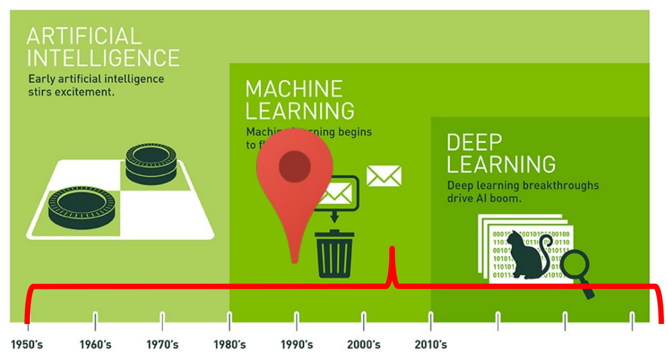
Artificial Intelligence: Introduction to Neural Networks

Perceptron, Backpropagation

Today

- Neural Networks
  - Perceptrons
  - Backpropagation



https://www.linkedin.com/pulse/goedels-incompleteness-theorem-emergence-ai-eberhard-schoeneburg/

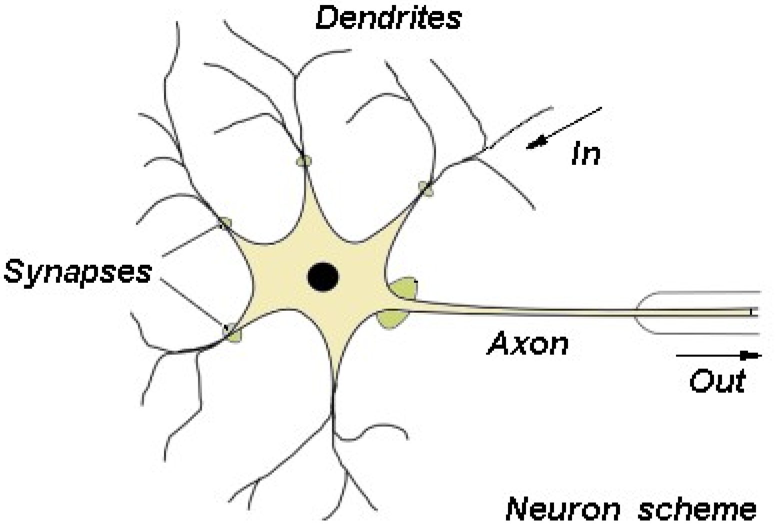
Neural Networks

- Radically different approach to reasoning and learning
- Inspired by biology
  - the neurons in the human brain
- Set of many simple processing units (neurons) connected together
- Behavior of each neuron is very simple
  - but a collection of neurons can have sophisticated behavior and can be used for complex tasks
- In a neural network, the behavior depends on weights on the connection between the neurons
- The weights will be learned given training data

Biological Neurons

- Human brain =
  - 100 billion neurons
  - each neuron may be connected to 10,000 other neurons
  - passing signals to each other via 1,000 trillion **synapses**

- A neuron is made of:
  - Dendrites: filaments that provide input to the neuron
  - Axon: sends an output signal
  - Synapses: connection with other neurons – releases neurotransmitters to other neurons



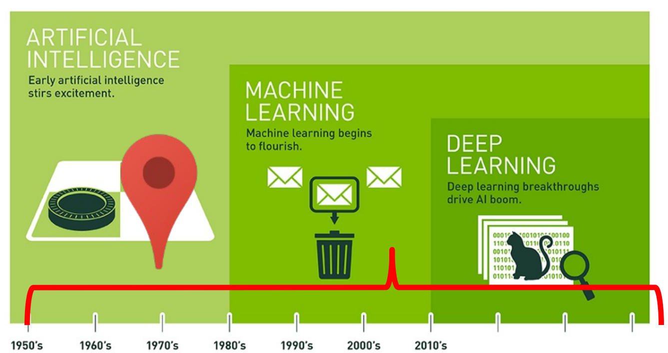
Source: http://www.human-memory.net/brain_neurons.html

Behavior of a Neuron

- A neuron receives inputs from its neighbors
- If enough inputs are received at the same time:
  - the neuron is activated
  - and fires an output to its neighbors
- Repeated firings across a synapse increases its sensitivity and the future likelihood of its firing
- If a particular stimulus repeatedly causes activity in a group of neurons, they become strongly associated

Today

- Neural Netwo
  - Perceptrons
  - Backpropagation



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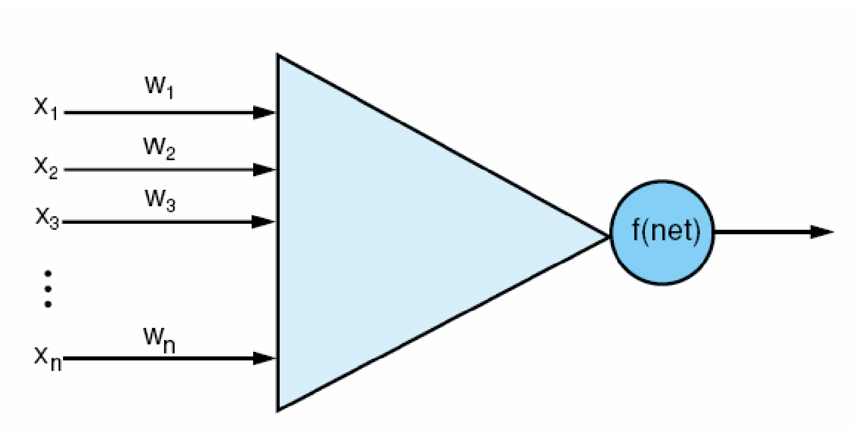
A Perceptron

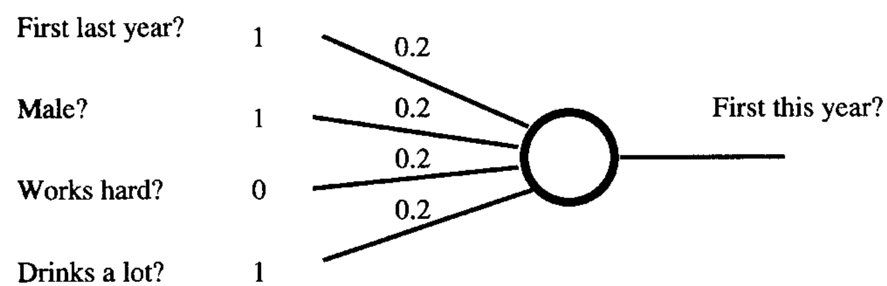


- A <u>single</u> computational neuron (no network yet…)
- Input:
  - input signals x_i
  - weights w_i for each feature x_i
    - represents the strength of the connection with the neighboring neurons
- Output:
  - if sum of input weights >= some threshold, neuron fires (output=1)
  - otherwise output = 0
    - If $(w_1 x_1 + \ldots + w_n x_n) >= t$
    - Then output = 1
    - Else output = 0
- Learning :
  - use the training data to adjust the weights in the percetron

source: Luger (2005)

The Idea

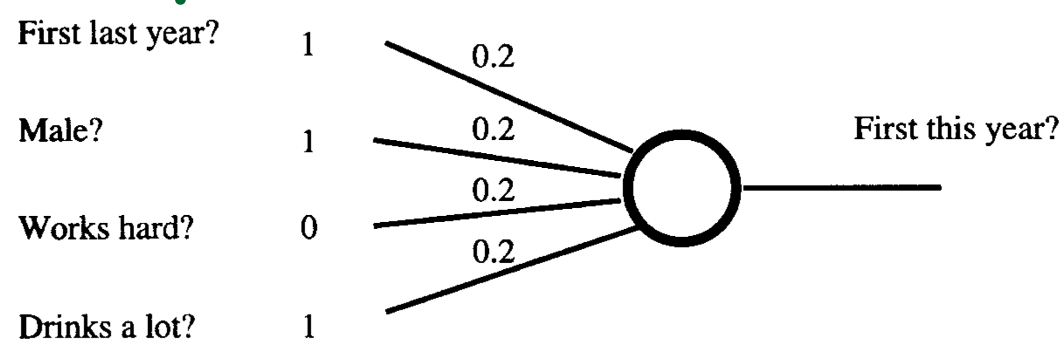
	Features (x_i)				Output
Student	First last year?	Male?	Works hard?	Drinks ?	**First this year?**
Richard	Yes	Yes	No	Yes	**No**
Alan	Yes	Yes	Yes	No	**Yes**
...					



1. Step 1: Set weights to random values
2. Step 2: Feed perceptron with a set of inputs
3. Step 3: Compute the network outputs
4. Step 4: Adjust the weights
    1. if output correct → weights stay the same
    2. if output = 0 but it should be 1 →
        1. *increase* weights on *active* connections (i.e. input x_i =1)
    3. if output = 1 but should be 0 →
        1. *decrease* weights on *active* connections (i.e. input x_i =1)
5. Step 5: Repeat steps 2 to 4 a large number of times until the network converges to the right results for the given training examples

source: Cawsey (1998)

A Simple Example



- Each feature (works hard, male, ...) is an x_i
  - if $x_1 = 1$, then student got an A last year,
  - if $x_1 = 0$, then student did not get an A last year,
  - ...
- Initially, set all weights to random values (all 0.2 here)
- Assume:
  - threshold = 0.55
  - constant learning rate = 0.05

source: Cawsey (1998)

A Simple Example (2)

	Features (x_i)				Output
Student	'A' last year?	Male?	Works hard?	Drinks?	**'A' this year?**
Richard	Yes	Yes	No	Yes	**No**
Alan	Yes	Yes	Yes	No	**Yes**
Alison	No	No	Yes	No	**No**
Jeff	No	Yes	No	Yes	**No**
Gail	Yes	No	Yes	Yes	**Yes**
Simon	No	Yes	Yes	Yes	**No**

- Richard:
  - → **Worksheet #5 ("Perceptron")**

A Simple Example (3)

	Features (x_i)				Output
Student	'A' last year?	Male?	Works hard?	Drinks?	**'A' this year?**
Richard	Yes	Yes	No	Yes	**No**
Alan	Yes	Yes	Yes	No	**Yes**
Alison	No	No	Yes	No	**No**
Jeff	No	Yes	No	Yes	**No**
Gail	Yes	No	Yes	Yes	**Yes**
Simon	No	Yes	Yes	Yes	**No**

- Alan:
  - → **Worksheet #5 ("Perceptron Learning")**
- After 2 iterations over the training set (2 epochs), we get:
  - w_1= 0.25 w_2= 0.1 w_3= 0.2 w_4= 0.1

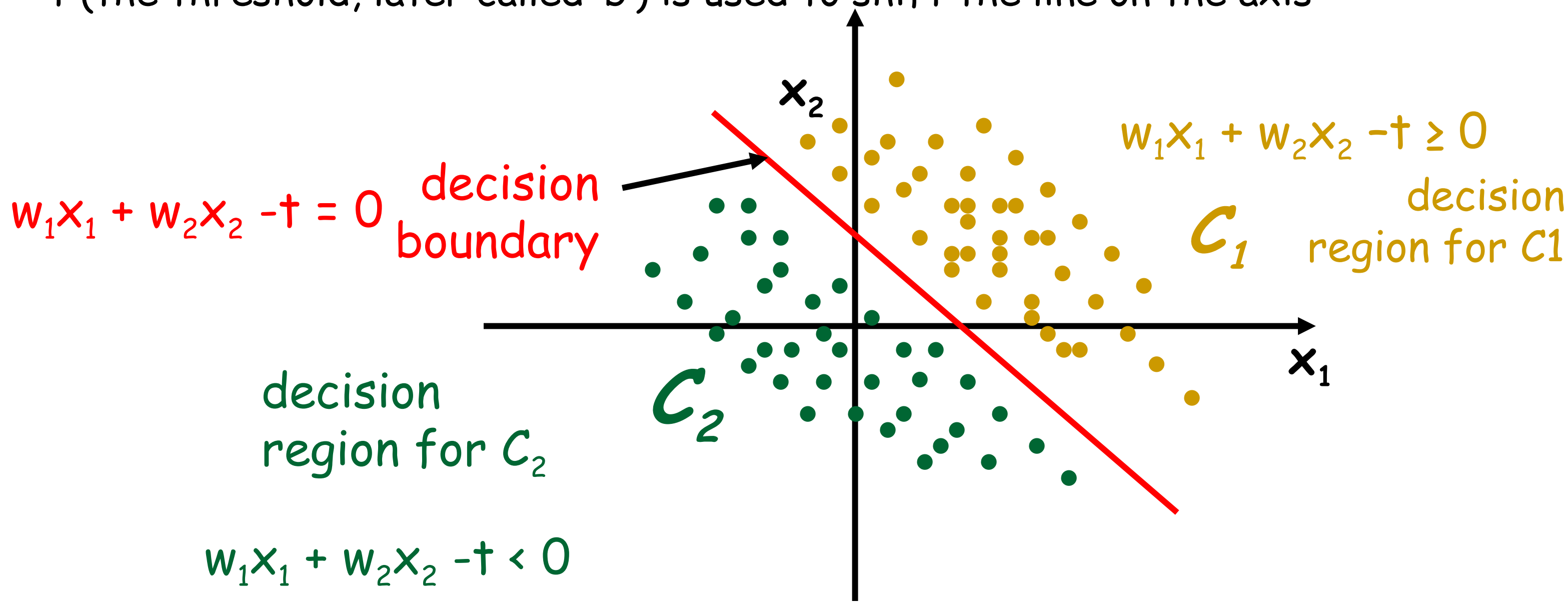
A Simple Example (3)

	Features (x_i)				Output
Student	'A' last year?	Male?	Works hard?	Drinks?	**'A' this year?**
Richard	Yes	Yes	No	Yes	**No**
Alan	Yes	Yes	Yes	No	**Yes**
Alison	No	No	Yes	No	**No**
Jeff	No	Yes	No	Yes	**No**
Gail	Yes	No	Yes	Yes	**Yes**
Simon	No	Yes	Yes	Yes	**No**

- Let's check… (w_1= 0.2 w_2= 0.1 w_3= 0.25 w_4= 0.1)
  - Richard: $(1\times0.2) + (1\times0.1) + (0\times0.25) + (1\times0.1) = 0.4 < 0.55$ -> output is 0 ✓
  - Alan: $(1\times0.2) + (1\times0.1) + (1\times0.25) + (0\times0.1) = 0.55 \geq 0.55$ -> output is 1 ✓
  - Alison: $(0\times0.2) + (0\times0.1) + (1\times0.25) + (0\times0.1) = 0.25 < 0.55$ -> output is 0 ✓
  - Jeff: $(0\times0.2) + (1\times0.1) + (0\times0.25) + (1\times0.1) = 0.2 < 0.55$ -> output is 0 ✓
  - Gail: $(1\times0.2) + (0\times0.1) + (1\times0.25) + (1\times0.1) = 0.55 \geq 0.55$ -> output is 1 ✓
  - Simon: $(0\times0.2) + (1\times0.1) + (1\times0.25) + (1\times0.1) = 0.45 < 0.55$ -> output is 0 ✓

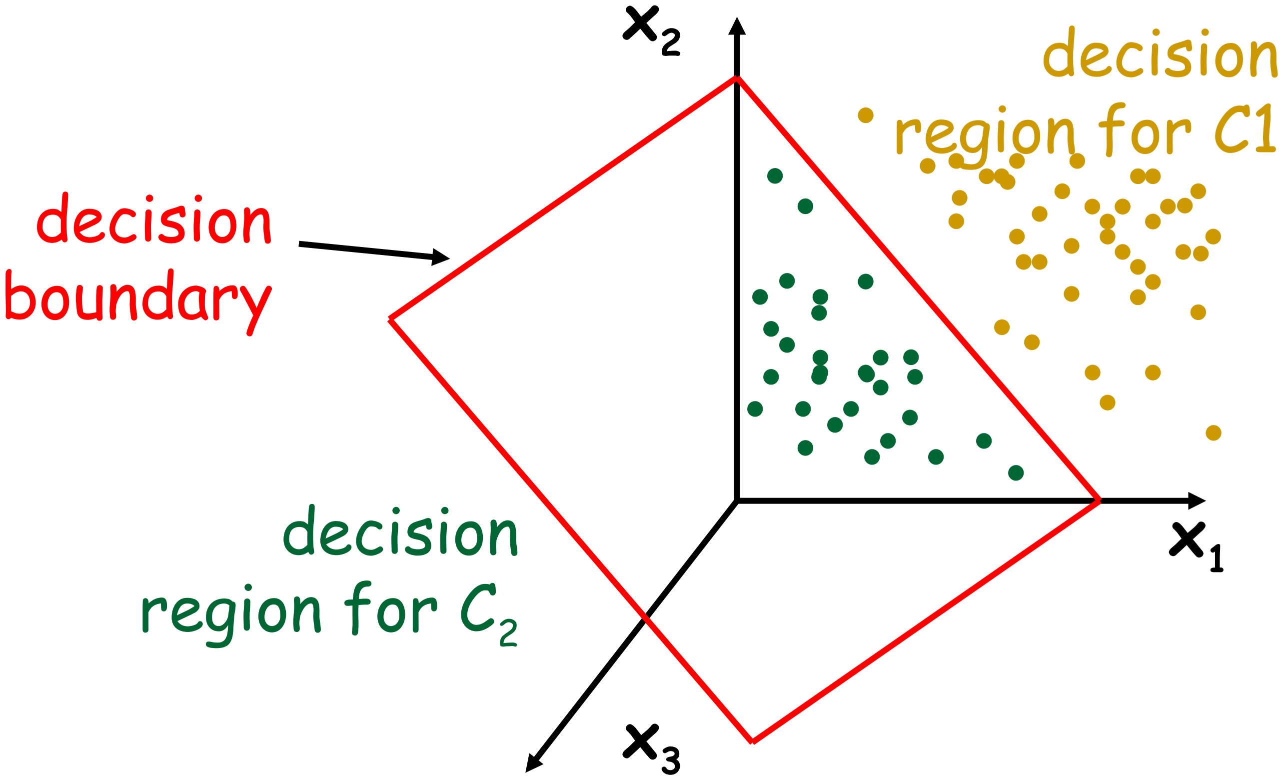
Decision Boundaries of Perceptrons

- So we have just learned the function:
  - If ($0.2x_1 + 0.1x_2 + 0.25x_3 + 0.1x_4 \geq 0.55$) then 1 otherwise 0
  - If ($0.2x_1 + 0.1x_2 + 0.25x_3 + 0.1x_4 - 0.55 \geq 0$) then 1 otherwise 0
- Assume we only had 2 features:
  - If ($w_1x_1 + w_2x_2 - t >= 0$) then 1 otherwise 0
  - The learned function describes a line in the input space
  - This line is used to separate the two classes C1 and C2
  - t (the threshold, later called 'b') is used to shift the line on the axis



Decision Boundaries of Perceptrons

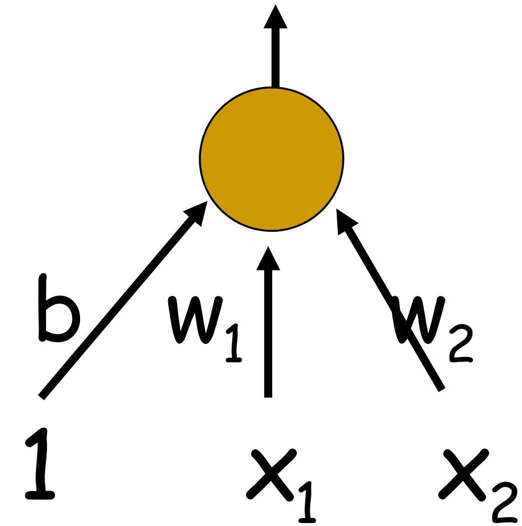
- More generally, with n features, the learned function describes a hyperplane in the input space.



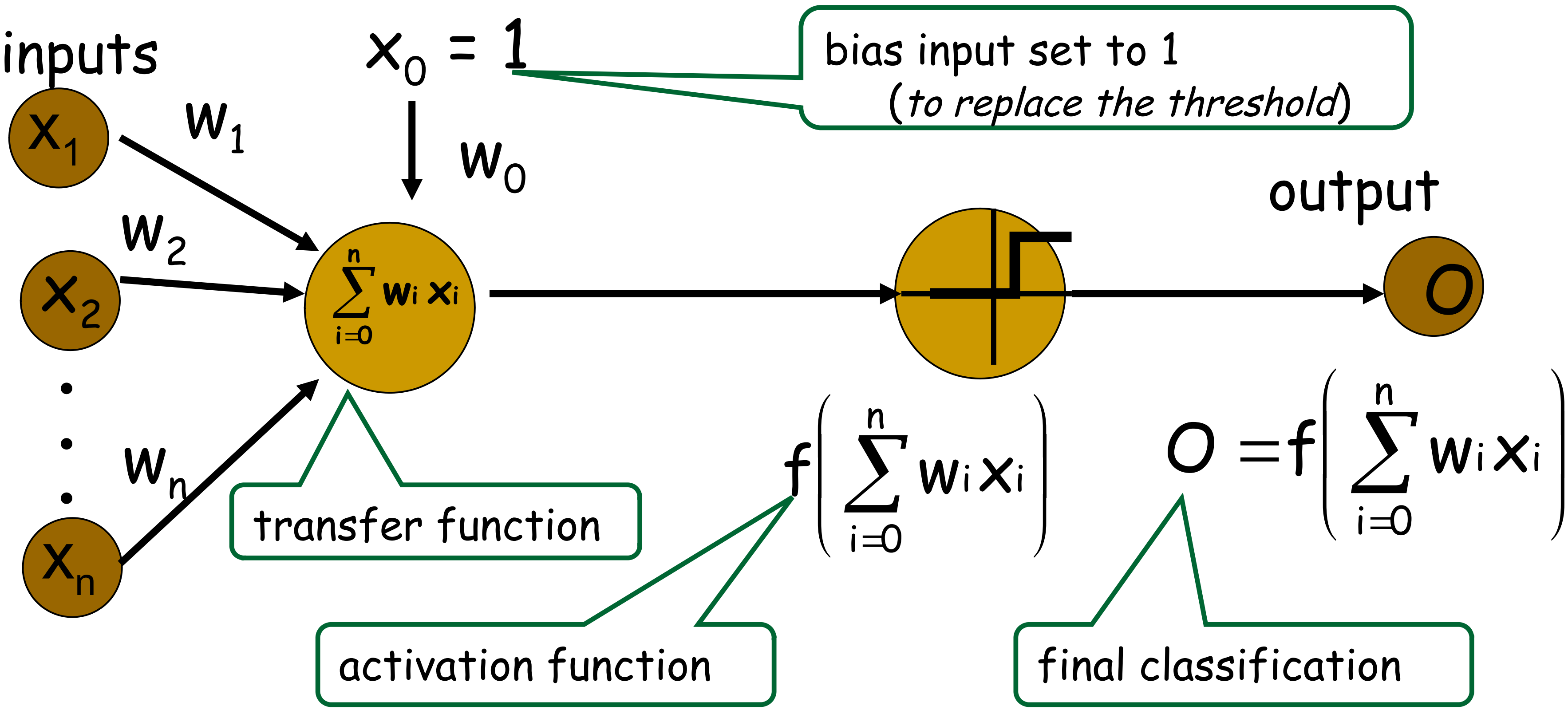
Adding a Bias

- We can avoid having to figure out the threshold by using a "bias"
- A bias is equivalent to a weight on an extra input feature that always has a value of 1.

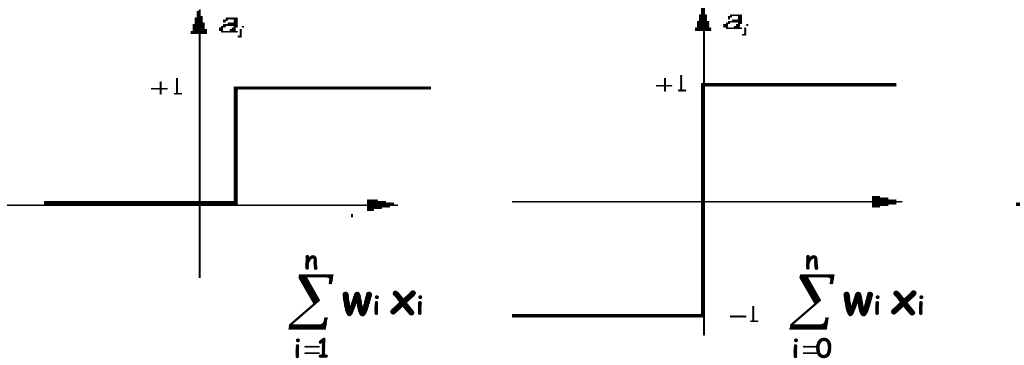
$$b + \sum_i x_i w_i$$



Perceptron - More Generally



Common Activation Functions



(a) Step function (b) Sign function

- Hard Limit activation functions:
  - step $O = \begin{cases} 1 & \text{if } \left(\sum_{i=1}^{n} w_i x_i \right) \geq t \\ 0 & \text{otherwise} \end{cases}$
  - sign $O = \begin{cases} +1 & \text{if } \left(\sum_{i=0}^{n} w_i x_i \right) \geq 0 \\ -1 & \text{otherwise} \end{cases}$

[Russell & Norvig, 1995]

Learning Rate

1. Learning rate can be a constant value (as in the previous example)

$$\Delta w = \eta(T - O)$$

learning rate

Error = target output – actual output

- So:
  - if T=zero and O=1 (i.e. a false positive) -> decrease w by η
  - if T=1 and O=zero (i.e. a false negative) -> increase w by η
  - if T=O (i.e. no error) -> don't change w

2. Or, a fraction of the input feature x_i

$$\Delta w_i = \eta(T - O)\, x_i$$

value of input feature x_i

- So the update is proportional to the value of x
  - if T=zero and O=1 (i.e. a false positive) -> decrease w_i by ηx_i
  - if T=1 and O=zero (i.e. a false negative) -> increase w_i by ηx_i
  - if T=O (i.e. no error) -> don't change w_i
- This is called the delta rule or perceptron learning rule

Perceptron Convergence Theorem

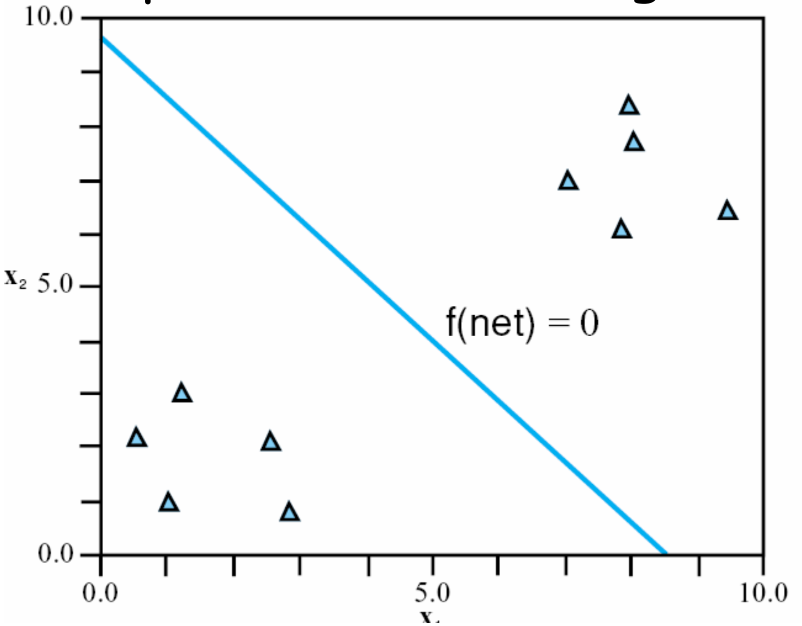
- Cycle through the set of training examples.
- Suppose a solution with zero error exists.
- The delta rule will find a solution in finite time.

Example of the Delta Rule

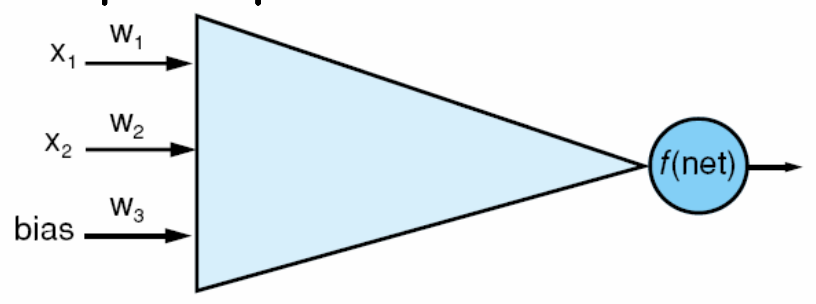
- training data:

x_1	x_2	Output
1.0	1.0	1
9.4	6.4	–1
2.5	2.1	1
8.0	7.7	–1
0.5	2.2	1
7.9	8.4	–1
7.0	7.0	–1
2.8	0.8	1
1.2	3.0	1
7.8	6.1	–1

- plot of the training data:



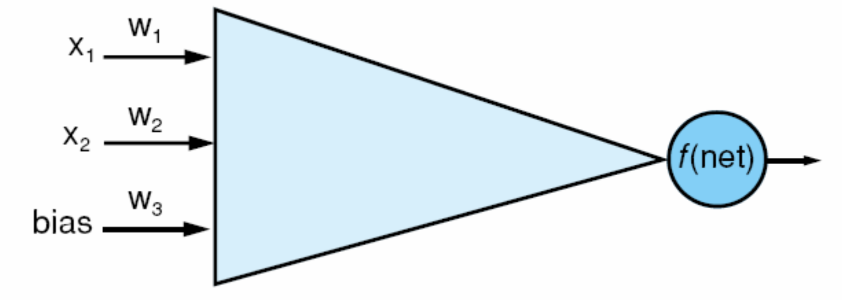
- perceptron



source: Luger (2005)

Let's Train the Perceptron

- assume random initialization
  - w1 = 0.75
  - w2 = 0.5
  - w3 = -0.6



- Assume:
  - sign function (threshold = 0)
  - learning rate η = 0.2

source: Luger (2005)

Training

x_1	x_2	Output
1.0	1.0	1
9.4	6.4	−1
2.5	2.1	1
8.0	7.7	−1
0.5	2.2	1

- data #1:
- data #2:
- data #3:
- ...
- **→ Worksheet #5 ("Delta Rule")**

- repeat… over 500 iterations, we converge to:
  $w_1 = -1.3$ $w_2 = -1.1$ $w_3 = 10.9$

source: Luger (2005)

Remember this slide?

History of AI

- Reality hits (late 60s - early 70s)
  - 1966: the ALPAC report kills work in machine translation (and NLP in general)
  - People realized that scaling up from micro-worlds (toy-worlds) to reality is not just a manner of faster machines and larger memories…
  - Minsky & Papert's paper on the limits of perceptrons (cannot learn just any function…) kills work in neural networks
  - in 1971, the British government stops funding research in AI due to no significant results
  - it's the first major *AI Winter…*

https://www.vectorstock.com/royalty-free-vector/freezing-snowman-vector-689086

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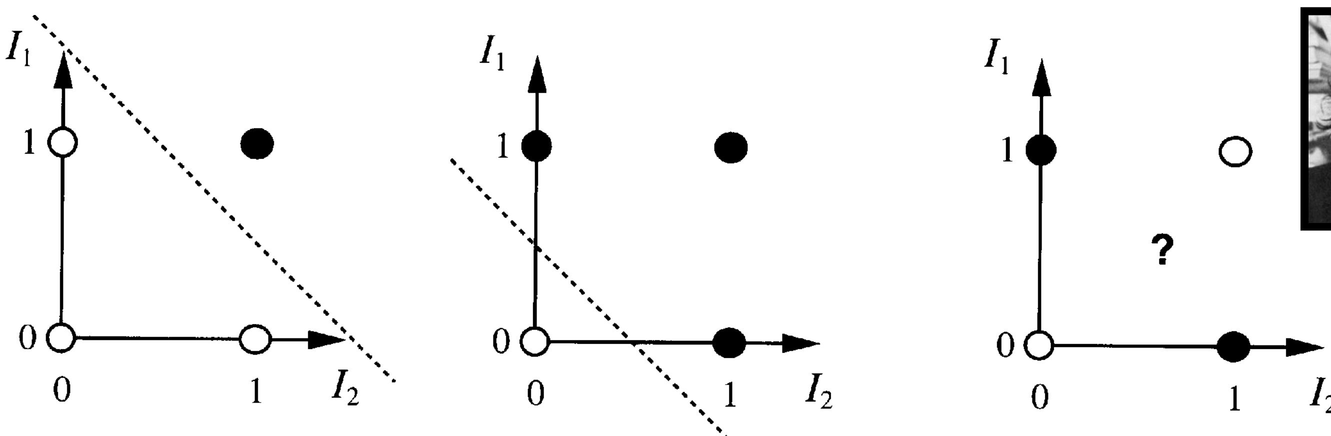
Limits of the Perceptron

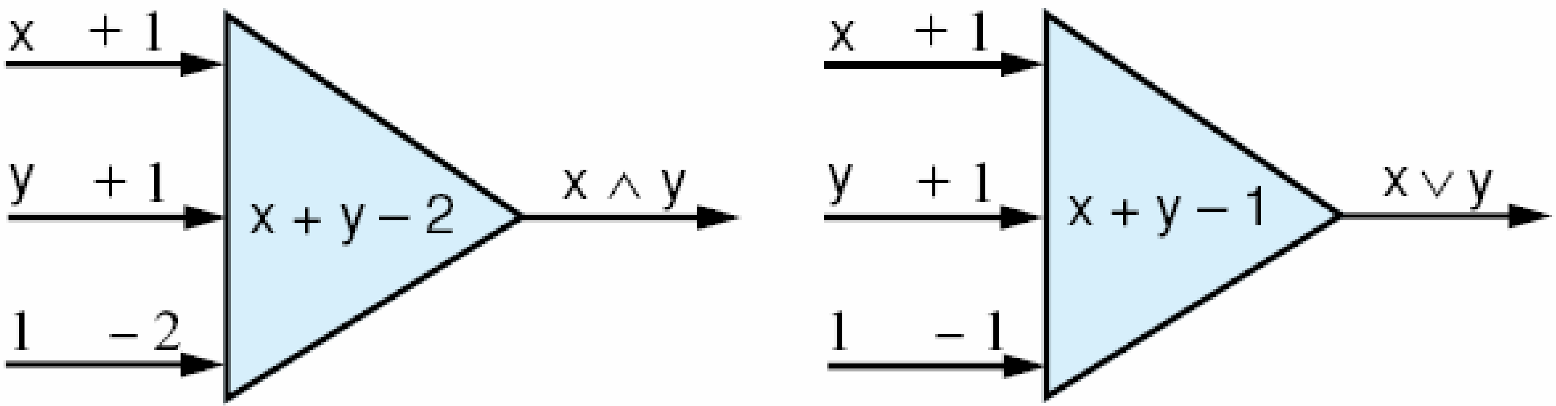
- In 1969, Minsky and Papert showed formally what functions could and could not be represented by perceptrons
- Only linearly separable functions can be represented by a perceptron



(a) I_1 and I_2 (b) I_1 or I_2 (c) I_1 xor I_2

source: Luger (2005)

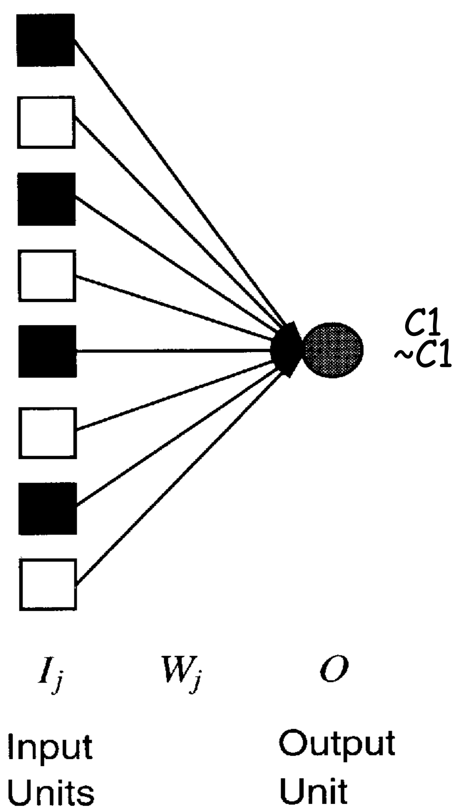
AND and OR Perceptrons



x	y	x + y − 2	Output
1	1	0	1
1	0	−1	−1
0	1	−1	−1
0	0	−2	−1

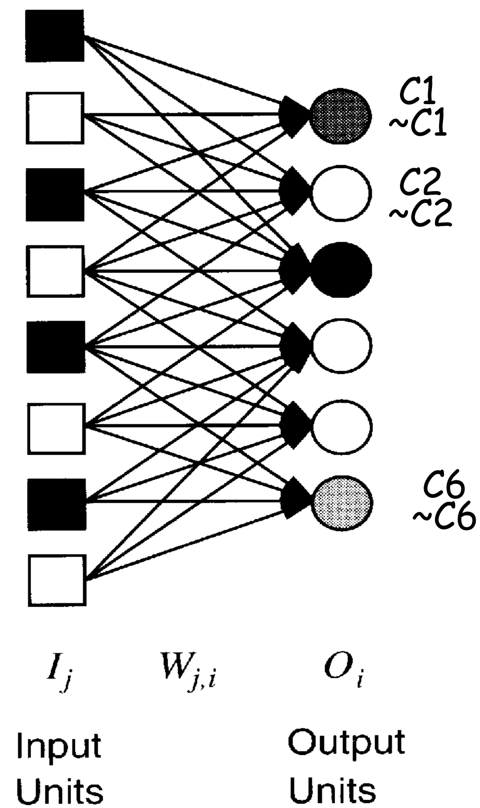
source: Luger (2005)

A Perceptron Network



Single Perceptron

- So far, we looked at a single perceptron
- But if the output needs to learn more than a binary (yes/no) decision
- Ex: learning to recognize digit --> 10 possible outputs --> need a perceptron network



Perceptron Network

Example: the XOR Function

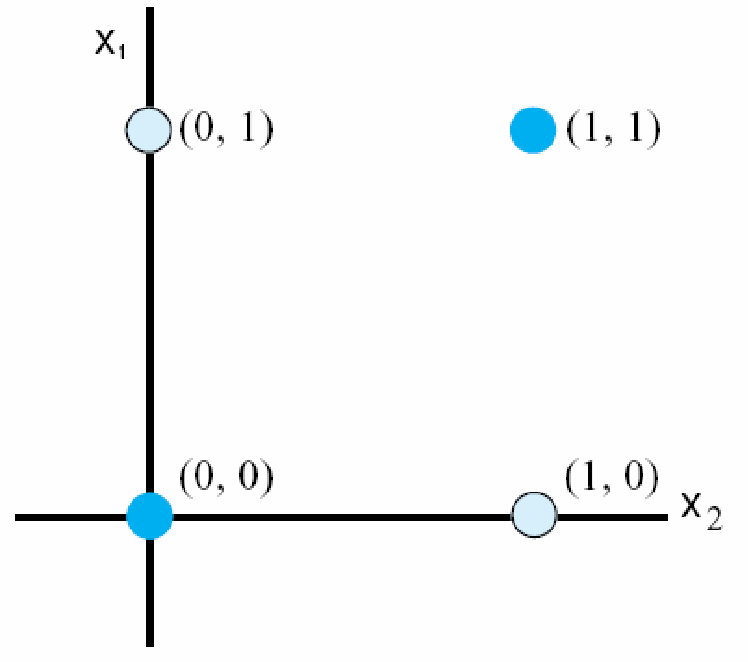
- We cannot build a perceptron to learn the exclusive-or function
- To learn the XOR function, with:
  - two inputs x_1 and x_2
  - two weights w_1 and w_2
  - A threshold t

x1	x2	Output
1	1	0
1	0	1
0	1	1
0	0	0

- i.e. must have:
  - $(1 \times w_1) + (1 \times w_2) < t$ (for the first line of truth table)
  - $(1 \times w_1) + 0 >= t$
  - $0 + (1 \times w_2) >= t$
  - $0 + 0 < t$
- Which has no solution… so a perceptron cannot learn the XOR function

The XOR Function - Visually

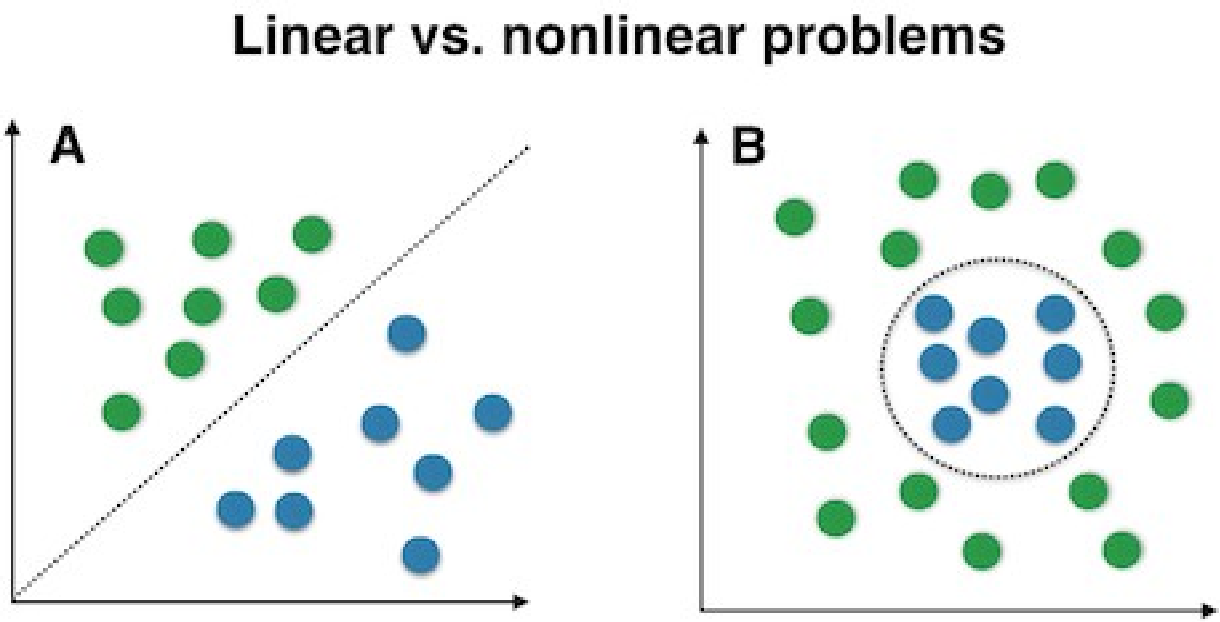
- In a 2-dimentional space (2 features for the X)
- No straight line in two-dimensions can separate
  - (0, 1) and (1, 0) from
  - (0, 0) and (1, 1).



source: Luger (2005)

Non-Linearly Separable Functions

- Real-world problems cannot always be represented by linearly-separable functions…



- This caused a decrease in interest in neural networks in the 1970's

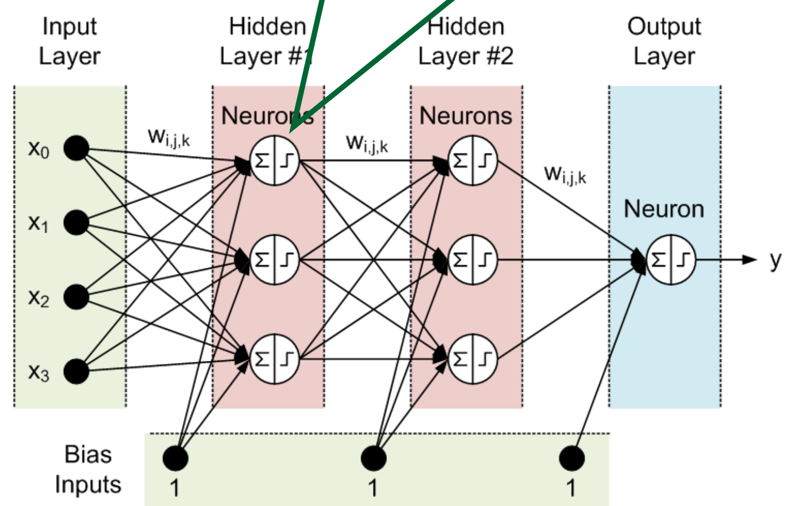
http://sebastianraschka.com/Articles/2014_kernel_pca.html

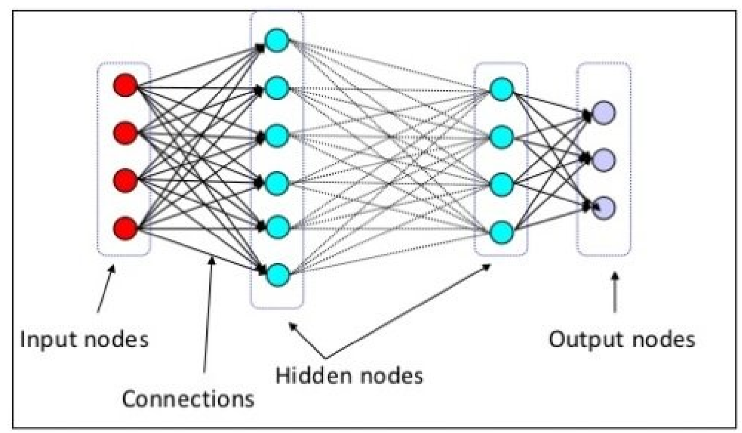
Multilayer Neural Networks

- Solution:

1. to learn more complex functions (more complex decision boundaries), have hidden nodes
2. and for non-binary decisions, have multiple output nodes
3. use a non-linear activation function

Non-linear, differentiable function



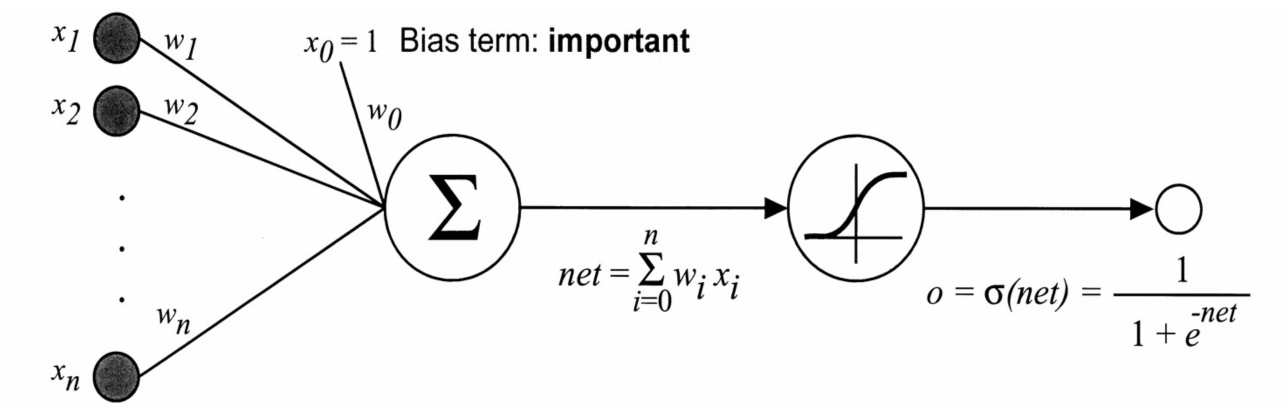


http://www.kdnuggets.com/2016/10/deep-learning-key-terms-explained.html

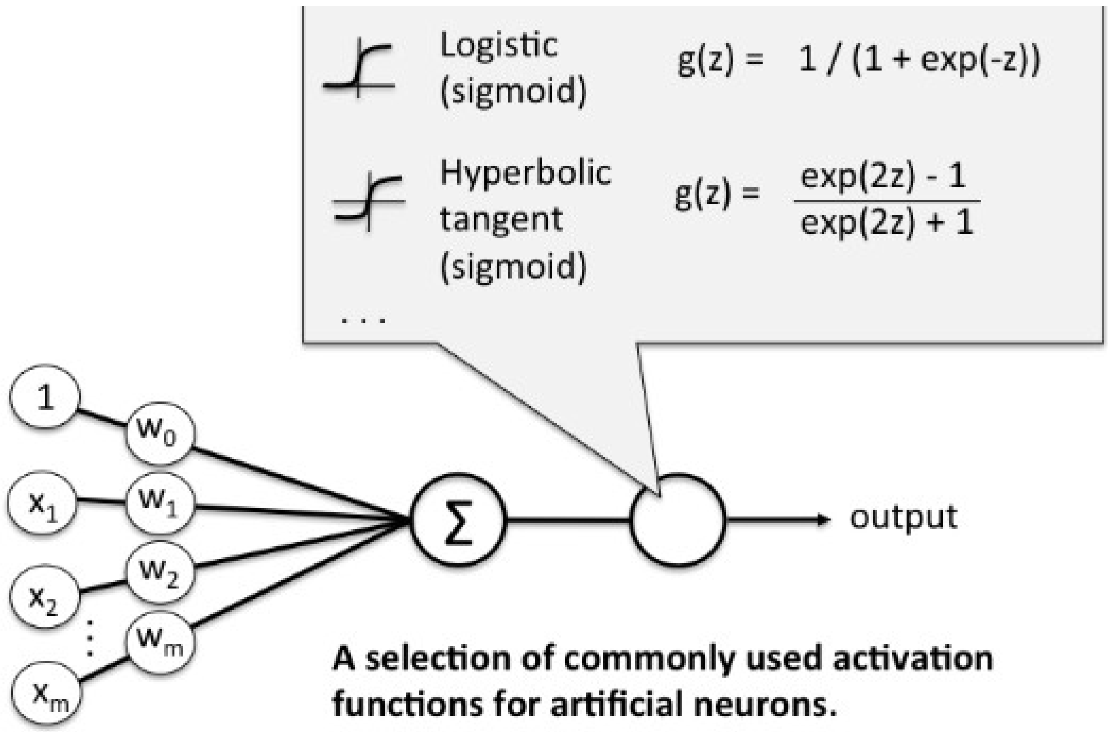
The Sigmoid Function

- Backpropagation requires a differentiable activation function
- sigmoidal (or squashed or logistic) function

- f returns a value *between* 0 and 1 (instead of 0 or 1)
- f indicates how close/how far the output of the network is compared to the right answer (the *error term*)



Typical Activation Functions



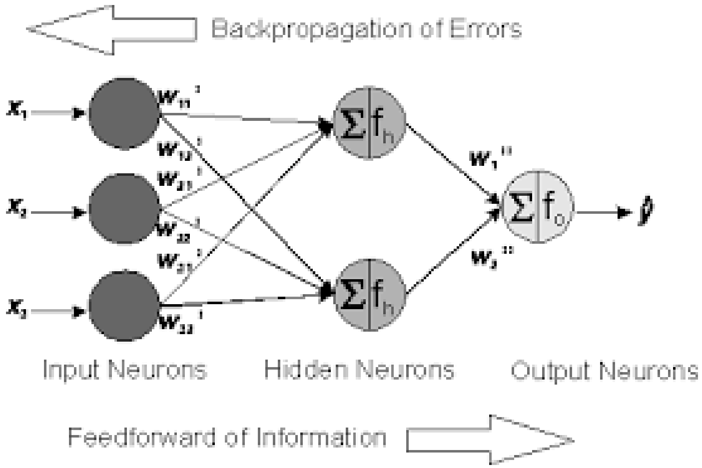
https://medium.com/towards-data-science/activation-functions-and-its-types-which-is-better-a9a5310cc8f

Learning in a Neural Network

- Learning is the same as in a perceptron:
  - feed network with training data
  - if there is an error (a difference between the output and the target), adjust the weights
- So we must assess the blame for an error to the contributing weights

Feed-forward + Backpropagation

- Feed-forward:
  - Input from the features is fed forward in the network from input layer towards the output layer



- Backpropagation:
  - Error rate flows backwards from the output layer to the input layer (to adjust the weights in order to minimize the output error)
- Iterate until error rate is minimized
  - repeat the forward pass and back pass for the next data points until all data points are examined (1 epoch)
  - repeat this entire exercise (several epochs) until the overall error is minimised
  - Eg: MSR = mean squared errors $= \frac{1}{2} \frac{\sum_{i=1}^{n}(T_i - O_i)^2}{n} < \varepsilon$

where ε ~ 0.0001 and
n = nb of training examples

Backpropagation

- In a multilayer network…
  - Computing the error in the output layer is clear.
  - Computing the error in the hidden layer is not clear, because we don't know what its output should be

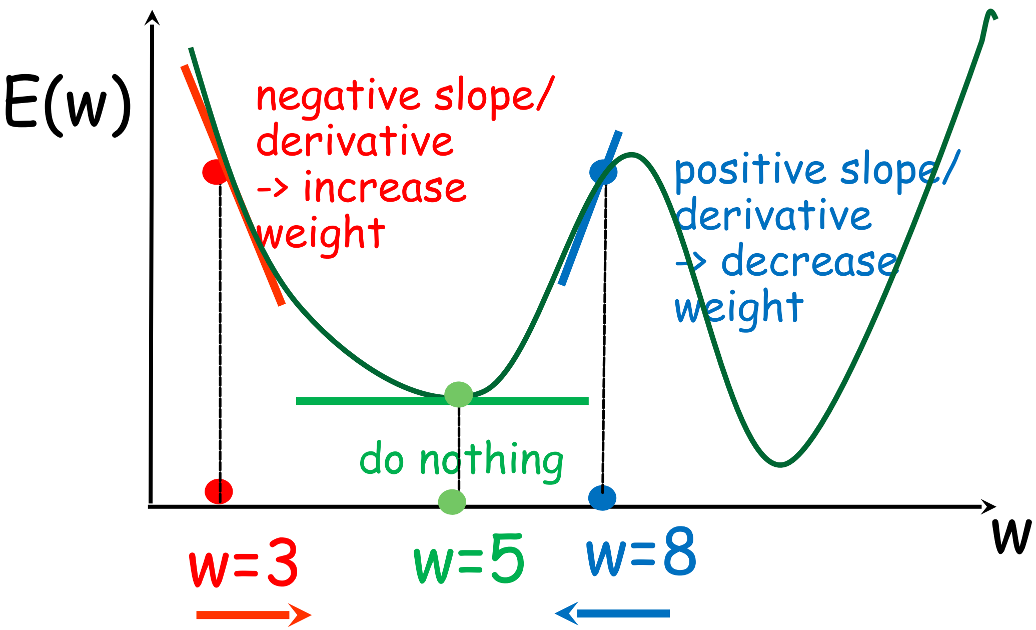
- Intuitively:
  - A hidden node h is "responsible" for some fraction of the error in each of the output node to which it connects.

  - So the error values (δ):
    - are divided according to the weight of their connection between the hidden node and the output node
    - and are propagated back to provide the error values (δ) for the hidden layer.

Gradients

Gradient is just derivative in 1D

Ex: $E(w) = (w-5)^2$ derivative is: $\frac{\partial}{\partial w} E = 2(w-5)$



If w=3 $\frac{\partial}{\partial w} E(3) = 2(3-5) = -4$

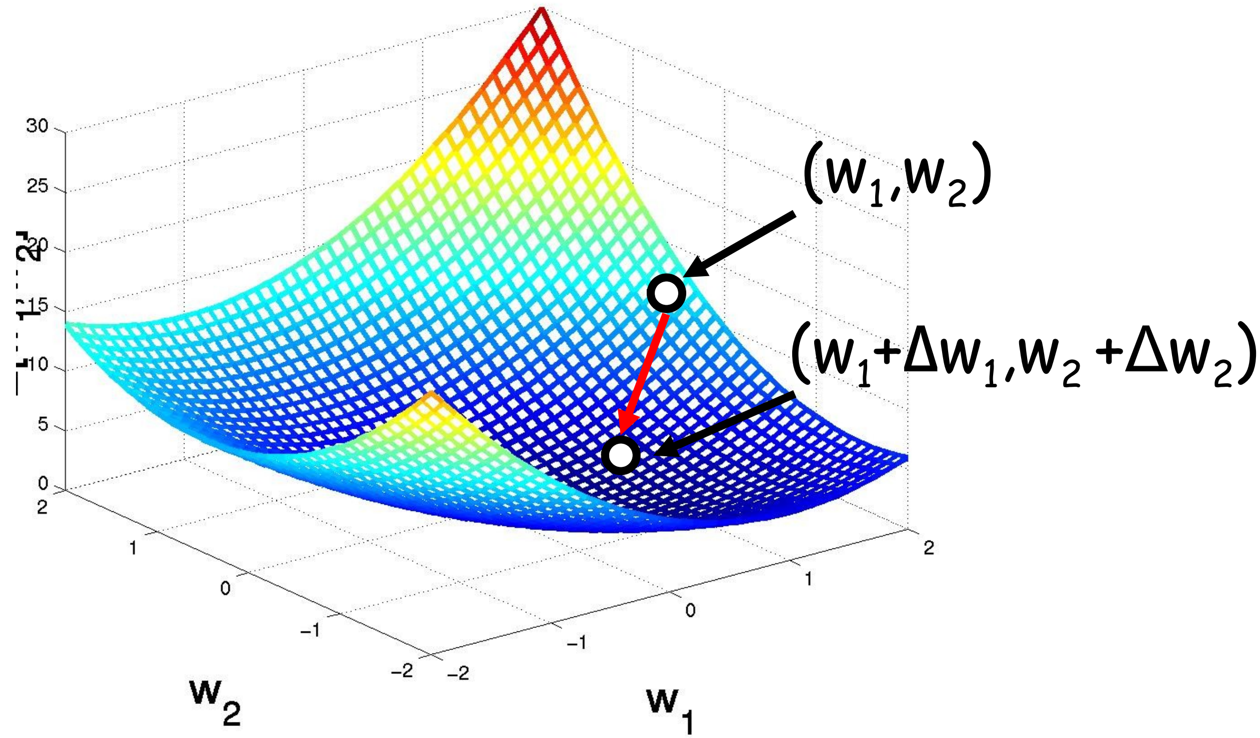
derivative says increase w
(go in opposite direction
of derivative)

If w=8 $\frac{\partial}{\partial w} E(8) = 2(8-5) = 6$

derivative says decrease w
(go in opposite direction
of derivative)

Gradient Descent Visually

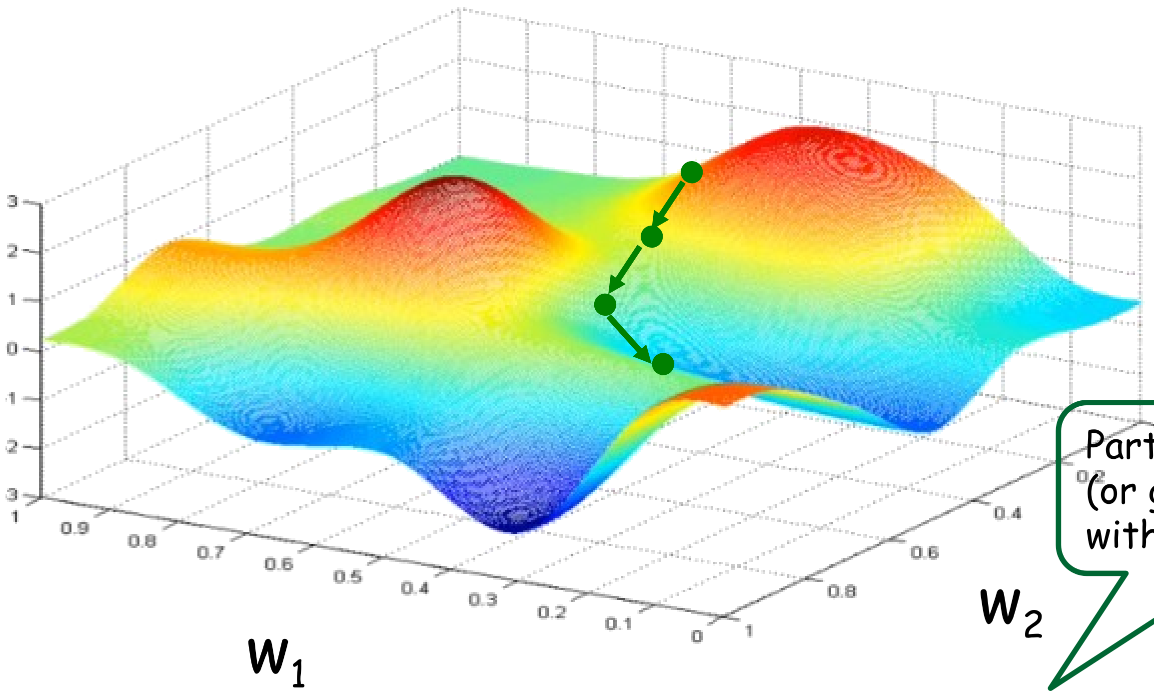
$$E(w_1, w_2) = \frac{1}{2}\frac{\sum_{i=1}^{n}(T_i - O_i)^2}{n}$$



- Goal: minimize E(w1,w2) by changing w1 and w2
- But what is the best combination of change in w1 and w2 to minimize E faster?
- The delta rule is a gradient descent technique for updating the weights in a single-layer perceptron.

Gradient Descent Visually

$$E(w_1, w_2) = \frac{1}{2}\frac{\sum_{i=1}^{n}(T_i - O_i)^2}{n}$$



Partial derivative (or gradient) of E with respect to w1

- need to know how much a change in w1 will affect E(w1,w2) i.e $\frac{\partial E}{\partial w1}$
- need to know how much a change in w2 will affect E(w1,w2) i.e $\frac{\partial E}{\partial w2}$
- **Gradient** ∇E <u>points</u> in the opposite direction of steepest decrease of E(w1,w2)
- i.e. hill-climbing approach…

Source: Andrew Ng

Training the Network

After some calculus (see: https://en.wikipedia.org/wiki/Backpropagation) we get…

- Step 0: Initialise the weights of the network randomly

// feedforward

- Step 1: Do a forward pass through the network (use sigmoid)

$$O_i = g\left(\sum_j w_{ji} x_j\right) = \text{sigmoid}\left(\sum_j w_{ji} x_j\right) = \frac{1}{1 + e^{-\left(\sum_j w_{ji} x_j\right)}}$$

Note: To be consistent with Wikipedia, we'll use O-T instead of T-O, but we will subtract the error in the weight update

// propagate the errors backwards

- Step 2: For each output unit k, calculate its error term δ_k

$$\delta_k \leftarrow g'(x_k) \times Err_k = O_k(1 - O_k) \times (O_k - T_k)$$

Derivative of sigmoid

note, if we use g = sigmoid :

$g'(x) = g(x)(1 - g(x))$

- Step 3: For each hidden unit h, calculate its error term δ_h

$$\delta_h \leftarrow g'(x_h) \times Err_h = O_h(1 - O_h) \times \sum_{k \in outputs} w_{hk} \delta_k$$

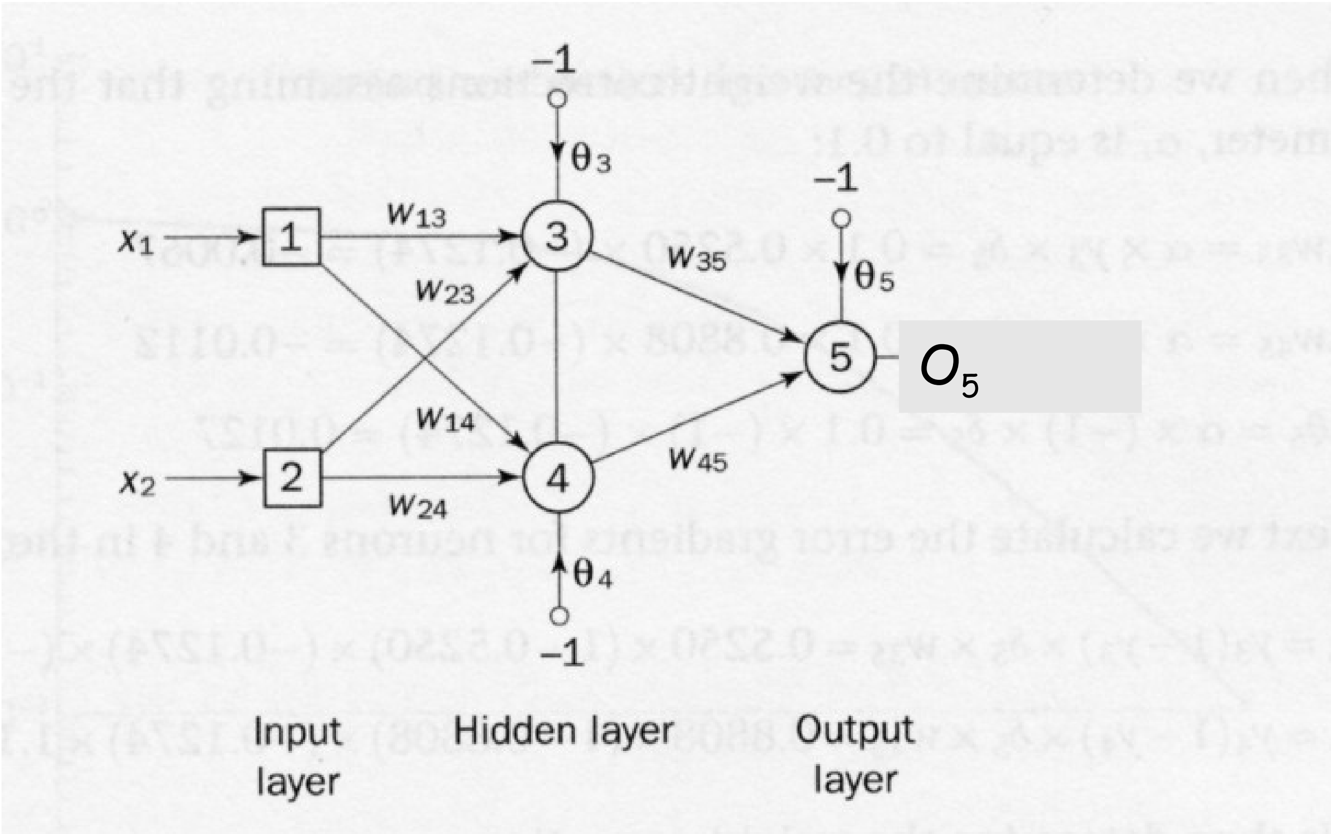
Sum of the weighted error term of the output nodes that h is connected to (ie. h contributed to the errors δ_k)

- Step 4: Update each network weight w_{ij}:

$$w_{ij} \leftarrow w_{ij} + \Delta w_{ij} \quad \text{where } \Delta w_{ij} = -\eta \, \delta_j \, O_i$$

- Repeat steps 1 to 4 until the error is minimised to a given level

Example: XOR

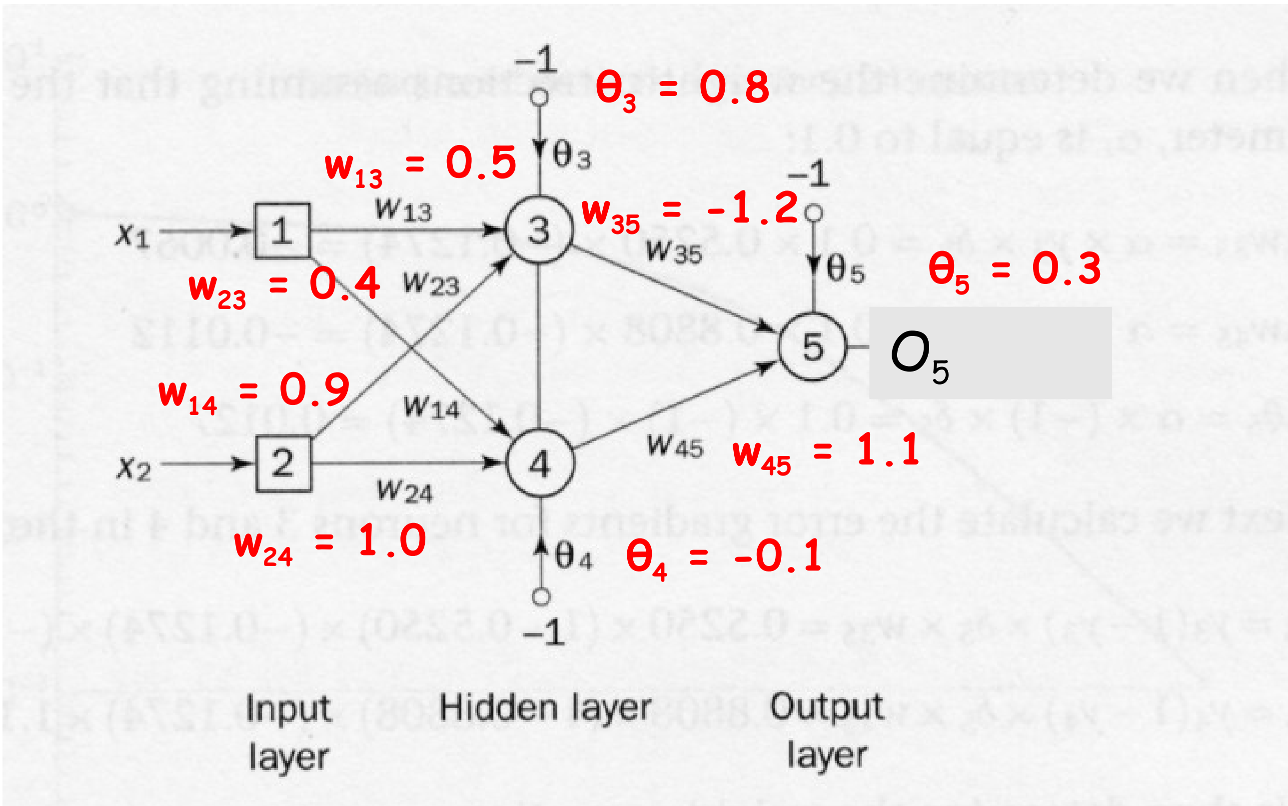


- 2 input nodes + 2 hidden nodes + 1 output node + 3 biases

source: Negnevitsky, Artificial Intelligence, p. 181

Example: Step 0 (initialization)

- Step 0: Initialize the network at random



Step 1: Feed Forward

- Step 1: Feed the inputs and calculate the output

$$O_i = \text{sigmoid}\left(\sum_j w_{ji} x_j\right) = \frac{1}{1 + e^{-\left(\sum_j w_{ji} x_j\right)}}$$

x_1	x_2	Target output T
1	1	0
0	0	0
1	0	1
0	1	1

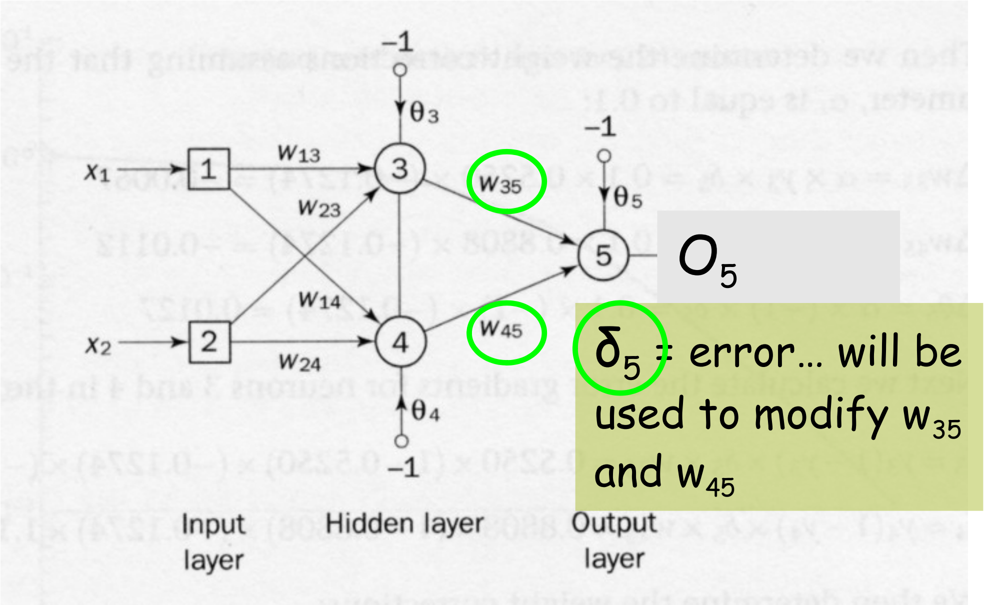
→ **Worksheet #5 ("Neural Network for XOR")**

Step 2: Calculate error term of output layer

$$\delta_k \leftarrow g'(x_k) \times Err_k = O_k(1 - O_k) \times (O_k - T_k)$$

- Error term of neuron 5 in the output layer:

→ **Worksheet #5** **("Neural Network for XOR")**



Step 3: Calculate error term of hidden layer

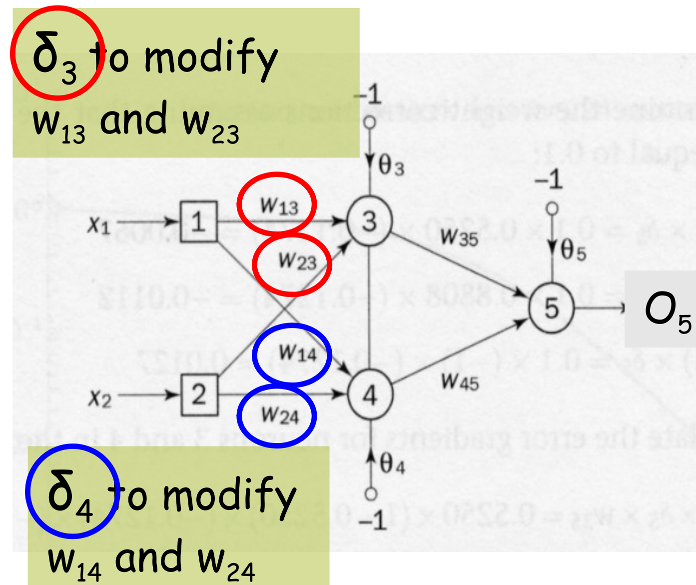
$$\delta_h \leftarrow g'(x_h) \times Err_h = O_k(1 - O_k) \times \sum_{k \in outputs} w_{kh}\delta_k$$

- Error term of neurons 3 & 4 in the hidden layer:
  - $\delta_3 = O_3\,(1\text{-}O_3)\ \ \delta_5\, w_{35}$

    = …
  - $\delta_4 = O_4\,(1\text{-}O_4)\, \delta_5\, w_{45}$

    = …

→ Worksheet #5
(“Neural Network for XOR”)

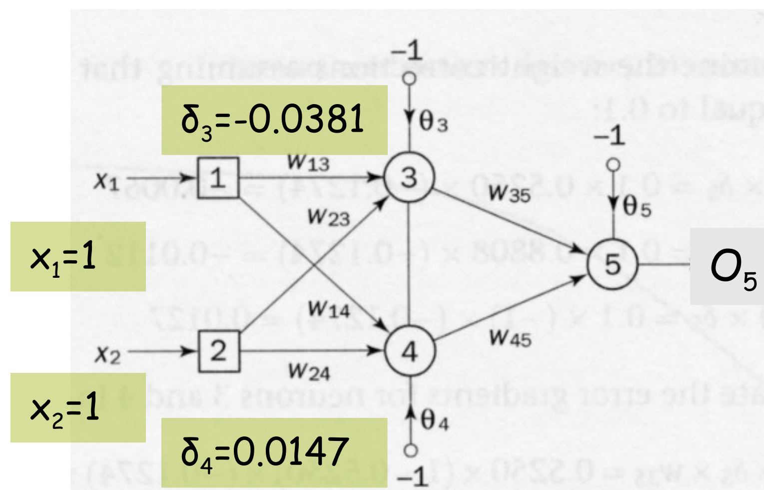


Step 4: Update Weights

$$w_{ij} \leftarrow w_{ij} + \Delta w_{ij} \quad \text{where } \Delta w_{ij} = -\eta\, \delta_j\, x_i$$

- Update all weights (assume a constant learning rate η = 0.1)
  - $\Delta w_{13} = -\eta\, \delta_3\, x_1 = -0.1 \times -0.0381 \times 1 = 0.0038$
  - $\Delta w_{14} = -\eta\, \delta_4\, x_1 =$
  - $\Delta w_{23} = -\eta\, \delta_3\, x_2 = -0.1 \times -0.0381 \times 1 = 0.0038$
  - $\Delta w_{24} = -\eta\, \delta_4\, x_2 =$
  - $\Delta w_{35} = -\eta\, \delta_5\, O_3 = -0.1 \times 0.1274 \times 0.5250 = -0.00669$ // O_3 is seen as x_5 (output of 3 is input to 5)
  - $\Delta w_{45} = -\eta\, \delta_5\, O_4 =$
  - $\Delta \theta_3 = -\eta\, \delta_3\, (-1) = -0.1 \times -0.0381 \times -1 = -0.0038$
  - $\Delta \theta_4 = -\eta\, \delta_4\, (-1) = -0.1 \times 0.0147 \times -1 = 0.0015$
  - $\Delta \theta_5 = -\eta\, \delta_5\, (-1) =$

→ Worksheet #5
("Neural Network for XOR")

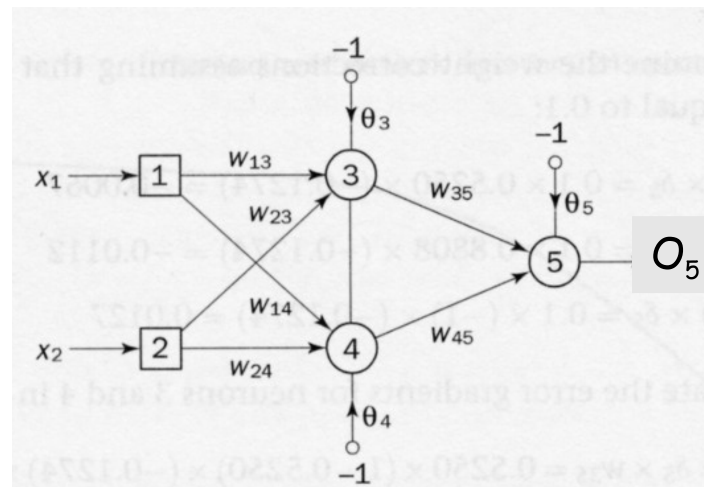


Step 4: Update Weights (con't)

$$w_{ij} \leftarrow w_{ij} + \Delta w_{ij} \quad \text{where } \Delta w_{ij} = -\eta\, \delta_j\, x_i$$

- Update all weights (assume a constant learning rate η = 0.1)

  - $w_{13} = w_{13} + \Delta w_{13} = 0.5 + 0.0038 = 0.5038$
  - $w_{14} = w_{14} + \Delta w_{14} =$
  - $w_{23} = w_{23} + \Delta w_{23} = 0.4 + 0.0038 = 0.4038$
  - $w_{24} = w_{24} + \Delta w_{24} =$
  - $w_{35} = w_{35} + \Delta w_{35} = -1.2 - 0.00669 = -1.20669$
  - $w_{45} = w_{45} + \Delta w_{45} =$
  - $\theta_3 = \theta_3 + \Delta\theta_3 = 0.8 - 0.0038 = 0.7962$
  - $\theta_4 = \theta_4 + \Delta\theta_4 = -0.1 + 0.0015 = -0.0985$
  - $\theta_5 = \theta_5 + \Delta\theta_5 =$



→ **Worksheet #5 ("Neural Network for XOR" contd.)**

Step 4: Iterate through data

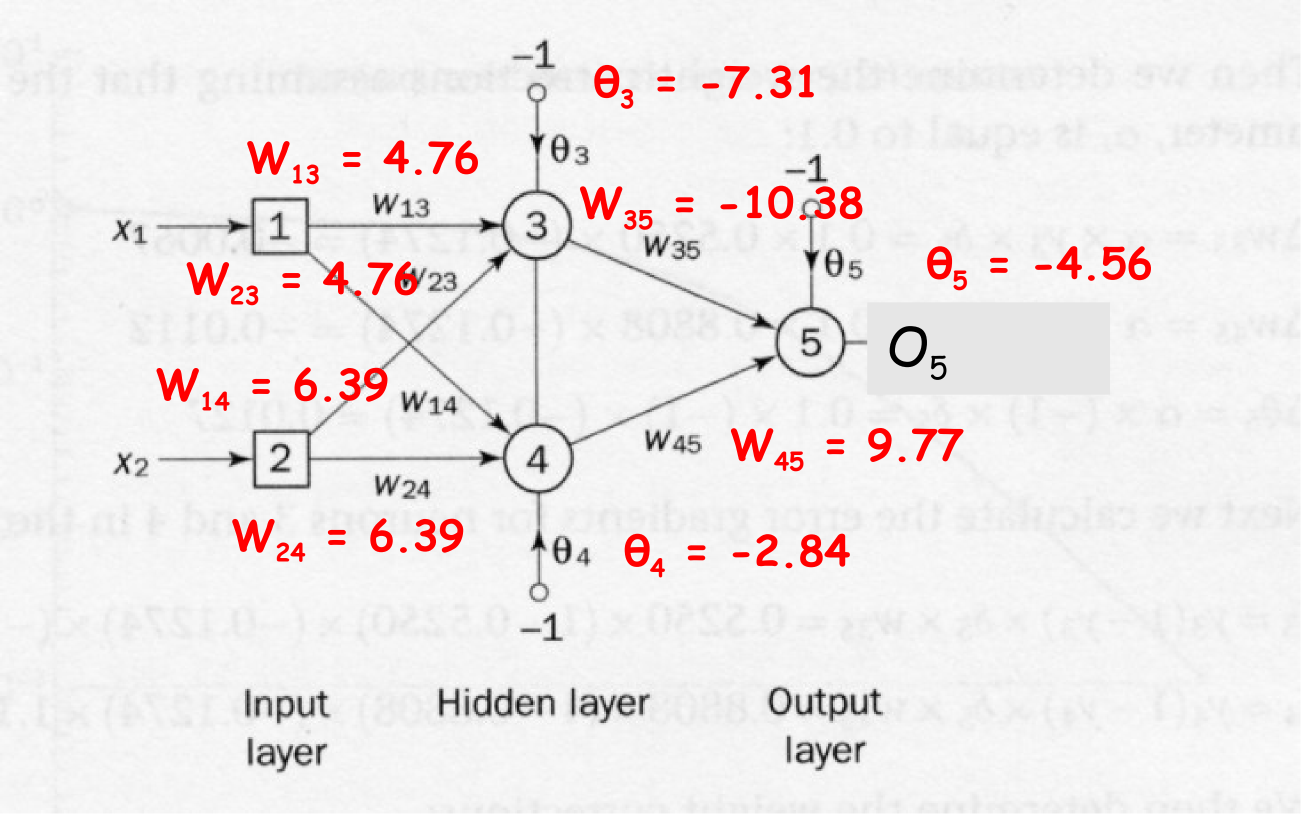
- after adjusting all the weights, repeat the forward pass and back pass for the next data point until all data points are examined
- repeat this entire exercise until the overall error is minimised
  - Ex: $Mean\ Squared\ Error\ (MSE)$=

$$\frac{1}{2}\frac{\sum_{i=1}^{n}(T_i - O_i)^2}{n} < \ \varepsilon$$

where ε ~ 0.0001 and n = nb of training examples

The Result…

- After 224 epochs, we get:
  - (1 epoch = going through all data once)



Error is minimized

Inputs		Target Output	Actual Output	Error
x_1	x_2	T	O	T-O
1	1	0	0.0155	-0.0155
0	1	1	0.9849	0.0151
1	0	1	0.9849	0.0151
0	0	0	0.0175	-0.0175

$$Mean\ Squared\ Error = \frac{1}{2} \cdot \frac{(-0.0155^2 + 0.0151^2 + \ 0.0151^2 + \ 0.0175^2)}{4}$$

$$= 0.000125 < \ 0.001\ (some\ threshold\ \varepsilon) \ \ldots\ stop!$$

May be a local minimum…

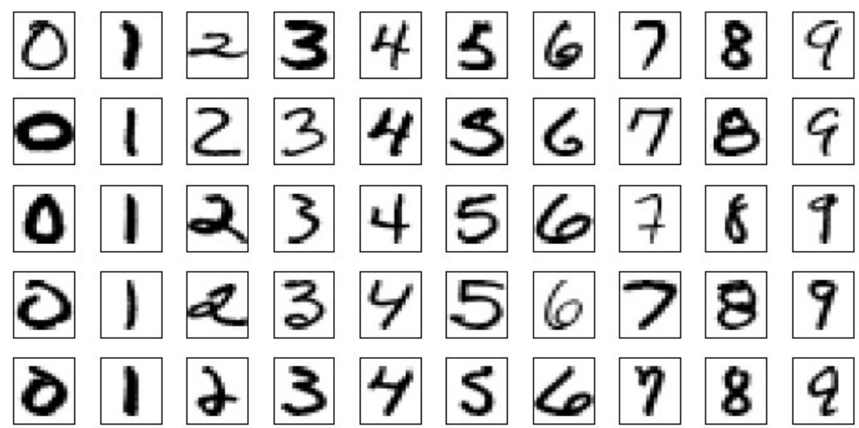
Stochastic Gradient Descent

- Batch Gradient Descent (GD)
  - updates the weights after 1 epoch
  - can be costly (time & memory) since we need to evaluate the whole training dataset before we take one step towards the minimum.
- Stochastic Gradient Descent (SGD)
  - updates the weights after each training example
  - often converges faster compared to GD
  - but the error function is not as well minimized as in the case of GD
  - to obtain better results, shuffle the training set for every epoch
- MiniBatch Gradient Descent:
  - compromise between GD and SGD
  - cut your dataset into sections, and update the weights after training on each section

Applications of Neural Networks

- Handwritten digit recognition
  - Training set = set of handwritten digits (0…9)
  - Task: given a bitmap, determine what digit it represents
  - Input: 1 feature for each pixel of the bitmap
  - Output: 1 output unit for each possible character (only 1 should be activated)
  - After training, network should work for fonts (handwriting) never encountered

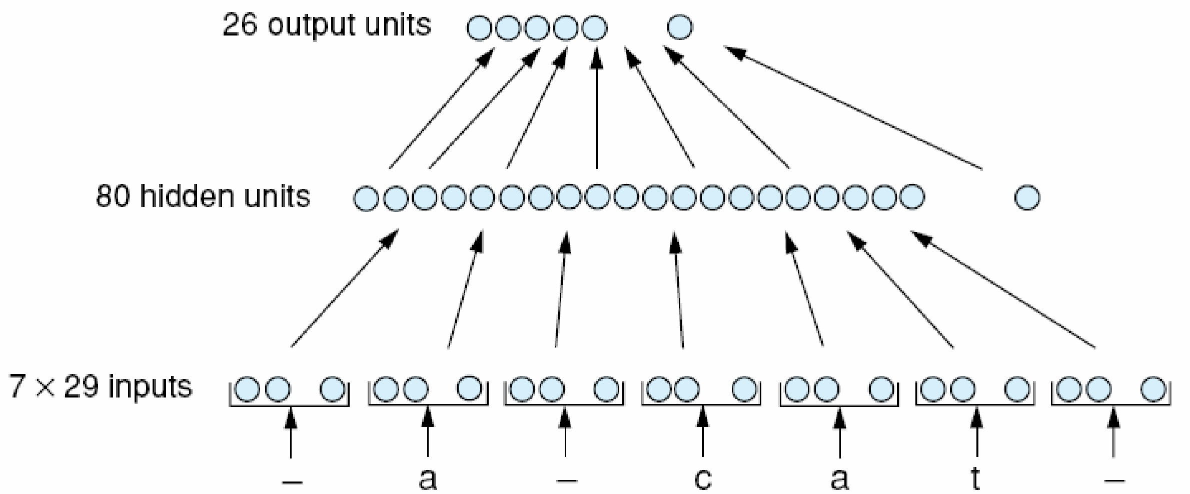
- Related pattern recognition applications:
  - recognize postal codes
  - recognize signatures
  - …



Applications of Neural Networks

- Speech synthesis
  - Learning to pronounce English words
  - Difficult task for a rule-based system because English pronunciation is highly irregular
  - Examples:
    - letter "c" can be pronounced [k] (*cat*) or [s] (*cents*)
    - *Woman* vs *Women*
  - NETtalk:
    - uses the context and the letters around a letter to learn how to pronounce a letter
    - Input: letter and its surrounding letters
    - Output: phoneme

NETtalk Architecture



Ex: *a cat* → *c is pronounced K*

- Network is made of 3 layers of units
- input unit corresponds to a 7 character window in the text
- each position in the window is represented by 29 input units (26 letters + 3 for punctuation and spaces)
- 26 output units – one for each possible phoneme

Listen to the output through iterations: https://www.youtube.com/watch?v=gakJlr3GecE

source: Luger (2005)

Neural Networks

- Disadvantage:
  - result is not easy to understand by humans (set of weights compared to decision tree)… it is a black box
- Advantage:
  - robust to noise in the input (small changes in input do not normally cause a change in output) and graceful degradation

Today

- Introduction to Neural Networks
  - Perceptrons
  - Backpropagation