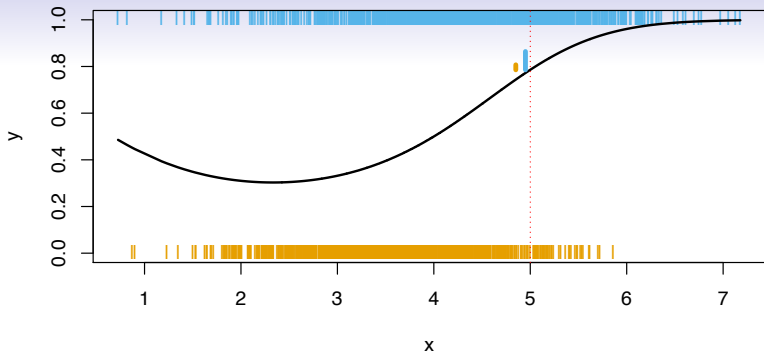


Classification Problems

Here the response variable Y is *qualitative* — e.g. email is one of $\mathcal{C} = (\text{spam}, \text{ham})$ (ham =good email), digit class is one of $\mathcal{C} = \{0, 1, \dots, 9\}$. Our goals are to:

- Build a classifier $C(X)$ that assigns a class label from \mathcal{C} to a future unlabeled observation X .
- Assess the uncertainty in each classification
- Understand the roles of the different predictors among $X = (X_1, X_2, \dots, X_p)$.



Is there an ideal $C(X)$? Suppose the K elements in \mathcal{C} are numbered $1, 2, \dots, K$. Let

$$p_k(x) = \Pr(Y = k | X = x), \quad k = 1, 2, \dots, K.$$

These are the *conditional class probabilities* at x ; e.g. see little barplot at $x = 5$. Then the *Bayes optimal* classifier at x is

$$C(x) = j \text{ if } p_j(x) = \max\{p_1(x), p_2(x), \dots, p_K(x)\}$$

Classification: some details

- Typically we measure the performance of $\hat{C}(x)$ using the misclassification error rate:

$$\text{Err}_{\text{Te}} = \text{Ave}_{i \in \text{Te}} I[y_i \neq \hat{C}(x_i)]$$

- The Bayes classifier (using the true $p_k(x)$) has smallest error (in the population).

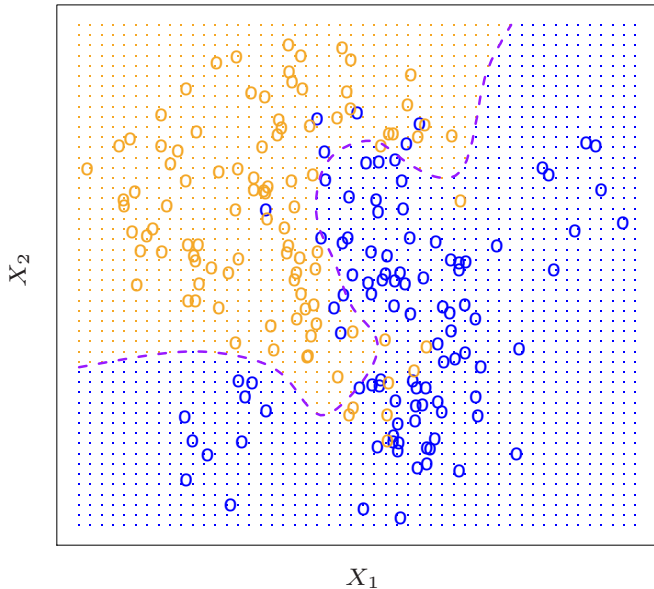
Classification: some details

- Typically we measure the performance of $\hat{C}(x)$ using the misclassification error rate:

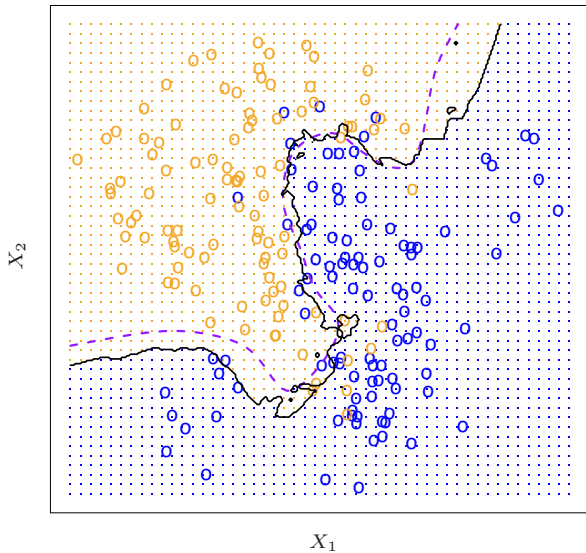
$$\text{Err}_{\text{Te}} = \text{Ave}_{i \in \text{Te}} I[y_i \neq \hat{C}(x_i)]$$

- The Bayes classifier (using the true $p_k(x)$) has smallest error (in the population).
- Support-vector machines build structured models for $C(x)$.
- We will also build structured models for representing the $p_k(x)$. e.g. Logistic regression, generalized additive models.

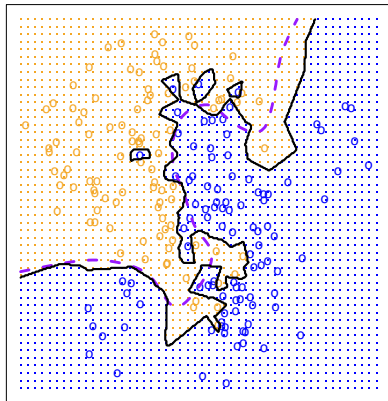
Example: K-nearest neighbors in two dimensions



KNN: K=10



KNN: $K=1$



KNN: $K=100$

