ALGORITHM FOR MONITORING AND PREVENTING COFFEE RUST

Simón Marín Giraldo
Universidad Eafit
Colombia
smaring1@eafit.edu.co

Miguel Fernando Ramos García
Universidad Eafit
Colombia
mframosg@eafit.edu.co

Mauricio Toro
Universidad Eafit
Colombia
mtorobe@eafit.edu.co

ABSTRACT

Coffee is one of the most important products for colombian economy because it represents 6.9% of our exportations, contributing $2.7 billion dollars to our country each year.

Coffee rust is a plague that affects plants leaving devastating loss in agricultural industry around the world. Coffee industry loses more than 30% of the production because of rust.

It is necessary to create a solution to reduce the impact of this plague and returning greater profits (or smaller loss) to colombian coffee industry.

Keywords

Llenar con las palabras clave

ACM CLASSIFICATION Keywords

Sacar las palabras clave con http://bit.ly/2oVE5 2i

1. INTRODUCTION

Agricultural industry is fundamental for all the world. It provides food from crops and the work of the people living in the countryside. For our country, agriculture is one of the basis in our national economy. In Colombia we generate most of our food and we export to all the world mainly fruits and coffee. Coffee is the most important of our agricultural exportations, being the 6.9% of these and bringing more than $2.7 billion dollars every year.

Many plant plagues exist around the world affecting agricultural industry. One of the most lethal is Rust. It affects mostly coffee crops, leaving, for Latin America, devastating loss of more than 30% of the crops, discouraging the production and reducing the profits, affecting, mainly, the coffee producers.

2. PROBLEM

In this agricultural problem, we must follow up a coffee crop, reporting opportunely about plagues emergence. Eafit researchers have developed a conservatory with the ability of monitoring multiple variables that are associated with rust emergence such as: illumination, environmental temperature, ground temperature and ground pH. With this variables we have the objective of predicting whether a caturra coffee, in a determined time interval, has coffee rust. Furthermore, for each data sample we have an expert's evaluation confirming if the crop is affected by the plague.

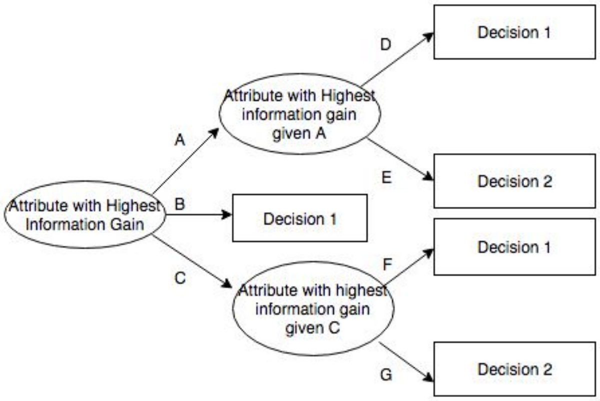
We are looking forward to give an early warning about rust occurrence in the crop in order to control it and reducing the loss because many crops get ruined due to this plague.

3. RELATED WORK

3.1 ID3 Algorithm

ID3 algorithm keeps generating a node and splitting the training instances until there is no more instance left. The attribute selection criterion is choosing the largest value of the information gain among the remaining attributes.

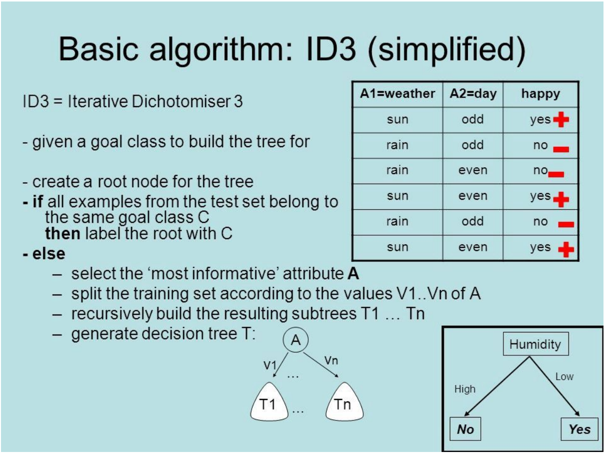
The examples set must be conformed by an ordered values series, each one of them known as an attribute, in which one of them, (the attribute to be classified) is the objective, that is binary (positive or negative, yes or no, valid or not valid, etc.).


Decision 1
D
Attribute with Highest information gain given A
A
E
Decision 2
Attribute with Highest Information Gain
B
Decision 1
Decision 1
F
C
Attribute with highest information gain given C
G
Decision 2

3.2 C4.5 Algorithm

C4.5 is an extension of ID3 algorithm, developed previously by Quinlan. Decision trees generated by C4.5 can be used for classification. Due to this, C4.5 is frequently known as a statistic classifier. C4.5 generates decision trees from a data training set as ID3 does, using entropy of information concept. Training data is a data example group that has already been classified. Each example is a vector where the example's attributes or characteristics are represented. Training data are increased with a vector that represents the class where each data sample belongs.

In which tree node, C4.5 picks the attribute from the data that most efficiently divides the samples set in enriched subsets in one or other class. C4.5's criteria is normalizing for information gaining (entropy difference) that results in selecting an attribute for dividing the data. The attribute with the highest information gaining is picked as the decision parameter.



Basic algorithm: ID3 (simplified)

ID3 = Iterative Dichotomiser 3

- given a goal class to build the tree for

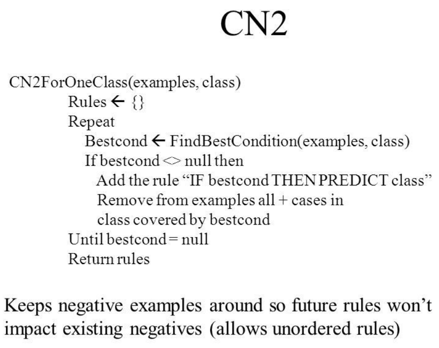
- create a root node for the tree
- **if** all examples from the test set belong to the same goal class C **then** label the root with C
- **else**
  - select the 'most informative' attribute **A**
  - split the training set according to the values V1..Vn of A
  - recursively build the resulting subtrees T1 … Tn
  - generate decision tree T:

A1=weather	A2=day	happy
sun	odd	yes +
rain	odd	no −
rain	even	no −
sun	even	yes +
rain	odd	no −
sun	even	yes +

3.3 CN2 Algorithm

The CN2 induction algorithm is a learning algorithm for rule induction. It is designed to work when the training data is imperfect. It is designed to work even when the training data is imperfect. It is based on ideas from the AQ algorithm and the ID3 algorithm. As a consequence it creates a rule set like that created by AQ but is able to handle noisy data like ID3.

The algorithm must be given a set of examples, TrainingSet, which have already been classified in order to generate a list of classification rules. A set of conditions, SimpleConditionSet, which can be applied, alone or in combination, to any set of examples is predefined to be used for the classification.



CN2

```
CN2ForOneClass(examples, class)
        Rules ← {}
        Repeat
           Bestcond ← FindBestCondition(examples, class)
           If bestcond <> null then
              Add the rule "IF bestcond THEN PREDICT class"
              Remove from examples all + cases in
              class covered by bestcond
        Until bestcond = null
        Return rules
```

Keeps negative examples around so future rules won't impact existing negatives (allows unordered rules)

3.4 CHAID (Chi-square automatic interaction detection) Algorithm

Chi-square automatic interaction detection (CHAID) is a decision tree technique, based on adjusted significance testing (Bonferroni testing).

CHAID can be used for prediction (in a similar fashion to regression analysis, this version of CHAID being originally known as XAID) as well as classification, and for detection of interaction between variables. CHAID is based on a formal extension of the United States' AID (Automatic Interaction Detection) and THAID (THeta Automatic Interaction Detection) procedures of the 1960s and 1970s, which in turn were extensions of earlier research, including that performed in the UK in the 1950s.

In practice, CHAID is often used in the context of direct marketing to select groups of consumers and predict how their responses to some variables affect other variables, although other early applications were in the field of medical and psychiatric research.

Like other decision trees, CHAID's advantages are that its output is highly visual and easy to interpret. Because it uses multiway splits by default, it needs rather large sample sizes to work effectively, since with small sample sizes the respondent groups can quickly become too small for reliable analysis.

One important advantage of CHAID over alternatives such as multiple regression is that it is non-parametric.

4. Mushroom

Mushroom data structure works like a CART decision tree which creates child nodes with two branches for each conditional evaluated going through the tree. The height will be the same as the number of variables in the dataset.

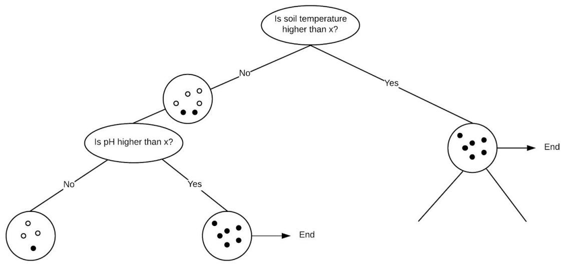


Figure 1: Mushroom data structure evaluates and creates new child nodes based on the results it obtains.

4.1 Operations of the data structure

Imagen

Figure 2: Tell what's going on in this picture.

4.2 Design criteria of the data structure

Decir por qué elegimos esta estructura de datos.

4.3 Complexity analysis

Hacer una tablita con la complejidad para cada operación de nuestra estructura de datos.

Operation	Complexity
leerArchivo(String data)	O(n^2)
seleccionarDataset()	O(n)
llenarMatriz(double [][] matriz)	O(n^2)
llenarImpureza(double [][] matriz)	O(n^2)
menores(double [][] matriz)	O(n)
addChild(Node childNode, int position)	O(1)
addNewNode(Node u, Object info, int i)	O(1)
numberOfNodesInTree(Node rootNode)	O(n)

Table 1: Table to report complexity analysis

4.4 Execution time

Measure (I) execution and (II) memory used by the operations of the data structure, for the data set found in the .ZIP file.

Measure the execution and time used 100 for each data set and for each operation of the data structure. Report the average values.

Operation	Execution time
leerArchivo(String data)	0.0ms
seleccionarDataset()	0.0ms
llenarMatriz(double [][] matriz)	0.0ms
llenarImpureza(double [][] matriz)	0.0ms
menores(double [][] matriz)	0.0ms
addChild(Node childNode, int position)	0.0ms
addNewNode(Node u, Object info, int i)	0.0ms
numberOfNodesInTree(Node rootNode)	0.0ms

Table 2: Execution time of the operations of the data structure for each data set.

4.5 Memory used

Data set	Memory used
data_set.csv	7.84 MB
data_set_balanced.csv	7.0 MB
data_set_train.csv	6.84 MB
data_set_test.csv	6.56 MB

Table 3: Memory used for each operation of the data structure and for each data set data sets.

4.6 Result analysis

Explain the results obtained. As an example, compare different implementation of the data structure and report the comparison in a table or graph.

Tablita.

Table 4: Analysis of the results.

REFERENCES

1. Kaewrod, N. and Kietikul, J. 2018 22nd International Computer Science and Engineering Conference (ICSEC), (Chiang Mai, Thailand, Thailand), IEEE, 1-5.

2. Wikipedia. 2016. CN2 algorithm. (8 September 2016). Retrieved *August 11, 2019* from https://en.wikipedia.org/wiki/CN2_algorithm

3. Wikipedia. 2018. C4.5. (9 April 2018). Retrieved *August 11, 2019* from https://es.wikipedia.org/wiki/C4.5

4. Cárdenas, J. Roya del cafeto. Retrieved *August 11, 2019* from https://www.croplifela.org/es/plagas/listado-de-plagas/roya-del-cafeto

5. OEC. 2017. Colombia (COL) Exportaciones, Importaciones, y Socios comerciales. Retrieved *August 11, 2019* from https://oec.world/es/profile/country/col/

6. Wikipedia. 2019. ID3 algorithm. (22 May 2019). Retrieved *August 11, 2019* from https://en.wikipedia.org/wiki/ID3_algorithm

7. synergy37AI. 2019. Tree algorithms: ID3, C4.5, C5.0 and CART. (20 February 2019). Retrieved *August 11, 2019* from https://medium.com/datadriveninvestor/tree-algorithms-id3-c4-5-c5-0-and-cart-413387342164

8. Wikipedia. 2019. Chi-square automatic interaction detection. (5 January 2019). Retrieved *August 11, 2019* from https://en.wikipedia.org/wiki/Chi-square_automatic_interaction_detection