

# STAT406- Methods of Statistical Learning Lecture 14

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# Classification as prediction

- Most classifiers can be thought of as different ways to estimate or model

$$P(G = \mathbf{c}_j | \mathbf{X} = \mathbf{x})$$

- One way to model these probabilities is via Bayes' Thrm:

$$P(G = \mathbf{c}_j | \mathbf{X} = \mathbf{x}) = \frac{\mathbf{f}(\mathbf{x} | \mathbf{c}_j) P(G = \mathbf{c}_j)}{\mathbf{f}(\mathbf{x})}$$

# LDA vs QDA

LDA classifies an observation into the class  $c_j$  for which the estimated (under a normality assumption)

$$P(G = c_j | \mathbf{X} = \mathbf{x})$$

is highest.

If  $\mathbf{X} | G = c_j \sim \mathcal{N}(\boldsymbol{\mu}_j, \boldsymbol{\Sigma})$  it means the class for which

$$\delta_j(\mathbf{x}) = \mathbf{x}' \mathbf{a}_j + b_j$$

is highest, where

$$\mathbf{a}_j = \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu}_j \quad \text{and} \quad b_j = -\frac{1}{2} \boldsymbol{\mu}_j' \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu}_j + \log(p_j)$$

# QDA

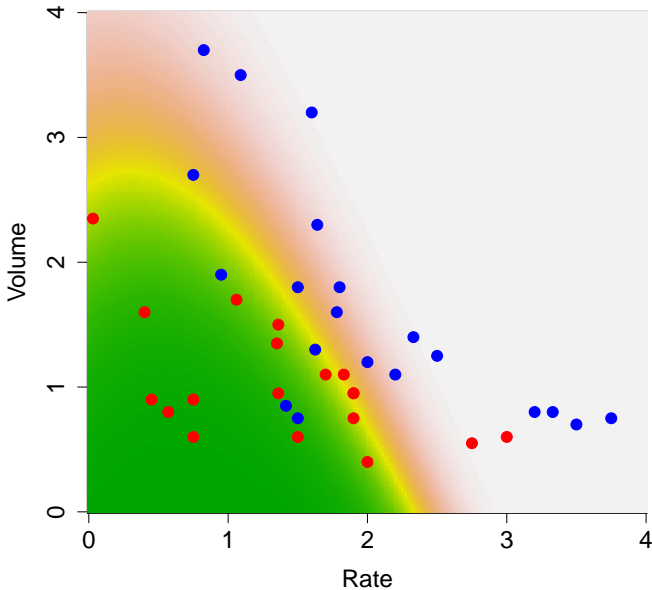
If  $\mathbf{X} | G = c_j \sim \mathcal{N}(\boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)$  then, the estimated posterior probabilities look different.

QDA classifies an observation into the class  $c_j$  that maximizes

$$\delta_j(\mathbf{x}) = \mathbf{x}' \mathbf{A}_j \mathbf{x} + \mathbf{x}' \mathbf{d}_j + b_j$$

(see the book for details)

# QDA-based probabilities



# LDA - QDA - Logistic classifiers

- Multiclass: LDA, QDA and Logistic classifiers extend to the case of more than 2 classes
- Examples in R (Zip-code hand-written digits)

# LDA - QDA - Logistic classifiers

- LDA vs QDA: presents the usual “flexibility vs. variability” trade-off
- LDA & QDA vs Logistic classifiers:  
**Gaussian MLE estimates**  
(non-robust, sensitive to the Gaussian assumption) vs. **Binomial MLE estimates** (no distributional assumption of  $\mathbf{X} | G = c_j$  required).

# Nearest-neighbours

- We need to estimate

$$P(G = \mathbf{g} | \mathbf{X} = \mathbf{x})$$

- An intuitive and “model-free” estimator is the nearest-neighbours estimator



# Nearest-neighbours

- Same spirit as the local-constant (kernel) regression estimator
- The K-NN estimator is

$$\hat{P}(G = \mathbf{g} | \mathbf{X} = \mathbf{x}) = \frac{1}{|N_{\mathbf{x}}^K|} \sum_{j \in N_{\mathbf{x}}^K} \mathbf{I}\{Y_j = \mathbf{g}\}$$

where

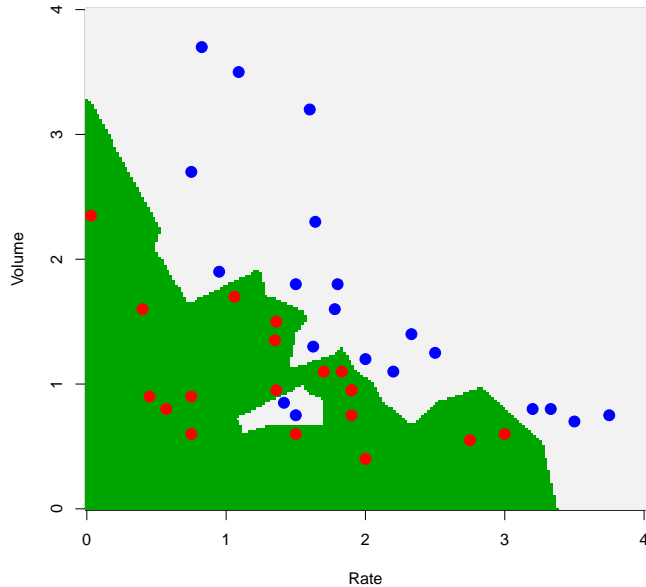
$$N_{\mathbf{x}}^K = \{i : d(\mathbf{X}_i, \mathbf{x}) \leq d_{(K)}\}$$

and  $d_{(K)}$  is the distance from  $\mathbf{x}$  to the  $K$ -th closest point in the sample ( $\mathbf{X}_i$ )

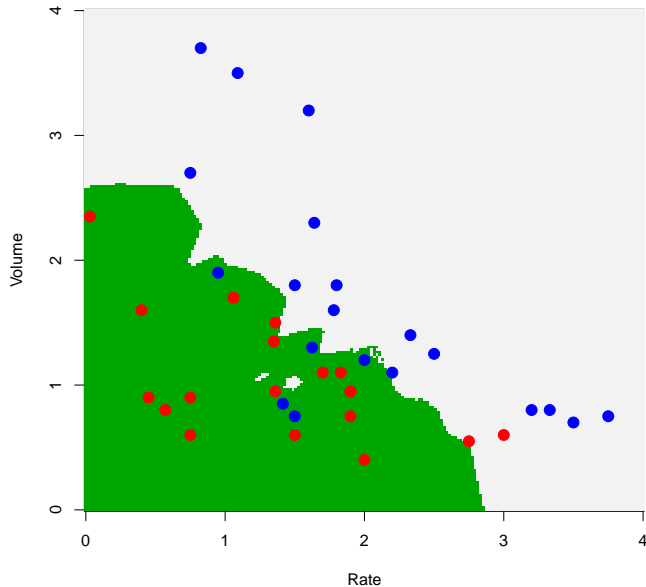
# Nearest-neighbours

- The K-NN estimator is the proportion of observations from class **g** among the closest  $K$  neighbours
- The K-NN classifier assigns a point to the class most represented among its  $K$  neighbours (“peer pressure”)

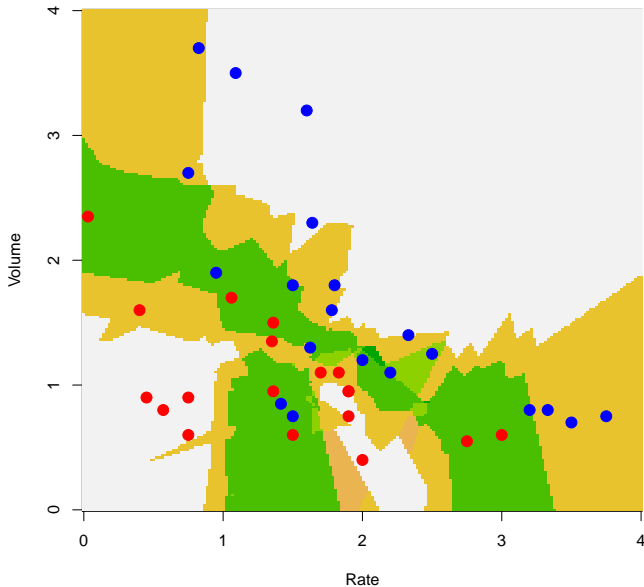
# Vaso - 1-NN



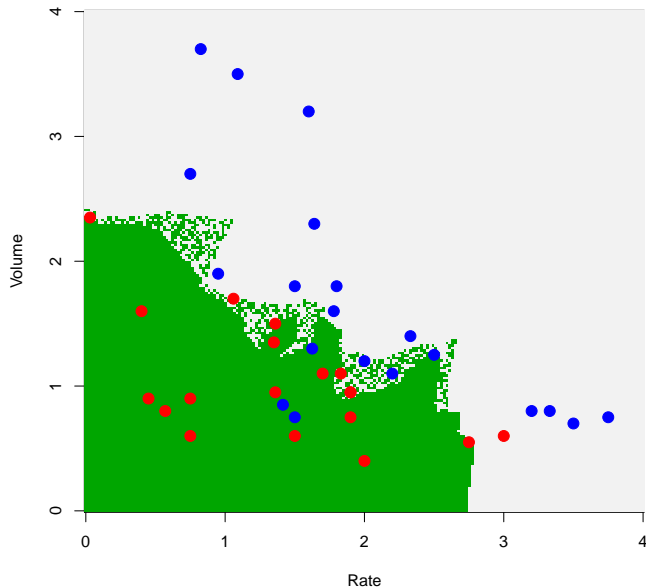
# Vaso - 5-NN



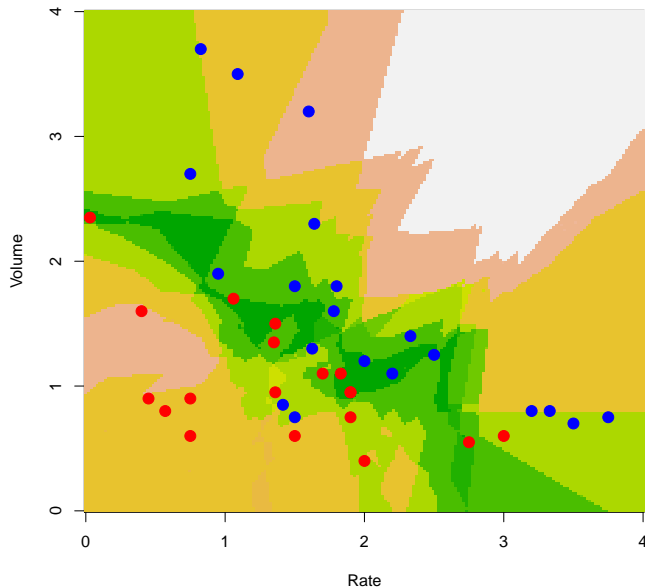
# Vaso - 5-NN - votes



# Vaso - 10-NN



# Vaso - 10-NN - votes



# Nearest-neighbours

- How can we select the number  $K$  of neighbours?
- Zip-code example



# Nearest-neighbours - Challenge

- What's wrong with this picture?

