CS564 Machine Learning

Project 1: Decision Trees

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Introduction

Decision trees are one of the predictive modelling methods and are a "supervised" machine learning practice. In supervised learning, input and corresponding output is fed into the model using training data. Once the model is trained, it can be used to predict results for other data sets. In decision trees, data is continuously split according to a certain factor until a final decision class is obtained.

Building decision tree using ID3 with Entropy and Information Gain

In this project, we use the ID3 algorithm to construct a decision tree using the training data and predict results for the given test data. According to this algorithm, every unvisited attribute is visited in each iteration and one best attribute is selected as the splitting factor. The best attribute is selected based on ***Entropy*** *(measure of disorder)* or ***Information gain*** – lowest entropy or largest information gain.

Project implementation details:

- Iterate through the data set and select the splitting attribute by calculating minimum entropy and maximum information gain.
- At every iteration, we are dropping the previously selected attribute(column) from the dataset and repeating the above step.
- At the end, if there are any attributes left out in the dataset which could not be brought under common decision class, we are assigning the most probable outcome to that branch.

Building decision tree using CART with Gini Impurity

Gini impurity is used by Classification and Regression Tree Algorithm (CART) to determine the splitting factor.

- Iterate through the data set and select the splitting attribute by calculating minimum Gini impurity
- At every iteration, we are dropping the previously selected attribute(column) from the dataset and repeating the above step.

Building decision tree using Misclassification Error

Misclassification error is one of the common cost functions used to build a decision tree, like entropy and Gini impurity.

- Iterate through the data set and select the splitting attribute by calculating minimum error
- At every iteration, we are dropping the previously selected attribute(column) from the dataset and repeating the above step.

Decision tree and post pruning

In this method, we are building the decision tree using ID3 algorithm and then prune the tree using bottom up approach.

- At every iteration, we remove the node at the end and check accuracy.
- If there is an increase in accuracy, we accept the removal.
- Else we reject the removal and repeat the process with other nodes.

Decision tree with Chi square split stopping

In this method, we have used chi-square test to stop growing the tree earlier (pre-pruning). We have used two confidence intervals – 0%, 99% (p-value = 0.01) and 95% (p-value = 0.05) for the test and degree of freedom.

- Calculate the chi-square value at each iteration using actual and expected probability values
- Compare the chi-square value from above step with corresponding p-value obtained from table (with confidence interval and DOF)
- If chi-square Value < p-value, we accept the split and if chi-square Value > p-value, we reject the split.

	Percentage								
	2.5	*5*	*50*	*75*	*90*	*95*	*97.5*	*99*	*99.9*
D	*Upper one-sided* α								
	.975	*.95*	*.50*	*.25*	*.10*	*.05*	*.025*	*.01*	*.001*
1	.001	.004	.455	1.32	2.71	3.84	5.02	6.63	10.83
2	.051	.103	1.39	2.77	4.61	5.99	7.38	9.21	13.82
3	.216	.352	2.37	4.11	6.25	7.82	9.35	11.34	16.27
4	.484	.711	3.36	5.39	7.78	9.49	11.14	13.28	18.47
5	.831	1.15	4.35	6.63	9.24	11.07	12.83	15.09	20.52
6	1.24	1.64	5.35	7.84	10.64	12.59	14.45	16.81	22.46
7	1.69	2.17	6.35	9.04	12.02	14.07	16.01	18.47	24.32
8	2.18	2.73	7.34	10.22	13.36	15.51	17.53	20.09	26.12
9	2.70	3.33	8.34	11.39	14.68	16.92	19.02	21.67	27.88

Training dataset and calculating accuracy

From the available dataset with Type result, $3/4^{th}$ portion is used to train our decision tree. The rest of the data is used to predict result class and is compared to the actual result set we have from the data, to get an estimate of accuracy.

Prediction using decision tree

Once the decision tree is built using one of the above methods, we use the predict method to get results for the test data. In this function, test data and decision tree are passed as parameters. For every row in the data set, tree is traversed, and decision class is obtained. This function lets us traverse the tree while looking for a match in the branch searched (A, G, C, T) and the branch of the tree.

Implementation

The algorithm is implemented in python 3.8.1. The libraries used are Pandas (handling dataset), Graphviz (Visualizing the tree), NumPy (calculating log values).

Tree:

The tree data structure is stored as an object of class tree. Tree object consists:

- *tree.data* (Node)
- *branches* (List of branch objects)
  --The branch object consists of a *branch value* and a *tree* object

Build tree function:

This function finds highest Information gain/lowest Gini impurity/lowest Misclassification Error, depending on the algorithm used and calls itself recursively passing the sub dataset to the function thus building a tree.

Accuracy values obtained

CART (Gini Impurity) with Chi square split stopping and post pruning:

- 91.806% *(*95% confidence interval)
- **92.857%** (99% confidence interval)

ID3 (Entropy & Information Gain) with Chi square split stopping and post pruning:

- 90.2461% *(*95% confidence interval)
- 91.386% (99% confidence interval)

Misclassification Error with Chi square split stopping and post pruning:

- 89.705% (99% confidence interval)

Misclassification Error with Chi square split stopping and post pruning:

- 90.87% (0% confidence interval)

CART with Gini Impurity and post pruning:

- 90.6%

ID3 (Entropy & Information Gain) with Chi square split stopping:

- 89.6% (0% confidence interval)

ID3 (Entropy & Information Gain) with Chi square split stopping:

- 88.46% (99% confidence interval)

ID3 (Entropy & Information Gain) with Chi square split stopping and post pruning:

- 87.931% (0% confidence interval)

CART with Gini Impurity with Chi square split stopping:

- 87.216% (0% confidence interval)

Misclassification Error with Chi square split stopping:

- 87.6% (0% confidence interval)

CART (Gini Impurity) with Chi square split stopping:

- 87.18% (99% confidence interval)

Result Analysis

From the tests we have observed that, best result was seen while using *CART* (Gini index), implementing *Chi Square* test (with 99% confidence) to stop splitting and *post pruning* the resulting tree with an accuracy of **92.857%**. A similar accuracy had been observed with the same configuration but with 95% confidence interval. The decision tree is at its best accuracy when insignificant nodes are removed using pruning. Chi square test takes care of removing the unwanted splits before the tree is built and post pruning guarantees that there are no unwanted nodes after the tree is built hence giving a second level of verification. We believe that this combination of methods prove to be most useful in acquiring maximum accuracy.

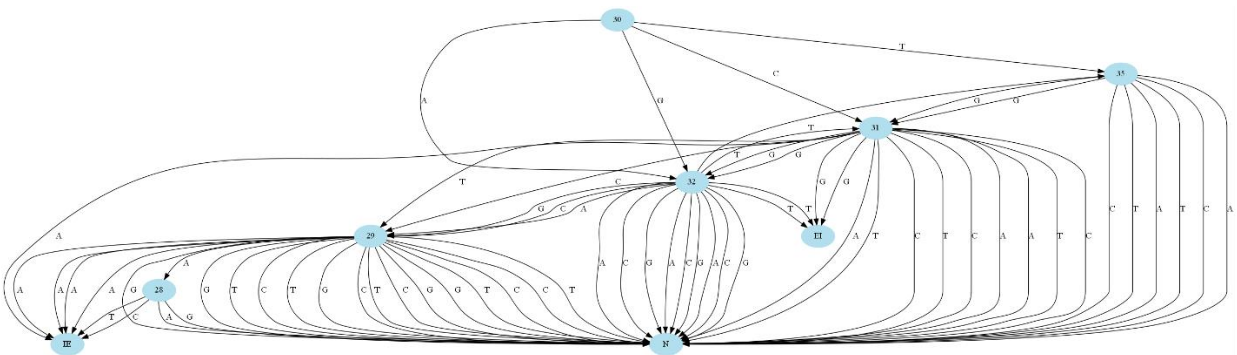
ID3 using *Entropy* gave the next best outcome, resulting in an accuracy of **91.38%** under the configuration of *Chi square* test and *post pruning* the tree.

The decision tree built using the *Misclassification Error* stood as the least accurate tree, which resulted in an accuracy of 89.7%.

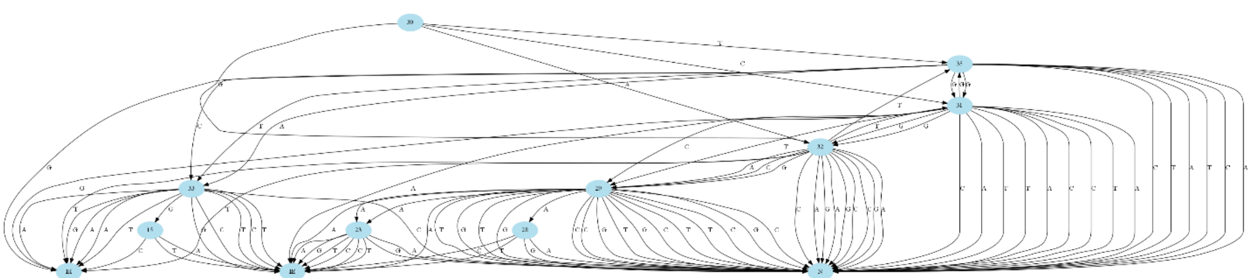
Visualization of the Decision Trees

Below are the images of graphical visualization of some of the decision trees built in this project. These are provided to give an idea of the trees that are built. Install "Graphviz" as mentioned in the instructions, in order to obtain similar images for all other methods.

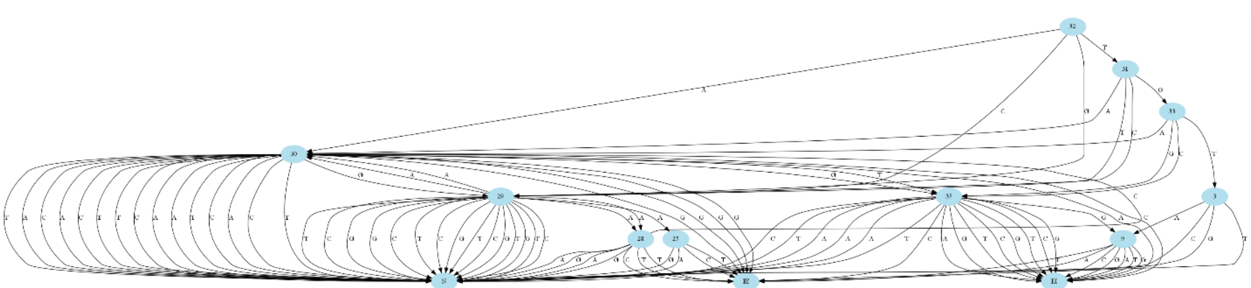
CART (Gini Impurity) with Chi square split stopping and post pruning:



ID3 (Entropy & Information Gain) with Chi square split stopping and post pruning:



Misclassification Error with Chi square split stopping and post pruning:



CART with 0% confidence interval: