

## E1 213 Pattern Recognition and Neural networks

### Problem Sheet 5

1. Given two sets of points in  $\mathbb{R}^d$ , show that they are linearly separable if and only if their convex hulls do not intersect. (Given a set of points,  $x_1, \dots, x_n$ , their convex hull is the set of all points  $z$  which can be written as  $z = \sum_{j=1}^n \lambda_j x_j$  where  $\lambda_j \geq 0$  and  $\sum_j \lambda_j = 1$ ).

2. Consider the joint density of  $X, Y$  given by

$$f_{XY}(x, y) = \frac{1}{2\pi\sigma^2\sqrt{1-\rho^2}} \exp\left(\frac{-1}{2\sigma^2(1-\rho^2)}(x^2 + y^2 - 2\rho xy)\right), \quad -\infty < x, y < \infty$$

Here  $X, Y$  are jointly Gaussian with mean zero, variance  $\sigma^2$  and correlation coefficient  $\rho$ . From the above, find the marginal density of  $X$  and show that it is Gaussian with mean zero and variance  $\sigma^2$ . Now show that the conditional density  $f_{Y|X}$  is also Gaussian. From this, show that  $E[Y | X]$  is a linear function of  $X$ .

3. Suppose we have  $y = \mathbf{a}^T X + \xi$  where  $\xi$  is a zero-mean random variable with variance  $\sigma^2$ . Under this model we have calculated in the class the variance of the least squares solution,  $W^*$ . Calculate the expected value of the least squares solution.
4. We can pose the problem of learning a linear classifier as minimizing

$$J(W) = \sum_{i=1}^n L(W^T X_i, y_i)$$

where  $L$  is a loss function. For least squares criterion, we take  $L(a, b) = (a - b)^2$ . If, instead we want to minimize absolute value of error, we can take  $L(a, b) = |a - b|$ . Show that logistic regression (in the 2-class case) can also be put in this framework with  $L(W^T X, y) = \ln(1 + \exp(-yW^T X))$ , where we assume that the class labels are  $+1$  and  $-1$ . What would be the loss function corresponding to mult-class logistic regression?

5. Consider a classification problem with  $K$  classes:  $C_1, \dots, C_K$ . We say that the training set is linearly separable if there are  $K$  functions:  $g_j(X) = W_j^T X + w_{j0}$ ,  $j = 1, \dots, K$ , such that we have  $g_i(X) \geq$

$g_j(X), \forall j$ , whenever  $X \in C_i$ . We say that a set of examples is totally linearly separable if given any  $C_i$ , there is a hyperplane that separates examples of  $C_i$  from the set of examples of all other classes. Show that totally linearly separable implies linearly separable but the converse need not be true.

6. Let  $\mathcal{X} = \mathbb{R}^2$ ,  $\mathcal{Y} = \{0, 1\}$ . Let  $c^r$  denote the circle (or circular disc) of radius  $r$  with center at origin. That is  $c^r = \{(x, y) \in \mathbb{R}^2 : x^2 + y^2 \leq r^2\}$ . Let  $\mathcal{C}$  be family of such concentric circles with centre at origin. Show that this concept class is PAC learnable.