

Decision Trees

Author: Rodriguez Noh Santiago Miguel Professor: Ph.D. Anabel Martin Gonzalez

Link to code: https://github.com/Santiagomrn/Decision_Trees.git

I. Introduction

A Decision tree is a flowchart like tree structure, where each internal node denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node (terminal node) holds a class label.

A. Theoretical framework

Entropy:

Entropy basically tells us how impure a collection of data is.

$$Entropy(S) = -(P(yes)log_2P(yes) + P(no)log_2P(no))$$
(1)

Information Gain:

The measure we will use called information gain, is simply the expected reduction in entropy caused by partitioning the data set according to this attribute. The information gain (Gain(S,A) of an attribute A relative to a collection of data set S, is defined as

$$Gain(S, A) = Entropy(S) - \sum_{v \in Values(A)} \frac{|Sv|}{S} Entropy(Sv)$$
(2)

II. DECISION TREES

A. Using the training data, construct a decision tree for the binary classification of customers of the restaurant "Mama's Pasta" into 'Satisfied' or 'Unsatisfied'. Use the Information Gain (IG) as the decision criterion to select which attribute to split on. Show your calculations for the IG for all possible attributes for every split.

	OVERCOOKED_PASTA	WAITING_TIME	RUDE_WAITER	SATISFIED
0	yes	long	no	yes
1	no	short	yes	yes
2	yes	long	yes	no
3	no	long	yes	yes
4	yes	short	yes	no

Fig. 1. Training set.

Selection of the root:

OVERCOOKED_PASTA	WAITING_TIME	RUDE_WAITER	SATISFIED	
0 yes	long	no	yes	
1 no	short	yes	yes	
2 yes	long	yes	no	
3 no	long	yes	yes	
4 yes	short	yes	no	
OVERCOOKED_PASTA	: 0.4199730940	219749		
WAITING_TIME : 0.0	01997309402197	489		
RUDE_WAITER : 0.17	70950594454668	54		
best gain: 0.4199	730940219749 b	est feature	: OVERCOOKE	D_PASTA

Fig. 2. Compare gains.

The algorithm determined that the best characteristic for the root is OVERCOOKED_PASTA.

Now looking at the table and relating OVER-COOKED_PASTA = yes

W	AITING_TIME RU	DE_WAITER S	SATISFIED		
0	long	no	yes		
2	long	yes	no		
4	short	yes	no		
WAI	TING_TIME : 0	.2516291673	8878229		
RUD	E_WAITER : 0.	91829583405	44896		
bes:	t gain: 0.918	29583405448	396 best featu	re :	RUDE_WAITER

Fig. 3. Compare gains.

The second and last division occurs with the RUDE_WAITER characteristic.

As a result I get the following decision tree.

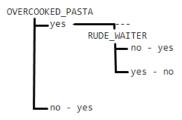


Fig. 4. Decision tree.

After observing the decision tree we notice that the WAIT-ING_TIME variable is not part of the tree, and this is because it does not provide enough information to make a prediction, in this way the algorithm discarded it.



B. Now use the decision tree you have created to predict whether each of the test users will be satisfied or not after their visit to "Mama's Pasta".

Person ID	Overcooked pasta?	Waiting time	Rude waiter?
6	No	Short	No
7	Yes	Long	Yes
8	Yes	Short	No

Fig. 5. Test data.

```
{'OVERCOOKED_PASTA': 'no', 'WAITING_TIME': 'short', 'RUDE_WAITER': 'no'} SATISFIED : yes 
{'OVERCOOKED_PASTA': 'yes', 'WAITING_TIME': 'long', 'RUDE_WAITER': 'yes'} SATISFIED : no 
{'OVERCOOKED_PASTA': 'yes', 'WAITING_TIME': 'short', 'RUDE_WAITER': 'no'} SATISFIED : yes
```

Fig. 6. Predictions.

III. FINAL COMMENTS

A. other decision tree

In order to verify the correct operation of the algorithm, I also generated the decision tree of the material seen in class and I obtained the following.

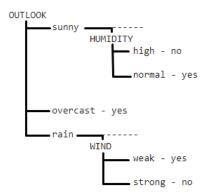


Fig. 7. Decision tree.

For the development of this practice use recursive functions, I think it is something that should not be overlooked because recursion is one of the most complicated issues when learning to program, something that caught my attention about decision trees, is the possibility that some variables of your data set are not found in the final decision tree, that is, they are not considered when making a prediction.

REFERENCES

[1] Pranto, B. (2020, 4 marzo). Entropy Calculation, Information Gain Decision Tree Learning., https://medium.com/analytics-vidhya/entropy-calculation-information-gain-decision-tree-learning-771325d16f.