

# Lab 1

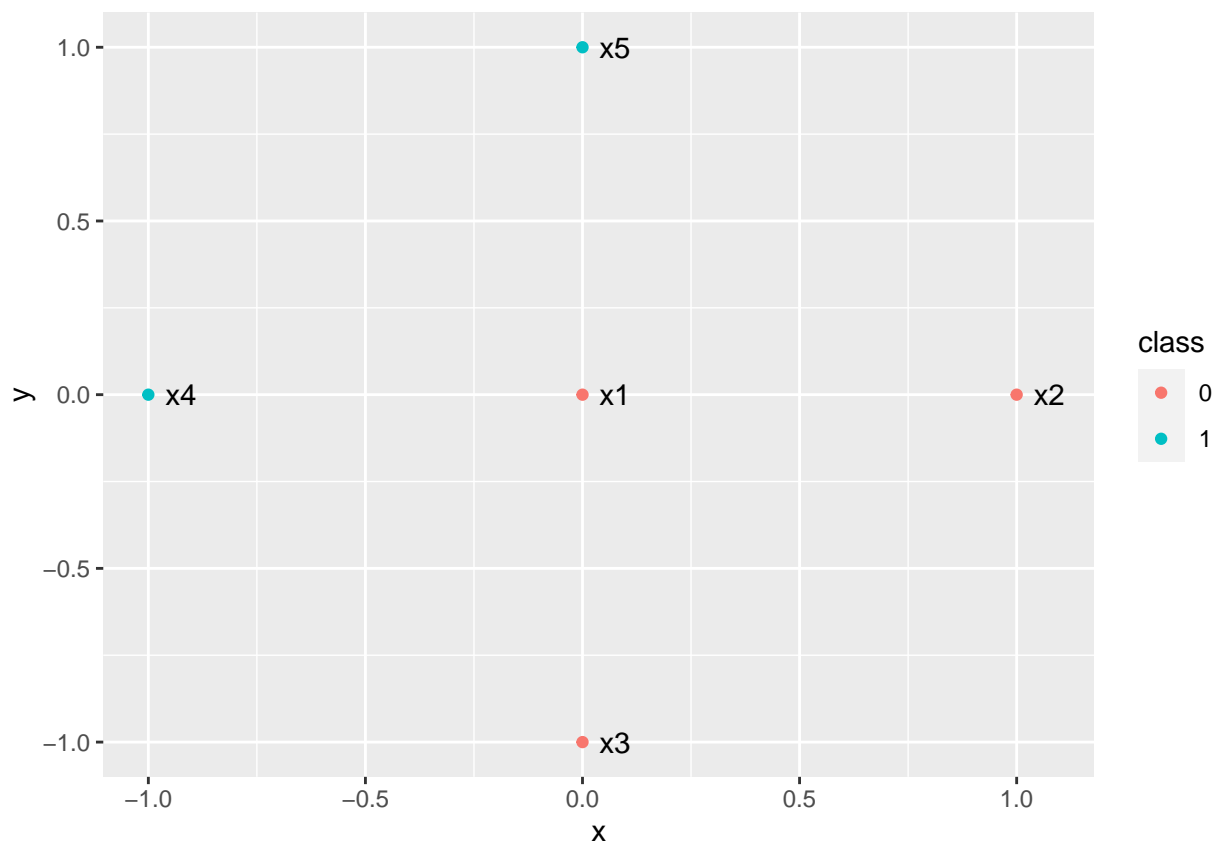
Emilio Dorigatti

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Welcome to the very first lab, in which we will have fun with logistic regression.

## Exercise 1

Suppose you have five input points,  $\mathbf{x}_1 = [0, 0]^T$ ,  $\mathbf{x}_2 = [1, 0]^T$ ,  $\mathbf{x}_3 = [0, -1]^T$ ,  $\mathbf{x}_4 = [-1, 0]^T$  and  $\mathbf{x}_5 = [0, 1]^T$ , and the corresponding classes are  $y_1 = y_2 = y_3 = 0$  and  $y_4 = y_5 = 1$ :



Consider a logistic regression model  $\hat{y}_i = \sigma(\alpha_0 + \alpha_1 x_{i1} + \alpha_2 x_{i2})$ , with  $\sigma(\cdot)$  the sigmoid function,  $\sigma(x) = (1 + e^{-x})^{-1}$ . What values for  $\alpha_0$ ,  $\alpha_1$  and  $\alpha_2$  would result in the correct classification for this dataset? A positive label is predicted when the output of the sigmoid is larger or equal than 0.5.

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**Note:** do not use any formulas or automated methods to find the answer. Think for yourself. A logistic regression classifier is nothing more than a hyper-plane separating points of the two classes. If necessary, review vectors, dot-products and their geometrical interpretation in linear algebra. This applies to the following exercises, too.

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```

a0 = (
  -5
)

a1 = (
  -10
)

a2 = (
  10
)

# the first column is always one and is used for the "bias"
xs = matrix(c(
  1, 0, 0,
  1, 1, 0,
  1, 0, -1,
  1, -1, 0,
  1, 0, 1
), ncol = 3, byrow = T)

sigmoid = function(x) {
  1 / (1 + exp(-x))
}

sigmoid(xs %*% c(a0, a1, a2))

##           [,1]
## [1,] 6.692851e-03
## [2,] 3.059022e-07
## [3,] 3.059022e-07
## [4,] 9.933071e-01
## [5,] 9.933071e-01

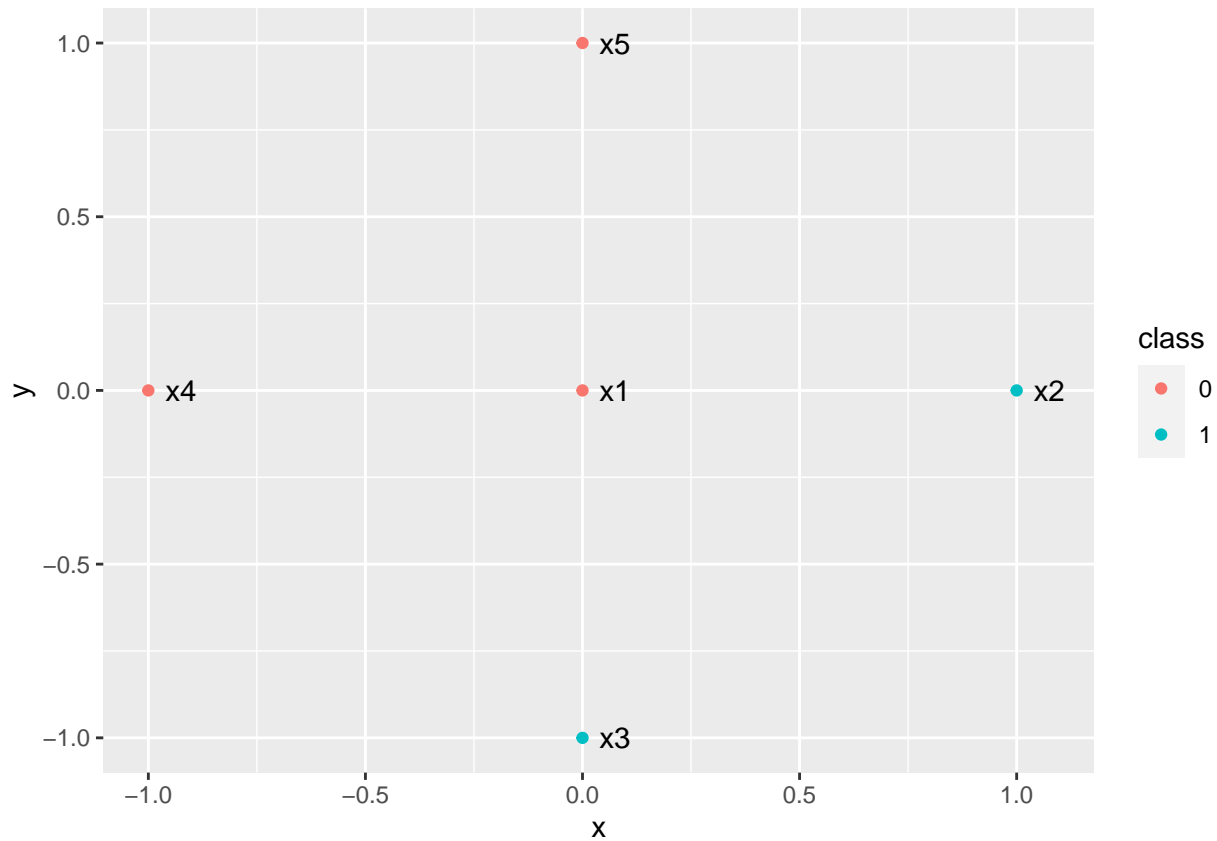
```

You should make sure that the last two values are close to one, and the others are close to zero.

**Note:** There are many valid parametrization that lead to a separating hyperplane. How would you prioritize between them?

## Exercise 2

Continuing from the previous exercise, suppose now that  $y_2 = y_3 = 1$  and  $y_1 = y_4 = y_5 = 0$ :



Consider the same logistic regression model above with coefficients  $\beta_0$ ,  $\beta_1$  and  $\beta_2$ , how would you need to set these coefficients to correctly classify this dataset?

```
b0 = (
-5
)

b1 = (
10
)

b2 = (
-10
)

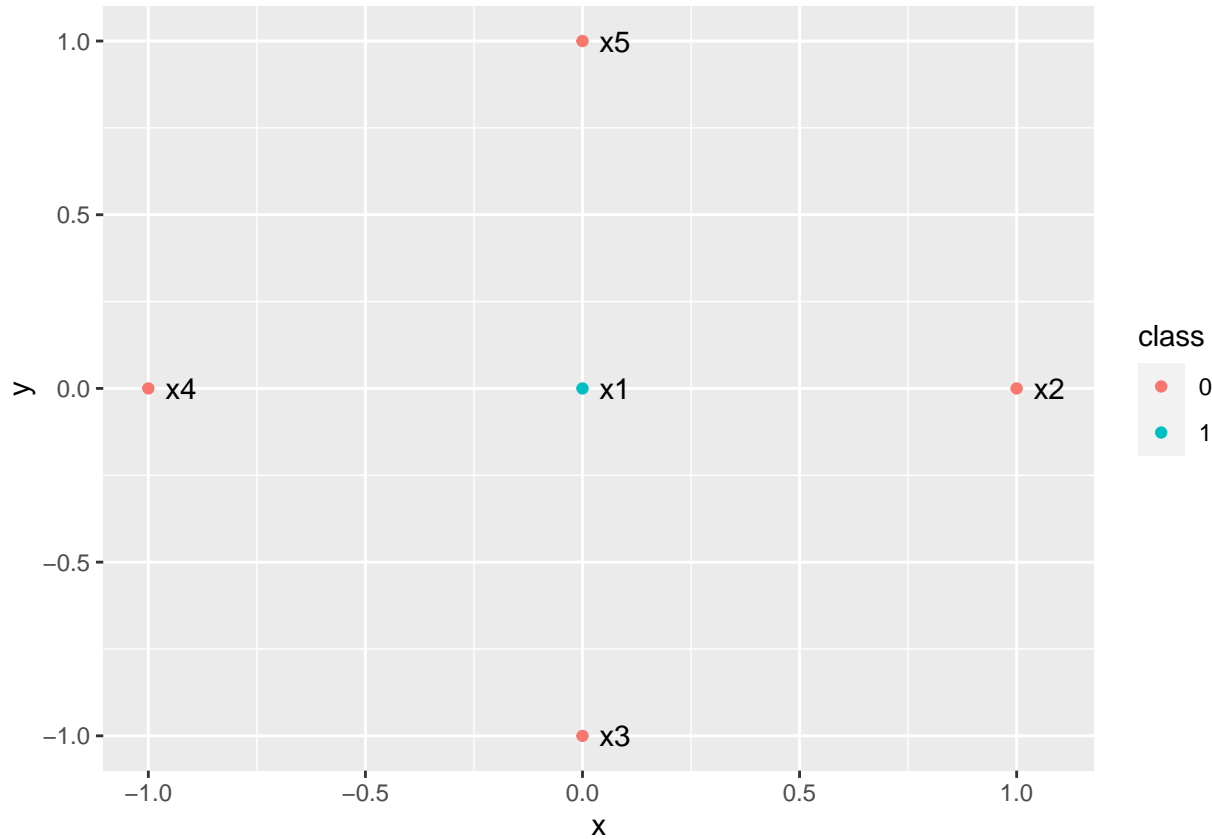
sigmoid(xs %*% c(b0, b1, b2))

##           [,1]
## [1,] 6.692851e-03
## [2,] 9.933071e-01
## [3,] 9.933071e-01
## [4,] 3.059022e-07
## [5,] 3.059022e-07
```

Make sure that the second and third elements are close to one, and the others close to zero.

### Exercise 3

Finally, with the same data as before, suppose that  $y_1 = 1$  and  $y_2 = y_3 = y_4 = y_5 = 0$ :



Clearly, logistic regression cannot correctly classify this dataset, since the two classes are not linearly separable (optional: prove it).

However, as we have shown in the previous exercises, it is possible to separate  $x_2$  and  $x_3$  from the rest, and  $x_4$  and  $x_5$  from the rest.

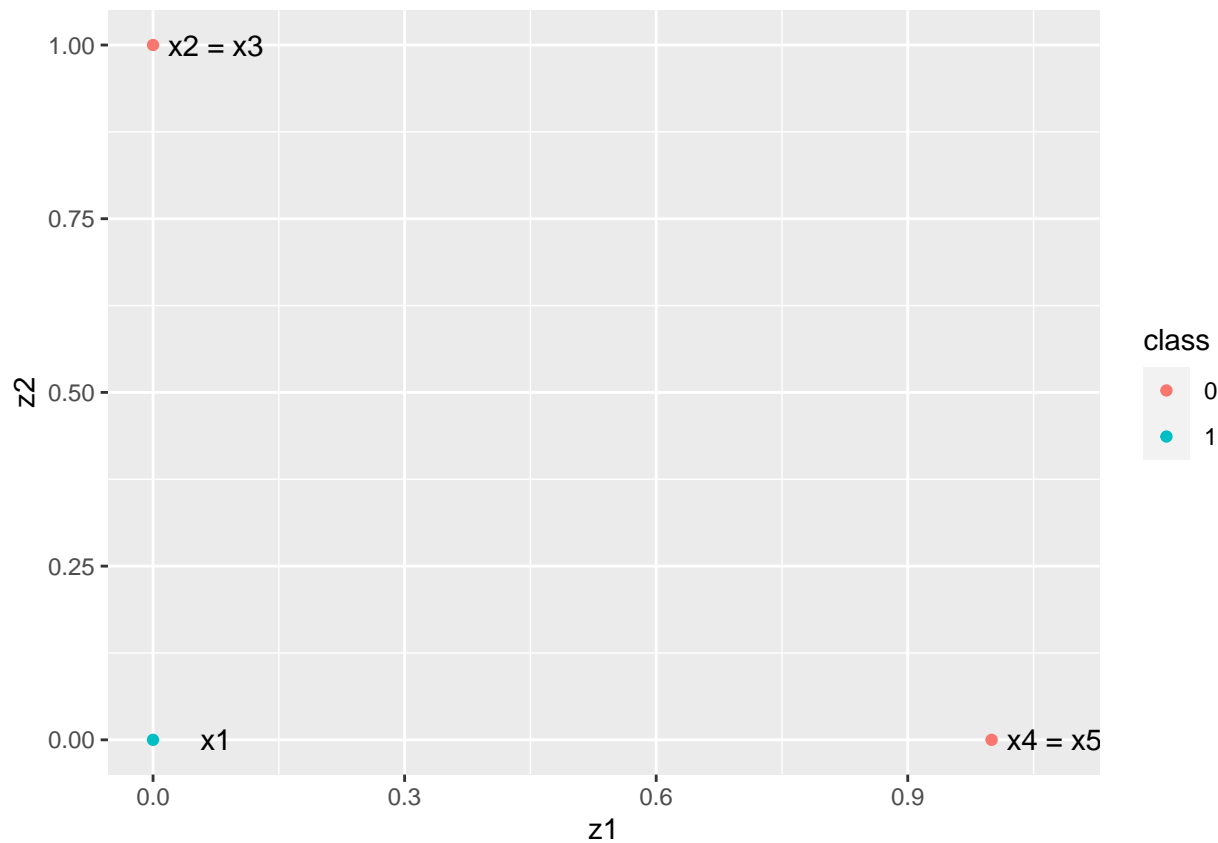
Can these two simple classifiers be composed into one that is powerful enough to separate  $x_1$  from the rest?

Can we use their predictions as input for another logistic regression classifier?

Let  $z_{i1} = \sigma(\alpha_0 + \alpha_1 x_{i1} + \alpha_2 x_{i2})$  and  $z_{i2} = \sigma(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2})$  be the output of the two logistic regression classifiers for point  $i$ . Then, the dataset would become:

$i$	$z_{i1}$	$z_{i2}$	$y$
1	0	0	1
2	0	1	0
3	0	1	0
4	1	0	0
5	1	0	0

In graphical form:



This sure looks linearly separable! As before, find the coefficients for a linear classifier  $\hat{y}_i = \sigma(\gamma_0 + \gamma_1 z_{i1} + \gamma_2 z_{i2})$ :

```
g0 = (
    5
)

g1 = (
    -10
)

g2 = (
    -10
)

zs = matrix(c(
    1, 0, 0,
    1, 0, 1,
    1, 0, 1,
    1, 1, 0,
    1, 1, 0
), ncol = 3, byrow = T)

sigmoid(zs %*% c(g0, g1, g2))

##           [,1]
## [1,] 0.993307149
## [2,] 0.006692851
```

```
## [3,] 0.006692851
## [4,] 0.006692851
## [5,] 0.006692851
```

Make sure that the first element is close to one, and the others close to zero.

This big classifier can be summarized as follows:

```
z1 = sigmoid(xs %*% c(a0, a1, a2))
z2 = sigmoid(xs %*% c(b0, b1, b2))

yhat = sigmoid(g0 + g1 * z1 + g2 * z2)
yhat
```

```
##           [,1]
## [1,] 0.99235864
## [2,] 0.007152788
## [3,] 0.007152788
## [4,] 0.007152788
## [5,] 0.007152788
```

And this is just what a neural network looks like! Each neuron is a simple linear classifier, and we just stack linear classifiers on top of linear classifiers. And we could go on and on, with many layers of linear classifiers.