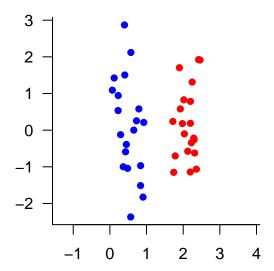
### perceptron

Joyce Robbins 8/13/2018

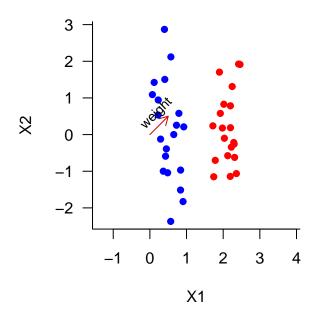
The perceptron is a simple algorithm that learns to classify inputs into two classes by adjusting the weights (w) in the equation  $y_i = \text{sign}(w_i x_i)$  until all inputs in a training set are correctly classified. Here the steps of algorithm will be presented visually in two-dimensional space.

### The basics

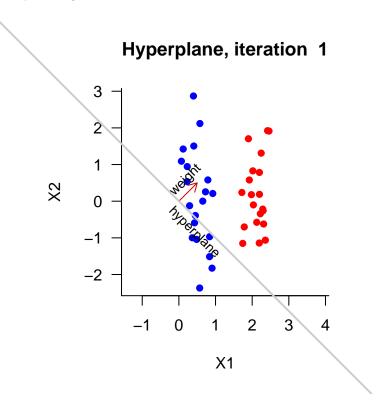
We start by plotting  $(x_1, x_2)$ , coloring each point by class. Note that the points can be separated by a line; if this is not the case, the algorithm won't work.



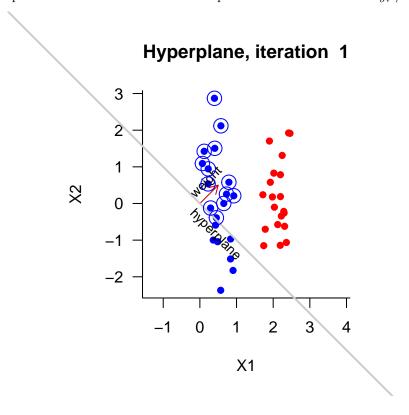
We start with an arbitrary weight vector, (w0, w1, w2). Often (0, 0, 0) is used, but we'll start with (0, 0.5, 0.5) so we can visualize it:



The decision boundary, or hyperplane, is the line orthogonal to the weight vector. For points on the line, the sign of  $(w_i x_i)$  equals zero. On one side of the line, the sign of  $(w_i x_i)$  is greater than zero whereas on the other side the sign of  $(w_i x_i)$  is less than zero; hence the line serves to divide all points into two classes according to the perceptron logic.



Note the circled points – these are the misclassified points – the ones for which  $y_i \neq \text{sign}(w_i x_i)$ .



### The Algorithm

The perceptron algorithm works by updating the weight vector based on a randomly selected misclassified point, calculating the new hyperplane, and repeating until the hyperplane separates all points into the two classes.

The formula for the new weight vector is:

 $w_{t+1} = w_t + \eta y_i x_i$ , where

 $x_i$  = the misclassified point

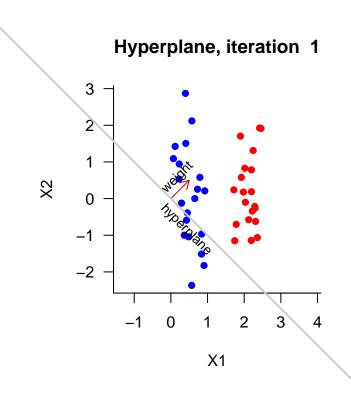
 $y_i$  = the true label of the misclassified point (-1 or 1)

 $\eta =$  the learning rate, which we'll set to 1 for the sake of simplicity

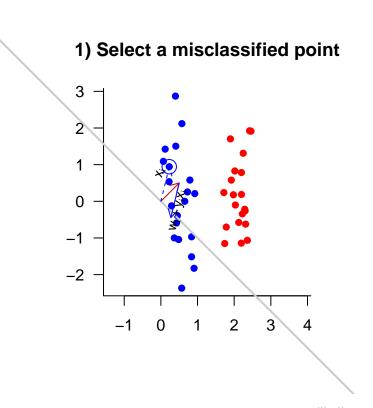
Visually, the new weight vector,  $w_{t+1}$ , is determined by adding  $y_i x_i$  to  $w_t$  and then shifting by the offset  $w_0/||w||_2$ .

We'll go through the algorithm one step at a time.

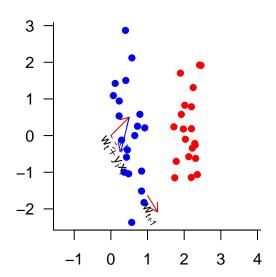
We begin with our original weight vector and hyperplane:



Next we randomly select a misclassified point. In the diagram below,  $x_i$  is shown as a **dashed blue arrow**, and  $y_i x_i$  added to  $w_t$  as a **solid blue arrow**:

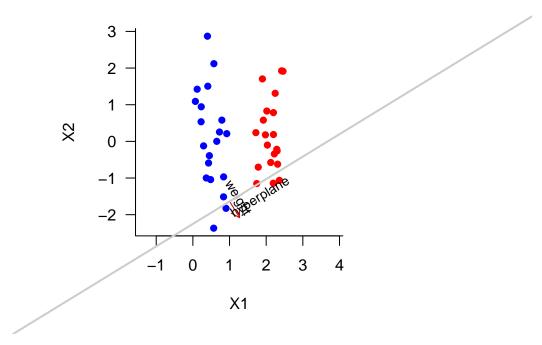


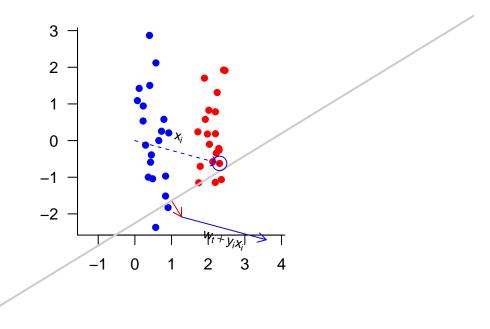
Next we determine the new weight vector by shifting the vector sum by  $w_0/||w||_2$ :

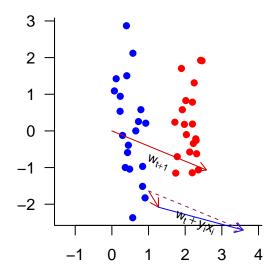


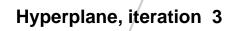
Finally, we draw the new hyperplane:

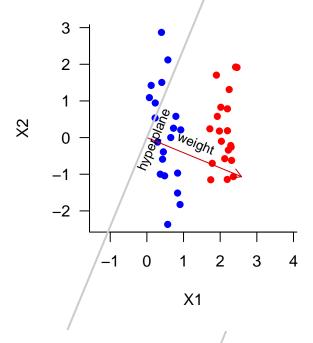
### Hyperplane, iteration 2

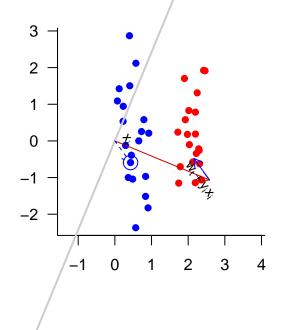


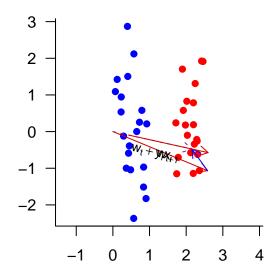


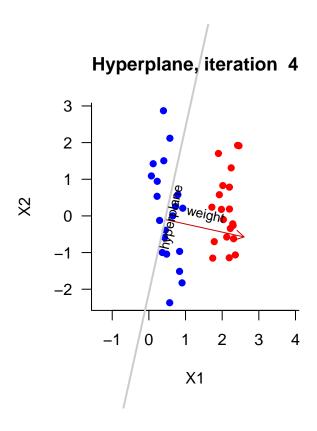


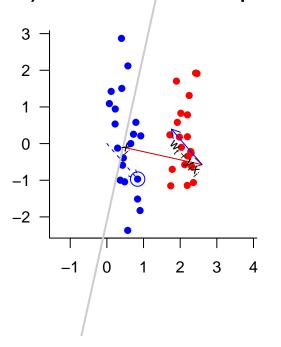


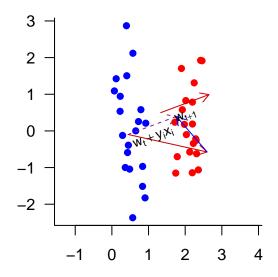




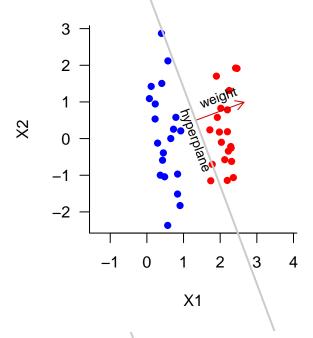


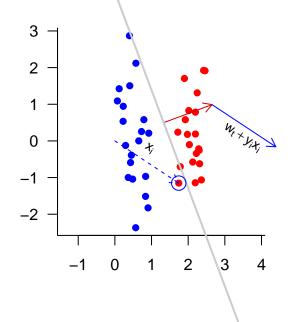


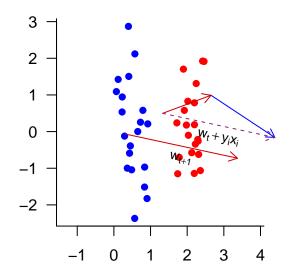


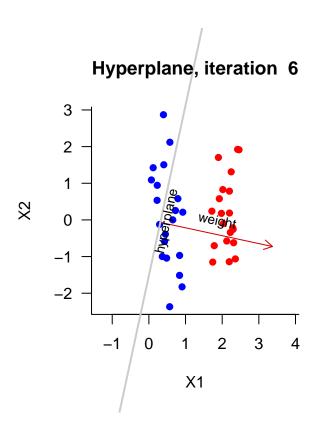


### Hyperplane, iteration 5

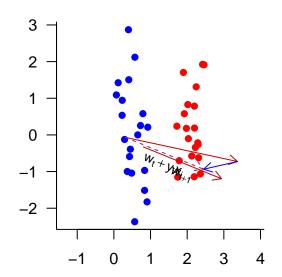


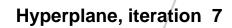


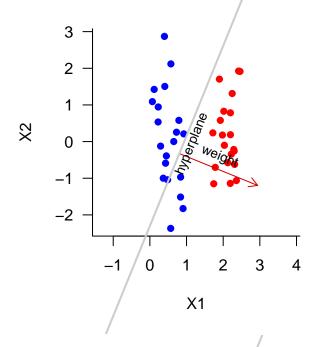


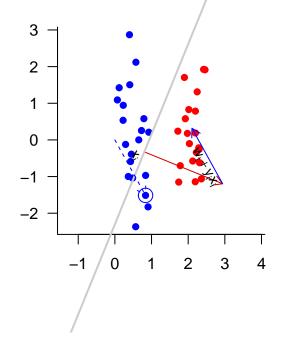


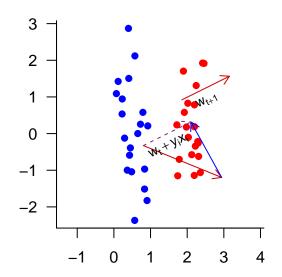
## 1) Select a misclassified point 3 - 2 - 1 - 0 - 1 - 2 - 3 4

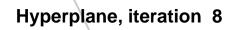


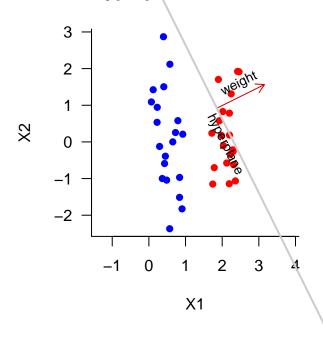


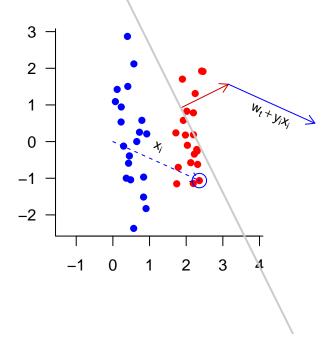


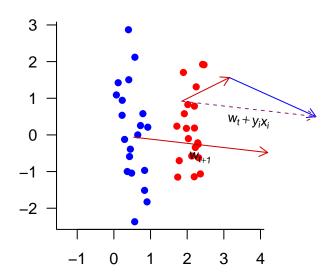


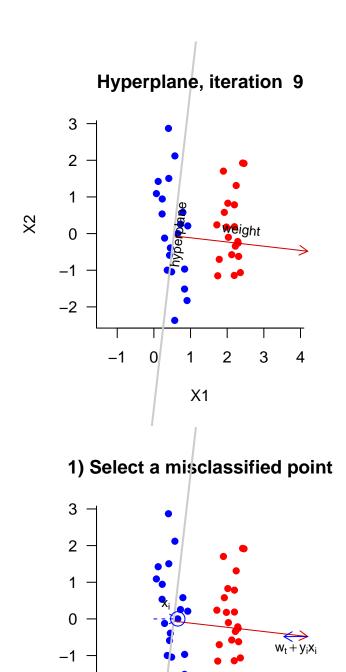






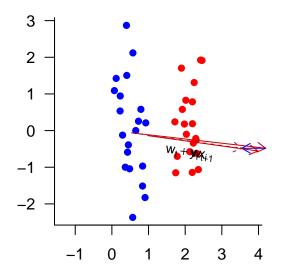


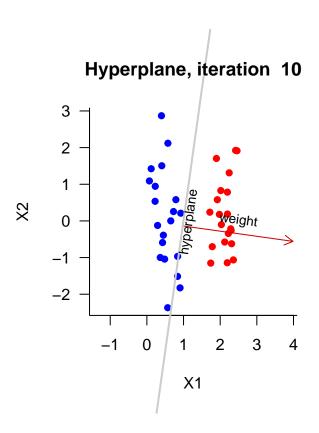




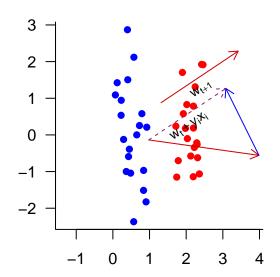
-2 -

-1

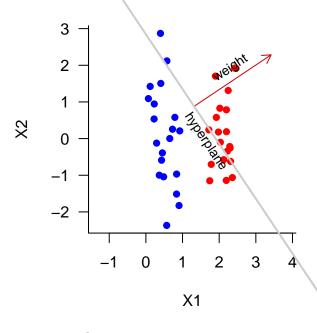


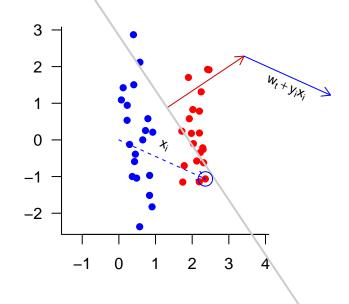


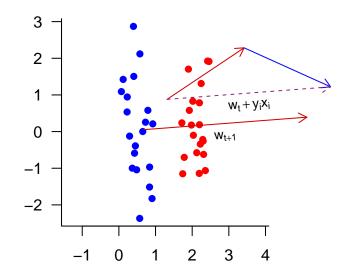
## 

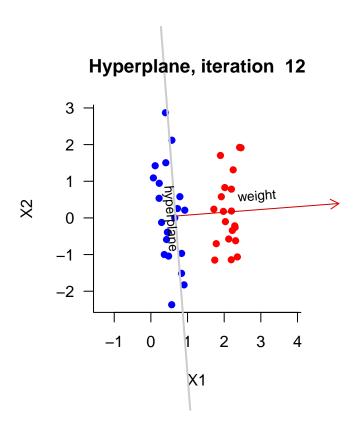


### Hyperplane, iteration 11

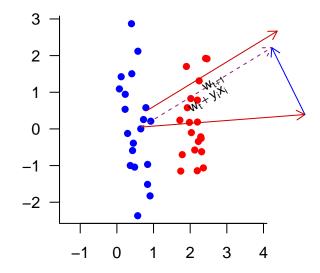




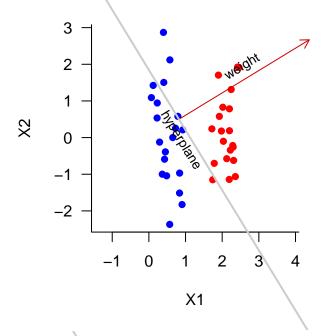


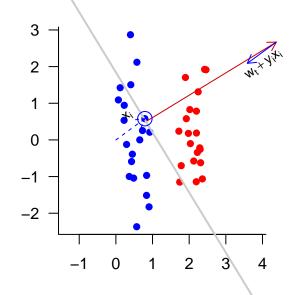


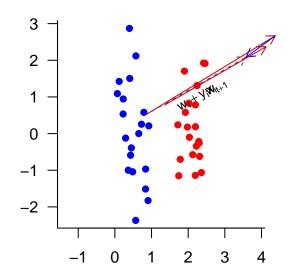
# 1) Select a misclassified point 3 - 2 - 1 - 0 - 1 - 2 - 3 4



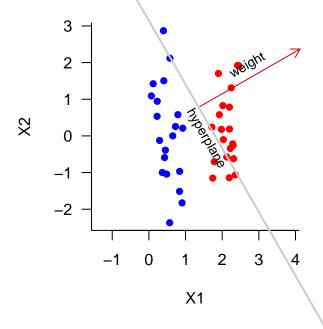
### Hyperplane, iteration 13

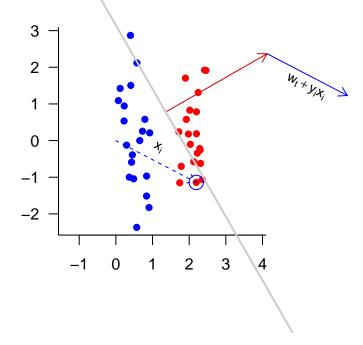


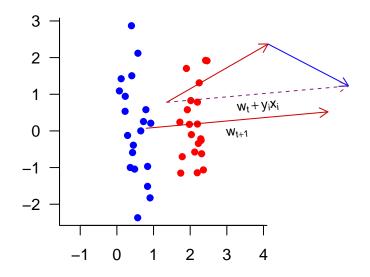


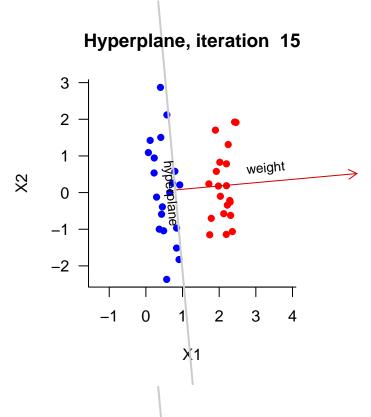


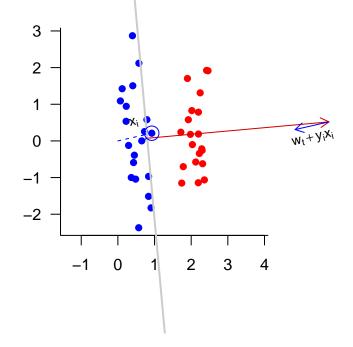
### Hyperplane, iteration 14

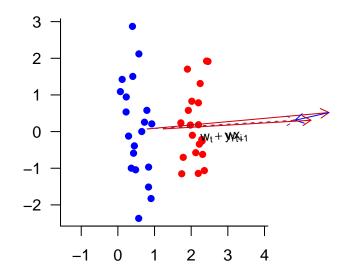


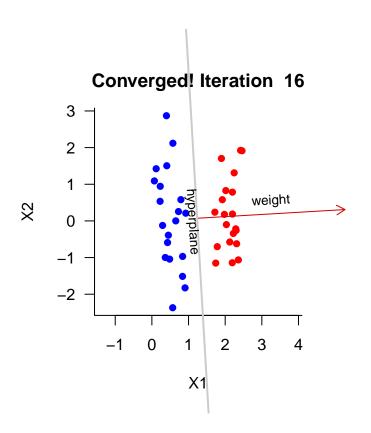












### Summary of 16 iterations:

