# Elements of Statistical Learning Chapter 2 Overview of Supervised Learning

Content: 2.1 - 2.5 Exercises: 2.1 - 2.3

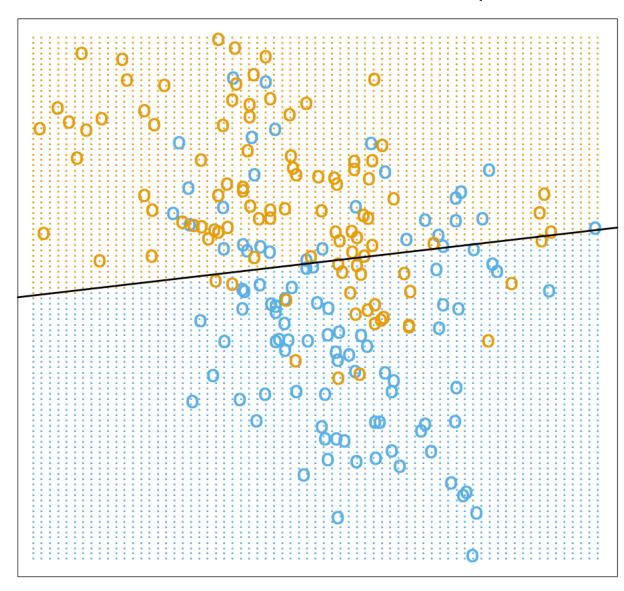
## **Nearest Neighbour**

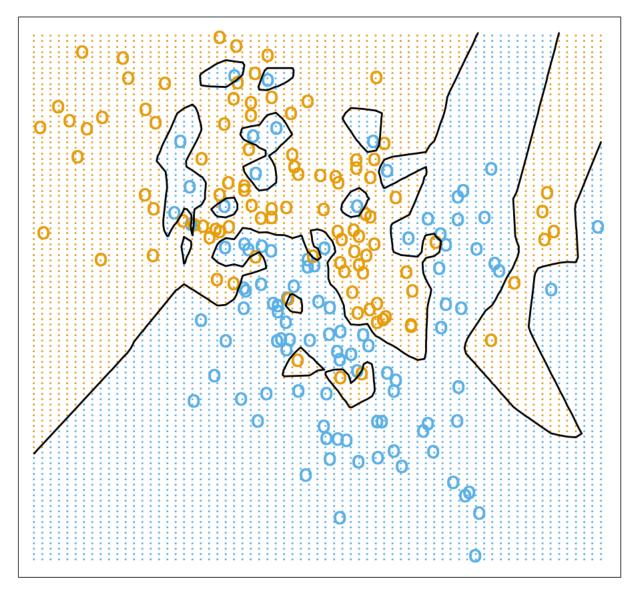
$$\hat{Y}(x) = \frac{1}{k} \sum_{x_i \in N_k(x)} y_i$$

## **Linear Model & Least Squares**

$$\hat{Y} = X^T \hat{\beta}$$

$$RSS(\beta) = \sum_{i=1}^{N} (y_i - x_i^T \beta)^2$$





#### **Scenario 1:**

The training data in each class were generated from bivariate Gaussian distributions with uncorrelated components and different means

High bias, low variance

#### **Scenario 2:**

The training data in each class came from a mixture of 10 low variance Gaussian distributions, with individual means themselves distributed as Gaussian

Low bias, high variance

#### 2.4 STATISTICAL DECISION THEORY

$$L(Y, f(X)) = (Y - f(X))^2$$

$$EPE(f) = E(Y - f(X))^2$$

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#### 2.4 STATISTICAL DECISION THEORY

$$EPE = E[L(G, \hat{G}(X))]$$

$$\hat{G}(x) = G_k \text{ if } \max_{g \in G} P(g \mid X = x)$$

**Bayes-optimal decision boundary** 

So for a reasonably large set of training data why not just use Nearest Neighbour as an approximation of E(Y|X=x)?

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# The curse of dimensionality!

Consider nearest neighbour in a unit hypercube of uniformly distributed inputs - Capturing a fraction r of the unit volume in p dimensions requires edge length:

$$e_p(r) = r^{1/p}$$

All sample points are close to the edge of the sample Median distance from the origin to the nearest data point is given by:

$$d(p,N) = (1 - \frac{1}{2}^{1/N})^{1/p}$$

The sampling density is proportional to  $N^{1/p}$ 

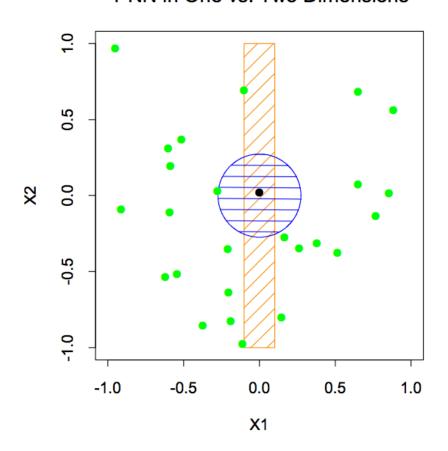
E.g. if 100 samples is dense for a given problem in 1-d then 100^10 samples is required to match that density in 10-d

# **Example:**

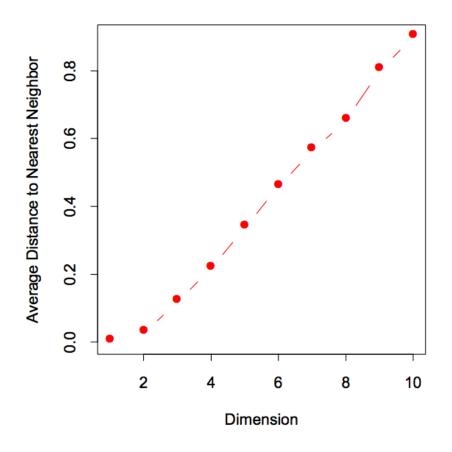
$$Y = f(X) = e^{-8||X||^2}$$

# **Example:**

1-NN in One vs. Two Dimensions



Distance to 1-NN vs. Dimension



# **Example:**

$$MSE(x_0) = E_T[f(x_0) - \hat{y}_0]^2$$
  

$$MSE(x_0) = Var_T(\hat{y}_0) + Bias^2(\hat{y}_0)$$

# **EXERCISES**