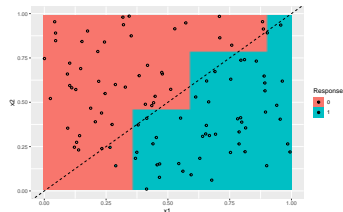


Introduction to Machine Learning

CART

Advantages & Disadvantages

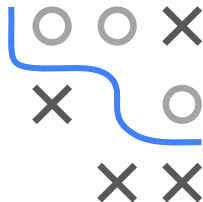


Learning goals

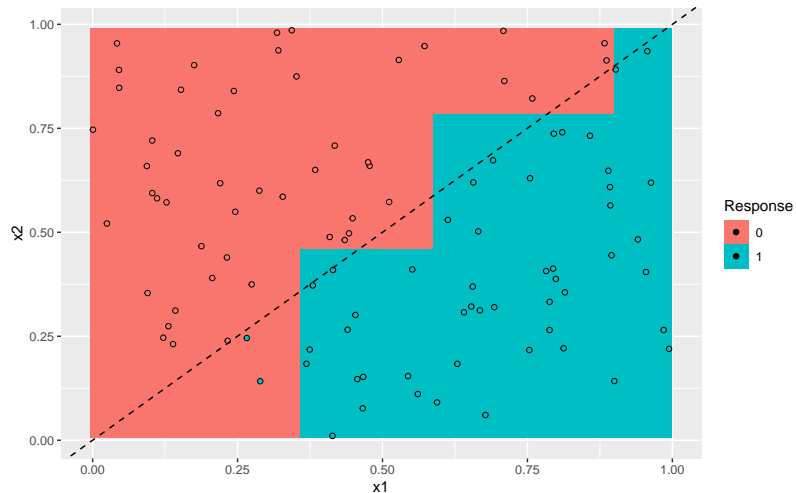
- Understand the advantages and disadvantages of CART
- Know when and where CART are applied

ADVANTAGES

- Fairly easy to understand, interpret and visualize.
- Not much preprocessing required:
 - Automatic handling of non-numerical features
 - Automatic handling of missing values via surrogate splits
 - No problems with outliers in features
 - Monotone transformations do not affect the model fit: scaling becomes irrelevant
- Interaction effects between features are easily possible
- Can model discontinuities and non-linearities
- Performs automatic feature selection
- Relatively fast, scales well with larger data
- Flexibility through the definition of custom split criteria or leaf-node prediction rules: clustering trees, semi-supervised trees, density estimation, etc.

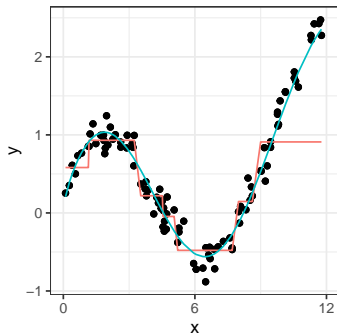
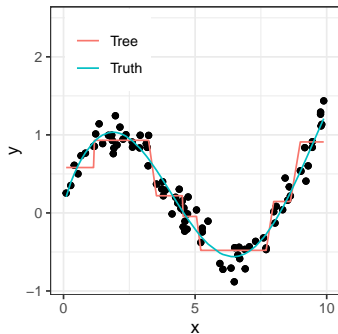


DISADVANTAGE: LINEAR DEPENDENCIES



Linear dependencies must be modeled over several splits. Logistic regression would model this easily with fewer parameters.

DISADVANTAGES: SMOOTH FUNCTIONS AND EXTRAPOLATION



Prediction functions of trees are never smooth as they are always step functions and do not extrapolate well beyond the training observations.

DISADVANTAGE: INSTABILITY

- High instability (variance) of the trees
- Small changes in the data may lead to very different splits/trees
- This leads to a) less trust in interpretability b) is a reason why the prediction error of trees is usually comparably high

Consider the Wisconsin Breast Cancer data set with 699 observations on 9 features and binary target (“benign” vs. “malignant”). We fit two trees: (A) with the full data set and (B) where we eliminated a single observation. Results in label flip for 17 observations of the training data:

	benign	malignant
benign	445	6
malignant	11	236

Rows: Predictions of (A), columns: Predictions of (B)



A 3x3 grid with a blue path starting at the top-left cell (0,0) and ending at the bottom-right cell (2,2). The path moves right from (0,0) to (0,1), then down to (1,1), then right to (1,2), and finally down to (2,2). The cells (0,2), (1,0), and (2,0) are marked with 'X', while the other cells are empty.

Left Decision Tree (Baseline Model):

- Root Node (1): benign (.66 .34, 100%)
 - Yes (CellSize < 2.5): benign (.97 .03, 61%)
 - Leaf (2): benign (.99 .01, 90%)
 - Leaf (3): malignant (.12 .88, 1%)
 - No: malignant (.15 .85, 35%)
 - Internal Node (2): benign (.78 .22, 3%)
 - Leaf (1): benign (.90 .10, 2%)
 - Leaf (3): malignant (.12 .88, 1%)
 - Internal Node (7): malignant (.09 .91, 35%)
 - Internal Node (14): malignant (.26 .74, 10%)
 - Leaf (24): benign (.71 .29, 2%)
 - Leaf (34): malignant (.14 .86, 8%)
 - Leaf (35): malignant (.03 .97, 25%)

Right Decision Tree (Model with Cell.size < 3.5):

- Root Node (1): benign (.66 .34, 100%)
 - Yes (Cell.size < 3.5): benign (.92 .08, 69%)
 - Internal Node (4): benign (.97 .03, 65%)
 - Leaf (2): benign (.99 .01, 90%)
 - Leaf (3): malignant (.12 .88, 1%)
 - Internal Node (5): malignant (.08 .92, 3%)
 - Leaf (3): malignant (.06 .94, 31%)
 - No: malignant (.15 .85, 35%)
 - Leaf (3): malignant (.06 .94, 31%)

CART IN PRACTICE

- Compared to other learners CART has suboptimal predictive performance, mainly because of the problems previously shown.
- However, most disadvantages can be overcome when trained in ensembles: bagging or random forests.
- Furthermore, trees are attractive tools if an interpretable model is desired or legally required.



