

CLASSIFICATION TREES

Data Mining

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INTRODUCTION

- A model to predict a categorical response with k levels
- Example
 - Predict the gender of a new customer
 - based on customer attributes (predictors)
 - attributes may be continuous or categorical

INTRODUCTION

- A model to predict a categorical response with k levels
- How?
 - Divide the predictors space into many regions
 - In each region there are observations from the k classes (levels)
 - Find p_{mk} the proportion of observations from the k class in the m^{th} region
 - For each region m , the prediction \hat{y}_m is the most common class
 - For each region, the error rate is the fraction of obs that do not belong to the most common class

INTRODUCTION

- A model to predict a categorical response with k levels
- How?
- Example - Consider a response with $k = 3$ classes

– For region $m = 4$
$$\begin{cases} p_{41} = 10\% & \text{members from class 1} \\ p_{42} = 20\% & \text{class 2} \\ p_{43} = 70\% & \text{class 3} \end{cases}$$

– Prediction is $\hat{y}_4 = 3$

– error rate for regions 4 is $e_4 = 0.3$

– region 4 would be *pure* if $p_{4j} = 1$ for some class j

INTRODUCTION

- Different measures of *purity*

- E: classification error rate

$$E = \sum_{m=1}^T e_m$$

- G: Gini Index

$$G = \sum_{m=1}^T \sum_{i=1}^K p_{im} (1 - p_{im})$$

- D: Cross entropy

$$D = - \sum_{m=1}^T \sum_{i=1}^K p_{im} \ln(p_{im})$$

CROSS VALIDATION

- Fit trees of different depths using the training set
- Find their training error rates
- Select depth of the tree with the smallest training error rate
- Prune a full tree to the selected depth
- Find the *test* error rate of the pruned tree

CROSS VALIDATION

- Use function `cv.tree`
- `cv.tree(tree1)` compares regression trees based on *deviance*
- Use `cv.tree(tree1, FUN=prune.misclass)`
to compare categorical trees based on the number of misclassified observations

CROSS VALIDATION

- The MSE or RSS of a tree with two regions R_1 and R_2 is

$$RSS = \sum_{i \in R_1} (y_i - \hat{y}_1)^2 + \sum_{i \in R_2} (y_i - \hat{y}_2)^2$$

- The MSE or RSS of a tree with T regions is

$$RSS = \sum_{m=1}^T \sum_{i=1}^{r_m} (y_i - \hat{y}_m)^2$$

r_m : n. of observations in region m

CROSS VALIDATION (CV)

- The MSE or RSS of a tree with two regions R_1 and R_2 is

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- The MSE or RSS of a tree with T regions is

$$RSS = \sum_{m=1}^T \sum_{i=1}^{r_m} (y_i - \hat{y}_m)^2$$

r_m : n. of observations in region m

- CV minimizes

$$RSS = \sum_{m=1}^T \sum_{i=1}^{r_m} (y_i - \hat{y}_m)^2 + kT$$

k : shrinkage (complexity) parameter