

Artificial Neural Networks in Artificial Intelligence

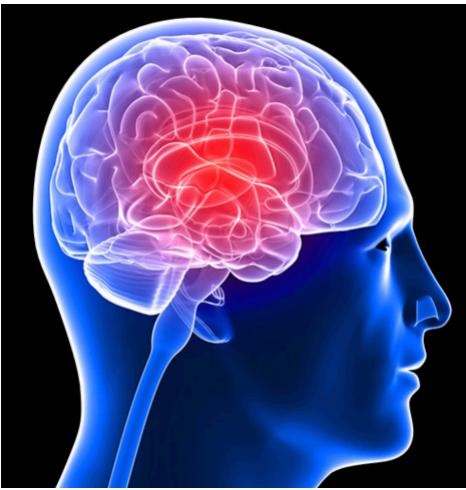
Artificial Intelligence involves several different approaches, including

- **Symbolic artificial intelligence** is the collection of all methods in artificial intelligence research that are based on high-level "symbolic" (human-readable) representations of problems, logic and search.
- **Bayesian decision networks** are graphical models that represent a set of variables and their dependencies ... ideal for taking an event that occurred and predicting the likelihood that any one of several possible causes was the contributing factor.
- **Evolutionary algorithms** use mechanisms inspired by biological evolution, such as reproduction, mutation, recombination, and selection. Candidate solutions play the role of individuals in a population, and the fitness function determines the quality of the solutions. Evolution of the candidate population then takes place after the repeated application of the mechanisms.

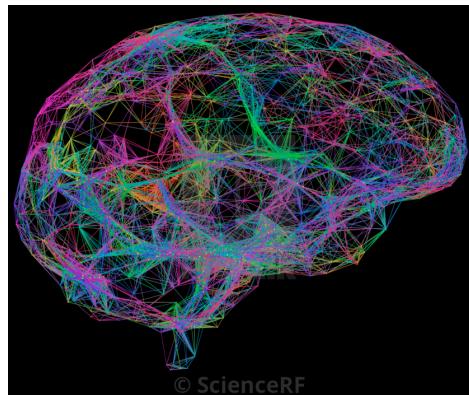
Wikipedia

Here we illustrate a fourth approach

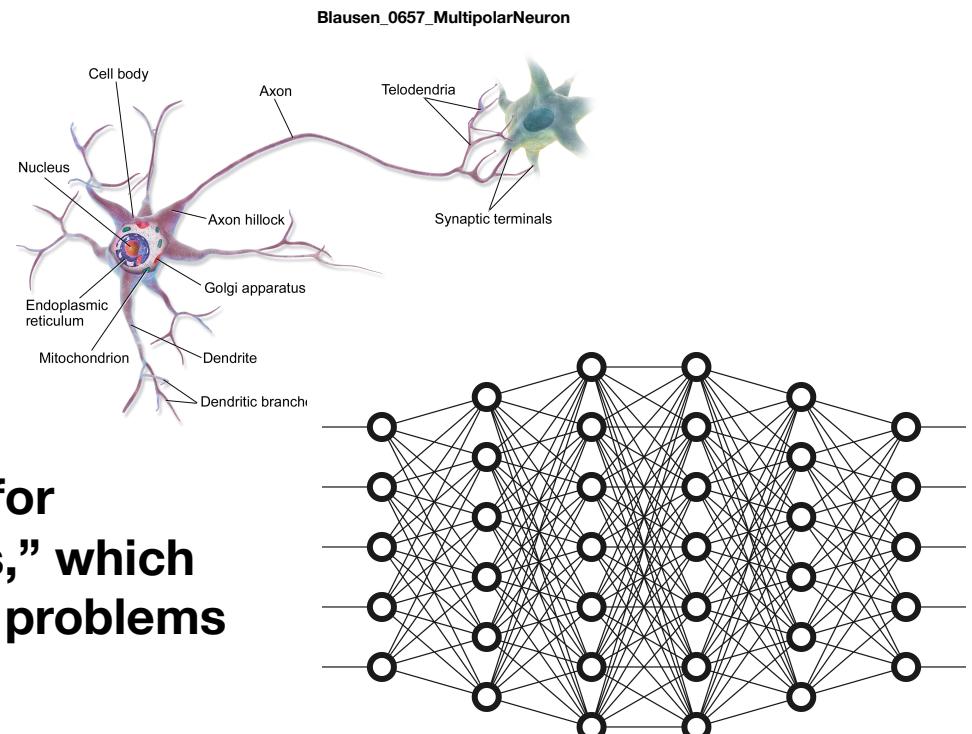
- **Artificial Neural Networks** - with basic introductory examples here



www.braininjuryaustralia.org.au



Our brains sense and think using connected networks of cells called neurons



These networks are the inspiration for computer simulations of “neural networks,” which can be trained to sense and solve complex problems

neural_network_shutterstock_all_is_magic.jpg

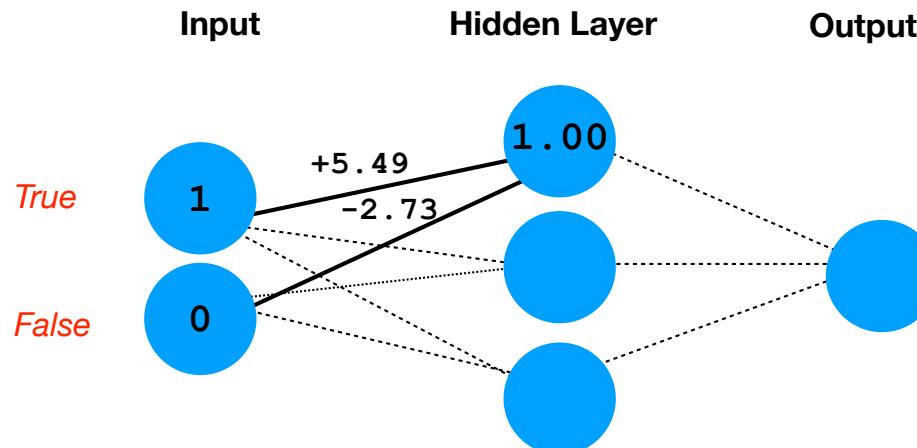
github.com/RichardHerz

Neural Network

Simulates XOR logic - exclusive or

Output is TRUE when one input is TRUE but not both

**2 inputs, 1 output,
1 hidden layer
with 3 neurons &
9 synapses**



EXAMPLE for input of
1
0

node value = sigmaFunc(sum of (connection weight * node activation))

where $\text{sigmaFunc}(x) = \exp(x) / (1 + \exp(x))$ >> converts all input x values into range 0 to 1

INPUT > HIDDEN LAYER

$$\text{sigmaFunc}(5.4868 * 1 + (-2.7276) * 0) = 0.9959 = \text{hidden node 1 activation}$$

Every node - neuron - has a connection - synapse - to every neuron in nearest-neighbor layers of neurons in this basic type of neural network.

The values are held in memory locations and the CPU executes the math - there are no physical, hardware neurons and synapses.

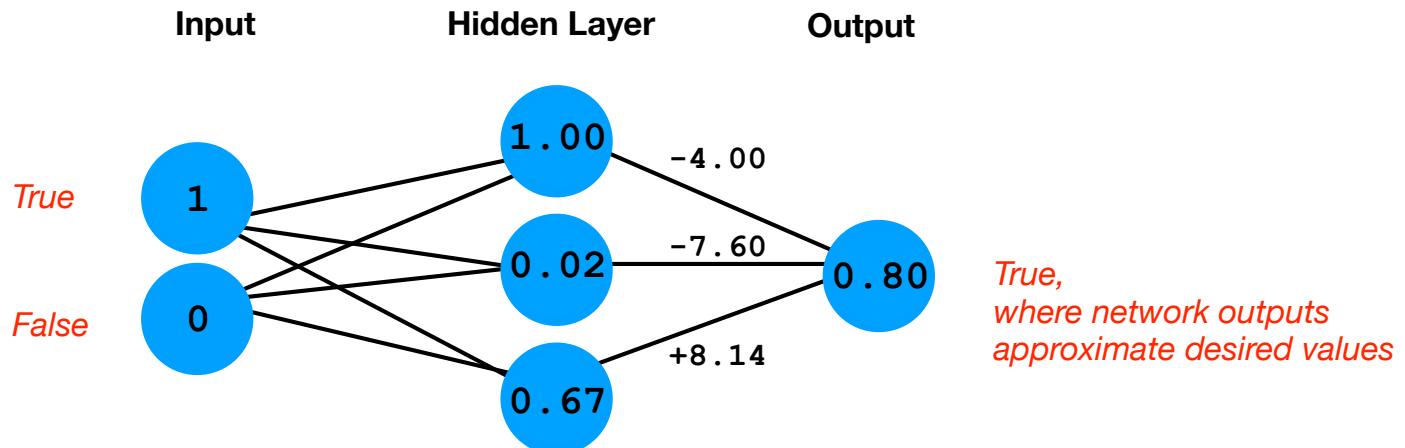
These sums over all nodes in a layer are the product of matrix multiplication. Matrix multiplication is well suited to being accelerated in hardware Graphical Processing Units, since graphic transformations also involve matrix multiplication.

Neural Network

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HIDDEN LAYER > OUTPUT

$$\text{sigmaFunc}((-4.0030) * 0.9959 + (-7.5988) * 0.0153 + 8.1402 * 0.6719) = 0.7969 = \text{output node}$$

The MATLAB code to solve for the output remains the same as that below, regardless of the size of the network:

```
for i = 2 : numHiddenLayers + 2
    a{i} = sigmaFunc( W{i-1} * a{i-1} );
end
```

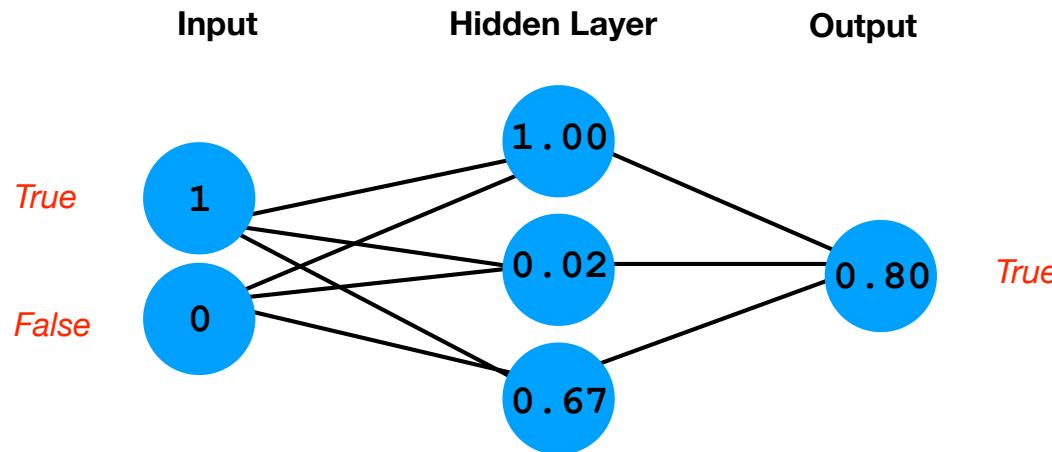
W is a cell array whose elements are the matrices of synapse weights for each layer; **a** is a cell array whose elements are the vectors of neuron activation values. Each set of **W** and **a** are matrix-multiplied to obtain the neuron activation values for the next layer in the series of neuron layers.

Neural Network

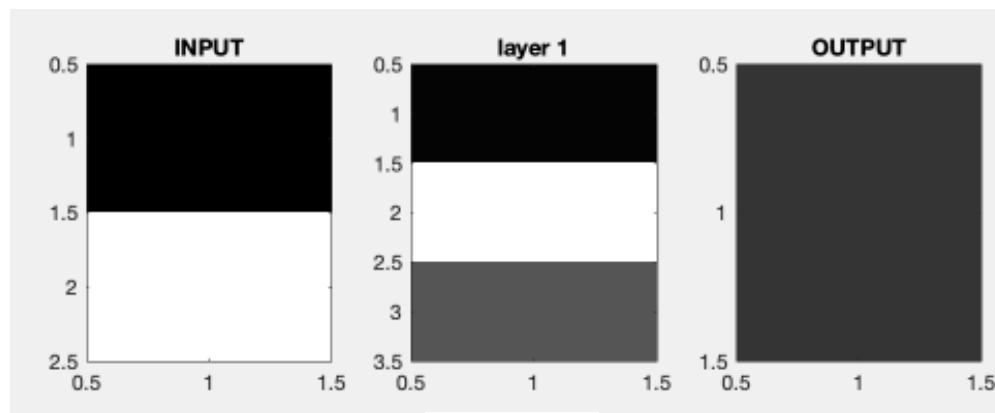
Simulates XOR logic - exclusive or

Output is TRUE when one input is TRUE but not both

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Visualization of neuron values - “activations” - for this input



1	0.9959	
0	0.0153	
	0.6719	

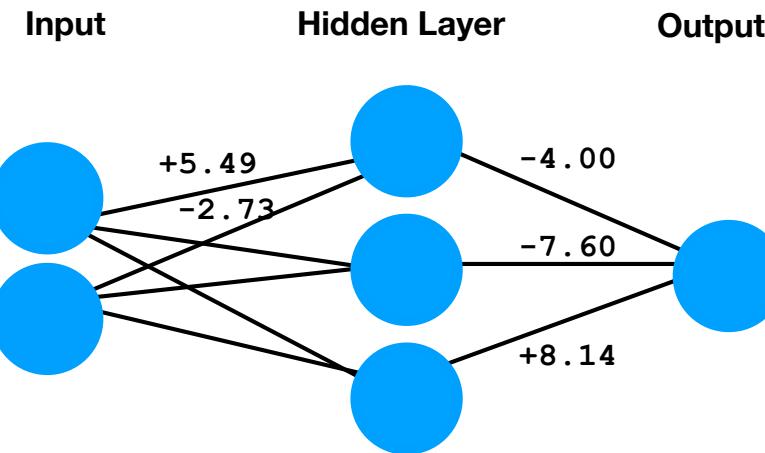
True

Neural Network

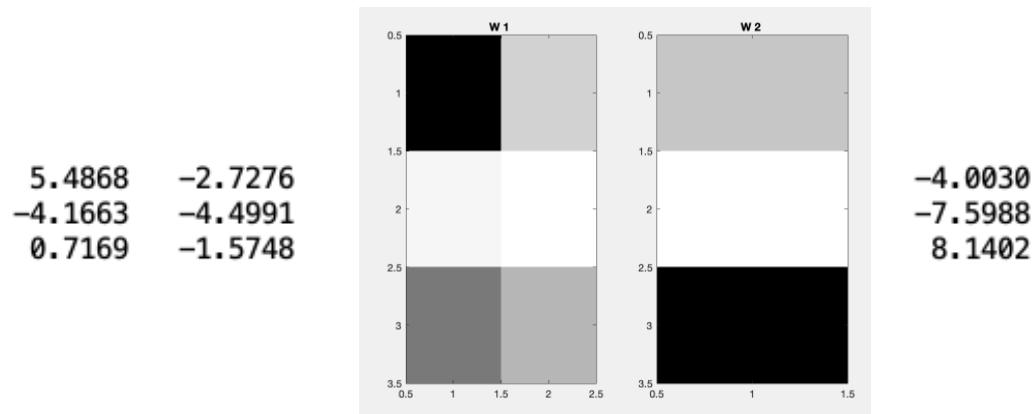
Simulates XOR logic - exclusive or

Output is TRUE when one input is TRUE but not both

**2 inputs, 1 output,
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with 3 neurons &
9 synapses**

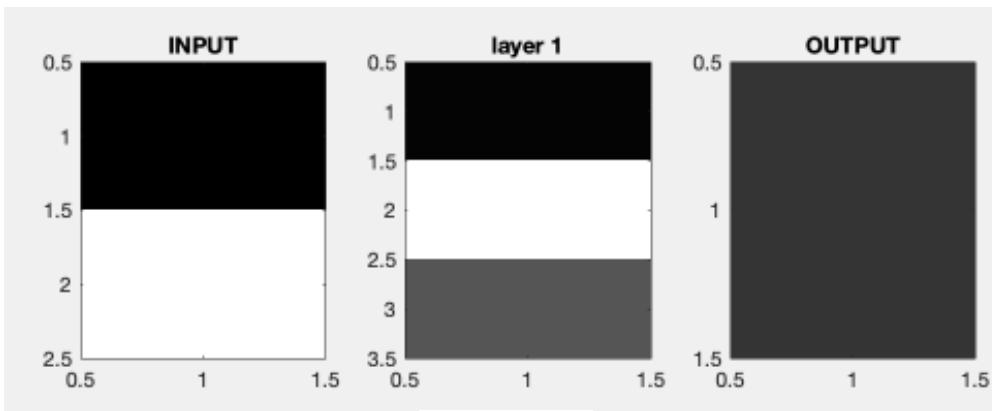


**Visualization of synapse connection “weights” to hidden layer and to output
min = -7.60 (white), max = +8.14 (black)**



*The synapse connection weights were determined when the network was “trained”
using combinations of known inputs and outputs.*

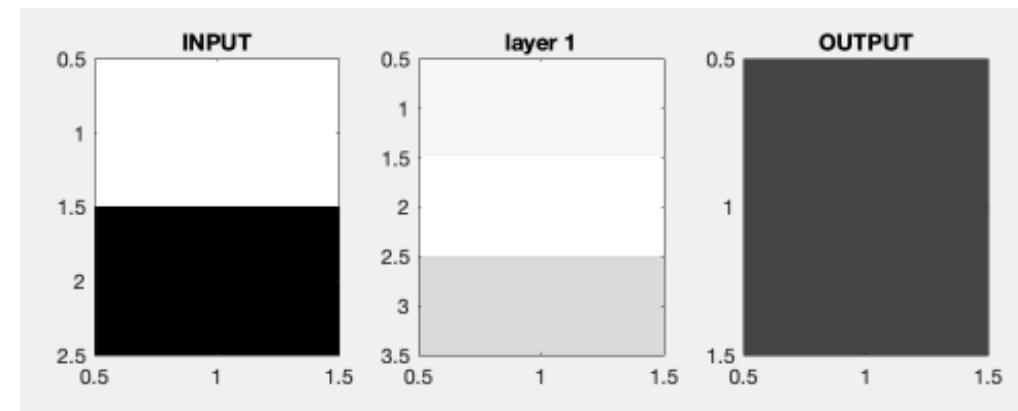
Visualizations of node activations: input > hidden layer > output



1
0

0.9959
0.0153
0.6719

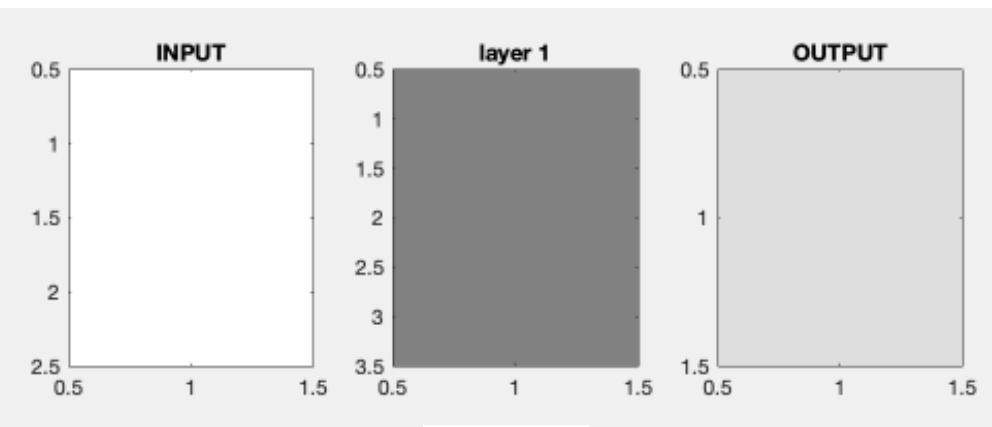
0.7969
True



0
1

0.0614
0.0110
0.1715

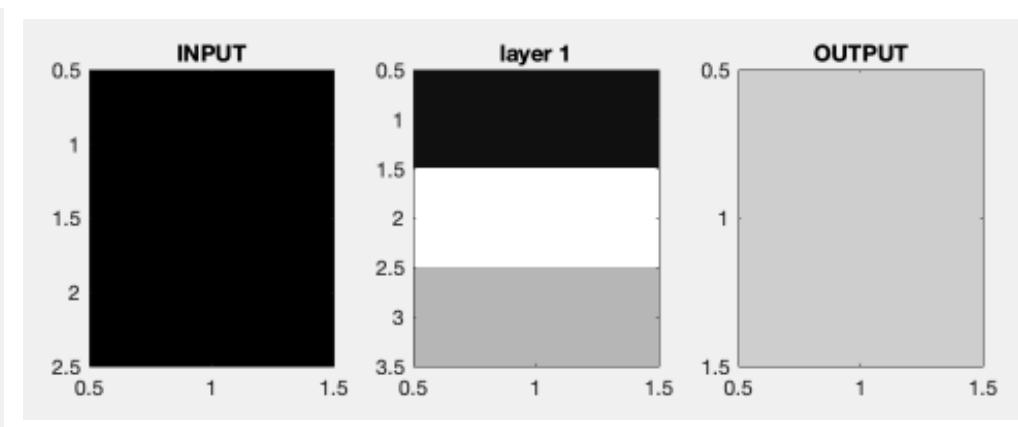
0.7440
True



0
0

0.5000
0.5000
0.1505

False



1
0

0.9404
0.0002
0.2978

False

Output is **TRUE** when one input is **TRUE** but not both

Neural Network

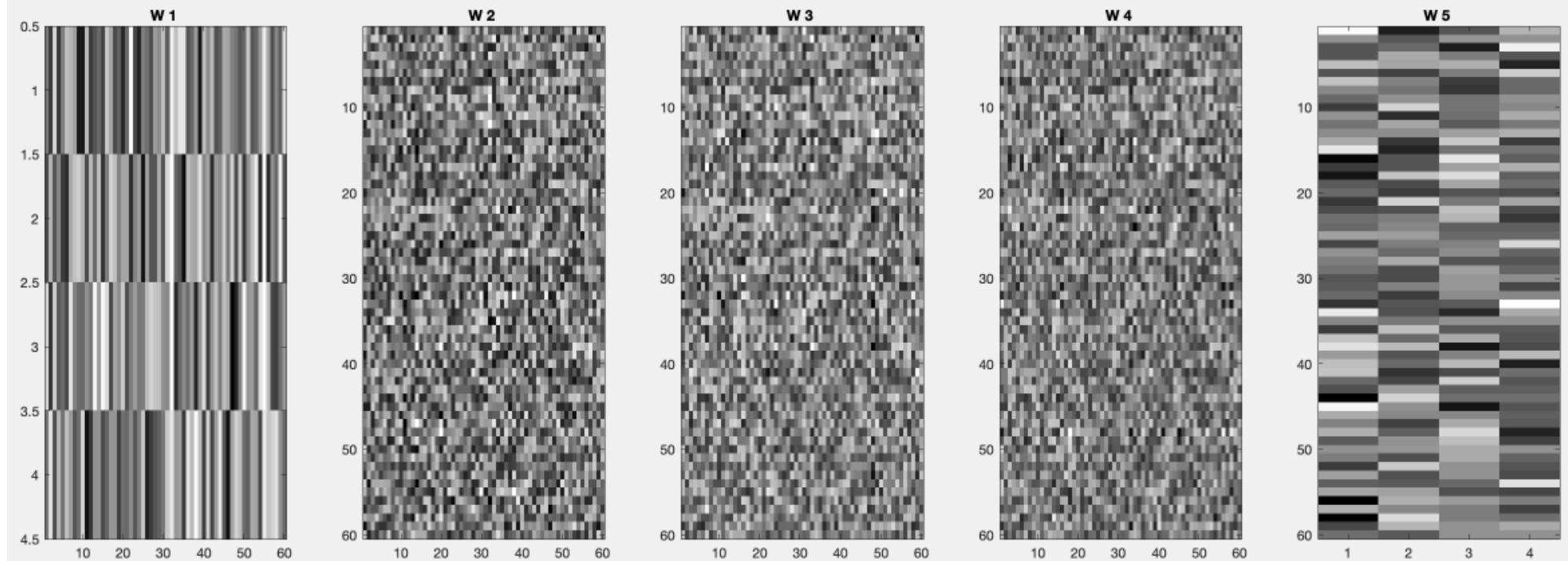
4 inputs, 4 outputs

**4 hidden layers, each
with 60 neurons =
240 neurons &
11,280 synapses**

*A more complex network which
detects diagonal, horizontal and vertical
inputs to a 2 x 2 “touch screen”*

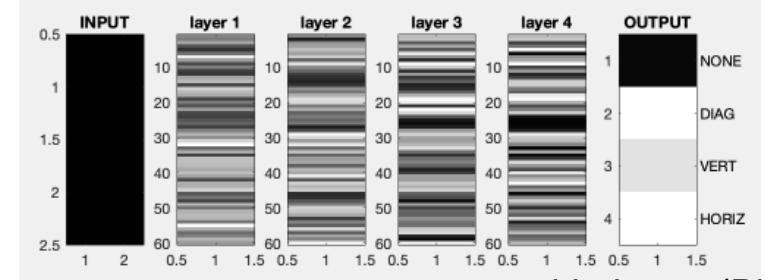
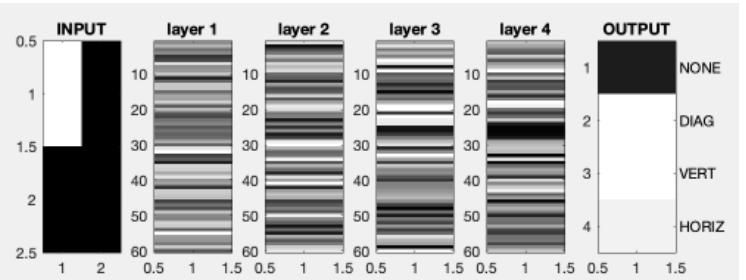
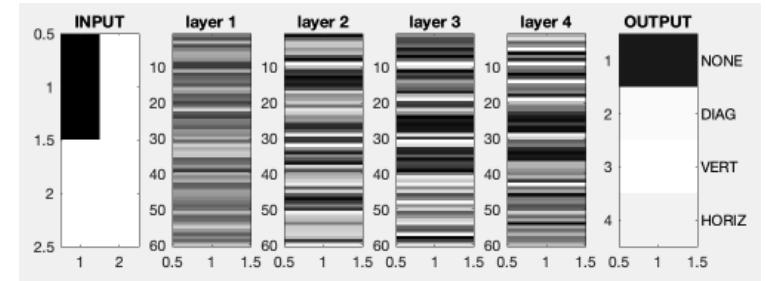
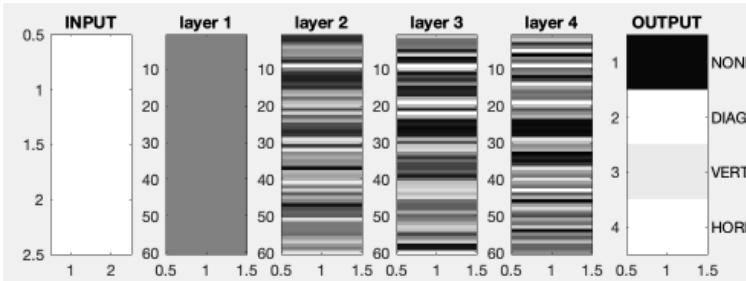
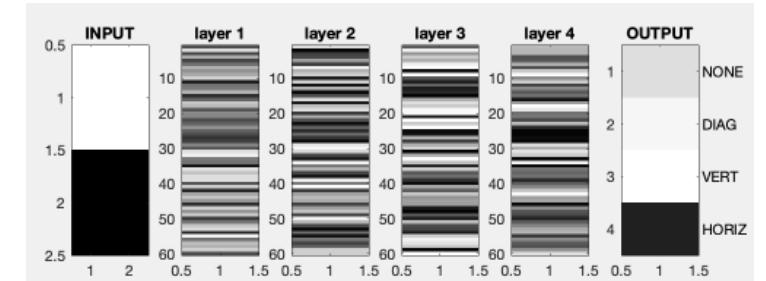
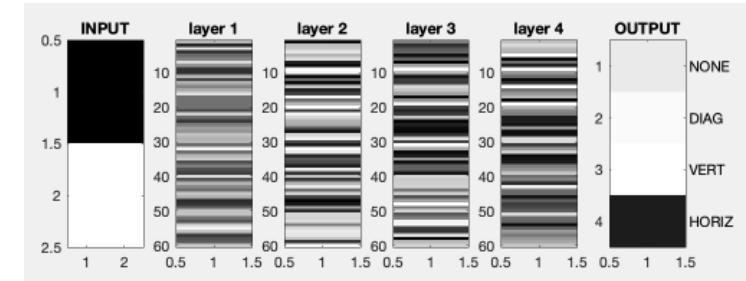
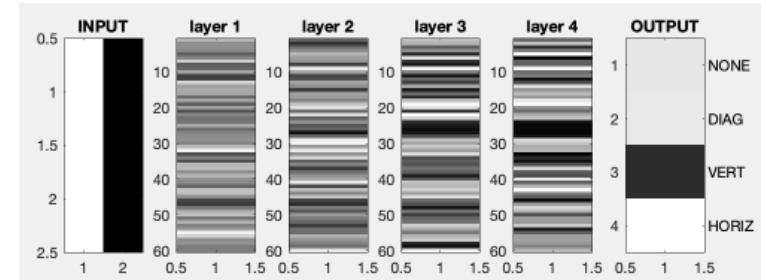
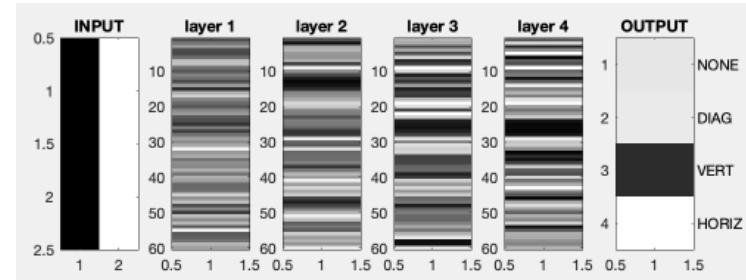
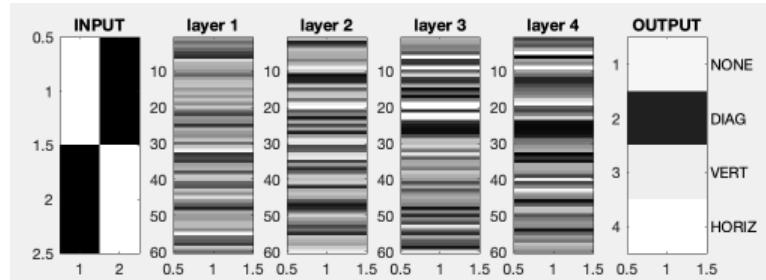
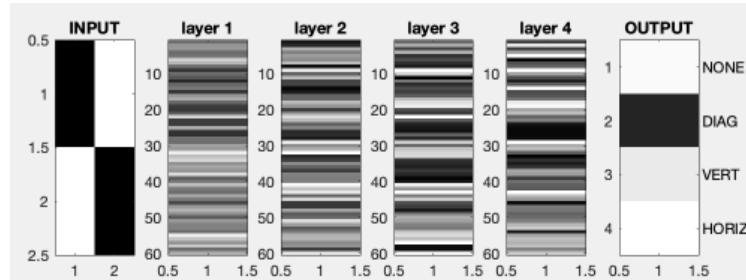
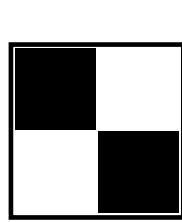


**Visualization of synapse weights to hidden
layers 1-4 and to output,
min = -1.23 (white), max = +1.25 (black)**



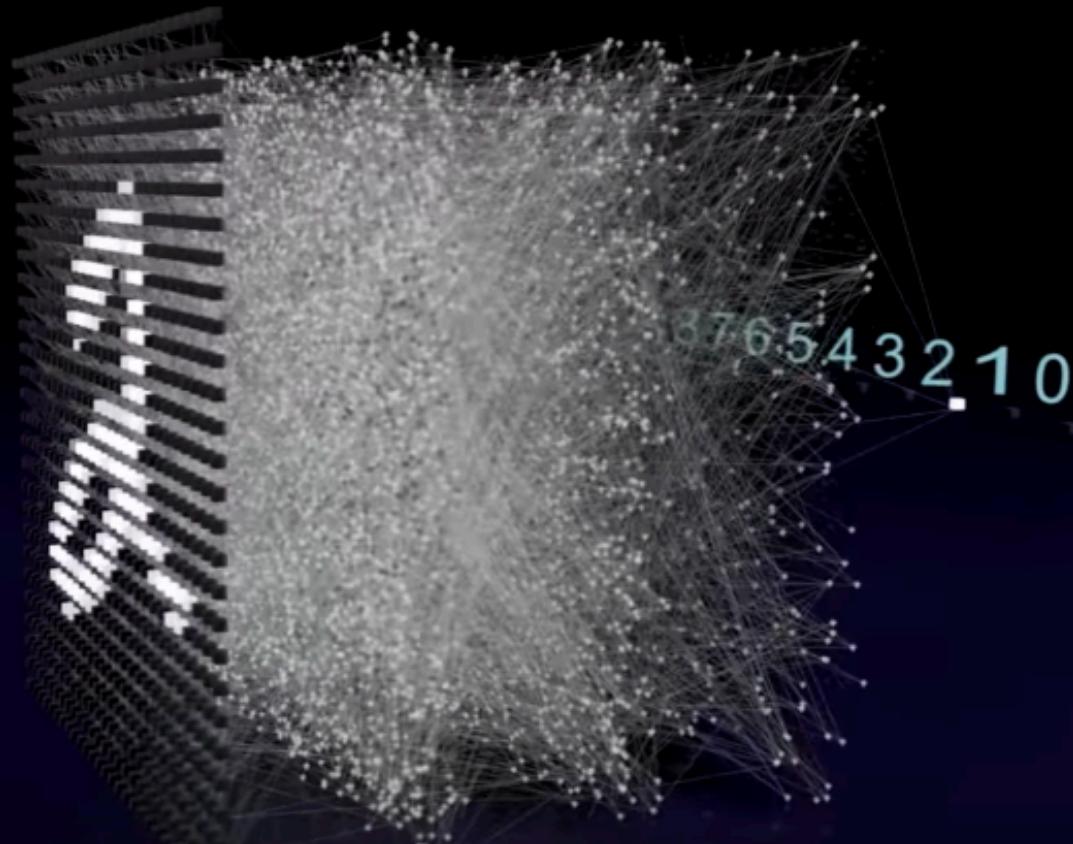
Prior to training the network with known input and output cases, the connection weights were assigned random values in the range -1 to +1. Then the weights were adjusted during training in order to match input cases with their corresponding outputs. The resulting weights are not random. Different sets of weights will be obtained with different random initializations

Visualization of node activations: input > 4 hidden layers > output



**A neural network for a 28 x 28 “touch screen”
note that only 2% of the 24+ million “synapses” are shown**

Type: ML Perceptron
Data Set: MNIST
Hidden Layers: 3
Hidden Neurons: 10000
Synapses: 24864180
Synapses shown: 2%
Learning: BP



Denis Dmitriev <https://youtu.be/3JQ3hYko51Y>

A neural network represents a large number of coupled equations which, when given a set of input values, can produce a set of desired output values.

The more neurons and synapses - the more equations - and the greater complexity of inputs and outputs which can be "fit" by the system of equations. Note the significant increase in complexity going from the XOR example to the 2 x 2 “touch screen” example to the 28 x 28 touch screen in the figure above.

"Deep learning" refers to solving complex problems using many hidden layers of neurons - many equations - and more complex network structures.

This is the expanded equation for the XOR neural network. The output is a function of the inputs:

$$\begin{aligned} a^{(3)} = f(a^{(1)}) &= \sigma\left(W_1^{(2)}a_1^{(2)} + W_2^{(2)}a_2^{(2)} + W_3^{(2)}a_3^{(2)}\right) \\ &= \sigma\left(W_1^{(2)}\sigma\left(W_{1,1}^{(1)}a_1^{(1)} + W_{1,2}^{(1)}a_2^{(1)}\right) + W_2^{(2)}\sigma\left(W_{2,1}^{(1)}a_1^{(1)} + W_{2,2}^{(1)}a_2^{(1)}\right) + W_3^{(2)}\sigma\left(W_{3,1}^{(1)}a_1^{(1)} + W_{3,2}^{(1)}a_2^{(1)}\right)\right) \end{aligned}$$

where the nonlinear activation function for this network, which constrains activation values between 0 and 1, is

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

and where, for more compact notation, the superscript {n} of cell arrays a and W denotes a matrix in cell array element n, and the subscripts are the indices within that matrix

Variables

$a^{(1)}$ = inputs

$a^{(2)}$ = hidden layer activations

$a^{(3)}$ = outputs

Constants, whose values were determined during training

$W^{(1)} = W\{1\}$ = connection weights between inputs and hidden layer

$W^{(2)} = W\{2\}$ = connection weights between hidden layer and outputs