

points

 $2\sqrt{2}$ 

in this example we are not learning the bias.

Let's say that at time t we observe that we have misclassified some point  $\hat{\mathbf{x}}$  with target t. Then the learning algorithm will proceed as:  $\mathbf{w}^{(t)} = \begin{cases} \mathbf{w}^{(t-1)} + \hat{\mathbf{x}} & \text{if } \hat{t} = 1 \\ \mathbf{w}^{(t-1)} - \hat{\mathbf{x}} & \text{if } \hat{t} = 0 \end{cases}$ 

 $||\mathbf{w}^{(t-1)} - \mathbf{w}^{(t-1)} \pm \hat{\mathbf{x}}||_2 = ||\pm \hat{\mathbf{x}}||_2 = ||\hat{\mathbf{x}}||_2 \leq \sqrt{2}$  since this is the length of

In either case, the distance between  $\mathbf{w}^{(t)}$  and  $\mathbf{w}^{(t-1)}$  will be

weights  $\mathbf{w}^* = c\mathbf{w}$  by scaling  $\mathbf{w}$  by some positive constant c.

the largest input vector (in this case, (1, 1)).

amount by which the weight vectors can change between successive iterations? Note that

Suppose that we have a perceptron with weight vector 
$${f w}$$
 and we create a new set of

Assume that the bias is zero.

 $^{2}$ 

True or false: if the perceptron now uses  $\mathbf{w}^*$  instead then it's classification decisions might change (that is, we have moved the classification boundary). False

If the bias term is zero, all of the hyperplanes that represent individual cases go through the origin of weight space. So changing the length of the weight vector without changing its direction cannot change which side of the plane it lies on.

True or false: if the perceptron now uses  $\mathbf{w}^*$  instead then it's classification decisions

might change (that is, we have moved the classification boundary).

Suppose that we have a perceptron with weight vector w and we create a new set of weights  $\mathbf{w}^* = \mathbf{w} + \mathbf{c}$  by adding some constant vector  $\mathbf{c}$  to  $\mathbf{w}$ . Assume that the bias is

True

False

 $0, 1 \rightarrow 0$  $0,0 \to 1$ 

Un-selected is correct

Correct

that input vector.

two diagonally opposite corners.

True

Correct

Adding a constant vector can change the direction of the weight vector. This might change the side on which some data points lie.

6.

5.

Suppose we are given four training cases:  $\mathbf{x} \rightarrow t$  $1, 1 \rightarrow 1$  $1,0 \to 0$ 

It is impossible for a binary threshold unit to produce the desired target outputs for all four cases. Now suppose that we add an extra input dimension so that each of the four

Which of the following ways of setting the value of the extra input will create a set of four input vectors that is linearly separable (i.e. that can be given the right target values by a

Make the third value of each input vector be the same as the first value.

Make the third value of each input vector be the same as the target value for

input vectors consists of three numbers instead of two.

binary threshold unit with appropriate weights and bias).

three. Correct

Imagine the four input vectors as lying at the corners of a horizontal square. If we raise one corner of the square in the third dimension we can now insert a tilted plane that goes beneath two diagonally opposite corners and above the other

use 1 if the first value is 0 and 0 if the first value is 1)

Make the third value be 1 for one of the four input vectors and 0 for the other

Make the third value of each input vector be the opposite of the first value (i.e.

Brian wants to use a neural network to predict the price of a stock tomorrow given

today's price and the price over the last 10 days. The inputs to this network are price over the last 10 days and the output is tomorrow's price. The hidden units in this network receive information from the layer below, transmit information to the layer above and do not send information within the same layer. Is this an example of a feed-forward network

Feed-forward

Recurrent

or a recurrent network?

Un-selected is correct

7.

Correct

8.

Correct

Brian and Andy are having an argument about the perceptron algorithm. They have a dataset that the perceptron cannot seem to classify (that is, it fails to converge to a solution). Andy reasons that if he could collect more examples, that might solve the

problem by making the data set linearly separable and then the perceptron algorithm will

Even though Brian's network is modelling a sequence, it is doing this in an

entirely feed-forward fashion. Another name for this kind of model is a nonlinear autoregressive process. Recurrent networks are much more powerful for this task and can do a much better job, however they are also more difficult to train.



converge. Brian claims that collecting more examples will not help. Which one of them is correct? Andy Brian

> If any set A of points is not linearly separable from set B, then adding more examples to either set cannot make them linearly separable.