

STAT406- Methods of Statistical Learning

Lecture 15

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Classification Trees

- To estimate the probabilities of each class \mathbf{g} for a particular value of the feature vector \mathbf{x} , **nearest neighbours** constructs estimates

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

= prop. of objects of class \mathbf{g}
among \mathbf{x} 's neighbours

Classification Trees

- Drawback: may not be “local” for moderate number of features (hence, may not represent the distribution of \mathbf{g} for $\mathbf{X} = \mathbf{x}$)
- Yet another incarnation of the “curse of dimensionality”

Classification Trees

- If we assume a model for the distribution of the features \mathbf{X} for each class

$$f(\mathbf{x} | \mathbf{g} = \mathbf{g}) = f_{\mathbf{g}}(\mathbf{x})$$

then we have a formula for

$$P(\mathbf{g} = \mathbf{g} | \mathbf{X} = \mathbf{x}) = \frac{f_{\mathbf{g}}(\mathbf{x}) P(\mathbf{g} = \mathbf{g})}{\sum_{\mathbf{g}} f_{\mathbf{g}}(\mathbf{x}) P(\mathbf{g} = \mathbf{g})}$$

Classification Trees

- We typically have estimates for these probabilities
- Only the numerator is needed
- Drawback: the model may not be correct.
- Model-based inferences are typically more stable than model-free ones
- But they may be biased if the model is a poor approximation to the truth

Classification Trees

- Classification trees provide another family of estimates for $P(\mathbf{g} = \mathbf{g}|\mathbf{X} = \mathbf{x})$
- They do not need a model
- Instead of estimating the local proportion (probability) of each class around a point \mathbf{x} , CART's attempt to find regions of the feature space that are “dominated” by one class.

Classification Trees

- Classification trees try to identify **regions** of the domain where **one class** clearly **dominates** the others (i.e. where the class proportions are far from being “uniform”)
- They **search** for these regions in a **very specific way**.

Classification Trees

- These regions are searched using a sequential algorithm that at each step **partitions** the current level (“leaf”) into two “leaves” / “children” **according** to the value of **one of the feature variables**, for example:

$$X_j \leq \mathbf{a} \quad \text{versus} \quad X_j > \mathbf{a}$$

Classification Trees

- At every step, the algorithm searches for the variable X_j and level a that produce the largest increase in “homogeneity” (alternatively: the largest decrease in “heteroscedasticity”)
- We need a measure of “homogeneity” (or lack of it)

Classification Trees

Some practical considerations in building (spanning) the tree:

- Do not partition nodes / leaves with fewer elements than a fixed threshold (say, 5)
- Do not partition a node if the “gain” in less homogeneity is less than a certain percentage of the current value
- Or both...

Classification Trees

Let **N** denote a “node”, that is: a subset of the data.

Let $\hat{p}_j, j = 1, \dots, K$ be the proportion of observations of each class in this node

$$\hat{p}_j = \frac{\text{\# of observations of class } j \text{ in node } \mathbf{N}}{\text{total \# of observations in node } \mathbf{N}}$$

Classification Trees

Maximum homogeneity when

$$\hat{p}_1 \approx \hat{p}_2 \approx \cdots \approx \hat{p}_K$$

Minimum homogeneity when $\hat{p}_r \approx 1$ for
some $1 \leq r \leq K$

Classification Trees

Measures of homogeneity

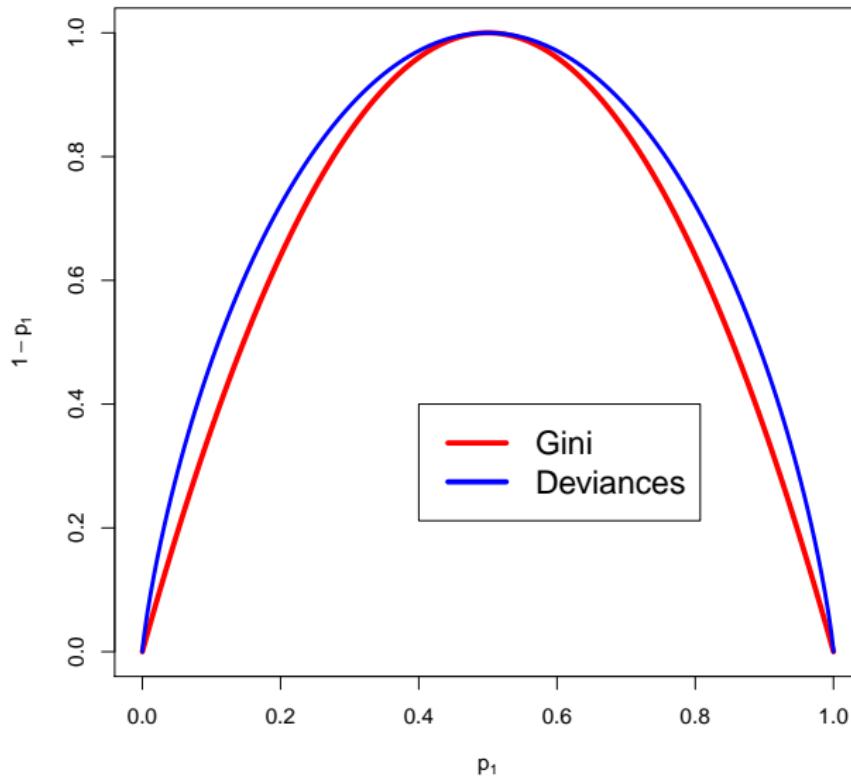
- Gini index:

$$Q_G(\hat{p}_1, \dots, \hat{p}_K) = \sum_{j \neq i}^K \hat{p}_j \hat{p}_i = \sum_{j=1}^K \hat{p}_j (1 - \hat{p}_j)$$

- Entropy or deviance:

$$Q_D(\hat{p}_1, \dots, \hat{p}_K) = -2 \sum_{j=1}^K \hat{p}_j \log(\hat{p}_j)$$

Gini & Deviances - 2 groups



Classification Trees

Define the “homogeneity” of a node \mathbf{N} as

$$Q(\mathbf{N}) = Q(\hat{p}_1, \dots, \hat{p}_K)$$

where

$$\hat{p}_j = \frac{\text{\# of observations of class } j \text{ in node } \mathbf{N}}{\text{total \# of observations in node } \mathbf{N}}$$

Q could be Q_G or Q_D , for example.

Classification Trees

- (a) Start with a node **N** containing all data points
- (b) Find the variable X_j and value **a** that minimize

$$\mathbf{n}_L Q(\mathbf{X} \in \mathbf{N} : X_j \leq \mathbf{a}) + \mathbf{n}_R Q(\mathbf{X} \in \mathbf{N} : X_j > \mathbf{a})$$

where $\mathbf{n}_L = \#\{\mathbf{X} \in \mathbf{N} : X_j \leq \mathbf{a}\}$

- (c) Define the corresponding two “children” of node **N**
- (d) Apply the same to each “child” / “leaf”

Classification Trees

- In practice, we need to weight the homogeneity by the number of observations in each leaf.
- This reflects a probabilistic model for the tree, and represents the probability that a point is observed in this leaf
- In other words: minimize homogeneity more in “larger” (in average) leaves.

Classification Trees

- Let n_c be the size of the node \mathbf{N}_c , its homogeneity is

$$n_c Q(\mathbf{N}_c) \propto \frac{n_c}{n} Q(\mathbf{N}_c)$$

- If we split \mathbf{N}_c into \mathbf{N}_1 and \mathbf{N}_2 the homogeneity is

$$n_1 Q(\mathbf{N}_1) + n_2 Q(\mathbf{N}_2) \propto \frac{n_1}{n} Q(\mathbf{N}_1) + \frac{n_2}{n} Q(\mathbf{N}_2)$$

The homogeneity of any split is less than that of the parent node (Breiman, Friedman, Olshen, Stone; 1984).

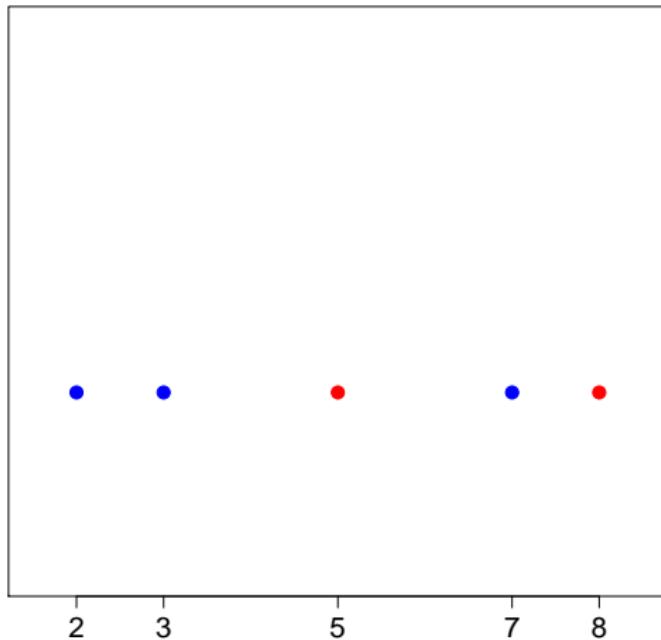
Classification Trees

- In the next 5 slides the reported “ Q_G ” is

$$Q_G = n_L Q_G(\mathbf{N}_L) + n_R Q_G(\mathbf{N}_R)$$

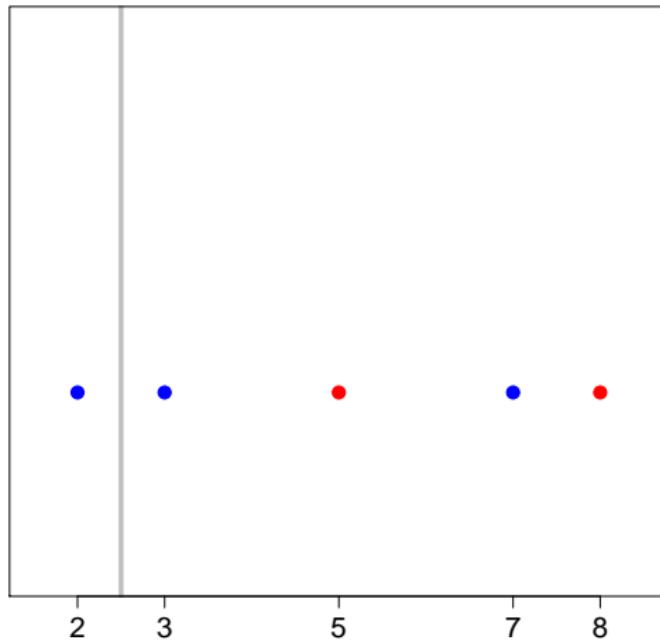
- Because of the lack of space on the slides, I used “ Q_G ” to indicate the combined homogeneity measure of the two child nodes resulting from each proposed split.

Classification Trees



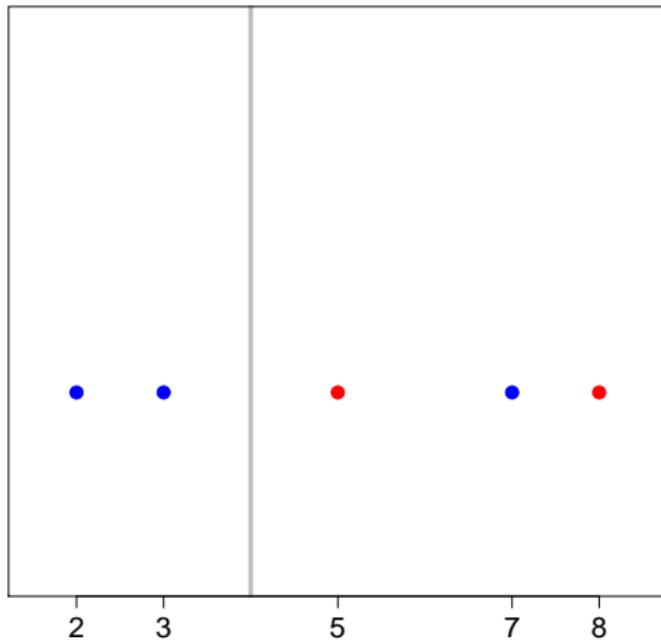
$$(\hat{p}_R = 2/5 \quad \hat{p}_B = 3/5) \quad Q_G = \mathbf{2.4}$$

Classification Trees



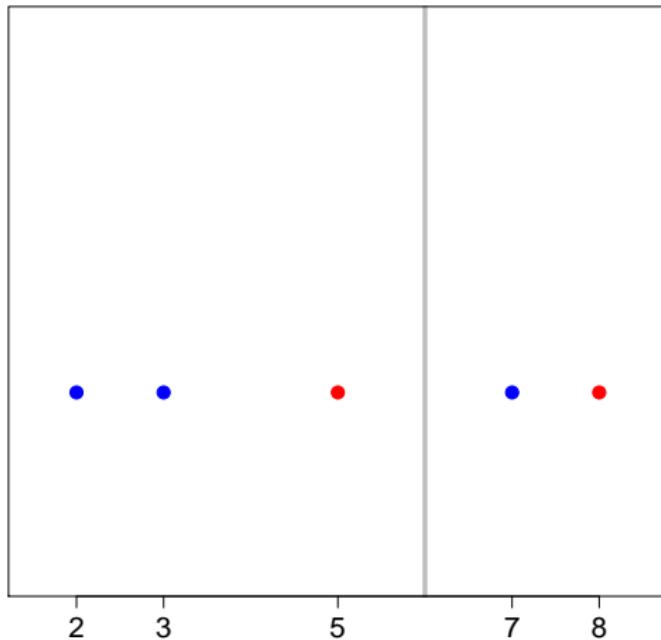
$$(\hat{p}_R = 0 \quad \hat{p}_B = 1) \quad (\hat{p}_R = 1/2 \quad \hat{p}_B = 1/2) \quad Q_G = 2$$

Classification Trees



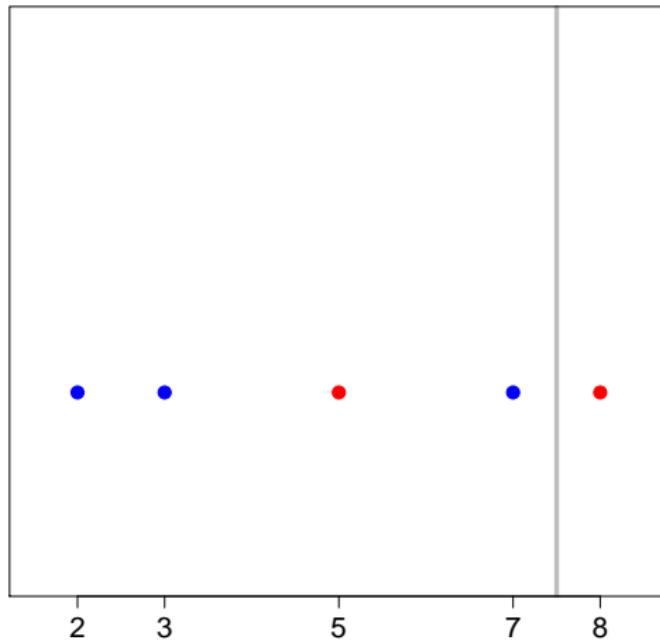
$$(\hat{p}_R = 0 \quad \hat{p}_B = 1) \quad (\hat{p}_R = 2/3 \quad \hat{p}_B = 1/3) \quad Q_G = \textcolor{red}{1.33}$$

Classification Trees



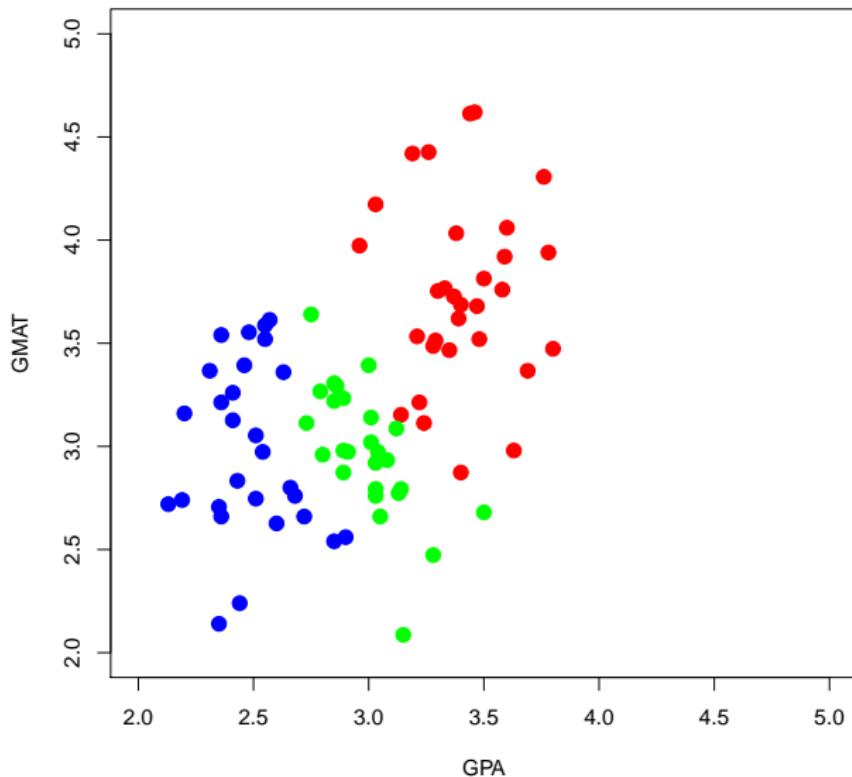
$$(\hat{p}_R = 1/3 \quad \hat{p}_B = 2/3) \quad (\hat{p}_R = 1/2 \quad \hat{p}_B = 1/2) \quad Q_G = \textcolor{red}{2.33}$$

Classification Trees

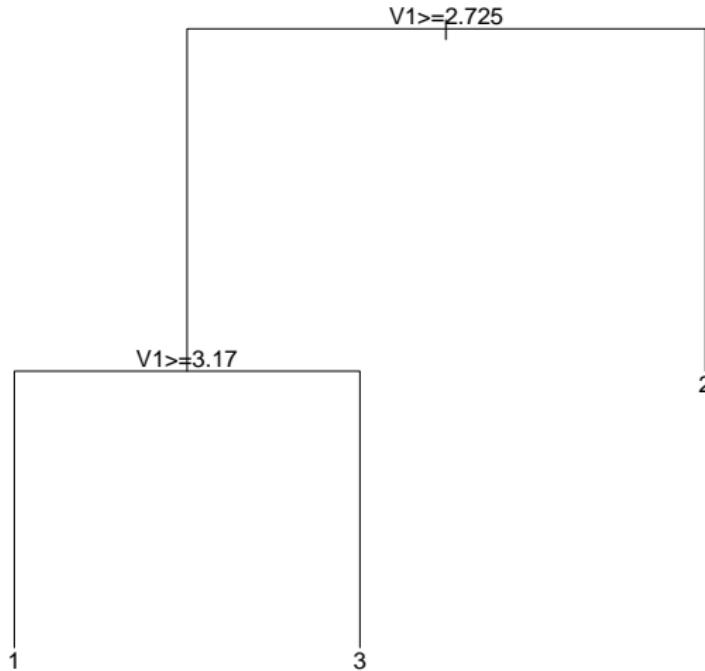


$$(\hat{p}_R = 1/4 \quad \hat{p}_B = 3/4) \quad (\hat{p}_R = 1 \quad \hat{p}_B = 0) \quad Q_G = \textcolor{red}{1.5}$$

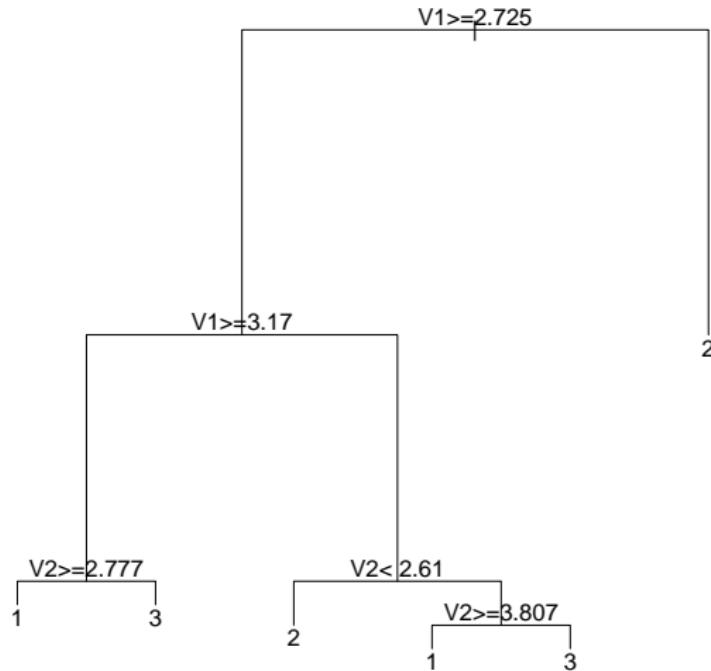
Grad admissions



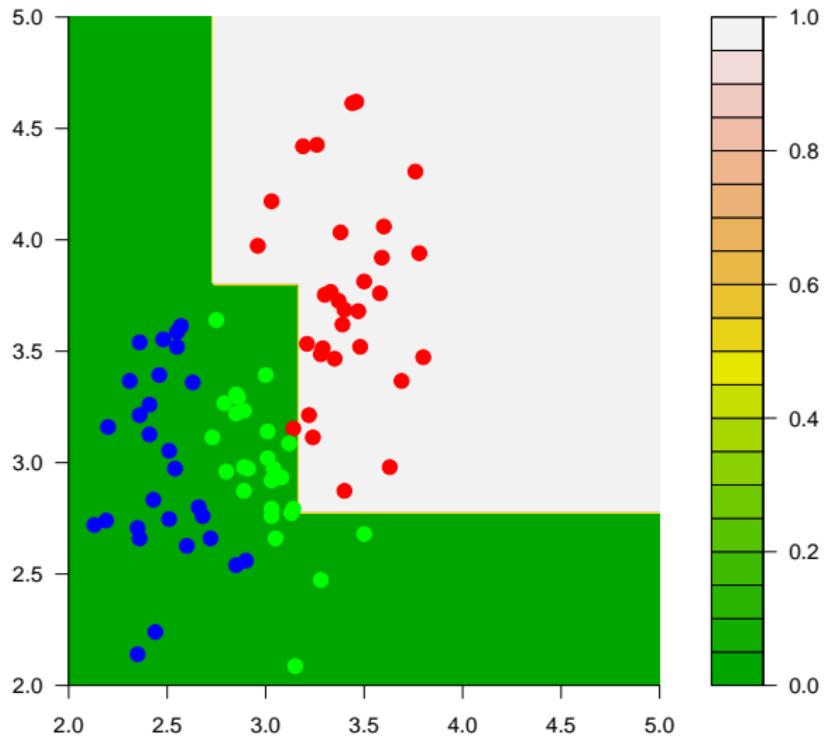
Grad admissions - Gini tree



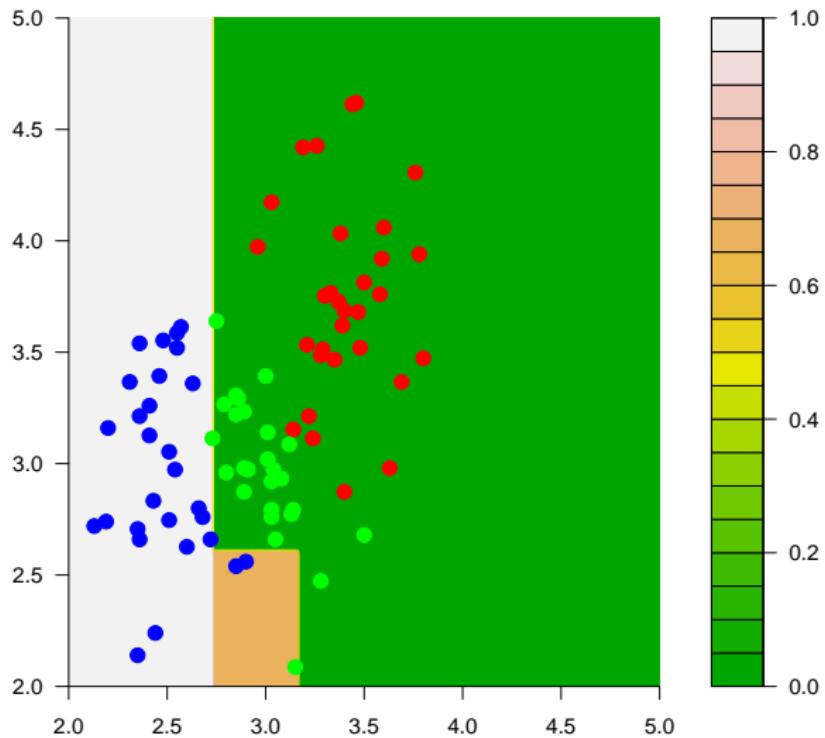
Grad admissions - Deviance tree



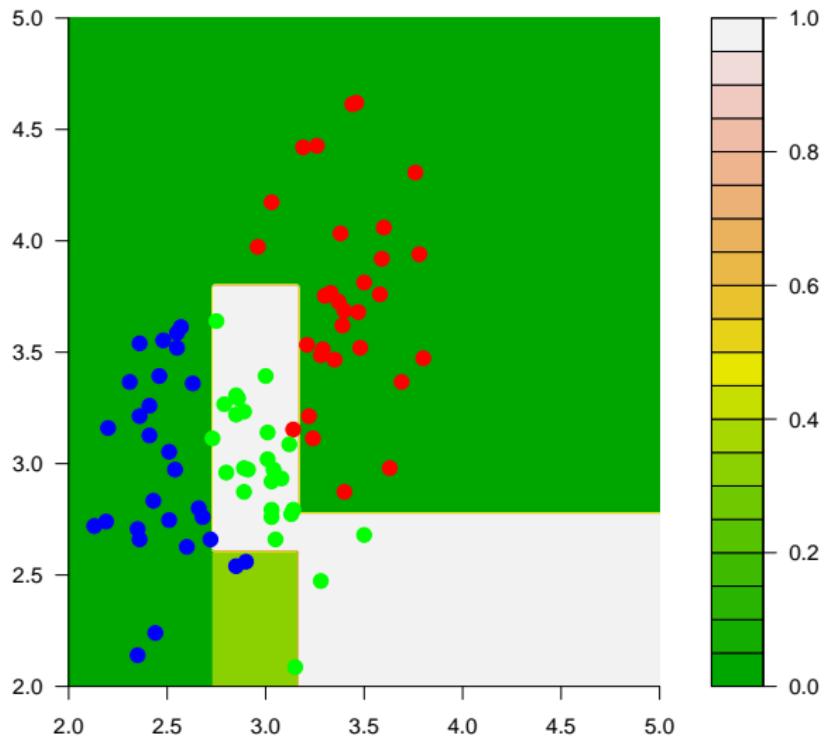
Grad admissions



Grad admissions



Grad admissions



Classification example

- ISOLET data
<http://archive.ics.uci.edu/ml/datasets/ISOLET>
- 150 subjects spoke the name of each letter twice
- 52 samples from each subject, 300 samples for each letter

Classification example

- 617 features (explanatory variables). They include: spectral coefficients; contour features, sonorant features, pre-sonorant features, and post-sonorant features.
- Data are split into training ($n = 6238$) and test ($n = 1559$)
- Mission: build a classifier to identify future spoken letters

Classification example

- I separated the letters C and Z

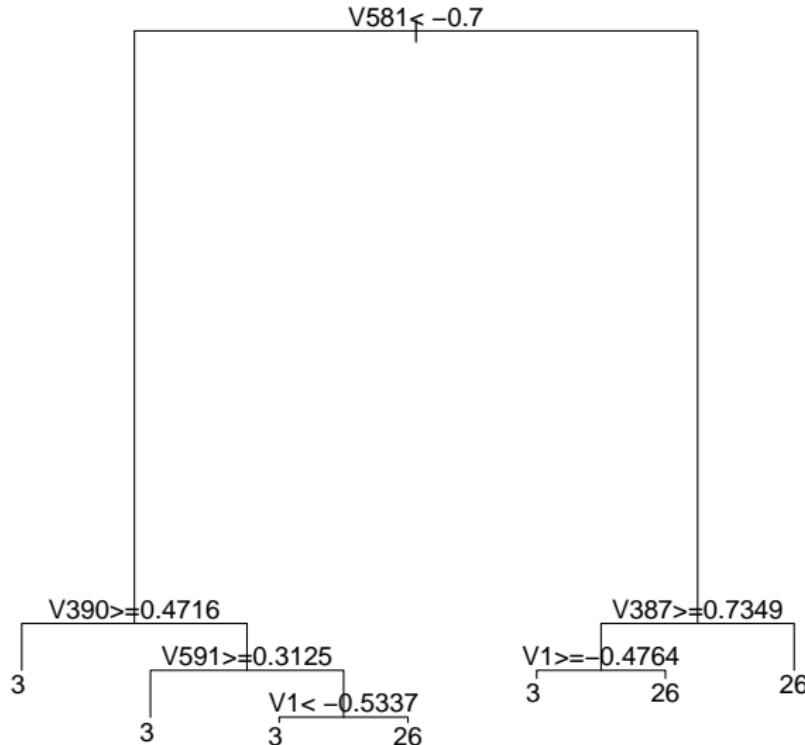
```
> x <- read.table('isolet-train.data', sep=',', )
> # 3 and 26 --- "C" and "Z"
>
> xa <- x[ x$V618 == 3, ]
> xb <- x[ x$V618 == 26, ]
>
> xx <- rbind(xa, xb)
> xx$V618 <- as.factor(xx$V618)
```

Classification example

- Fit a classification tree

```
> myc <- rpart.control(minsplit=7, cp=1e-7,
   xval=10)
>
>
> set.seed(123)
> a.t <- rpart(V618~., data=xx,
   parms = list(split = 'information'),
   control=myc)
> b <- a.t$cptable[
   which.min(a.t$cptable[, "xerror"]), "CP"]
> d.r <- prune(a.t, cp=b)
```

Classification example



Classification example

- Predict on the test data

```
> d.pr <- predict(d.r, newdata=dd,
                    type='class')
> table(truth, d.pr)
    d.pr
truth   3 26
      3 59  1
      26 0 60
```

- And we only used 5 explanatory variables!

Classification example

- The problem is not trivial
- Let's try a 1-NN nearest neighbour classifier

```
> u1 <- knn(train=xx[, -618], test=dd[, -618],  
+           cl=xx[, 618], k = 1)  
>  
> table(truth, u1)  
    u1  
truth 3 26  
      3 57 3  
    26 9 51
```

Classification example

- With 5-NN is not much better

```
> u5 <- knn(train=xx[,-618],  
+ test=dd[,-618], cl=xx[,618],  
+ k = 5)  
>  
> table(truth, u5)  
          u5  
truth   3 26  
      3 58  2  
    26  5 55
```

Classification example

- With a logistic classifier

```
> xx$V619 <- as.numeric(xx$V618==3)
> d.glm <- glm(V619 ~ . - V618, data=xx,
    family=binomial)
```

Warning message:

glm.fit: algorithm did not converge

[...]

```
> table(truth, pr.glm)
pr.glm
truth  0   1
      3 25 35
      26 33 27
```

- Can we explain the problem?

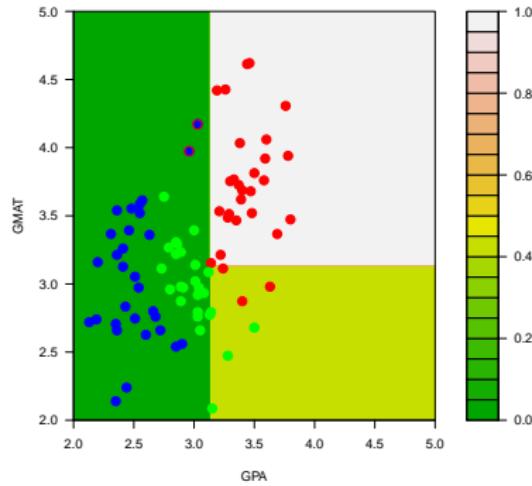
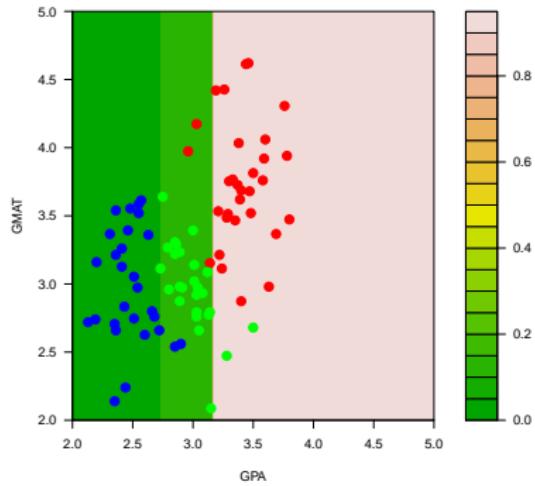
Classification example

- How about the approach based on the Gaussian distribution of the features (within each class)?

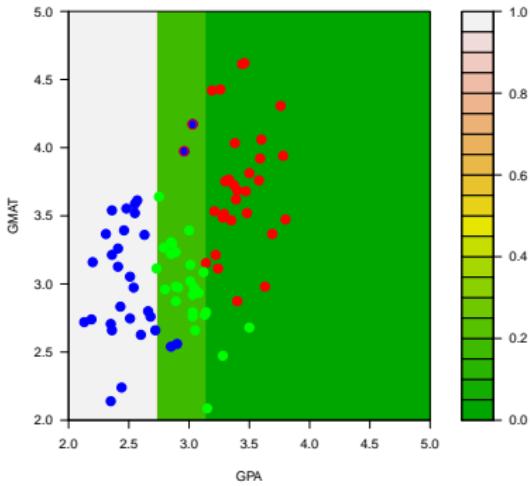
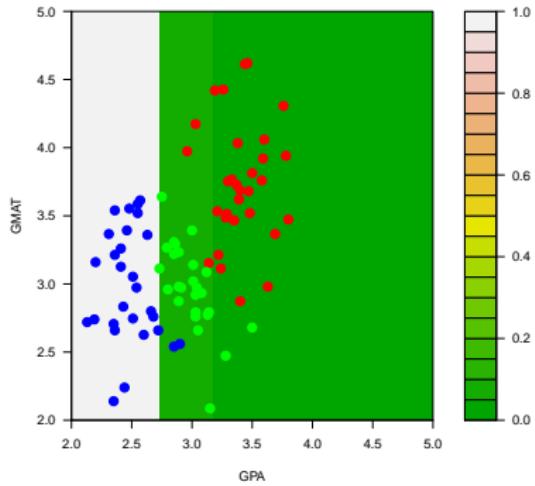
```
> library(MASS)
>
> d.lda <- lda(V618 ~ ., data=xx)
Warning message:
In lda.default(x, grouping, ...) :
  variables are collinear
```

- Can we explain the problem?

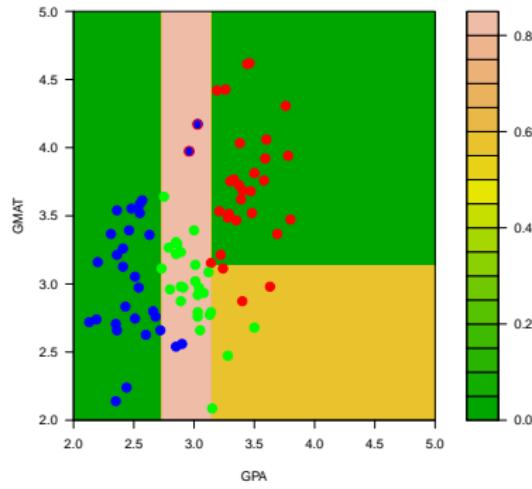
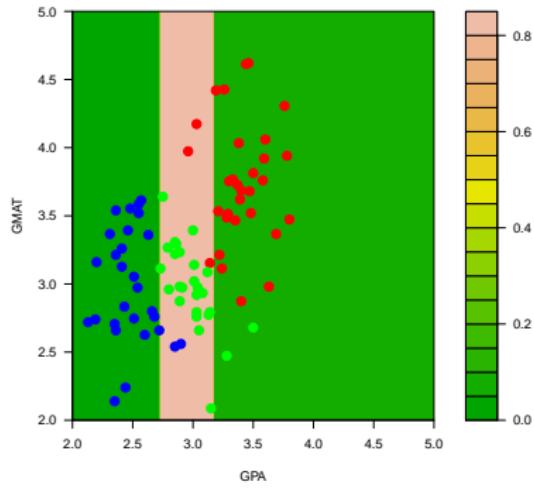
Trees are unstable...



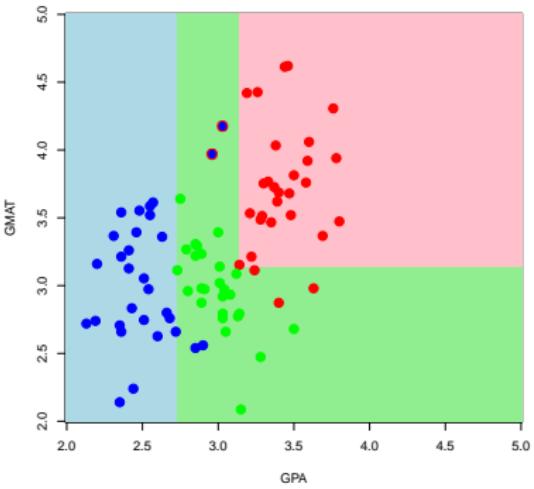
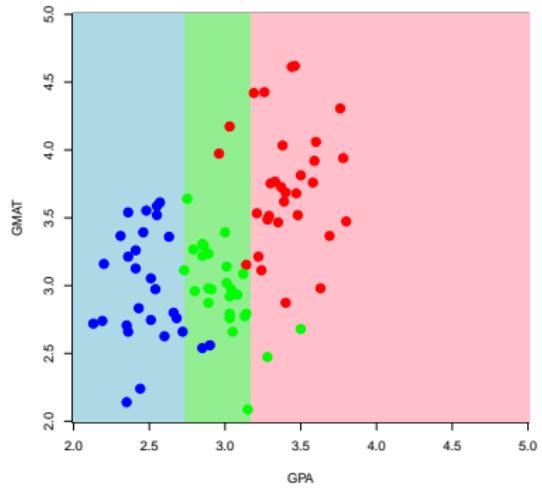
Trees are unstable...



Trees are unstable...



Trees are unstable...



Classification Trees - Bagging

- This problem can be alleviated sometimes using “**Bagging**” (Bootstrap aggregation)
- It is a **general principle**, applies to any classifier / estimator
- But it's not always equally effective (see the Midterm)

Classification Trees - Bagging

- Consider the predicted class $\hat{g}(\mathbf{X})$ or predicted probabilities $\hat{P}(g|\mathbf{X})$

$$\hat{f}(\mathbf{X}) = \left\{ \begin{array}{l} \left(\hat{P}(g_1|\mathbf{X}), \dots, \hat{P}(g_K|\mathbf{X}) \right) \\ \arg \max_g \hat{P}(g|\mathbf{X}) \end{array} \right\}$$

Classification Trees - Bagging

- If we had several **independent samples**, we could obtain a more stable (less variable) $\hat{f}(\mathbf{X})$ by using the **average over the samples**.
- Using **our sample distribution as an estimator of the population distribution**, the bootstrap simulates independent samples by randomly drawing samples from our data

Classification Trees - Bagging

- We can obtain a “large” number of **trees** and have them “**vote**” on the classification of future observations, or **average** their **conditional probabilities estimates** $\hat{P}(g_j | \mathbf{X})$

Classification Trees - Bagging

- Our aggregated classifier is

$$\bar{f}(\mathbf{X}) = \left\{ \begin{array}{l} (\bar{P}(g_1|\mathbf{X}), \dots, \bar{P}(g_K|\mathbf{X})) \\ \arg \max (\mathbf{n}_1, \mathbf{n}_2, \dots, \mathbf{n}_K) \end{array} \right\}$$

where $(\bar{P}(g_1|\mathbf{X}), \dots, \bar{P}(g_K|\mathbf{X}))$ are averaged conditional probabilities over the bootstrap samples;

$(\mathbf{n}_1, \mathbf{n}_2, \dots, \mathbf{n}_K)$ are the number of times each class was selected and

$\mathbf{n}_1 + \mathbf{n}_2 + \dots + \mathbf{n}_K =$
number of bootstrap samples