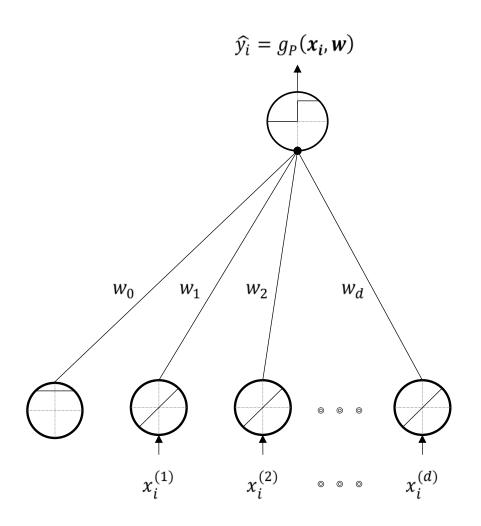
Learning in the Perceptron

"Learning": how does the neuron adapt its weights in response to the inputs?



The Perceptron Learning Algorithm

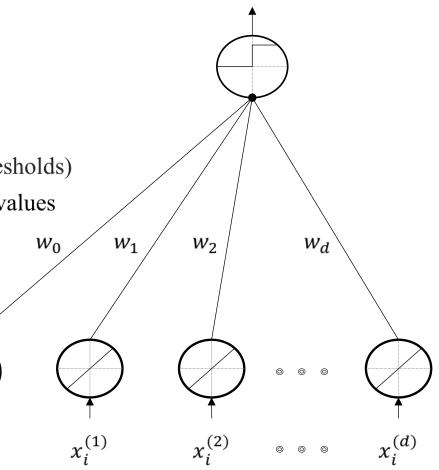
Input

- Training set

$$D = \{(x_i, y_i), i \in [1, 2, \dots n]\}, y_i = [0, 1].$$

Initialization

- Initialize the weights w(0) (and some thresholds)
- Weights may be set to 0 or small random values



 $\widehat{y}_i = g_P(x_i, \mathbf{w})$

The Perceptron Learning Algorithm

(cont'd)

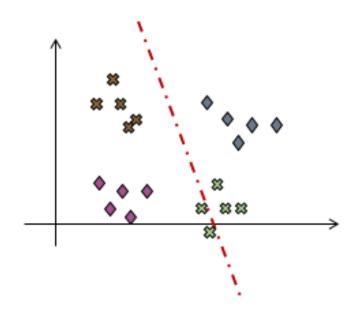
```
Iterate for t until a stop criterion is met
                                                                      \widehat{y}_i = g_P(\mathbf{x}_i, \mathbf{w})
for each sample x_i with label y_i:
     compute the output \hat{y}_i of the network
     estimate the error of the network e(w(t)) = y_i - \hat{y}_i
     update the weight w(t + 1) = w(t) + e(w(t))x_i
t++
                                                    w_0
                                                              W_1
                                                                       W_2
                                                                                     w_d
```

The Need for Multiple Layers

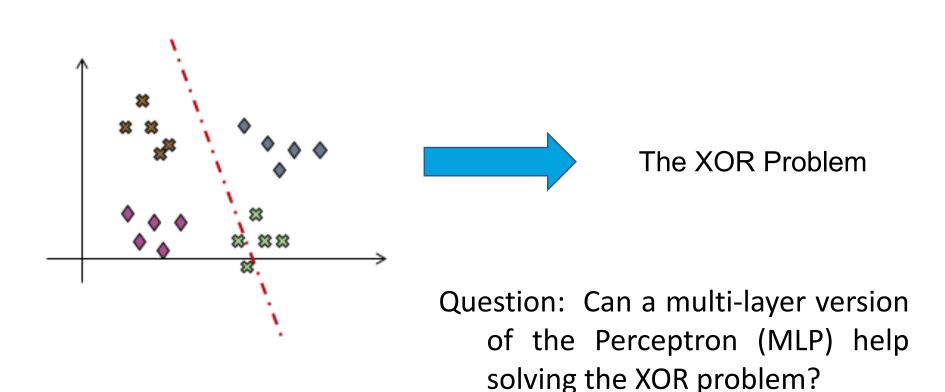
This is easy and can be learned by the Perceptron Algorithm

$$W_1 X_1 + W_2 X_2 + W_0 = 0$$

But how about this?



Extending to Multi-layer Neural Networks



An MLP Solving the XOR Problem

