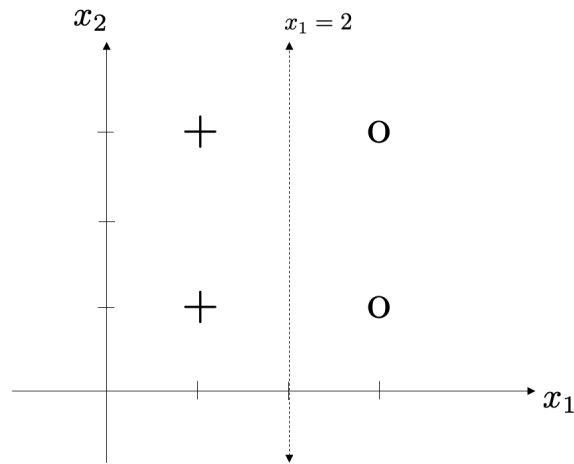


# Logistic Regression

*Submit a PDF of your answers to Canvas.*

1. Consider the four data points shown in the below. The data points at  $(1, 1)$  and  $(1, 3)$  belong to the class labeled  $y = 1$ , while the data points at  $(3, 1)$  and  $(3, 3)$  belong to the class labeled  $y = -1$ .



- a) A decision boundary at  $x_1 = 2$  can be expressed as the set of points that satisfy  $\mathbf{x}^T \mathbf{w} = 0$ , where

$$\mathbf{x} = \begin{bmatrix} 1 \\ x_1 \\ x_2 \end{bmatrix} \quad \text{and} \quad \mathbf{w} = \begin{bmatrix} w_0 \\ w_1 \\ w_2 \end{bmatrix}$$

Find  $w_0, w_1, w_2$  so that the set of points that satisfy  $\mathbf{x}^T \mathbf{w} = 0$  correspond to the vertical line at  $x_1 = 2$ . Note that your answer will not be unique. Express your answer for  $w_1$  in terms of  $w_0$ .

- b) The starting point for motivating logistic regression is to assume that  $y \in \{-1, 1\}$  is a Bernoulli random variable with bias that depends on  $\mathbf{x}$ :

$$p(y = 1|\mathbf{x}) = \frac{1}{1 + e^{-\mathbf{x}^T \mathbf{w}}}$$

and

$$p(y = -1|\mathbf{x}) = \frac{1}{1 + e^{\mathbf{x}^T \mathbf{w}}}$$

Find an expression for the likelihood  $L(\mathbf{w}) = p(y_1, y_2, y_3, y_4)$  given the data in the figure, and assuming *i*) independence and *ii*) that  $\mathbf{w}$  is restricted to correspond to the result from (a).

- c) Find an expression for the negative log-likelihood.
- d) Recall that we are usually interested in maximizing the likelihood  $L(\mathbf{w})$ , or equivalently minimizing the negative log-likelihood. Does the likelihood have a maximum value in this case?
- e) Sketch or describe the estimate of  $p(y = 1|\mathbf{x})$  for a large  $w_0$  over the  $x_1, x_2$  plane.

**SOLUTION:**

- a) Since the set of points is a vertical line, there is no dependence on  $x_2$  and  $w_2 = 0$ . Since  $x_1 = 2$ , we have  $w_0 + 2w_1 = 0$ , and conclude

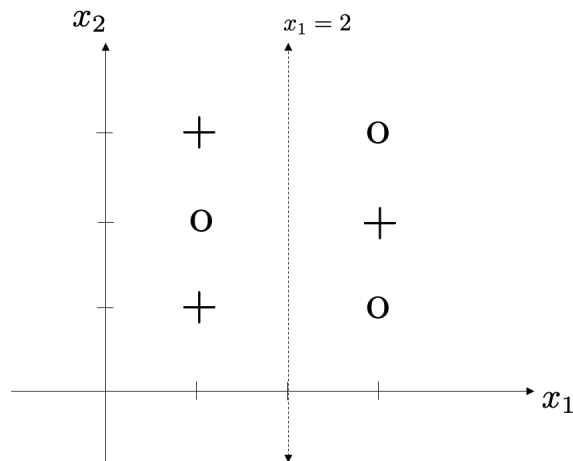
$$\mathbf{w} = \begin{bmatrix} w_0 \\ -\frac{w_0}{2} \\ 0 \end{bmatrix}.$$

- b) From the independence assumption, we have  $p(y_1, y_2, y_3, y_4) = p(y_1)p(y_2)p(y_3)p(y_4)$ . Next note that for all four points,  $y_i \mathbf{x}_i^T \mathbf{w} = \frac{w_0}{2}$ . Hence,

$$p(y_1, y_2, y_3, y_4) = \left( \frac{1}{1 + e^{-w_0/2}} \right)^4$$

- c)
- d) No. The function continues to approach 1 as  $w_0$  grows, so it has a supremum, but not a maximum.
- e) The surface becomes closer and closer to a step function centered at the decision boundary of  $x_1 = 2$ .

2. You collect two more labeled data points, which are show on the plot below. The points are at  $(1, 2)$  and  $(3, 2)$ .



- As before, find an expression for the likelihood  $L(\mathbf{w})$ , under the restriction that the decision boundary is a vertical line at  $x_1 = 2$ .
- Maximize the likelihood function to specify  $\mathbf{w}$  (note: you may need to use a computer to find an explicit answer, alternatively, you may leave your answer in a simple, but not explicit, analytic form).
- Sketch or describe the estimate of  $p(y = 1|\mathbf{x})$  over the  $x_1, x_2$  plane, and describe the effect of changing  $w_0$  on the surface. How does this compare to your result from problem 1?

### SOLUTION:

- As before, for the points we have  $y_i \mathbf{x}_i^T \mathbf{w} = \frac{w_0}{2}$ . For the additional two points, we have  $y_i \mathbf{x}_i^T \mathbf{w} = -\frac{w_0}{2}$ . Hence,

$$p(y_1, y_2, y_3, y_4) = \left( \frac{1}{1 + e^{-w_0/2}} \right)^4 \left( \frac{1}{1 + e^{w_0/2}} \right)^2$$

- To minimize the function, we take the log, and then differentiate and set to zero. After some algebra attempting to solve for  $w_0$ , we arrive at the expression  $1 = e^{w_0/2} - 2e^{-w_0/2}$ .
- The surface is no longer a step function at the decision boundary. This is to accommodate for the two new points which cannot be correctly classified.