

Classification Trees

Quarto

Quarto enables you to weave together content and executable code into a finished presentation. To learn more about Quarto presentations see <https://quarto.org/docs/presentations/>.

Bullets

When you click the **Render** button a document will be generated that includes:

- ▶ Content authored with markdown
- ▶ Output from executable code

Code

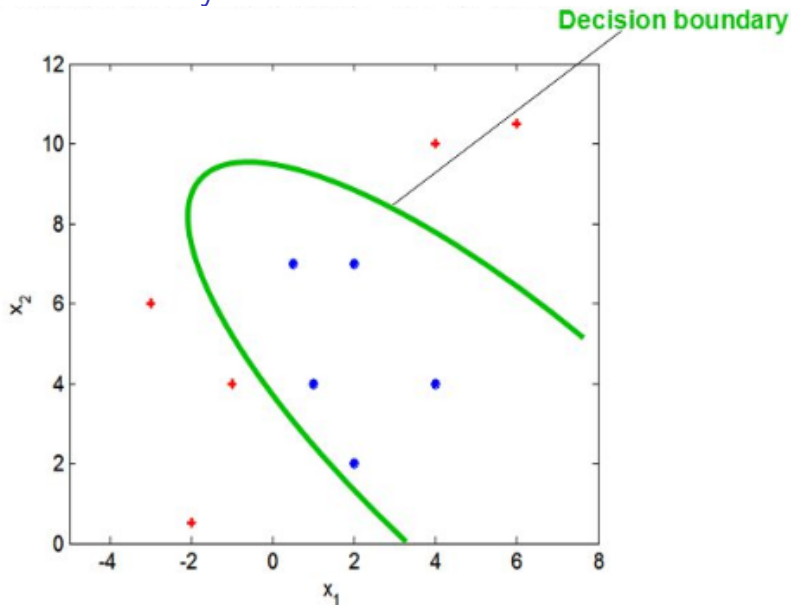
When you click the **Render** button a presentation will be generated that includes both content and the output of embedded code. You can embed code like this:

```
[1] 2
```

Reading Materials

- ▶ Max Kuhn. Chapter 14. Section 14.1

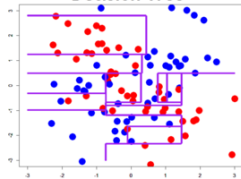
Decision Boundary in Classification



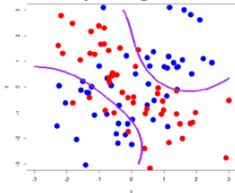
Classification is a process of finding the **decision boundary** that

Decision Boundary in Classification

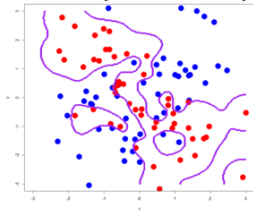
Decision Tree



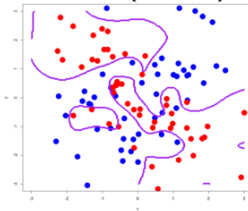
SVM #1 (much generalized)



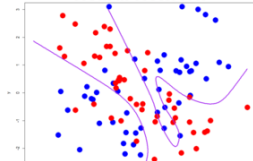
SVM #2 (much overfitted)



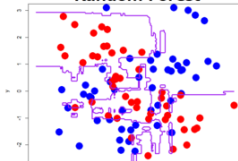
SVM #3 (moderate)



Neural Network



Random Forest



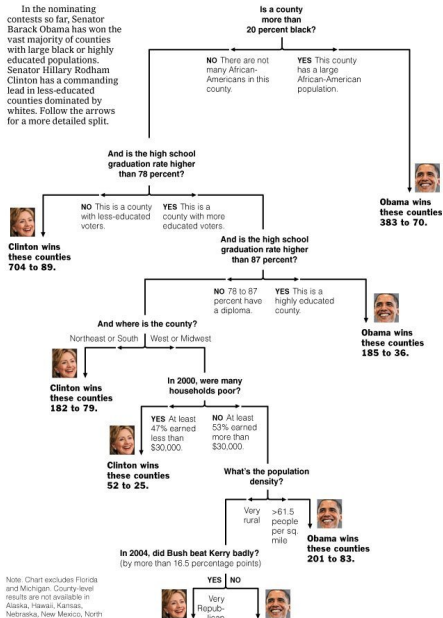
Decision Tree

- ▶ Decision Tree for classification is **Classification Tree**
- ▶ Decision Tree for Regression is **Regression Tree**

Example of Classification Tree

Decision Tree: The Obama-Clinton Divide

In the nominating contests so far, Senator Barack Obama has won the vast majority of counties with large black or highly educated populations. Senator Hillary Rodham Clinton has a commanding lead in less-educated counties dominated by whites. Follow the arrows for a more detailed split.

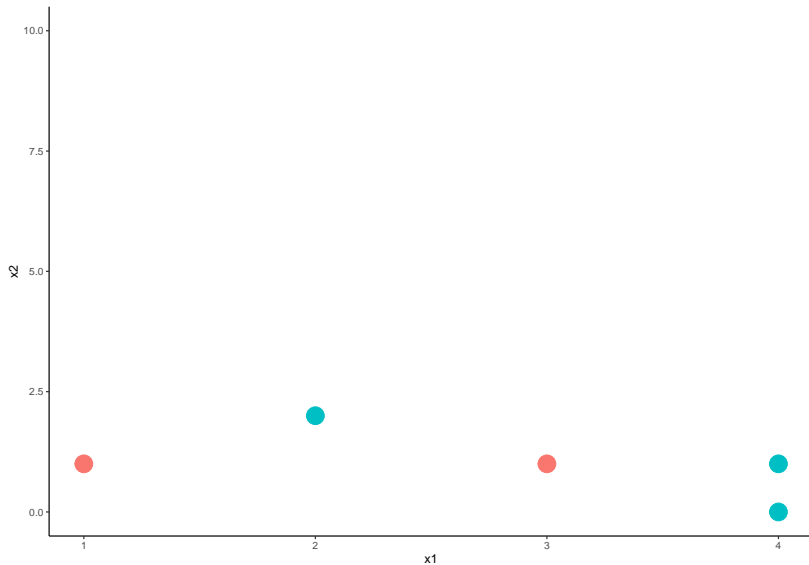


Note: Chart excludes Florida and Michigan. County-level results are not available in Alaska, Hawaii, Kansas, Nebraska, New Mexico, North Dakota, or Maine.

Classification Tree

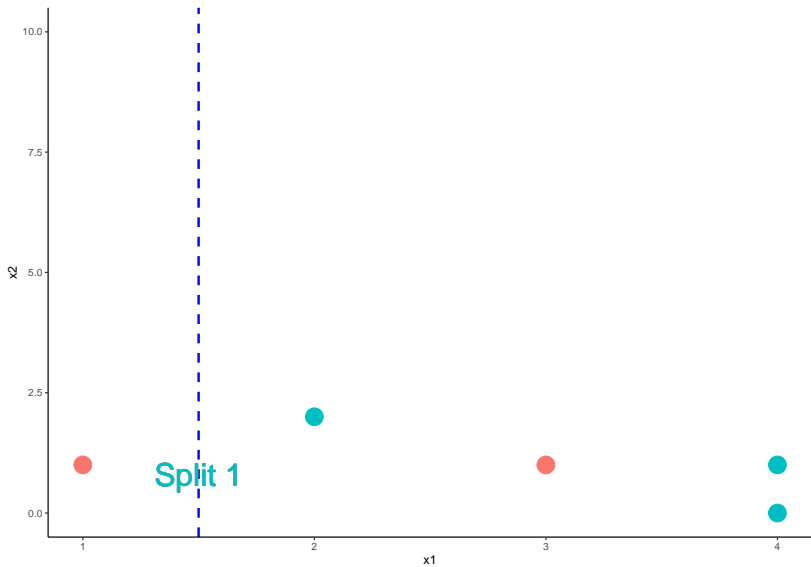
- ▶ In two dimension, classification Tree's decision boundary is a collection of horizontal and vertical line

Data

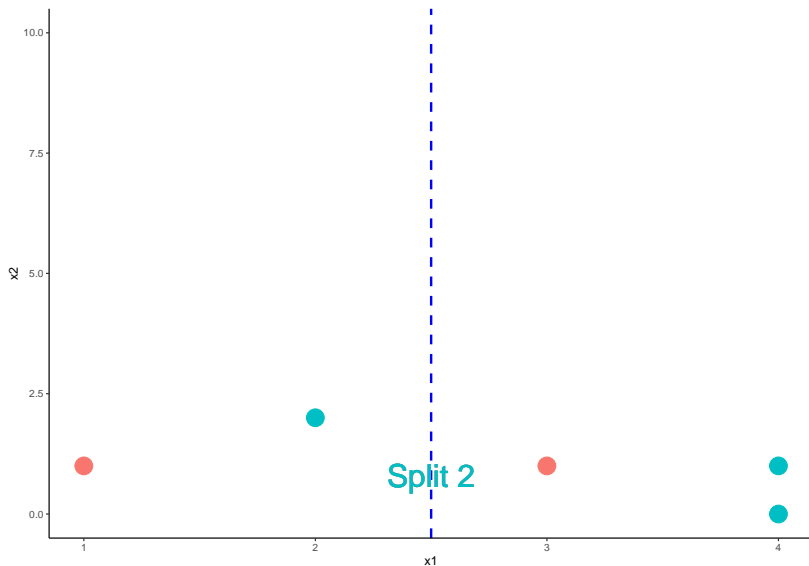


- ▶ The tree starts by a vertical or horizontal line that **best** separate the data

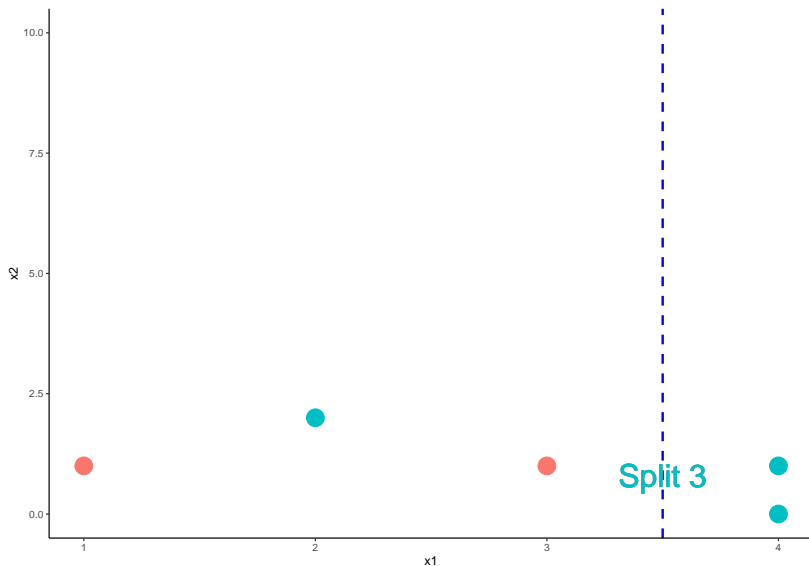
One way to separate the reds and greens



One way to separate the reds and greens



One way to separate the reds and greens



Question

► **Question:** Which is the best split?

Partial Answer

- ▶ It looks like Split 1 and 3 are better than Split 2 since it misclassifies less
- ▶ Which is the better split between Split 1 and Split 3?
- ▶ We need to find a way to measure *how good a split is*

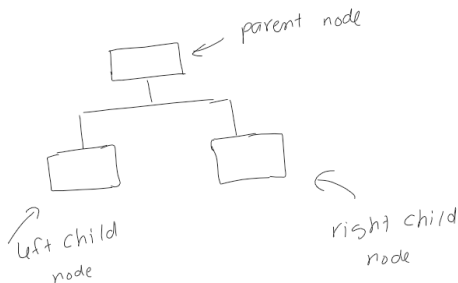
Impurity Measure

- ▶ The impurity of a node (**a node = a subset of the data or the original data**) measure how uncertain the node is.
- ▶ For example, node A with 50% reds and 50% greens would be more uncertain than node B with 90% reds and 10% greens. Thus, node A has greater impurity than node B.
- ▶ More uncertain = Greater impurity

Impurity Measure

- ▶ A split that *gains* more impurity is the **better split!**

Impurity Gain



$$IG = I_{parent} - \frac{N_{left}}{N} I_{left} - \frac{N_{right}}{N} I_{right}$$

- ▶ IG is Impurity Gain of the split
- ▶ N_{left} and N_{right} are the number of points in the left child node and right child node, respectively.
- ▶ $N_{left} + N_{right} = N$

Impurity Measure

- ▶ Impurity can be measured by: classification error, Gini Index, and Entropy.

Impurity Measure

- Let p_0 and p_1 be the proportion of class 0 and class 1 in a node.

By Classification Error: $I = \min\{p_0, p_1\}$

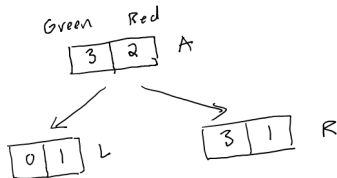
By Gini Index: $I = 1 - p_0^2 - p_1^2$

By Entropy: $I = -p_0 \log_2(p_0) - p_1 \log_2(p_1)$

Calculation

- ▶ Let's calculate the impurity gain of the three splits to decide which split is the best

IG By Classification Error



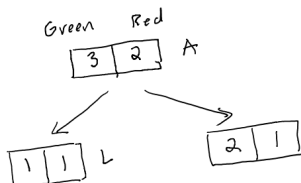
- ▶ Let **green** and **red** be class 0 and class 1, respectively.

For Split 1: $N = 5, N_{left} = 1, N_{right} = 4$

- ▶ Node *parent*, A: $p_0 = \frac{2}{5}, p_1 = \frac{3}{5}$. Thus, $I_A = \min(\frac{2}{5}, \frac{3}{5}) = \frac{2}{5}$
- ▶ Node *child left*, L: $p_0 = \frac{0}{1} = 0, p_1 = \frac{1}{1} = 1$. Thus, $I_L = \min(0, 1) = 0$
- ▶ Node *child right*, R: $p_0 = \frac{3}{4}, p_1 = \frac{1}{4}$. Thus, $I_R = \min(\frac{3}{4}, \frac{1}{4}) = \frac{1}{4}$
- ▶ Impurity Gain of Split 1:

$$IG = \frac{2}{5} - \frac{1}{5} \cdot 0 - \frac{4}{5} \cdot \frac{1}{4} = 0.2$$

IG By Classification Error



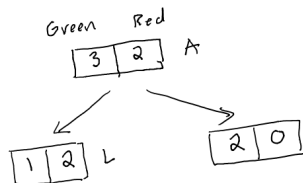
For Split 2: $N = 5, N_{left} = 2, N_{right} = 3$

- ▶ Node *parent*, A: $p_0 = \frac{2}{5}, p_1 = \frac{3}{5}$. Thus, $I_A = \min(\frac{2}{5}, \frac{3}{5}) = \frac{2}{5}$
- ▶ Node *child left*, L: $p_0 = \frac{1}{2}, p_1 = \frac{1}{2}$. Thus, $I_L = \frac{1}{2}$
- ▶ Node *child right*, R: $p_0 = \frac{2}{3}, p_1 = \frac{1}{3}$. Thus,
 $I_R = \min(\frac{2}{3}, \frac{1}{3}) = \frac{1}{3}$
- ▶ Impurity Gain of Split 2:

$$IG = \frac{2}{5} - \frac{2}{5} \cdot \frac{1}{2} - \frac{3}{5} \cdot \frac{1}{3} = 0$$

IG By Classification Error

For Split 3: $N = 5, N_{left} = 3, N_{right} = 2$



- ▶ Node *parent*, A: $p_0 = \frac{2}{5}, p_1 = \frac{3}{5}$. Thus, $I_A = \min(\frac{2}{5}, \frac{3}{5}) = \frac{2}{5}$
- ▶ Node *child left*, L: $p_0 = \frac{1}{3}, p_1 = \frac{2}{3}$. Thus,
 $I_A = \min(\frac{1}{3}, \frac{2}{3}) = \frac{1}{3}$
- ▶ Node *child right*, R: $p_0 = \frac{2}{2}, p_1 = \frac{0}{2}$. Thus,
 $I_R = \min(1, 0) = 0$
- ▶ Impurity Gain of Split 3:

$$IG = \frac{2}{5} - \frac{3}{5} \cdot \frac{1}{3} - \frac{2}{5} \cdot 0 = 0.2$$

Comparing IG By Classification Error

Split	IG
1	0.2
2	0
3	0.2

- By classification error, Split 1 and Split 3 are tie as the best because they have the same impurity gain.