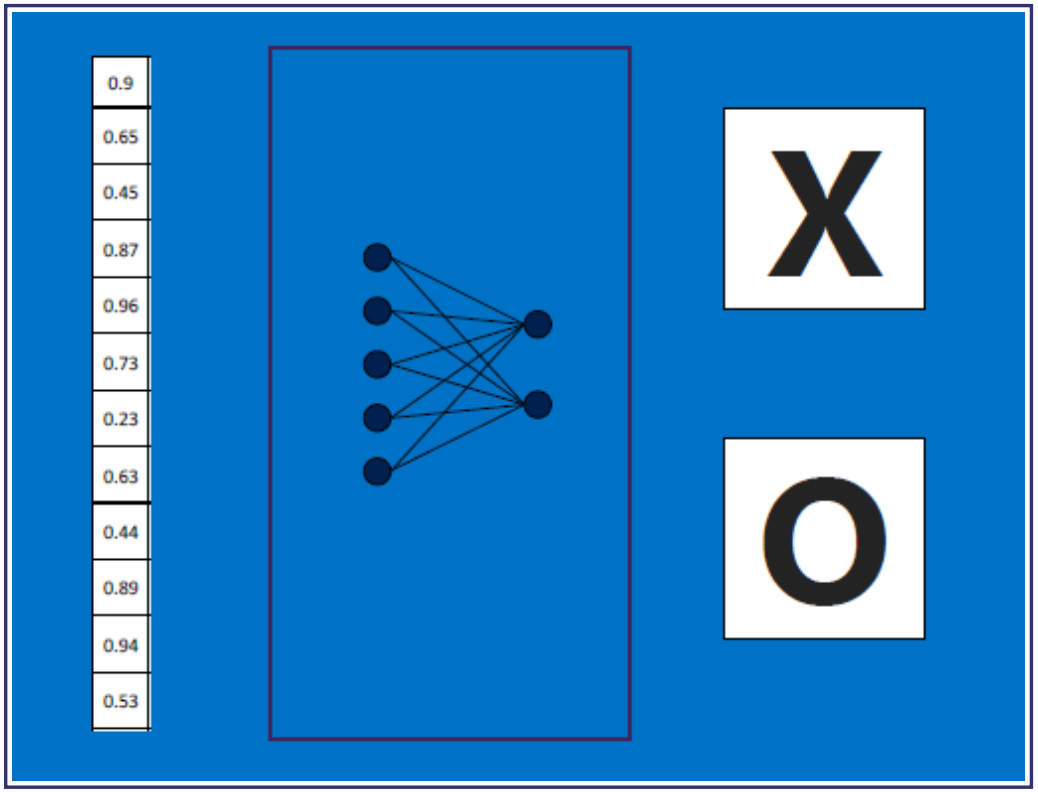

0.9
0.65
0.45
0.87
0.96
0.73
0.23
0.63
0.44
0.89
0.94
0.53
X
O
.92
.51

If we feed the network an O-like image instead, the X and O detectors will go to work, and produce an output array where the O features (at #1,#2..) would be higher. So when this array is fed to the X decider and the O decider, we expect the image to be classified as O, eg. because the output probabilities from the X decider and O decider come out to be 0.42 and 0.89.

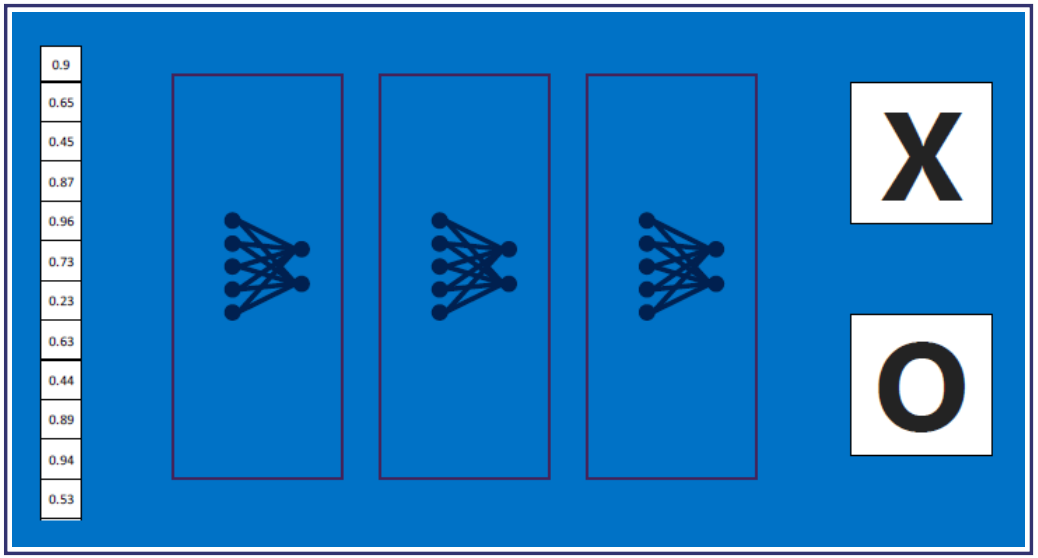
Repeat for each class that needs to be learned: test input => class detectors => outputs => train classifier.

This is very roughly equivalent to creating a "regression line" that "best fits" available data.

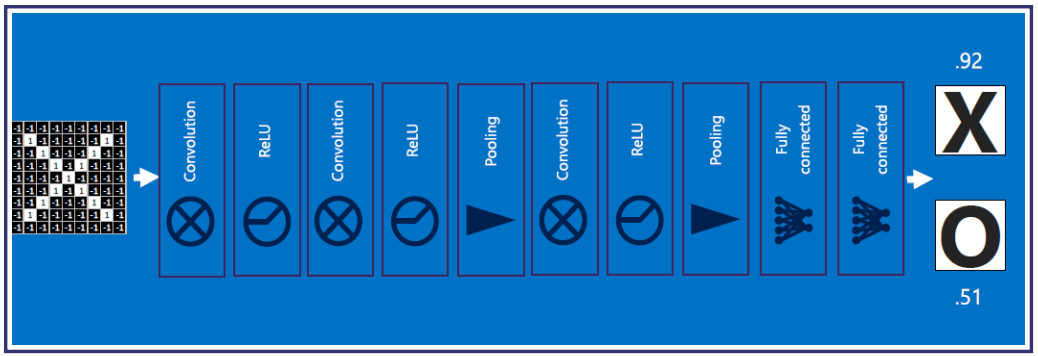
In summary:



In real world situations, these voting outputs can also be cascaded:

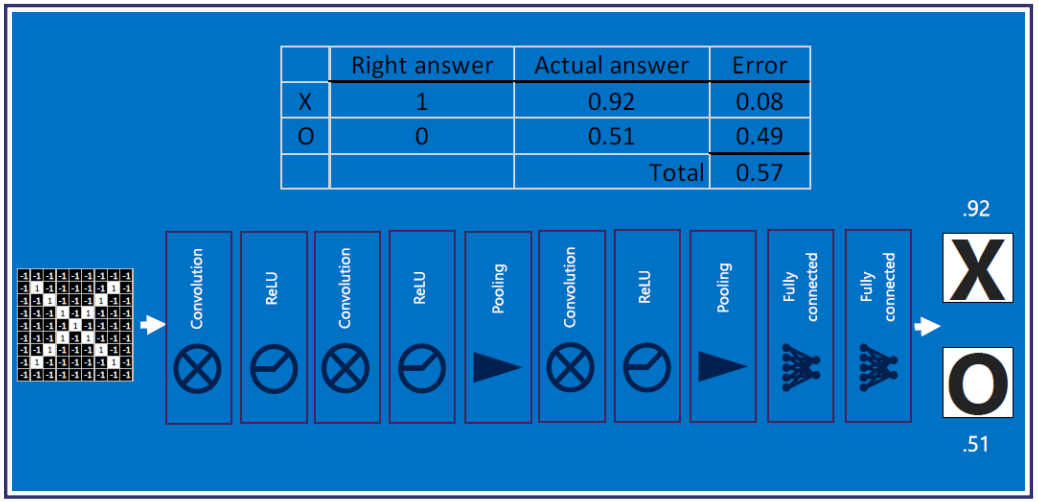


'All together now':

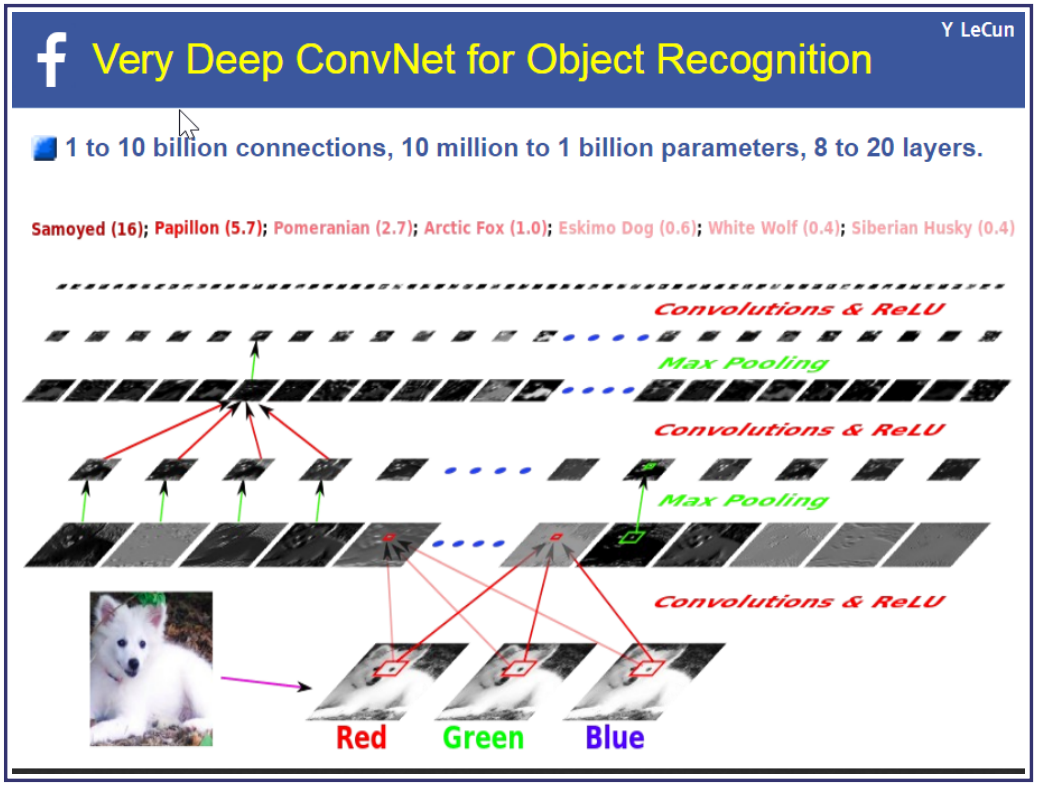


In the above, if we had fed an O-like image instead, the output probability would be higher for O.

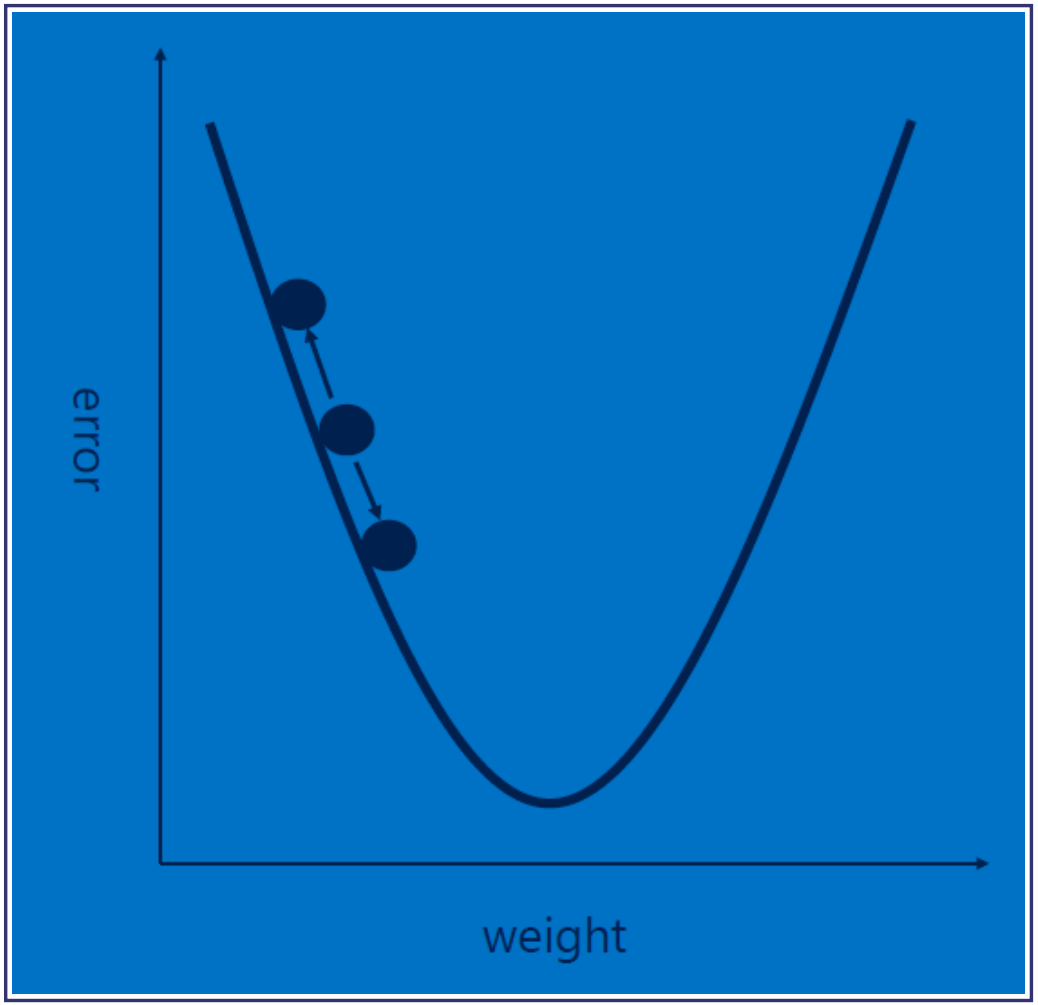
Errors are reduced via backpropagation. Error is computed by taking the absolute differences' sums between expected and observed outputs:



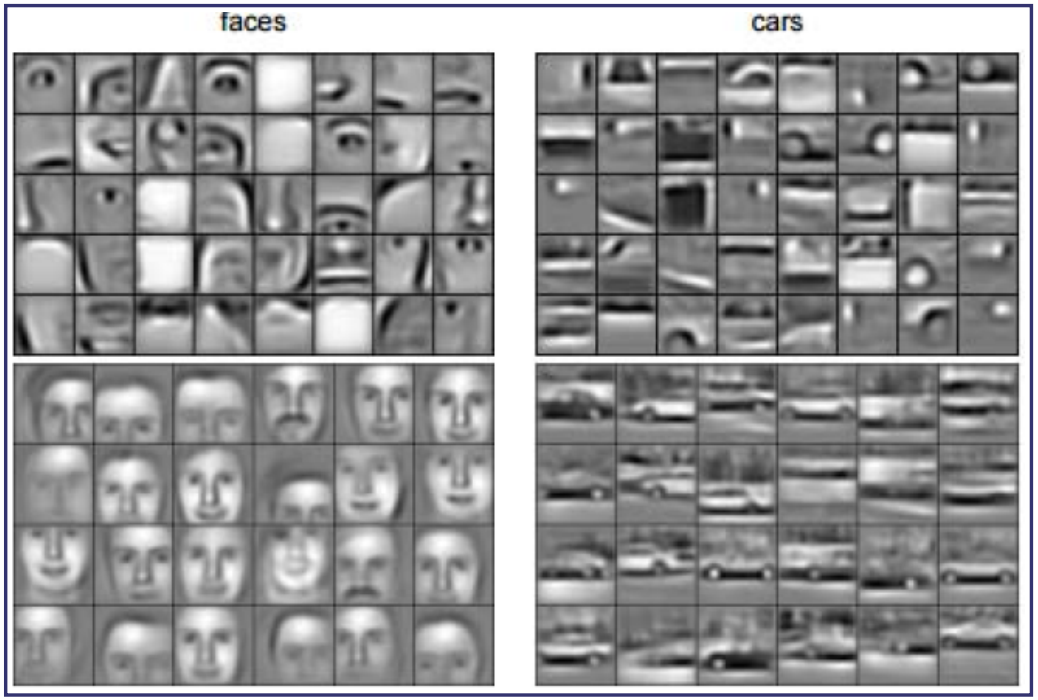
In RL, we'd use thousands of images for each class (outcome/label), and create a network that can detect dozens of classes - eg. here is a pictorial representation of an NN that can classify dogs:



For each feature, each weight (one at a time) is adjustly slightly (+ or -, using the given learning rate) from its current value, with the goal of reducing the error (use the modified weights to re-classify, recompute error, modify weights, reclassify.. iterate till convergence) - this is called backpropagation:



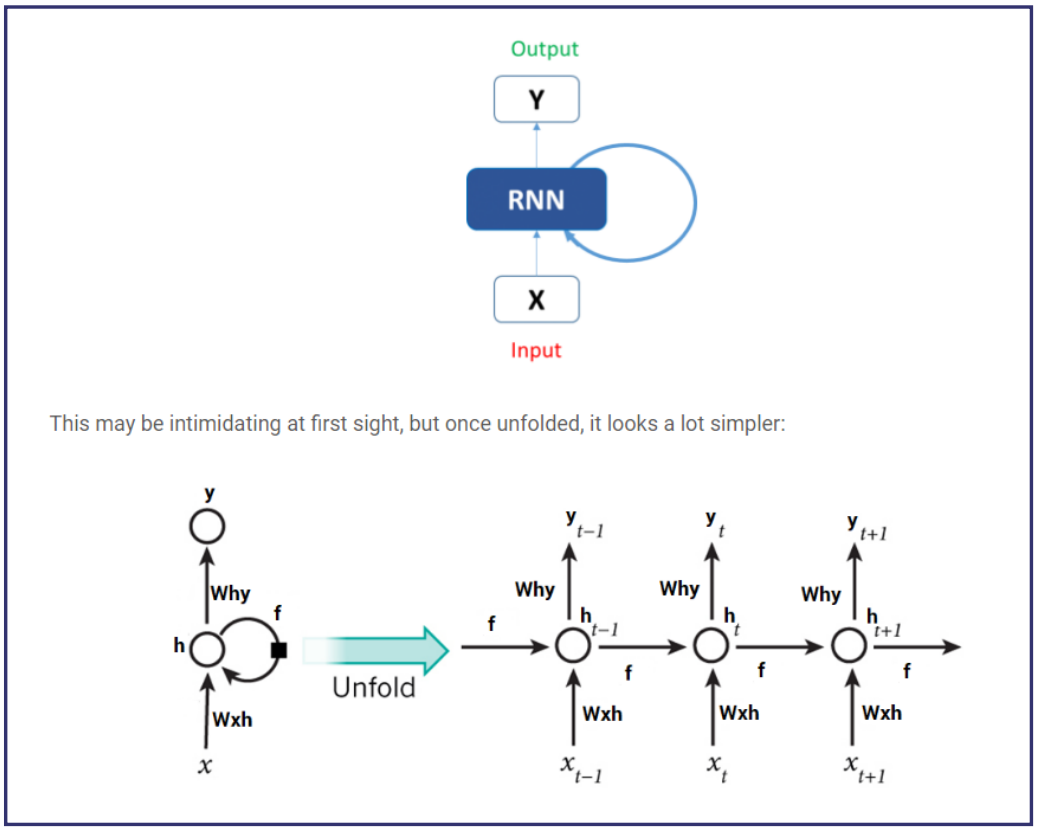
That was a whirlwind tour of the world of CNNs! Now you can start to understand how an NN can detect faces, cars..:



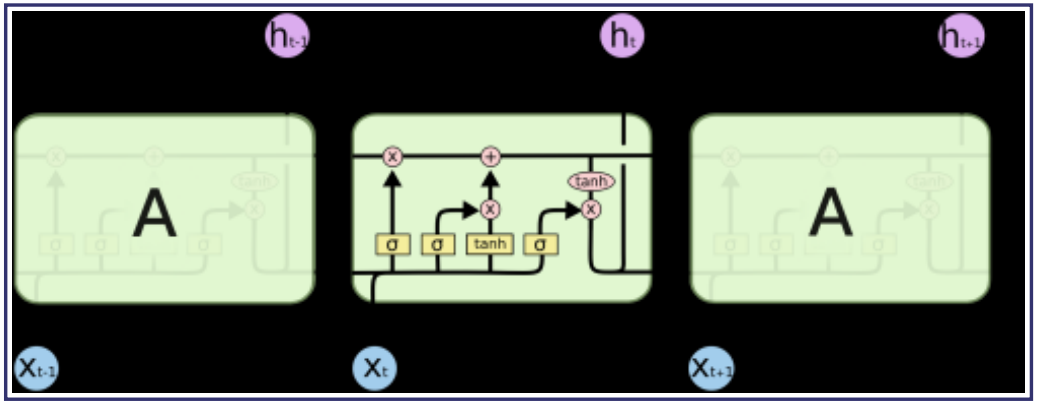
When is a CNN **not** a good choice? Answer: when data is not spatially laid out, ie. scrambling rows and columns of the data would still keep the data intact (like in a relational table) but would totally throw off the convolutional neurons!

RNN, LSTM, Transformers

An RNN is a history-dependent network where past predictions are used for future ones (by having outputs fed back):



An LSTM is a special kind of RNN, for being able to process longer chains of dependencies.



RNNs/LSTMs are especially good for 'sequence' problems such as speech recognition, language translation, etc.; they are not massively parallelizable the way CNNs can be.

Temporal Convolution Nets (TCNs) are a good, parallelizable alt to RNNs; Numenta's HTM - also a better alternative to RNNs.

The Transformer architecture (Google, 2017) is a 'game changer' for language processing - it STACKS encoders and decoders.

CapsNet

A Capsule Network (CapsNet) is a more robust (compared to regular CNNs) architecture for object detection; see also this page.

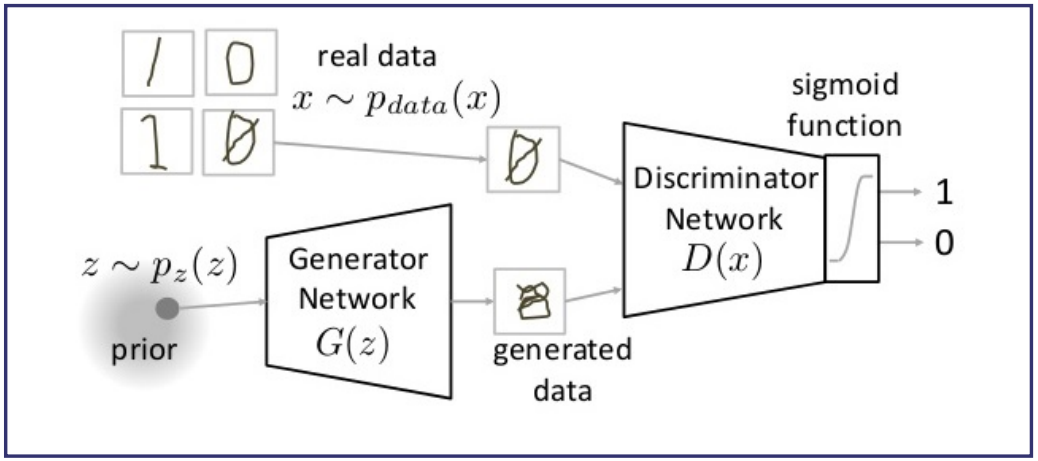
NN architectures

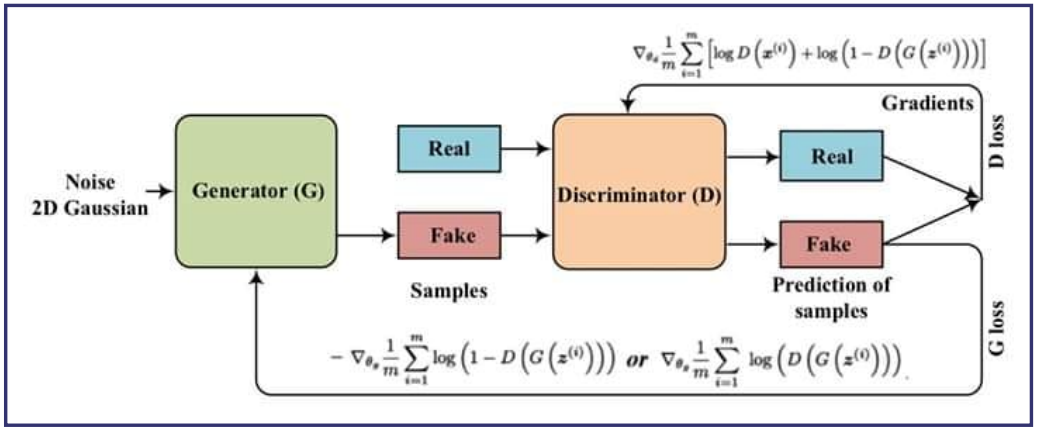
Specific architectures (numbers and types of layers) exist, for different NN tasks - eg. look at this page: https://medium.com/@sidereal/cnns-architectures-lenet-alexnet-vgg-googlenet-resnet-and-more-666091488df5

Before embarking on a big task, it is important to first identify, or create, a suitable architecture - otherwise, learning efficiency, and/or performance accuracy, will suffer.

GANs! And encoder-decoder pairs...

Adversarial learning methods, [esp GANs, that have dueling ["zero sum"] Generator and Discriminator networks] are very interesting.





GANs have MANY variations!

EBMs (a GAN alternative): https://openai.com/blog/energy-based-models/

As an alternative to GANs, a similar idea, called an Encoder-Decoder pair, can ALSO generate data (faces, words, music...). The encoder, specifically a 'VAE' learns to create a representation, a 'data generating distribution', of its input data, using latent-space features [of the input data]. Roughly, it learns to map an input datum into a point in multi-dim latent space. REVERSING this, **ANY random point in the latent feature space can be used to GENERATE (via a decoder) a NEW datum!**

Players (Top Six, plus others)

- Amazon uses deep learning for product recommendations, Alexa...
- Google: self-driving cars, TensorFlow, DeepMind
- Microsoft: ImageNet entry, CNTK, Skype Translator... Here are a bunch of their AI demos.
- Facebook: DeepFace can search 800M faces in <5 sec! Also, Facebook is planning to open source its hardware setup. Deep learning is also used in Instagram, for recognizing content in images, including text.
- IBM: Watson, AlchemyAPI, Watson Analytics
- Apple uses deep learning for Siri, iTunes, etc.
- Many others: Alibaba, Baidu, Tencent, Uber, Netflix, Visa, LinkedIn...

'AI hardware' (for DL)

GPUs and other forms of hardware are used to accelerate deep learning - advantages: massively parallel processing, and possibility of arbitrary speed increases over time just by upgrading hardware!

GPUs (multi-core, high-performance graphics chips made by NVIDIA etc.) and DNNs seem to be a match made in heaven!

NVIDIA has made available a LOT of resources related to DNNs using GPUs, including a framework called DIGITS (Deep Learning GPU Training System). NVIDIA's DGX-1 is a deep learning platform built atop their Tesla P100 GPUs. Here is an excellent intro' to deep learning - a series of posts. Here is a GPU-powered self-driving car (with 'only' 37 million neurons) :)

Microsoft has created a GPU-based network for doing face recognition, speech recognition, etc.

Untether: https://www.technologyreview.com/the-download/613258/intel-buys-into-an-ai-chip-that-can-transfer-data-1000-times-faster/

The following are GPU-based NN implementations, by others:

- AMD
- Fujitsu
- Inspur

TPU (TensorFlow Processing Unit) is a Google-developed chip, for DNNs [in their Waymo cars].

Intel has its Neural Compute Stick...

FPGAs also offer a custom path to DNN creation.

Also: TeraDeep, CEVA, Synopsis, Alluviate..

A new form of CPU, involving 'chiplets' (from AMD) might also be a suitable platform...

Intel also has Nervana NNP-T.

NN on the cloud

The top three players - Amazon, Google, Microsoft - all have cloud-based APIs. Others - eg. FloydHub, Paperspace... other cloud-based ML training and hosting.

NN on the edge

There is a push to also deploy models on edge devices - SoCs, smartphones, browsers...

Eg. one trend is to build ML into cameras, eg. as done in Pixy2.

Google's TensorFlow can also run on the browser.

Here is a ConvNet (ie CNN) demo, running in the browser.

Here is an example of language processing on a smartphone.

Crop disease detection, in Kenya, using TF on an Android smartphone:
https://www.youtube.com/watch?v=NIpS-DhayQA

simple object detection in the browser!

The 'big prize' in CS...

Last year, the 2018 Turing Award winners were announced - it's a win for AI (ML).

Current work (research directions)

Here is state-of-the-art [not including commercial applications, tools etc]:

- attention, eg. https://skymind.ai/wiki/attention-mechanism-memory-network
- DL+NLP, eg. ELMo, **Transformers**, eg. https://jalammar.github.io/illustrated-transformer/, BERT: https://ai.googleblog.com/2018/11/open-sourcing-bert-state-of-art-pre.html, GPT-3: https://www.infoq.com/news/2020/06/openai-gpt3-language-model/
- 'transfer' learning
- Selective tuning ["huh, what was that again", ie. 'doubletake']
- better NN designing, eg. https://papers.nips.cc/paper/7892-neural-ordinary-differential-equations and 'NAS'
- architecture pruning
- NNs for solving PDEs, eg. Fourier Neural Operator: https://arxiv.org/abs/2010.08895
- optics-based NN
- another approach to AI is to model the brain's structure, in software or in hardware. IBM has its SyNAPSE chip, and TrueNorth NN chip. Numenta is another player in neuromorphic computing. Another approach to neuromorphic chips is to incorporate some wetware into them.
- Vision Transformers!
- Neuro-symbolic integration
- Geoff Hinton: GLOM

Looking at the above, they could be grouped like so:

- better architecture: Transformer, variations of GANs, neuromorphic h/w, neuro-symbolic integration, GLOM...
- better tuning, search: auto ML, NAS...
- better deployment: lower power, pruning, on edge hardware, optical processing...
- more uses: eg. via GANs, neural ODEs...
-

The 'race' for AI

AI (ML, really) is tranforming world economies - everyone wants to participate, and WIN:

- US: this and this
- China: world domination
- India: address societal needs
- EU: strategy

DO watch the ~ 2 hour PBS documentary (link in 'Extras').

Problems...

Because it's ALL based on DATA, issues arise:

- bias
- deepfakes
- easy foolability
- lack of explainability
- unchecked power

'Learning' more

Look up papers/blogs by:

- Andrew Ng
- Yann LeCun
- Andrej Karpathy
- Chris Olah
- Brandon Rohrer

Also:

- https://www.youtube.com/channel/UCWN3xxRkmTPmbKwht9FuE5A - Siraj Raval :)
- https://www.facebook.com/groups/DeepNetGroup/ - AIDL
- this is a VERY comprehensive portal on DNN
- https://aischool.microsoft.com/en-us/home
- math for deep learning

Applications - a sampler

ML is a runaway **engineering** success, which is sure to lead to 1000s (!) of applications, covering every human activity! Remember - if ANYTHING has a 'PATTERN' (that a. sets it APART from others, and b. has VARIATIONS within itself), it can be LEARNED!

Below is an arbitrary ("random") sampling of applications [some we talked about or encountered earlier]. The point is that "AI", ie. ML, is now mature enough, widely deployable enough that we can start dreaming up NEW USES for it!

- https://www.youtube.com/channel/UCWN3xxRkmTPmbKwht9FuE5A - make the data 'lit'!
- SDCs, eg. https://www.youtube.com/watch?v=tiwVMrTLUWg
- Face detection, EU airports: https://www.cnn.com/travel/article/ai-lie-detector-eu-airports-scli-intl/index.html
- Face detection, Chinese classrooms(!): https://www.youtube.com/watch?v=3H1hj_C8F_A
- https://developer.amazon.com/blogs/alexa/post/ca34b954-1c5d-4a59-b326-f45c8df7c89c/alexa-skill-tech-for-good-challenge-winners
- https://ai.googleblog.com/2018/11/improved-grading-of-prostate-cancer.html
- ASL: https://www.youtube.com/watch?v=a4zvhJsBPa0
- 'master key' (uh oh): https://boingboing.net/2018/11/15/masterprints.html
- Google's Quick Draw, AutoDraw [here is an alternate implementation of QuickDraw; and, here is Google's dataset!]

- Inceptionism, DL portrait morph
- https://aiportraits.com/#
- neural style transfer [incl this clip :)]
- deepfakes, eg. https://www.bbc.co.uk/programmes/p06r8g4l [most are NSFW!!]
- https://medium.freecodecamp.org/chihuahua-or-muffin-my-search-for-the-best-computer-vision-api-cbda4d6b425d, http://www.evolvingai.org/fooling
- https://gallery.azure.ai/browse
- https://lobe.ai/
- https://research.google.com/seedbank/seeds
- https://thispersondoesnotexist.com/ [and https://thisrentaldoesnotexist.com/]
- https://ganbreeder.app/category/random
- https://www.askforgametask.com/html5/tutorials/tetris_ai_bot/source/ - an agent trained to play Tetris
- https://teachablemachine.withgoogle.com/