# Neural Networks

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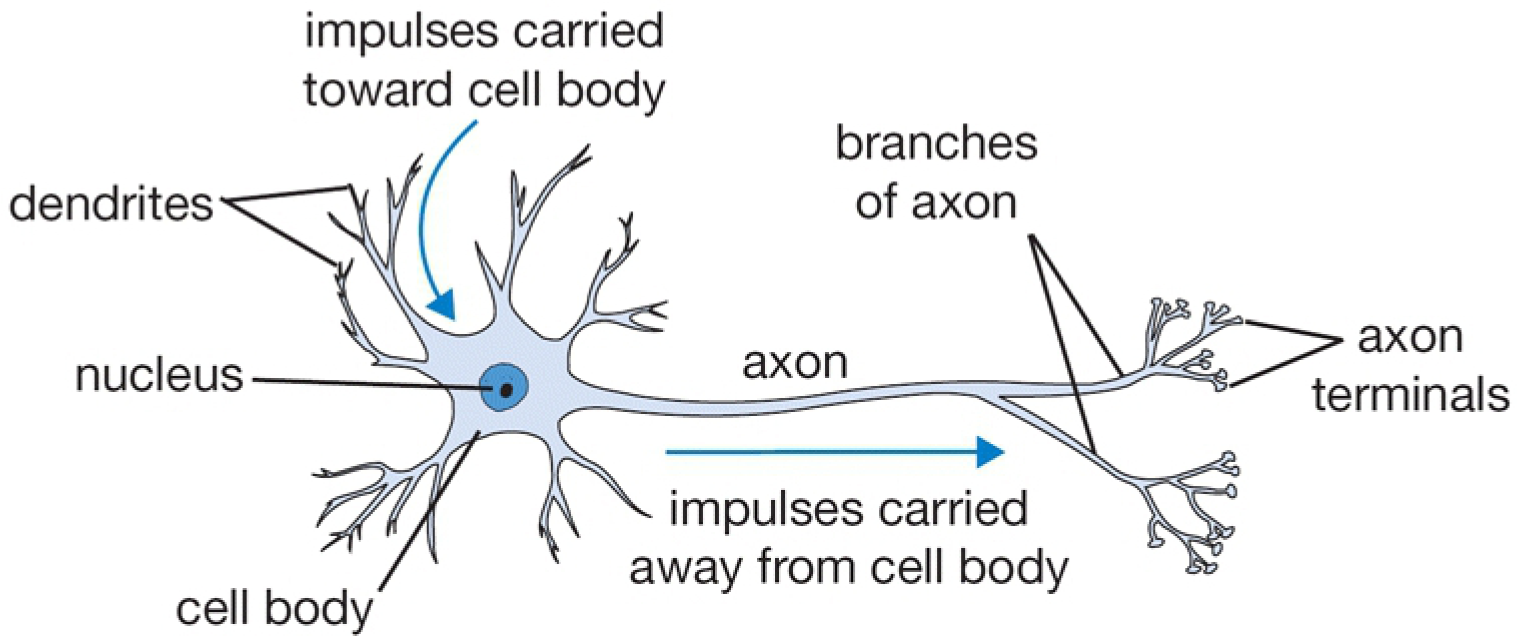
## Biological Neuron

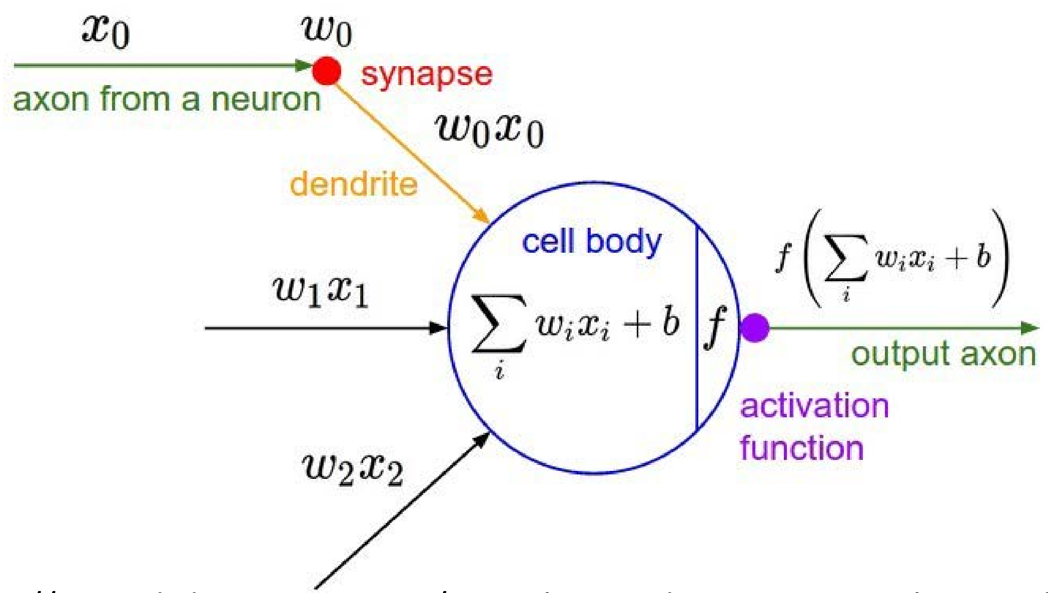
The basic computational unit of the brain is a **neuron**. Approximately 86 billion neurons can be found in the human nervous system and they are connected with approximately $10^{14}$—$10^{15}$ **synapses**.


impulses carried toward cell body
dendrites
branches of axon
axon
axon terminals
nucleus
impulses carried away from cell body
cell body

Source: David Fumo: https://towardsdatascience.com/a-gentle-introduction-to-neural-networks-series-part-1-2b90b87795bc

## Mathematical Model of a Neuron

The basic unit of computation in a neural network is the neuron (often called a node or unit). It receives input from some other nodes, or from an external source and computes an output. Each input has an associated weight (w), which is assigned on the basis of its relative importance to other inputs. The node applies a function to the weighted sum of its inputs.



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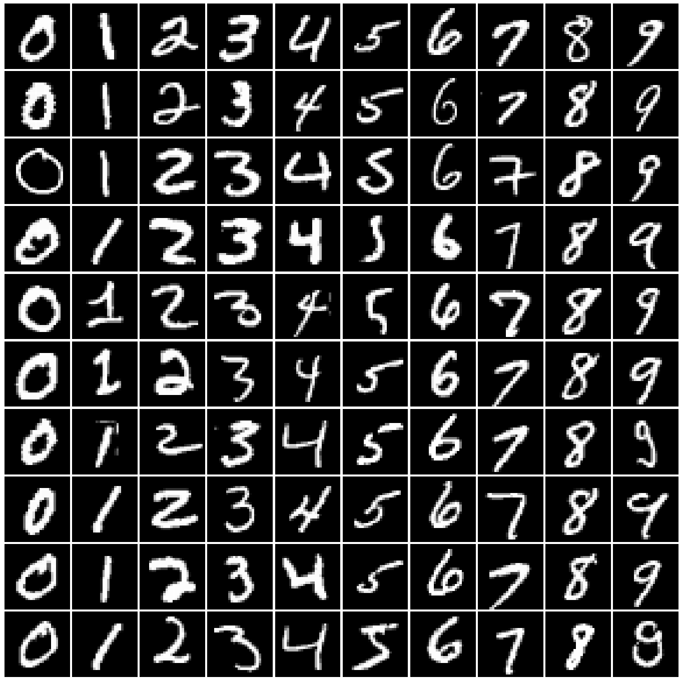
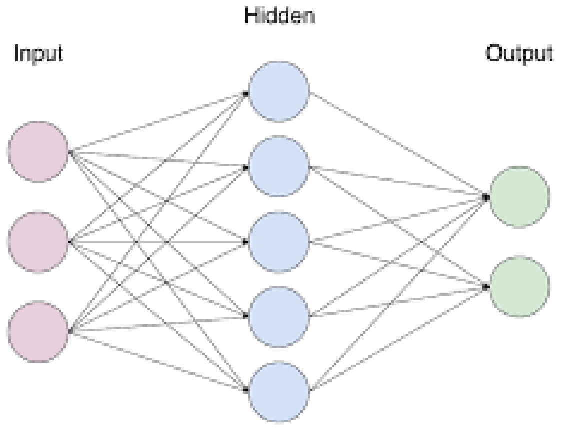
# “Backprops” (Neural Networks)

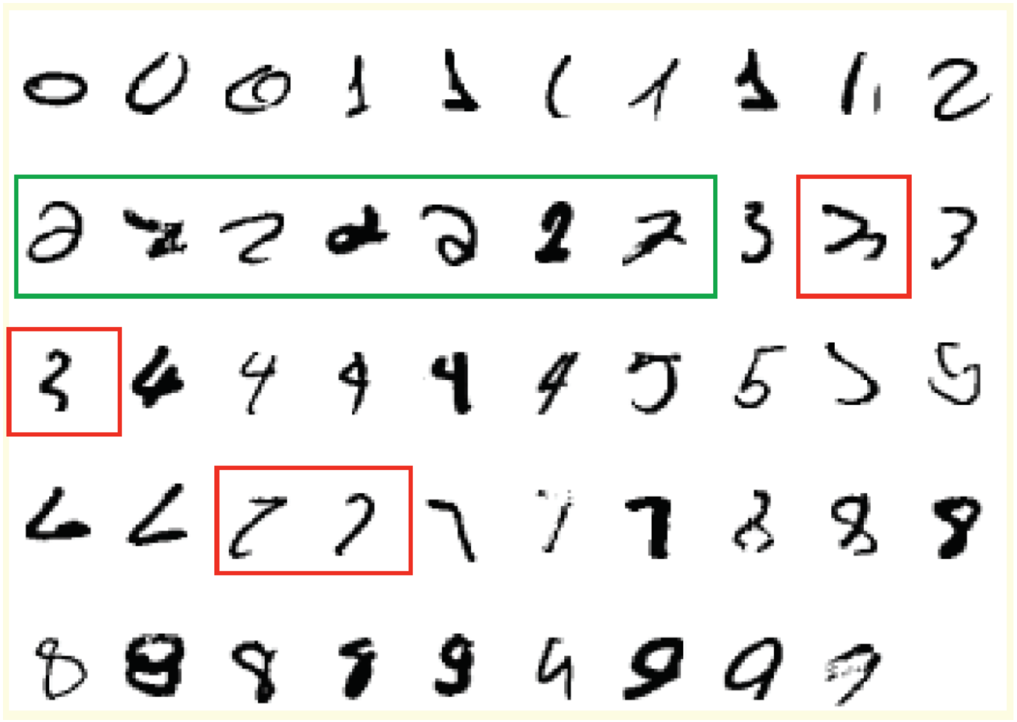




- Classify the numbers

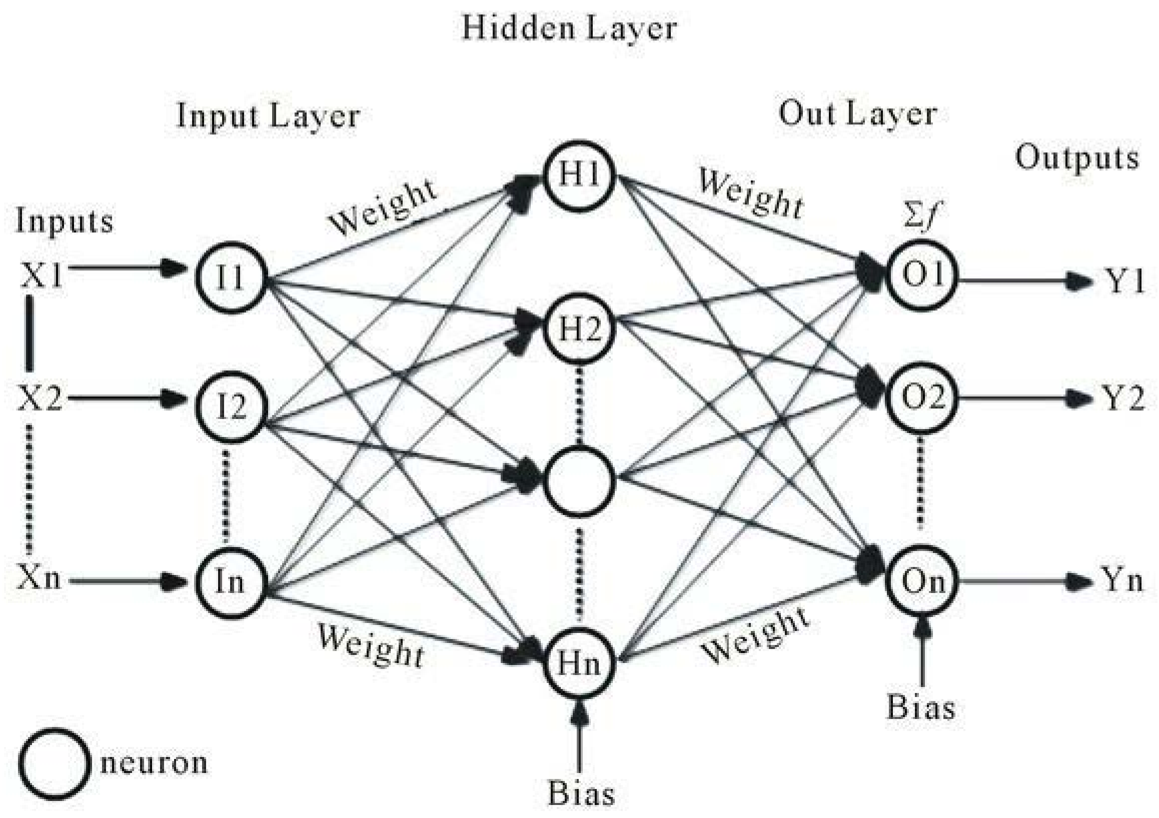
## Recognizing Numbers

- It is very hard to specify what makes a «2»



Source: Geoffrey Hinton, https://www.cs.toronto.edu/~tijmen/csc321/slides/lecture_slides_lec1.pdf

## Multi-layer Perceptrion



Source: David Fumo: https://towardsdatascience.com/a-gentle-introduction-to-neural-networks-series-part-1-2b90b87795bc

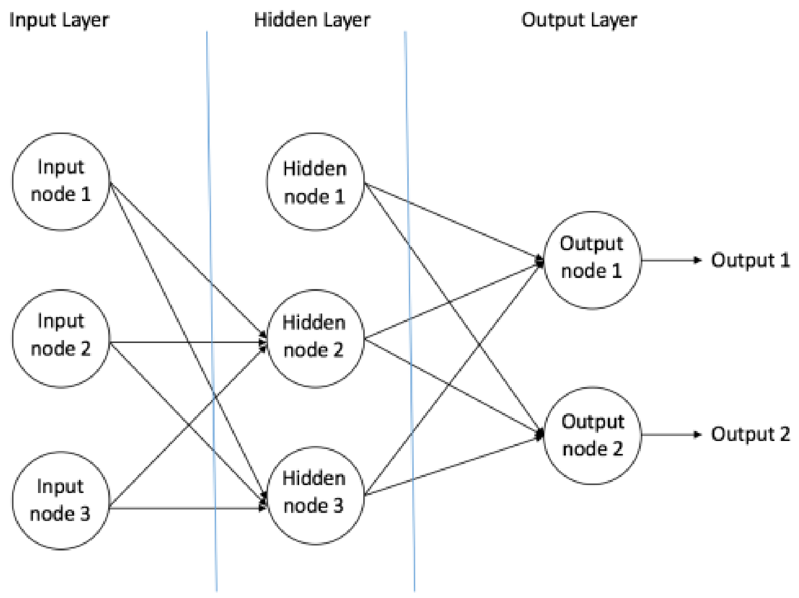
# Basic Concepts of Neural Networks

- **Input Nodes (input layer):** No computation is done here within this layer, they just pass the information to the next layer.
- **Output Nodes (output layer):** Here we finally use an activation function that maps to the desired output format.
- **Hidden nodes (hidden layer):** Hidden nodes transfer the weights from the input layer to the following layer (another hidden layer or to the output layer).
- **Connections and weights:** The *network* consists of connections, each connection transferring the output of a neuron i to the input of a neuron *j*. Each connection is assigned a weight *Wij.*
- **Activation function:** Defines the output of that node given an input or set of inputs. *Nonlinear* activation functions allows such networks to compute nontrivial problems using only a small number of nodes.
- **Learning rule:** The *learning rule* modifies weights and thresholds of the neural network, in order for a given input to the network to produce a favored output.

Source: David Fumo: https://towardsdatascience.com/a-gentle-introduction-to-neural-networks-series-part-1-2b90b87795bc

## Feedforward Network

- In a feedforward network, the information moves in only one direction – forward – from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network
- Two examples of feedforward networks are given below:
  - **Single Layer Perceptron** – This is the simplest feedforward neural network and does not contain any hidden layer.
  - **Multi Layer Perceptron** – A Multi Layer Perceptron has one or more hidden layers.



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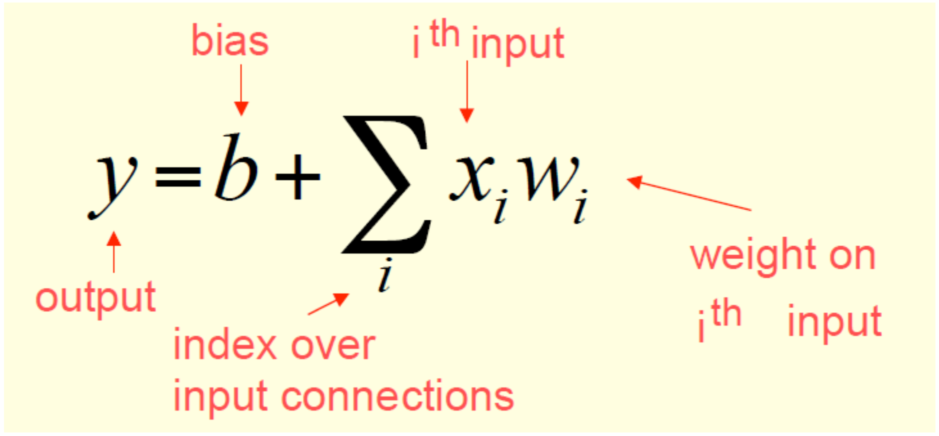
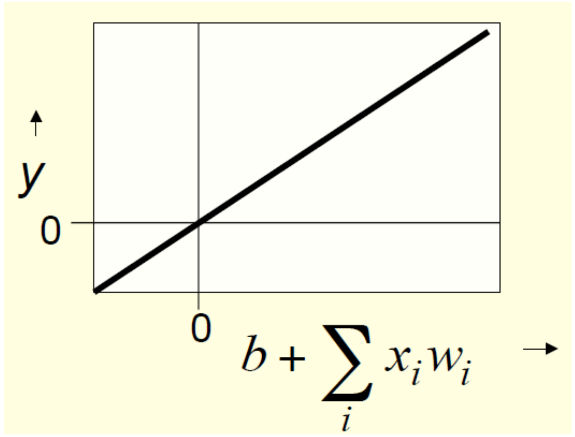
## Simple Type of Neuron: Linear Neuron

- Simple but computationally limited

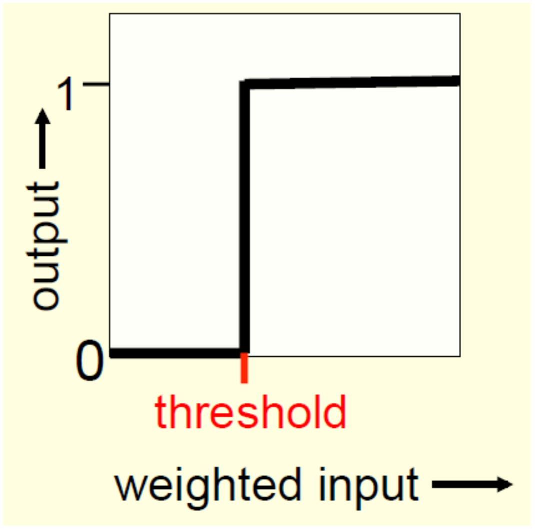




Source: Geoffrey Hinton, https://www.cs.toronto.edu/~tijmen/csc321/slides/lecture_slides_lec1.pdf

# Binary Threshold Neurons

- McCulloch-Pitts (1943)
  - First compute a weighted sum of the inputs.
  - Then send out a fixed size spike of activity if the weighted sum exceeds a threshold.
- There are two equivalent ways to write the equations for a binary threshold neuron:



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

$$\boxed{\theta = -b}$$

$$y = \begin{cases} 1 \text{ if } z \geq \theta \\ 0 \text{ otherwise} \end{cases} \qquad\qquad y = \begin{cases} 1 \text{ if } z \geq 0 \\ 0 \text{ otherwise} \end{cases}$$

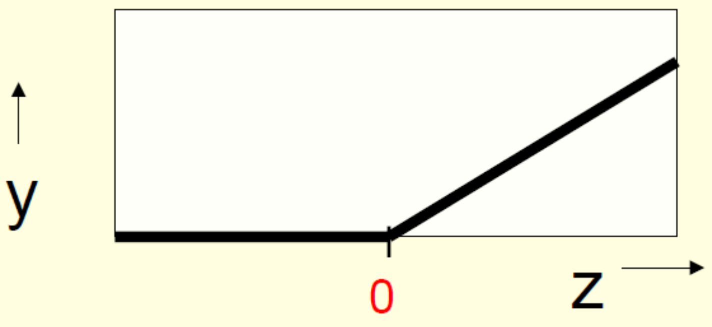
Source: Geoffrey Hinton, https://www.cs.toronto.edu/~tijmen/csc321/slides/lecture_slides_lec1.pdf

## Rectified Linear Neurons

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

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

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



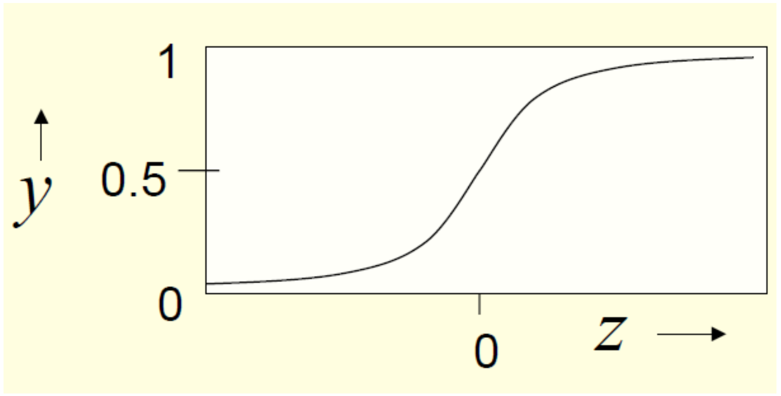
Source: Geoffrey Hinton, https://www.cs.toronto.edu/~tijmen/csc321/slides/lecture_slides_lec1.pdf

## Sigmoid Neuron

- These give a real-valued output that is a smooth and bounded function of their total input.
- – Typically they use the logistic function

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

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



Source: Geoffrey Hinton, https://www.cs.toronto.edu/~tijmen/csc321/slides/lecture_slides_lec1.pdf

## Learning: Backpropagation

- **Backward Propagation of Errors,** often abbreviated as BackProp is one of the several ways in which an artificial neural network (ANN) can be trained.
- It is a supervised training scheme, which means, it learns from labeled training data.
- To put in simple terms, BackProp is like "**learning from mistakes**". The supervisor ***corrects*** the ANN whenever it makes mistakes.

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## Backprop Algorithm

- Initially all the edge weights are randomly assigned.
- For every input in the training dataset, the ANN is activated and its output is observed. This output is compared with the desired output that we already know, and the error is "propagated" back to the previous layer. This error is noted and the weights are "adjusted" accordingly.
- This process is repeated until the output error is below a predetermined threshold.
- Once the above algorithm terminates, we have a "learned" ANN.

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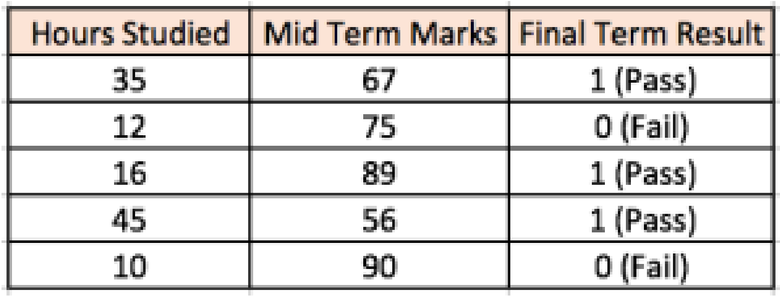
## Backprop Example (1)

- We want to learn the probability of a student to pass or fail an exam
- Training set:



| Hours Studied | Mid Term Marks | Final Term Result |
|---|---|---|
| 35 | 67 | 1 (Pass) |
| 12 | 75 | 0 (Fail) |
| 16 | 89 | 1 (Pass) |
| 45 | 56 | 1 (Pass) |
| 10 | 90 | 0 (Fail) |

- The two input columns show the number of hours the student has studied and the mid term marks obtained by the student. The Final Result column can have two values 1 or 0 indicating whether the student passed in the final term.

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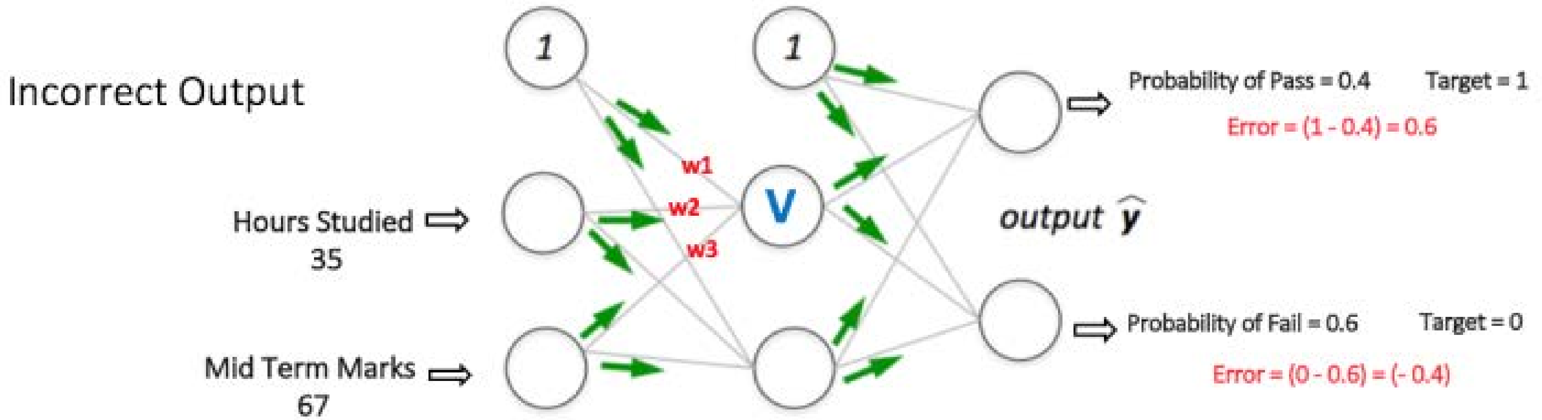
## Backprop Example (2)

- Step1: forward propagation step in a multi layer perceptron



In this example the calculated probabilities (0.4 and 0.6) are very far from the desired probabilities (1 and 0 respectively)

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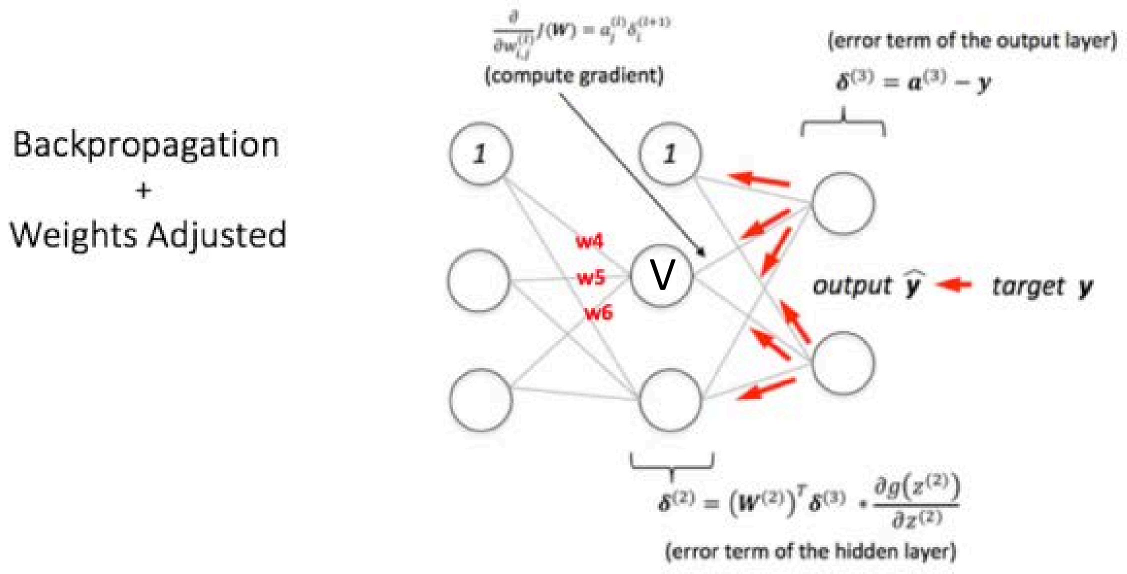
## Backprop Example (3)

- We calculate the total error at the output nodes and propagate these errors back through the network using Backpropagation (we ignore the mathematical equations in the figure for now).
- This leads to new weights w4, w5 and w6 for node V


Backpropagation
+
Weights Adjusted
$\frac{\partial}{\partial w_{i,j}^{(l)}} J(W) = a_j^{(l)} \delta_i^{(l+1)}$
(compute gradient)
(error term of the output layer)
$\delta^{(3)} = a^{(3)} - y$
1
1
w4
w5
w6
V
output $\hat{y}$
target $y$
$\delta^{(2)} = (W^{(2)})^T \delta^{(3)} \cdot \frac{\partial g(z^{(2)})}{\partial z^{(2)}}$
(error term of the hidden layer)

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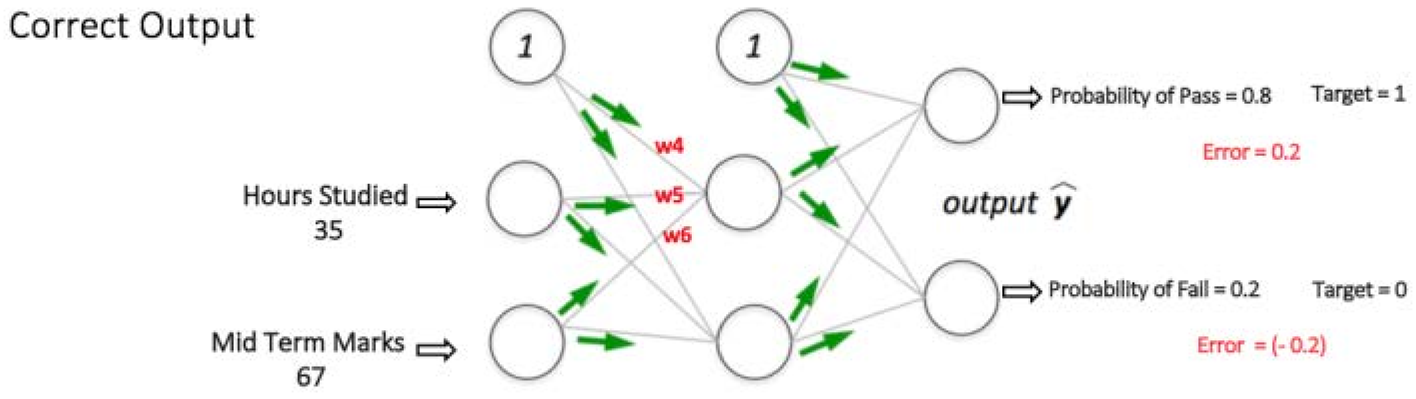
## Backprop Example (4)

- Using the same input data for the network with the adjusted weights leads to much better results



- This process is repeated with all other training data sets.
- When the network has *learnt* these examples, it can find the output probabilities for Pass and Fail also for new input data through the forward propagation step and.

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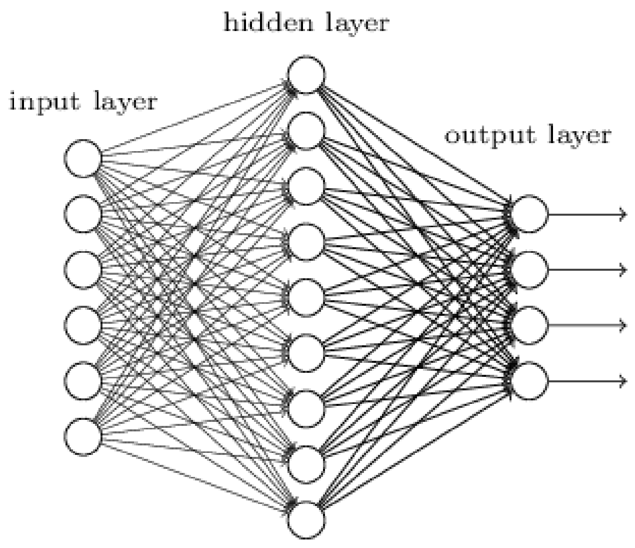
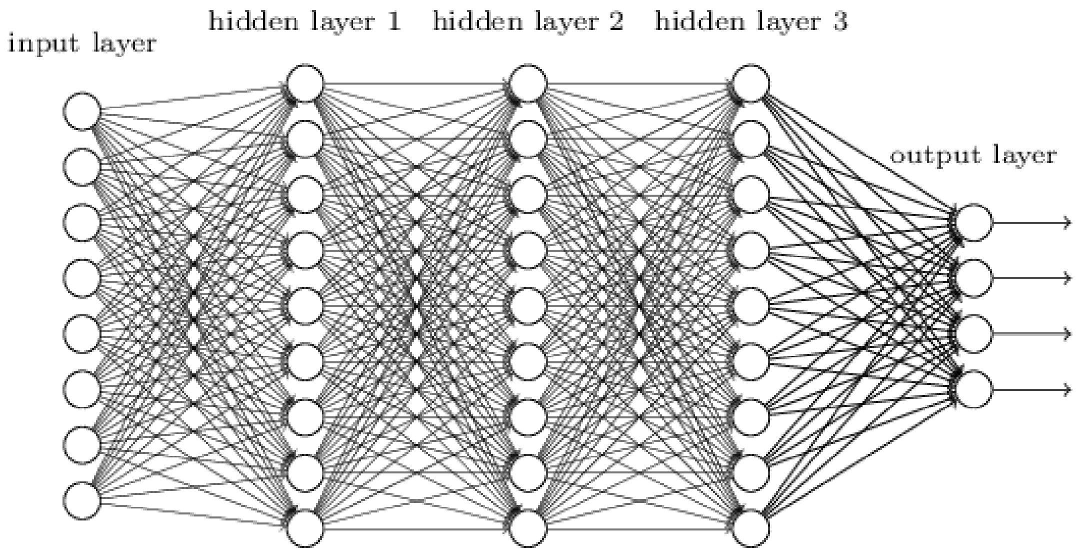
## Deep Neural Networks

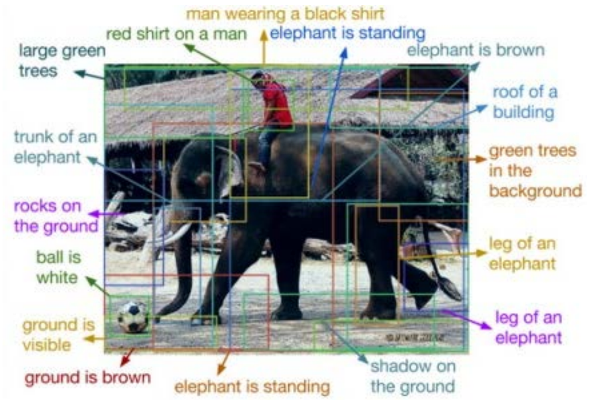
"Non-deep" feedforward neural network



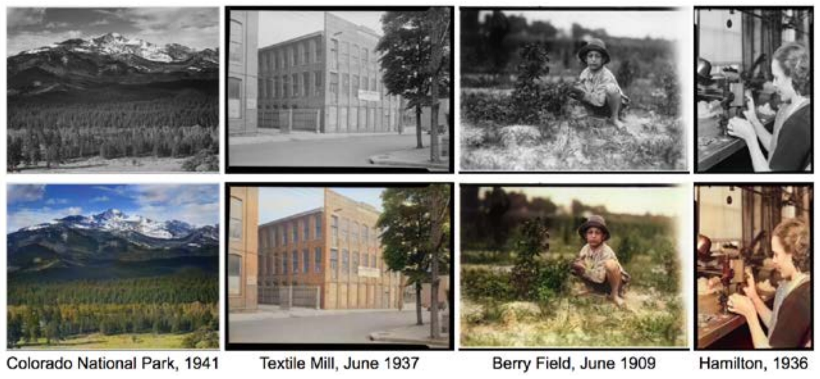
Deep neural network



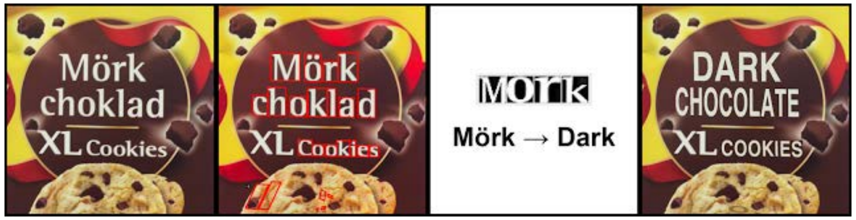
# Applications of Deep Learners



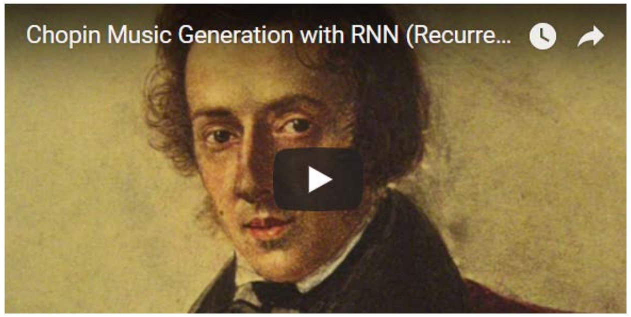
Describing photos



Picture coloring



Translation



Musik composition

Self-driving Cars

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