

# CARTs : Classification and Regression Trees

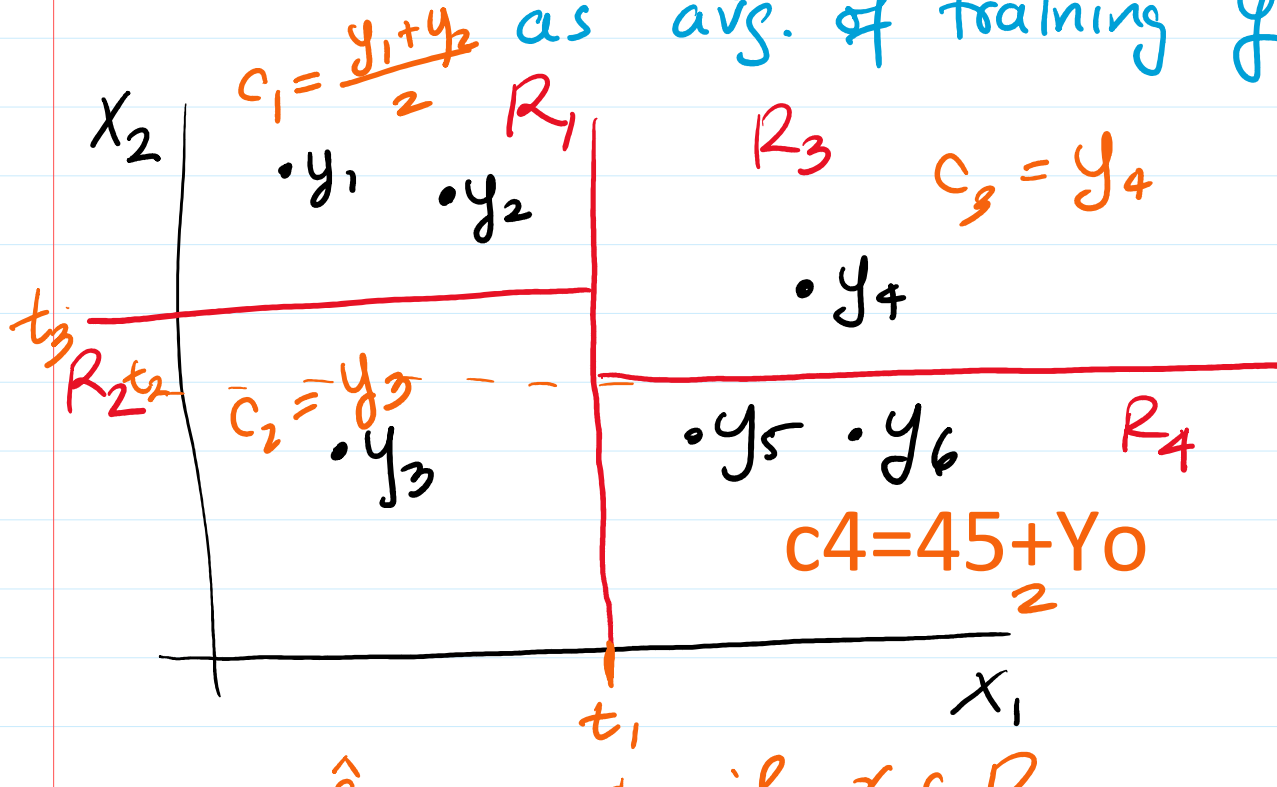
## Regression Trees

### Basic idea:

① break up space of  $X$ s into rectangles

② on each rectangle, fit some really simple method

(predict  $y$  in each rectangle as avg. of training  $y$ s)

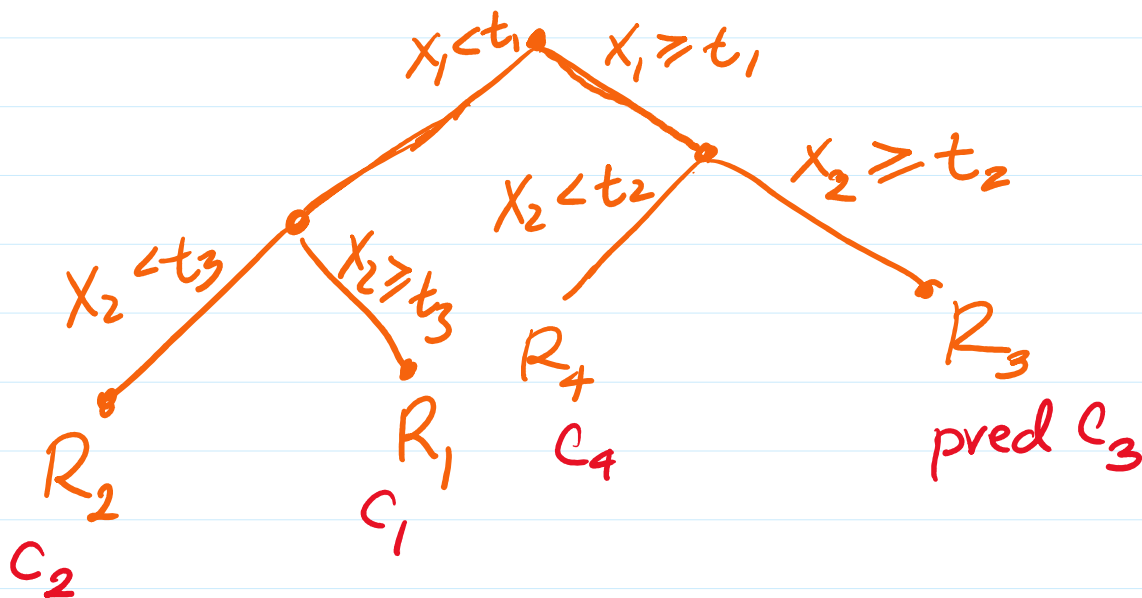


$$\hat{f}(\underline{x}) = c_i \text{ if } \underline{x} \in R_i$$

Why called a tree?

Can represent  $\hat{f}$  as a decision tree

e.g. (above)



Goal: do this well

Need to decide:

- ① which variable to split on ( $j$ )
- ② where I split the var ( $t$ )

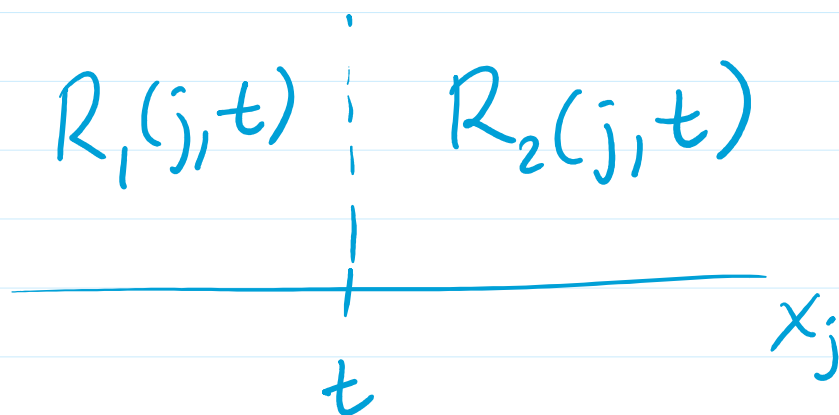
(2) where I split the var ( $t$ )

(3) when do I stop.

Optimal: try all possible trees - not computationally tractable

Soln: Use greedy approach

Define  $R_1(j, t)$  and  $R_2(j, t)$  to be the two half-spaces formed by splitting variable  $j$  at point  $t$



$$RSS(j, t) = RSS(R_1(j, t)) + RSS(R_2(j, t))$$



$$= \sum (y_i - c_1)^2 + \sum (y_i - c_2)^2$$

(  
error  
I get by  
splitting var  
j at point t

$$= \sum_{i \in R_1(j, t)} (y_i - c_1)^2 + \sum_{i \in R_2(j, t)} (y_i - c_2)^2$$

preds in rectangles  
i.e. means of  $y_i$  in  
each rectangle

## Algorithm : fitting tree

- ① For each j search over possible t and calc  $RSS(j, t)$
- ② choose j, t to minimize  $RSS(j, t)$
- ③ Split at var j at point t
- ④ recursively do this for each new half space.

When do I stop?

→ too many splits → overfit

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→ too few splits → underfit

① set some maximum depth and use something like x-val to set this value

② Bad idea: can split until RSS falls below some threshold

problem: bad split may lead to a better approach! better split later

① grow a really large tree

② prune its size (reduce)

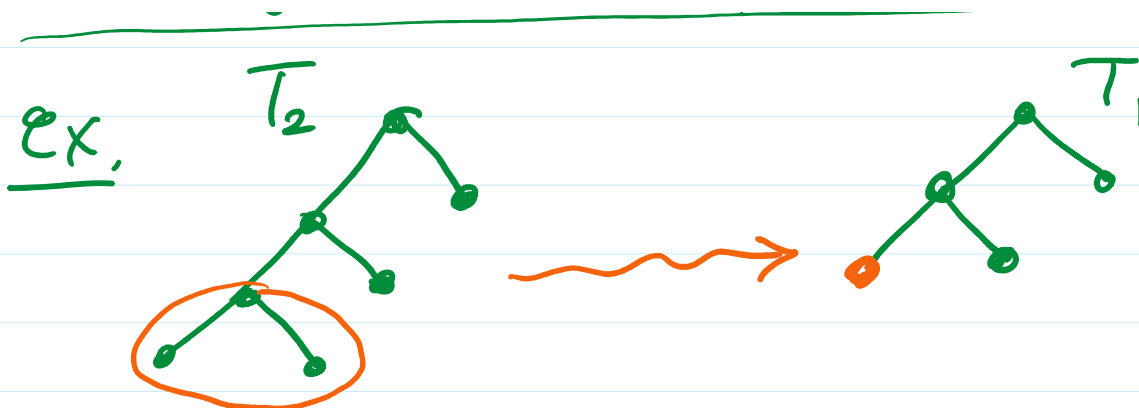
Aside: a tree  $T_1$  is called a

sub-tree of  $T_2$  if I can get

$T_1$  by collapsing part of  $T_2$

$T$

$T_1$



## Cost-Complexity Pruning

$$C_\alpha(T) = \text{RSS}(T) + \alpha |T|$$

penalty strength  $\alpha$  (points to  $\alpha$ )  
 penalty (points to  $|T|$ )  
 size = # of leaf nodes (points to  $|T|$ )

Want to find tree  $T$  that minimizes  $C_\alpha(T)$ .

Way to do this:

- ① grow a really large tree
- ② search over sub-trees (i.e. prune parts of tree) to find one that minimizes  $C_\alpha(T)$

to find one that minimizes  $C_\alpha(T)$

If  $\alpha = 0 \Rightarrow$  no pruning (largest possible tree)

$\alpha \rightarrow \infty \Rightarrow$  reduce size of tree

Turns out that:

① If I prune out parts of tree that increase RSS (least I get series of nested sub-trees:

$$T_0 \subset T_1 \subset T_2 \subset \dots \subset T_N$$

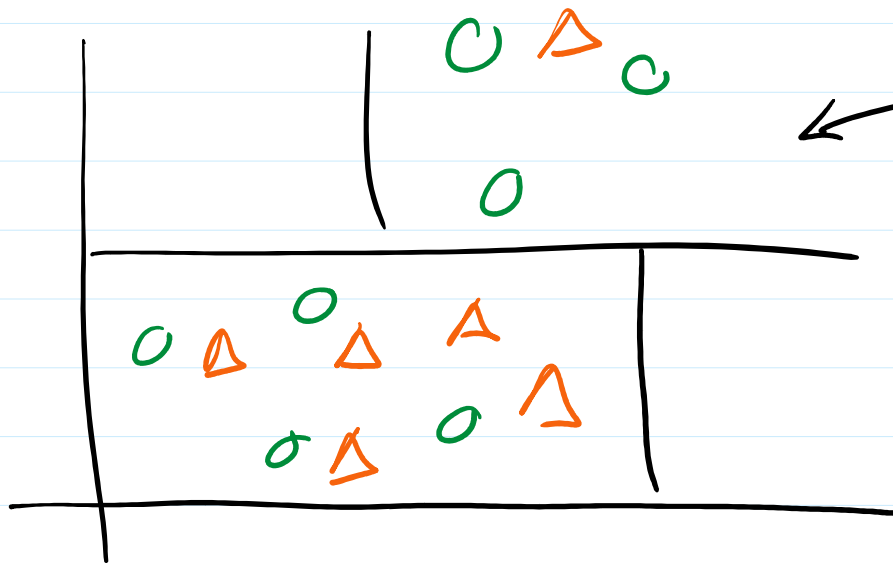
$\uparrow$  optimal tree that minimizes  $C_\alpha(T)$  is somewhere in this sequence

② If  $\alpha_1 \leq \alpha_2$  then the optimal tree  $T_{\alpha_1}$  to  $\min C_{\alpha_1}(T)$  contains the tree that  $\min T_{\alpha_2} C_{\alpha_2}(T)$ .

$$T_{\alpha_1} \supset T_{\alpha_2}$$

$1_{\alpha_1}, \cup, 1_{\alpha_2}$

## Classification



What makes a good split for a classification tree?

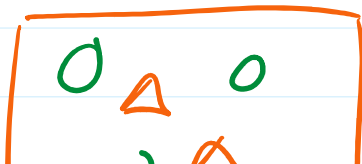
Regression  $\rightsquigarrow$  RSS

Classification  $\rightsquigarrow$  reduce node/leaf impurity

(increase purity)

Ex.

impure



pure

