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2.1

a

A nonlinear transfer function gives the neural network a universal property: Given enough layers and neurons, the network can model any function within a certain accuracy. In a network with a linear transfer function we can only compute a linear function. A network with a linear transfer function of n layers will always be equivalent to a network with only one layer: linear functions can always be concatenated.

Whenever the function that we are trying to model isn't a linear function, it is useful to use a nonlinear transfer function. Examples include image classification or speech recognition.

b

Consider a simple neural network with two input neurons that can both either be 0 or 1 and one output layer. We want to construct an AND gate with our network, so without bias our quest would be to find $w=(w_1,w_2)$ such that:

$$0 \le 0$$

$$w_1 \le 0$$

$$w_2 \le 0$$

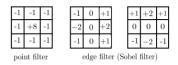
$$w_1 + w_2 > 0$$

which is impossible. We can easily however create the network with a bias, if we have the weights w=(1,1) and the bias $\theta=\frac{3}{2}$. Then $sgn(w^Tx-\theta)$ would give us AND.

would give us / live.								
w_0							1.5	
w_1		0	1	0	1		1	
w_2		0	0	1	1		1	
0 0	-	-	-	-	-		-	
0 1	_	-	_	+	+		-	
1 0	_	-	+	-	+		-	
1 1	+	-	+	+	+		+	

C

Point and edge filters are for example a connectionist neuron which gets values of a scalar field as input, that represent the color of each pixel or the color gradient or even a higher derivative and has weights in the following form: In the simple case of two colors (0 and 1) this point filter would



return zero for no point, 1 or -1 for a point in the outer region and 8 or -8 if the point is in the middle. This goes analogously for the other filter.

d

The first is deterministic and the second has a noise parameter and can return different states for set parameters and a given input.

2.2

The following two figures refer to exercise parts a and b.

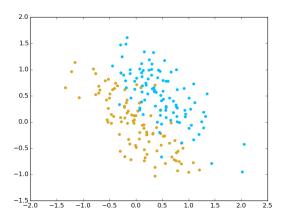


Figure 1: Plot where Y=1 (blue) and Y=0 (gold).

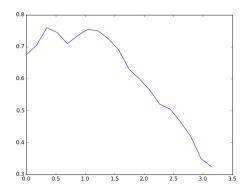


Figure 2: Classification performance given by $sign(w\cdot x)$ for varying angles determining w

c

The weight vector giving us the best performance is w=(0.93969262,0.342020) if we optimize it without respect to θ .

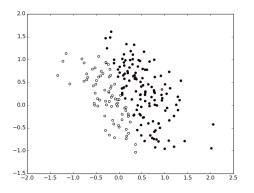


Figure 3: Classification performance with \boldsymbol{w} and theta optimized separately

е

If we optimize w and theta simultaneously we get a p=0.915 classification rate with optimal parameters w=(0.64278761,0.76604444) and $\theta=0.3393393393$

2.3

a

A MLP could decide between a horizontal and a vertical edge, whereas a perceptionist neuron would either be able to differ between vertical edge or no vertical edge OR horizontal edge or no horizontal edge.

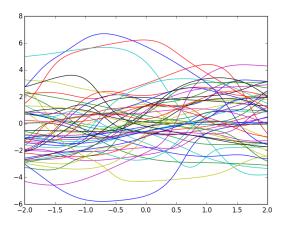


Figure 4: functions computed with normally distributed a_i with a standard deviation of 2

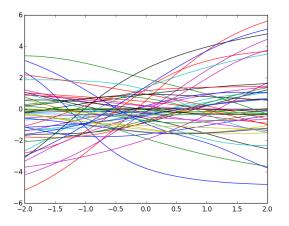


Figure 5: functions computed with normally distributed a_i with a standard deviation of 0.5

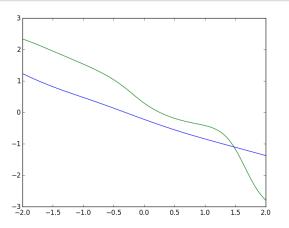


Figure 6: functions with least mean square error from f(x)=-x, computed with an std of 2 (green) and 0.5 (blue)

