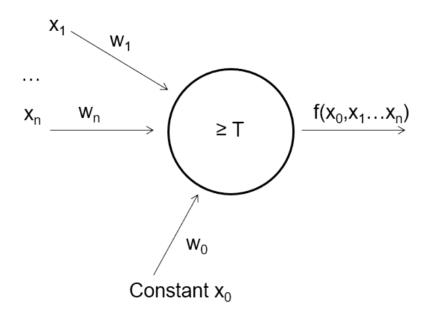
Perceptron Overview

- [[Artificial Neural Networks]] neutron
- inputs are now real numbers instead of just true or false
- each input has a certain weight

$$f(x_0...x_n): w_0x_0 + w_1x_1 + ... w_nx_n \ge T$$



• perceptron networks allow non-linear separation

Perceptron Learning Algorithm

$$f(x_0...x_n)$$
: $w_0x_0 + w_1x_1 + ... w_nx_n \ge T$ f is our hypothesis!

- Variables:
 - d_j = desired output of perceptron for example j D = training set of example pairs (x_j, d_j) $y_j(t)$ = actual output of perceptron for example j at time t
 - r = learning rate
- Algorithm:

- 1. Initialize weights, typically to small values
- 2. For each example *j* in the training set D perform the following steps:
 - 1. $y_i(t) = (\mathbf{w}(t) * \mathbf{x}_i) \ge T$
 - 2. For all i=0...n: $w_i(t+1)=w_i(t) + r * (d_i-y_i(t))* x_{i,i}$
- Weights stays the same if the output y_i(t) is the same as the desired output d_i

 Overall value needs to increase if actual output y_i(t) is smaller than desired -> increase weights at positive inputs, decrease weights at negative inputs.

 Overall value needs to decrease if actual output y_i(t) is larger than desired -> decrease weights at positive inputs, increase weights at negative inputs.
- correct guess ==> weights stay the same
- bad guess ==>
 - * output too small ==>
 - increase weight at positive inputs
 - decrease weight at negative inputs
 - * output too big ==>
 - decrease weight at positive inputs
 - increase weight at negative inputs
- repeated until
 - average error below pre-defined threshold
 - or after pre-determined number of iterations

Example: Learning the OR function

Choice:
$$f(x_0, x_1, x_2, x_3) = w_0 x_0 + w_1 x_1 + w_2 x_2 + w_3 x_3 \ge 1$$

 $x_0=1$, $r=0.5$, $w_i(0)=0$
Weight update formula from slide 13: $w_i(t+1)=w_i(t)+r^*(d_i-y_i(t))^*x_{i,i}$

t	Ex #	X ₁	X ₂	X ₃	w ₀ (t)	w ₁ (t)	w ₂ (t)	w ₃ (t)	y _{ex} (t)	Correct (yes/no)
t=0	1	1	1	1						
t=1	2	1	1	0						
t=2	3	1	0	1						
t=3	4	1	0	0						

PLA Properties

- goes over set of examples
- compares each example's output with desired output
- \bullet weight changes based on correct output or not
- \bullet convergence towards solution guaranteed if training set is linearly separable
- may not find best solution, quality jumps around

\bullet variants

- batch learning
 - * change weigths only after batch of training examples
 - * less quality jumps
- keep best seen solution in memory
- include optimization criteria
 - * maximizing distance of separation between both classes