COFFEE RUST DETECTION FOR CATURRA VARIETY USING DECISION TREES

Santiago Cartagena Agudelo Paulina Pérez Garcés Medellín, October 29th 2019.



Decision Tree and Random Forest

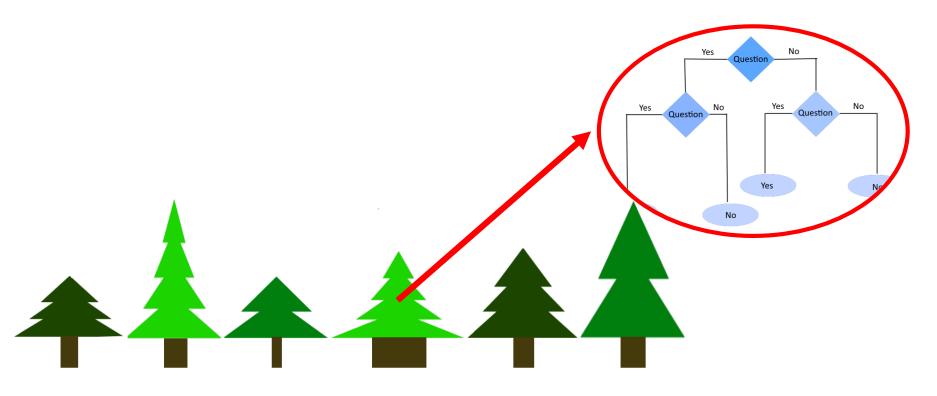


Figure 1: Random Forest filled with decision trees



Data Structure Operations

Taking into account the following notation, take a look of the chart about the complexity analysis in the algorithm:

- N represents the labels.
- M represents the rows.
- K represents the columns.
- L represents the values.

METHOD	COMPLEXITY	
GINI INDEX	O(n*m) + O(n) = O(n*m)	
INFORMATION GAIN	O(1) + O(n*m) = O(n*m)	
BEST DATA SPLIT	O(k*l) + O(1) + O(m*n) + O(m) = O(k*l) + O(m*l) + O(m)	
PARTITIONING	O(m) + O(1) = O(m)	
BUILDING THE TREE	O(m) + O(k*l) + O(1) + O(m*n) + O(m) = O(k*l) + O(m*l) + O(m)	

Table 1: Complexity analysis for the different methods implemented.



Gini Impurity Index

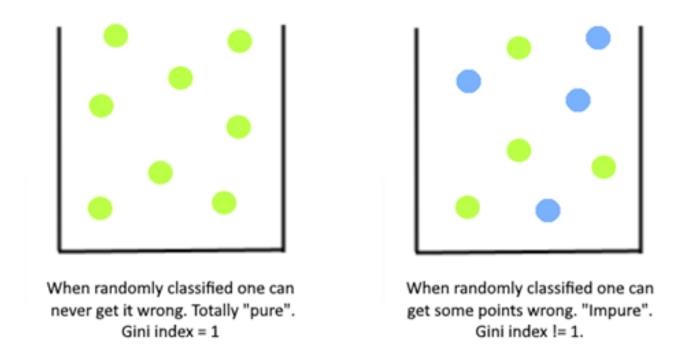


Figure 2: Gini calculation method explained.



Information Gain

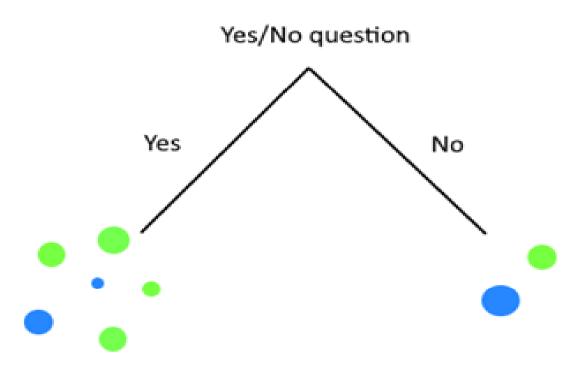


Figure 3: Information Gain explained.



Finding the Best Split

Is the information gain at split #1 higher than at split #2?

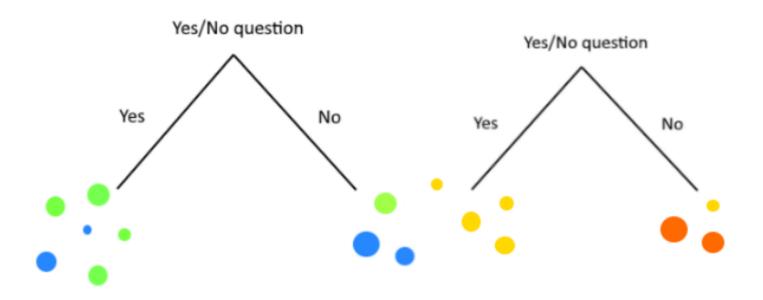


Figure 4: Representation of find_best_split



Partitions

When asked a certain question, which values are true?

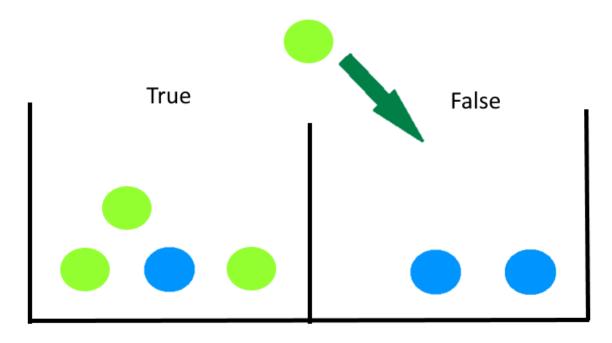


Figure 5: Graphic representation of partitioning the dataset.



Building the Tree

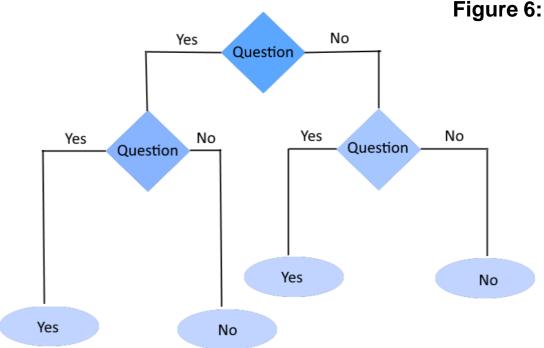


Figure 6: Decision Tree structure

Design Criteria of the Data Structure

- Decision Trees are considered "one of the best and mostly used supervised learning methods." (Brid, R. S; 2018)
- Easy to understand, since the tree analogy is fairly simple.
- Fast and mostly accurate.
- Can work with classifications as well as regressions.
- One of the decision trees' biggest flaws is overfitting, but with a random forest it stops being an overwhelming issue.
- Easy to adapt them to different circumstances.
- A single tree had an accuracy of almost 80%.



Time and Memory Consumption

METHOD	TRAINING DATA	TESTING DATA
GINI INDEX	0.2s	0.4s
INFORMATION GAIN	0.5s	0.7s
FIND BEST SPLIT	0.6s	0.8s
PARTITIONING	0.1s	0.1s
BUILDING THE TREE	1.5s	1.5s

TRAINING DATA	TESTING DATA
120 MB	160MB

Table 3 and 4: Time and memory consumption for the different methods.



Implementation

```
In [6]: import pandas as pd
        trainingData = pd.read csv('data set train.csv', delimiter = ',')
        header = []
        class Question:
            def init (self, column, value):
               self.column = column
               self.value = value
            def match(self, example): #Can the chosen value 'pass the test'
               val = example[self.column]
                return val >= self.value
           def repr (self): #Prints the question into words and numbers
                condition = ">="
                return "Is %s %s %s?" % (
                   header[self.column], condition, str(self.value))
        class Leaf:
            def init (self, rows):
               totals = {}
               labels = set([row[-1] for row in rows])
              for label in labels:
                   totals[label] = 0
               for row in rows:
                  if row[-1]==label:
                       totals[label]+=1
                self.predictions = totals
        class Decision Node:
            def init (self, question, true branch, false branch):
               self.question = question
               self.true branch = true branch
                self.false branch = false branch
```

```
a curaci.
            Is illuminance >= 948?
            --> True:
              Predict {'no': 1}
            --> False:
              Predict {'yes': 0, 'no': 1}
      --> False:
        Predict {'yes': 0, 'no': 1}
  --> False:
    Is env temperature >= 19?
    --> True:
     Is illuminance >= 1852?
      --> True:
       Is illuminance >= 2185?
       --> True:
         Predict {'yes': 0, 'no': 1}
       --> False:
          Predict {'yes': 0, 'no': 1}
     --> False:
        Predict {'yes': 0, 'no': 1}
    --> False:
      Predict {'yes': 0, 'no': 1}
--> False:
 Is illuminance >= 2106?
 --> True:
   Predict {'yes': 0, 'no': 1}
 --> False:
   Predict {'yes': 0, 'no': 1}
79.0% de aciertos.
```

Figures 7 and 8: Part of the implemented code and results.



Report in arXiv

S. Cartagena-Agudelo, P. Pérez-Garcés, and M. Toro. Coffee Rust detection for Caturra variety using decision trees. ArXiv e-prints, Oct. 2018. Available at: https://arxiv.org/submit/2905373/view

