Problem 2. We have seen that in a naive Bayes model with features $f_1, f_2 \ldots$, for a specific text with corresponding feature counts $n_1, n_2 \ldots$, the log probability that the text belongs in a particular class is given by the model as follows:

$$\log P(class|text) \approx \log P(class) + n_1 \log P(f_1|class) + n_2 \log P(f_2|class) + \cdots$$

That is, the log probability of class membership is proportional to the distance above a plane corresponding to the class. The normal to the plane is a weight vector $\mathbf{w} = w_1, w_2 \ldots$ where for all features f_i, $w_i = \log P(f_i|class)$. (We can consider the log prior probability $\log P(class)$ as an extra feature w_0 where for all texts, $n_0 = 1$.)

For the following parts, assume we have two classes C_1 and C_2, with associated weight vectors $\mathbf{w}_1$ and $\mathbf{w}_2$.

a. (4 points) Given a text represented by a feature count vector $\mathbf{n} = n_1, n_2 \ldots$, when will the model classify the text as belonging to class C_1? When will the model classify the text as belonging to class C_2? Give the answers in terms of $\mathbf{w}_1$, $\mathbf{w}_2$ and $\mathbf{n}$.

b. (4 points) Given your answer above, how can we represent the *decision boundary* between the classes C_1 and C_2? In which direction from the boundary are texts classified as C_1, and in which direction as C_2? Give the answers in terms of $\mathbf{w}_1$ and $\mathbf{w}_2$.