Christopher Morgan

CS478: Brother Christophe

Project 1: Decision Tree

**Correctly implement the ID3**

* + **Some mechanism to handle continuous-valued attributes.**

My algorithm will simply divide a continuous-valued attribute in two. The attribute is split along the mean of its data values.

* + **You should be able to get ~68% predictive accuracy on lenses data with cross-validation.**

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| Rep: 0, Fold: 0, Accuracy: 0.5  Rep: 0, Fold: 1, Accuracy: 0  Rep: 0, Fold: 2, Accuracy: 1  Rep: 0, Fold: 3, Accuracy: 1  Rep: 0, Fold: 4, Accuracy: 1  Rep: 0, Fold: 5, Accuracy: 0.5  Rep: 0, Fold: 6, Accuracy: 1  Rep: 0, Fold: 7, Accuracy: 0.5  Rep: 0, Fold: 8, Accuracy: 1  Rep: 0, Fold: 9, Accuracy: 0.5  Mean predictive accuracy: **0.7** | **Using Accuracy:**  Rep: 0, Fold: 0, Accuracy: 1  Rep: 0, Fold: 1, Accuracy: 0.5  Rep: 0, Fold: 2, Accuracy: 1  Rep: 0, Fold: 3, Accuracy: 0.5  Rep: 0, Fold: 4, Accuracy: 0  Rep: 0, Fold: 5, Accuracy: 0.5  Rep: 0, Fold: 6, Accuracy: 1  Rep: 0, Fold: 7, Accuracy: 1  Rep: 0, Fold: 8, Accuracy: 0.5  Rep: 0, Fold: 9, Accuracy: 1  Mean predictive accuracy: **0.7** |

**Use your ID3 algorithm on the**[**Iris**](http://dml.cs.byu.edu/~cgc/docs/mldm_tools/Assignments/Datasets/iris.arff)**problem.**

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| --- | --- |
| **Information Gain** | **Accuracy** |
| Node: Property: petallength  Node: Property: petalwidth  Node: Class: 0  Node: Property: sepalwidth  Node: Class: 1  Node: Class: 0  Node: Property: petalwidth  Node: Property: sepalwidth  Node: Property: sepallength  Node: Class: 1  Node: Class: 1  Node: Property: sepallength  Node: Class: 1  Node: Class: 1  Node: Property: sepalwidth  Node: Class: 2  Node: Property: sepallength  Node: Class: 2  Node: Class: 2 | Node: Property: petalwidth  Node: Property: petallength  Node: Class: 0  Node: Property: sepallength  Node: Property: sepalwidth  Node: Class: 1  Node: Class: 0  Node: Class: 1  Node: Property: petallength  Node: Property: sepallength  Node: Property: sepalwidth  Node: Class: 1  Node: Class: 1  Node: Property: sepalwidth  Node: Class: 1  Node: Class: 1  Node: Property: sepallength  Node: Property: sepalwidth  Node: Class: 2  Node: Class: 2  Node: Class: 2 |

* + **Compare this tree with the one obtained with information gain as the splitting criterion.**

The main order of the Entropy algorithm was to choose petalLength, petalWidth, and then sepalWidth in that order. However, when switching to the Accuracy algorithm it favored petalWidth, petalLenght, then sepalLength in that order. Changing algorithms to accuracy therefore cause an increase in weight for petalWidth, cause it to be selected first over petalLength. In addition to the order of attributes chosen the switch in algorithms also created a slightly larger tree when accuracy was used. The Entropy tree consisted of 19 nodes where the Accuracy tree was made up of 21.

* + **Evaluate predictive accuracy using 10-fold cross-validation for information gain and accuracy.**

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| Rep: 0, Fold: 0, Accuracy: 1  Rep: 0, Fold: 1, Accuracy: 1  Rep: 0, Fold: 2, Accuracy: 1  Rep: 0, Fold: 3, Accuracy: 1  Rep: 0, Fold: 4, Accuracy: 0.933333  Rep: 0, Fold: 5, Accuracy: 0.866667  Rep: 0, Fold: 6, Accuracy: 1  Rep: 0, Fold: 7, Accuracy: 0.933333  Rep: 0, Fold: 8, Accuracy: 0.933333  Rep: 0, Fold: 9, Accuracy: 0.933333  Mean predictive accuracy: **0.96** | **Using Accuracy:**  Rep: 0, Fold: 0, Accuracy: 1  Rep: 0, Fold: 1, Accuracy: 0.866667  Rep: 0, Fold: 2, Accuracy: 1  Rep: 0, Fold: 3, Accuracy: 0.933333  Rep: 0, Fold: 4, Accuracy: 0.866667  Rep: 0, Fold: 5, Accuracy: 1  Rep: 0, Fold: 6, Accuracy: 1  Rep: 0, Fold: 7, Accuracy: 0.933333  Rep: 0, Fold: 8, Accuracy: 1  Rep: 0, Fold: 9, Accuracy: 1  Mean predictive accuracy: **0.96** |

* + **Compare the results.**

On average the two different branching criteria appear to perform about the same, with a mean accuracy of .96 over 10 folds on the Iris data set. Using Information Gain the algorithm produced 5 perfect run where as the Accuracy driven algorithm produced 6. In the end they appear equally effective for training on the Iris data set.

**Repeat the experiment with the**[**Voting**](http://dml.cs.byu.edu/~cgc/docs/mldm_tools/Assignments/Datasets/voting.arff)**problem.**

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| --- | --- |
| **Information Gain** | **Accuracy** |
| Node: Property: 'physician-fee-freeze'  Node: Property: 'synfuels-corporation-cutback'  Node: Property: 'crime'  Node: Property: 'anti-satellite-test-ban'  …  Node: Property: 'anti-satellite-test-ban'  Node: Class: 0  Node: Property: 'el-salvador-aid'  …    Node: Class: 0  Node: Property: 'synfuels-corporation-cutback'  Node: Property: 'duty-free-exports'  N: P: 'adoption-of-the-budget-resolution'  …  Node: Property: 'immigration'  …  Node: P: 'adoption-of-the-budget-resolution'  Node: Property: 'el-salvador-aid'  Node: Class: 0  Node: Property: 'immigration'  Node: P: 'superfund-right-to-sue'  Node: Class: 0  N: P: 'anti-satellite-test-ban'  …  Node: Class: 1  Node: Property: 'anti-satellite-test-ban'  Node: Class: 0  Node: Class: 1 | Node: Property: 'physician-fee-freeze'  Node: Property: 'handicapped-infants'  Node: Property: 'religious-groups-in-schools'  Node: Class: 0  Node: P: 'water-project-cost-sharing'  …  Node: Property: 'water-project-cost-sharing'  Node: Property: 'anti-satellite-test-ban'  …  Node: Class: 0  Node: Property: 'handicapped-infants'  Node: Property: 'water-project-cost-sharing'  N: P: 'adoption-of-the-budget-resolution'  N: P: 'religious-groups-in-schools'  …  Node: Property: 'el-salvador-aid'  Node: Class: 1  N: P: 'religious-groups-in-schools'  …  Node: Property: 'el-salvador-aid'  …  Node: P: 'synfuels-corporation-cutback'  Node: Class: 1  Node: Property: 'mx-missile'  Node: P: 'water-project-cost-sharing'  …  Node: P: 'water-project-cost-sharing'  … |

* + **Compare this tree with the one obtained with information gain as the splitting criterion.**

The trees differ in attribute selection, number of branches, depth to first classification, and number of node. Both trees begin by splitting the data on the physician-fee-freeze attribute, but from there the trees diverge. The information gain tree follows synfuels-corporation-cutback, crime, duty-free-exports, and adoption-of-budget-restoration, where the accuracy tree follows handicapped-infants, religious-groups-in-school, water-project-cost-sharing, and synfuels-corporation-cutback.

The along this line of divergent attributes, the accuracy driven algorithm requires a lot more branches to classify all of the data. The accuracy tree consists of 68 different attribute selections, or branching points, where as the information gain tree has slightly fewer with 54 different attribute selections. Along these branches, the accuracy tree took longer to find its first classification. The accuracy tree found its first classification three nodes(attribute selections) deep, where as the information gain tree found its first two nodes deep.

Given that the accuracy tree already had to dive deeper to find its first classification, it is not surprising that the accuracy tree also contained more nodes that the information gain tree. The accuracy tree contained 137 nodes where as the information gained tree consisted of 109 nodes.

* + **Evaluate predictive accuracy using 10-fold cross-validation for information gain and accuracy.**

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| --- | --- |
| Rep: 0, Fold: 0, Accuracy: 0.883721  Rep: 0, Fold: 1, Accuracy: 0.906977  Rep: 0, Fold: 2, Accuracy: 0.976744  Rep: 0, Fold: 3, Accuracy: 0.883721  Rep: 0, Fold: 4, Accuracy: 0.930233  Rep: 0, Fold: 5, Accuracy: 0.906977  Rep: 0, Fold: 6, Accuracy: 0.953488  Rep: 0, Fold: 7, Accuracy: 0.953488  Rep: 0, Fold: 8, Accuracy: 0.930233  Rep: 0, Fold: 9, Accuracy: 0.953488  Mean predictive accuracy: **0.927907** | **Using Accuracy:**  Rep: 0, Fold: 0, Accuracy: 0.930233  Rep: 0, Fold: 1, Accuracy: 0.906977  Rep: 0, Fold: 2, Accuracy: 0.976744  Rep: 0, Fold: 3, Accuracy: 0.906977  Rep: 0, Fold: 4, Accuracy: 0.930233  Rep: 0, Fold: 5, Accuracy: 0.930233  Rep: 0, Fold: 6, Accuracy: 0.930233  Rep: 0, Fold: 7, Accuracy: 0.860465  Rep: 0, Fold: 8, Accuracy: 0.883721  Rep: 0, Fold: 9, Accuracy: 0.930233  Mean predictive accuracy: **0.918605** |

* + **Compare the results.**

The information gain model is 0.01 more accurate that the accuracy model. This seems to give backing to the idea that improving accuracy it a lot harder task than simply decreasing entropy.

* + **Describe and justify the method you used to handle missing values.**

For each missing attributes I calculate the majority value for that attribute from the original data set. I then replace the missing value with the majority for that attribute. This seems reasonable given that the majority value, for a missing attribute, is a simple best guess for what it might be given our current data set.

**Extend your algorithm so that, when accuracy is the splitting criterion, it may use up to 2 conditions in the tests at each node (e.g., attrX = Vx and attrY = Vy). You may choose to make that an user-specified option.**

* + **Induce a decision tree using the entire dataset with this extended algorithm for both the**[**Iris**](http://dml.cs.byu.edu/~cgc/docs/mldm_tools/Assignments/Datasets/iris.arff)**problem and the**[**Voting**](http://dml.cs.byu.edu/~cgc/docs/mldm_tools/Assignments/Datasets/voting.arff)**problem. Give a visual representation of the trees.**

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| --- |
| **Iris** |
| Node: Property: sepallength & sepalwidth  Node: Property: petallength  Node: Property: petalwidth  Node: Class: 0  Node: Class: 1  Node: Property: petalwidth  Node: Class: 1  Node: Class: 2  Node: Class: 0  Node: Property: petallength & petalwidth  Node: Class: 1  Node: Class: 2  Node: Class: 2  Node: Class: 2  Node: Property: petallength & petalwidth  Node: Class: 1  Node: Class: 2  Node: Class: 2  Node: Class: 2 |
| **Voting** |
| Node: Property: 'physician-fee-freeze' & 'superfund-right-to-sue'  Node: Property: 'handicapped-infants'  Node: Property: 'water-project-cost-sharing' & 'aid-to-nicaraguan-contras'  ~Class Nodes  Node: Property: 'el-salvador-aid' & 'religious-groups-in-schools'  Node: Property: 'adoption-of-the-budget-resolution' & 'crime'  ~Class Nodes  Node: Class: 0  Node: Class: 0  Node: Class: 0  Node: Property: 'handicapped-infants' & 'crime'  Node: Property: 'education-spending'  Node: Class: 0  Node: Class: 1  Node: Property: 'water-project-cost-sharing'  Node: Class: 0  Node: Property: 'adoption-of-the-budget-resolution' & 'mx-missile'  …  Node: Property: 'el-salvador-aid' & 'synfuels-corporation-cutback'  …  Node: Class: 0  Node: Class: 0  Node: Property: 'water-project-cost-sharing' & 'adoption-of-the-budget-resolution'  ~Class Nodes  Node: Property: 'adoption-of-the-budget-resolution' & 'synfuels-corporation-cutback'  Node: Property: 'water-project-cost-sharing' & 'duty-free-exports'  ~Class Nodes  Node: Property: 'anti-satellite-test-ban' & 'education-spending'  Node: Property: 'handicapped-infants'  …  Node: Property: 'handicapped-infants'  …  Node: Class: 0  Node: Class: 1  Node: Property: 'anti-satellite-test-ban' & 'immigration'  ~Class Nodes  Node: Property: 'water-project-cost-sharing'  Node: Class: 1  Node: Class: 0 |

* + **Compare them with those obtained above.**

The effects of allow the model to represent up to two attributes at once has similar effects in both the iris data the voting data with respect to branch nodes and number of nodes. The iris model was decreased by number of branching nodes from 10 branch nodes to 6. The voting data model was decreased by number of branching nodes from 68 nodes to 35. There was a similar effect to the overall number of nodes, where the number of nodes in the iris model went from 21 nodes to 19. The voting data also showed a decrease in the number of nodes from 137 nodes to 97.

However, the addition of allowing the model to hold up to two attributes at a time caused the order of attributes selected or path followed to differ between the two data sets. The iris data showed a flip in path of attibutes followed, where as the voting data follow a roughly similar path. The iris data with only one attribute selection followed a path of selecting on petalwidth and petallength followed by selections on sepallength and sepalwidth. However, the iris data with two attributes selected followed the path of sepallength and spealwidth first followed by petalwidth and petallength. The voting data using single and up to two attribute selection both roughly followed the attribute path of physician-fee-freeze, handicap-infants, and water-project-cost-sharing.

* + **Explain why it may be necessary to thus extend the decision tree learning algorithm when using accuracy as the splitting criterion (and why the extension is of little value when information gain is the splitting criterion).**

It is necessary because it is a much harder of a task to find an attribute to split on that will change the majority of an example set versus a spilt that just reduces the number of instances that differ. Thus, by giving the algorithm more attributes to select from it is easier to find a split that finds a meaningful change in the majority of a set of data. However, a entropy driven algorithm only seeks to change the distribution of a data set along an attribute split and it is likely that just the act of splitting the data set alone will be sufficient to cause a change in entropy, therefore, multiple attribute with entropy wont help the algorithm much, if any.