

### Homework 3

#### Question 1

GART modeling for regression

old tree,  $T_{old}$  has  $|T_{old}| = M$  terminal nodes/buckets,  
each bucket  $m=1, \dots, M$

- let
1.  $N_m$  denote num of observations in bucket  $m$
  2.  $Q_m(T_{old})$  denotes val of impurity function at bucket  $m$
  3.  $R_m$  denote the region in the feature space corresponding to bucket  $m$

$N =$  overall # of observations

$$Q_m(T_{old}) = \frac{1}{N_m} \sum_{i: x_i \in R_m} (y_i - \hat{y}_m)^2$$

$$\hat{y}_m = \frac{1}{N_m} \sum_{i: x_i \in R_m} y_i = \text{mean response in bucket } m$$

total impurity cost of the tree  $T_{old}$ :

$$C_{imp}(T_{old}) = \sum_{m=1}^M N_m Q_m(T_{old})$$

↳ consider split at final bucket  $M$

↳ new tree  $T_{new}$   $|T_{new}| = M+1$

$\tilde{N}_m$  denotes new # observations in bucket  $m$

$\tilde{Q}_m(T_{new}) =$  impurity function at bucket  $m$

$\tilde{R}_m$  denotes region in the feature space corresponding to bucket  $m$

Total impurity cost of tree  $T_{new}$

$$C_{imp}(T_{new}) = \sum_{m=1}^M \tilde{N}_m \tilde{Q}_m(T_{new})$$



1. a) let  $\Delta = C_{imp}(T_{old}) - C_{imp}(T_{new})$  -- absolute decrease  
in total impurity  
↳ only depend on  $R_m$

$$\Delta = C_{imp}(T_{old}) - C_{imp}(T_{new})$$

$$\Delta = \sum_{m=1}^M N_m Q_m(T_{old}) - \sum_{m=1}^M \tilde{N}_m \tilde{Q}_m(T_{new})$$

↳ buckets  $m=1$  to  $m=M-1$  are identical; only bucket  $M$  was altered

$$\Delta = \left( \sum_{m=1}^{M-1} N_m Q_m(T_{old}) \right) + N_M Q_M(T_{old}) - \left( \sum_{m=1}^{M-1} \tilde{N}_m \tilde{Q}_m(T_{new}) + \tilde{N}_M \tilde{Q}_M(T_{new}) + \tilde{N}_{M+1} \tilde{Q}_{M+1}(T_{new}) \right)$$

→ for  $m=1 \rightarrow m=M-1$ , nodes are unchanged,  $\therefore \hat{y}_m = \text{mean response}$   
in each bucket is the same,  $\therefore Q_m(T_{old}) = \tilde{Q}_m(T_{new})$  for  
all  $m \leq M-1$ ,  $\therefore \Delta$  function reduces to the following

$$\Delta = N_M Q_M(T_{old}) - (\tilde{N}_M \tilde{Q}_M(T_{new}) + \tilde{N}_{M+1} \tilde{Q}_{M+1}(T_{new}))$$

$$\Delta = N_M \left[ \frac{1}{N_M} \sum_{i: x_i \in R_M} (y_i - \hat{y}_M)^2 \right] - \left( \tilde{N}_M \frac{1}{\tilde{N}_M} \sum_{i: x_i \in R_M} (y_i - \hat{y}_M)^2 + \tilde{N}_{M+1} \frac{1}{\tilde{N}_{M+1}} \sum_{i: x_i \in R_{M+1}} (y_i - \hat{y}_{M+1})^2 \right)$$

$$\Delta = \sum_{i=1}^k (y_i - \hat{y}_M)^2 - \sum_{i=1}^j (y_i - \hat{y}_M)^2 - \sum_{i=j+1}^k (y_i - \hat{y}_{M+1})^2$$

where the indices of  $1 \rightarrow k$  indicate all of the values in the original bucket  $M$ , with  $i=1 \rightarrow j$  indicating the subset of these values which are split into  $M_{new}$  and  $i=j+1 \rightarrow k$  indicating the subset of these values which are split into the  $M+1$  bucket

$$\Delta = SSE_{old} - SSE_{new}$$



$$b) \Delta = \sum_{i=1}^k (y_i - \hat{y}_m)^2 - \sum_{i=1}^j (y_i - \tilde{y}_m)^2 - \sum_{i=j}^k (y_i - \tilde{y}_{m+1})^2$$

$$\Delta = \sum_{i=1}^j (y_i - \hat{y}_m)^2 + \sum_{i=j}^k (y_i - \hat{y}_m)^2 - \sum_{i=1}^j (y_i - \tilde{y}_m)^2 - \sum_{i=j}^k (y_i - \tilde{y}_{m+1})^2$$

$$\Delta = \left[ \sum_{i=1}^j (y_i - \hat{y}_m)^2 - \sum_{i=1}^j (y_i - \tilde{y}_m)^2 \right] + \left[ \sum_{i=j}^k (y_i - \hat{y}_m)^2 - \sum_{i=j}^k (y_i - \tilde{y}_{m+1})^2 \right]$$

→ given that  $\bar{z} = \frac{1}{n} \sum_{i=1}^n z_i$  is minimizer of  $RSS(\bar{z}) = \sum_{i=1}^n (z_i - \bar{z})^2$ ,  
the new means of the new buckets,  $\tilde{y}_m$  and  $\tilde{y}_{m+1}$  minimize the equations  $\sum_{i=1}^j (y_i - \tilde{y}_m)^2$  and

$\sum_{i=j}^k (y_i - \tilde{y}_{m+1})^2$ . Therefore;

$$\sum_{i=1}^j (y_i - \hat{y}_m)^2 \geq \sum_{i=1}^j (y_i - \tilde{y}_m)^2 \quad \text{and} \quad \sum_{i=j}^k (y_i - \hat{y}_m)^2 \geq \sum_{i=j}^k (y_i - \tilde{y}_{m+1})^2$$

Given this, it follows that  $\sum_{i=1}^j (y_i - \hat{y}_m)^2 - \sum_{i=1}^j (y_i - \tilde{y}_m)^2 \geq 0$

$$\text{and } \sum_{i=j}^k (y_i - \hat{y}_m)^2 - \sum_{i=j}^k (y_i - \tilde{y}_{m+1})^2 \geq 0$$

$$\therefore \Delta = [ \geq 0 ] + [ \geq 0 ] =$$

$$\therefore \Delta \geq 0$$

$$\Delta =$$



1. C) Let  $R^2_{old}$  be training set  $R^2$  for  $T_{old}$  model

$R^2_{new}$  = training set  $R^2$  for new model.

$$SST = \sum_{i=1}^N (y_i - \bar{y})^2 = \text{total sum square error}$$

$$\bar{y} = \frac{1}{n} \sum_{i=1}^N y_i = \text{overall mean}$$

↳ given rule  $c_p \geq 0$ , modified cost function

$$C_d(T) = C_{imp}(T) + d \cdot SST \cdot |T|$$

↳ show  $C_d(T_{new}) \leq C_d(T_{old})$  only if  $R^2_{new} - R^2_{old} \geq d$

$$C_d(T_{new}) \leq C_d(T_{old}) \Rightarrow C_d(T_{old}) - C_d(T_{new}) \geq 0$$

$$C_d(T_{old}) - C_d(T_{new}) = C_{imp}(T_{old}) - C_{imp}(T_{new}) + d \cdot SST \cdot |T_{old}|$$

$$C_d(T_{old}) - C_d(T_{new}) = \Delta - d \cdot SST \cdot |T_{new}| + d \cdot SST \cdot |T_{old}|$$

$$\text{Note: } R^2 = 1 - \frac{SSE}{SST} \quad SSE = \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

$$|T_{old}| = M \quad |T_{new}| = M+1 \quad \therefore |T_{old}| - |T_{new}| = -1$$

$$\therefore C_d(T_{new}) - C_d(T_{old}) = \Delta + d \cdot SST = (SSE_{old} - SSE_{new}) + d \cdot SST$$

Explore if  $C_d(T_{new}) \leq C_d(T_{old}) = 0$

$$0 \leq (SSE_{new} - SSE_{old}) + d \cdot SST$$

$$d \cdot SST \leq SSE_{new} - SSE_{old}$$

$$d \leq \frac{SSE_{new} - SSE_{old}}{SST} = \left(1 + \frac{SSE_{new}}{SST}\right) - \left(1 + \frac{SSE_{old}}{SST}\right)$$

$$\boxed{d \leq R^2_{new} - R^2_{old}}$$