## Problem 1

I did some consulting once for a businessman who told me that the way to distinguish a machine learning expert from a novice is to give them some of your data and see whether they can write a classifier which has very low error when applied to a withheld test set. Why was he wrong?

## Problem 2

Consider a binary classification problem where the two classes are equally probable, the class-0 conditional density is a standard multivariable normal distribution in two dimensions, and the class-1 conditional density is a multivariate normal distribution with mean [1,1] and covariance I.

Find the class boundary for the Bayes classifier.

#### Problem 3

(Problem 2 continued). Find the regression function  $r(x) = \mathbb{E}[Y \mid X = x] = \mathbb{P}(Y = 1 \mid X = x)$ . Plot a heatmap of this function.

#### Problem 4

(Problem 2 continued). Sample 1000 points by choosing one of the two distributions uniformly at random and then sampling from the selected distribution. Model the regression function by fitting the parametric model

$$r(\mathbf{x}) = \sigma(\alpha + \boldsymbol{\beta} \cdot \mathbf{x}),$$

where  $\sigma(x) = \frac{1}{1+e^{-x}}$ . Use the loss functional

$$L(r) = \sum_{i=1}^{n} \left[ y_i \log \frac{1}{r(x_i)} + (1 - y_i) \log \frac{1}{1 - r(x_i)} \right].$$

This is called **logistic regression**.

## Problem 5

(Problem 2 continued). Was the supposition that *r* took the given parametric form correct?

# Problem 6

How could we have modified the setup of Problem 2 so that our parametric assumption did not hold? Hint: begin by showing that the decision boundary is necessarily linear for a logistic model.

## Problem 7

How could we modify the logistic regression model so that it would accommodate multivariate normal class conditional distributions with distinct covariance matrices?