

## Problem set 5 Solution

### Probabilistic classifiers 2

#### Exercise 1

1. Let  $\bar{W}^T = (w_1, w_2, \dots, w_d)$  and  $\bar{P}^T = (p_1, p_2, \dots, p_d)$  be points from  $R^d$  and let  $b$  be a number from  $R$ . Compute the distance from  $\bar{P}$  to the hyperplane defined by the equation  $\bar{W}^T \bar{X} + b = 0$ .
2. Show that the distance is proportional to  $|\bar{W}^T \bar{P} + b|$ , that is the distance is equal to  $c \cdot |\bar{W}^T \bar{P} + b|$  for some number  $c$ .

#### Solution 1

We use the fact that the vector  $\bar{W}$  is perpendicular to the hyperplane  $\bar{W}^T \bar{X} + b = 0$ .

Let  $L$  be the line via the point  $\bar{P}$  and parallel to the vector  $\bar{W}$ , that is  $L = \{\bar{P} + t\bar{W} \mid t \in R\} \subseteq R^d$ . Line  $L$  intersects the hyperplane  $\bar{W}^T \bar{X} + b = 0$  when  $\bar{W}^T (\bar{P} + t\bar{W}) + b = 0$ , i.e. when

$$t = \frac{-(\bar{W}^T \bar{P} + b)}{\|\bar{W}\|^2}.$$

The distance between this point of intersection and the starting point  $\bar{P}$  is

$$d = \|\bar{P} + t\bar{W} - \bar{P}\| = \|t\bar{W}\| = |t| \cdot \|\bar{W}\| = \frac{|\bar{W}^T \bar{P} + b|}{\|\bar{W}\|^2} \cdot \|\bar{W}\| = \frac{|\bar{W}^T \bar{P} + b|}{\|\bar{W}\|}.$$

The latter is proportional to  $|\bar{W}^T \bar{P} + b|$ .

#### Solution 2

In this solution we use the method of Lagrange multipliers. We want to find a point  $\bar{X}$  in the hyperplane (meaning that  $\bar{W}^T \bar{X} + b = 0$ ) that has the smallest distance to  $\bar{P}$  (meaning that  $\|\bar{P} - \bar{X}\|$  is minimized).

In other words, we want to solve the following optimisation problem:

$$\min_{\bar{X} \in R^d} (\bar{P} - \bar{X})^T (\bar{P} - \bar{X})$$

\*\*subject to\*\*  $\bar{W}^T \bar{X} + b = 0$ .

The corresponding Lagrangian is  $\mathcal{L}(x_1, \dots, x_d, \lambda) = (\bar{P} - \bar{X})^T (\bar{P} - \bar{X}) - \lambda \cdot (\bar{W}^T \bar{X} + b)$ .

The derivative of the Lagrangian is  $2(\bar{P} - \bar{X}) - \lambda \bar{W}$ .

To solve  $2(\bar{P} - \bar{X}) - \lambda \bar{W} = 0$  we first take the dot product of each of the sides of the equation with vector  $\bar{W}$ :

$$2\bar{W}^T (\bar{P} - \bar{X}) - \lambda \cdot \bar{W}^T \bar{W} = 0,$$

from which we derive  $\lambda = \frac{2\bar{W}^T (\bar{P} - \bar{X})}{\|\bar{W}\|^2}$ .

Similarly, we take the dot product with  $(\bar{P} - \bar{X})$ :

$$2(\bar{P} - \bar{X})^T (\bar{P} - \bar{X}) - \lambda \cdot (\bar{P} - \bar{X})^T \bar{W} = 0,$$

from which, using the computed value of  $\lambda$ , we derive

$$2(\bar{P} - \bar{X})^T (\bar{P} - \bar{X}) = \frac{2\bar{W}^T (\bar{P} - \bar{X})}{\|\bar{W}\|^2} \cdot (\bar{P} - \bar{X})^T \bar{W}$$

$$\|\bar{P} - \bar{X}\|^2 = \frac{(\bar{W}^T (\bar{P} - \bar{X}))^2}{\|\bar{W}\|^2}$$

$$\|\bar{P} - \bar{X}\|^2 = \frac{(\bar{W}^T \bar{P} + b - \bar{W}^T \bar{X} - b)^2}{\|\bar{W}\|^2} = \frac{(\bar{W}^T \bar{P} + b)^2}{\|\bar{W}\|^2}$$

$$\|\bar{P} - \bar{X}\| = \frac{|\bar{W}^T \bar{P} + b|}{\|\bar{W}\|}$$

## Exercise 2

Show the following properties of the logistic sigmoid function  $\sigma(x) = \frac{1}{1+e^{-x}}$ .

1.  $\sigma(x) = 1 - \sigma(-x)$
2.  $\frac{\partial \sigma}{\partial x} = e^{-x} \sigma^2(x)$

## Solution

1.  $1 - \sigma(-x) = 1 - \frac{1}{1+e^x} = \frac{1+e^x-1}{1+e^x} = \frac{e^x}{1+e^x} \cdot \frac{e^{-x}}{e^{-x}} = \frac{1}{e^{-x}+1} = \sigma(x)$
2.  $\frac{\partial \sigma}{\partial x} = \frac{e^{-x}}{(1+e^{-x})^2} = e^{-x} \sigma^2(x)$