ML LAB-1

EXPT #1: Creating attributes and test and train sets

- 1. 1000 random examples were chosen from TRAINlabeledBow.feat and 1000 from TESTlabeledBow.feat such that half of them are positive and half are negative.
- 2. For attributes, I chose 5000 most frequently used words with 2500 having polarity>1 and 2500 with polarity<-0.5.
- 3. For different runs, the examples in train and test sets change as they are chosen randomly and so, the accuracy also changes by a slight amount

EXPT #2: ID3 with and without early stopping

Without early stopping:

Accuracy(avg): 69.5%

Num of leaves: 189

5 most used attributes(for splitting) Frequency

53 7

88 4

115 4

313

413

After early stopping:

Accuracy: 70.19%

Num of leaves: 119

5 most used attributes(for splitting) Frequency

156

115

297 3

83 2

856

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| Temp |
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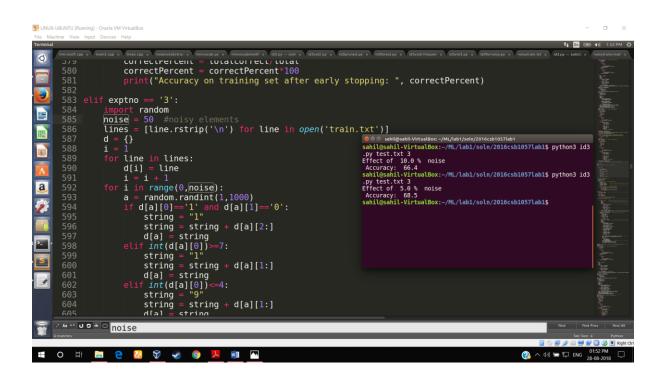
So, as we can see early stopping increases the accuracy by a percent as the size of tree decreases and thus the overfitting also decreases. But the stopping criteria must not be too high, in my case it was 30 examples in a node.

Too high or too low stopping criteria decreased the accuracy.

EXPT #3: ID3 with noisy examples:

Noise(in percent)	Accuracy
0.5%	70%
1%	69.19%
5%	68.5%
10%	65%

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EXPT #4: ID3 with post-pruning(reduced error pruning)

Nodes before pruning	Nodes after pruning	Accuracy
383	275	71.9
383	297	71.8%
383	383(no pruning)	69.6%

So, the number of nodes pruned directly affects the accuracy, if a lot of nodes are pruned then the accuracy decreases but up until a level the accuracy increases by upto 2% on pruning

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EXPT #5: Random forests using feature bagging

Randomly 2000 attributes were chosen from the list of 5000 attributes and then a number of trees were created and the maximum output of those trees was chosen as my output.

Number of trees	Accuracy
5	72.1%
10	72.8%
15	73%
25	77.3%

