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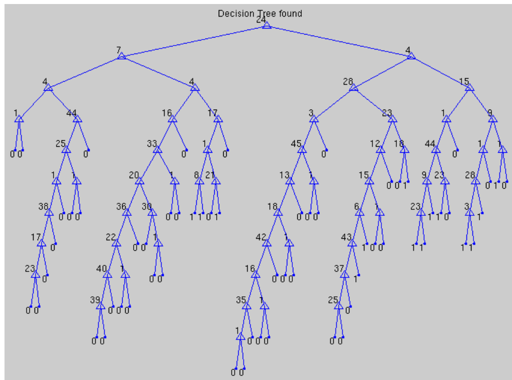
Group Number: 28

Assignment 2: Decision Trees Algorithm

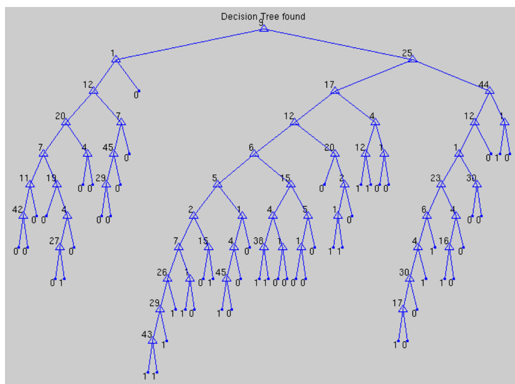
Implementation details

- Cross-validation was done by first generating a cell array of the binary targets for each emotion. Then, inside a for-loop, each fold is removed from the set of examples in turn, leaving a set used to train the decision tree, and the fold used to test the resulting trees for accuracy. A running total is kept of correct answers, along with a confusion matrix updated on each loop.
- Best attributes were selected in the suggested manner, by keeping track of p_0, n_0, p_1, and n_1 in the loop for each attribute, and using the provided formulae to compute whether or not the new attribute provides a greater information gain than the previous best.
- All data for the average cross-validation results is collected during the cross-validation, with a running total of correct answers, and the incrementation of entries in the confusion matrix. A call is made to a seperate function to get recall and precision rates, as well as F_1 measures, to keep the code tidier.

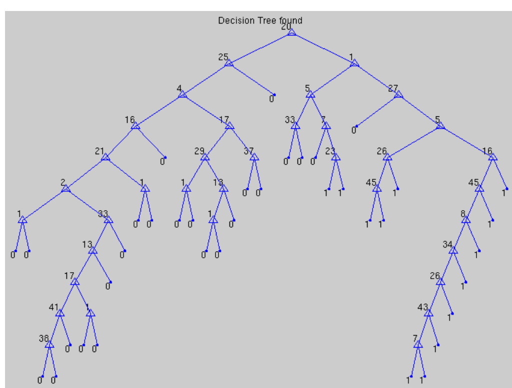
Generated trees



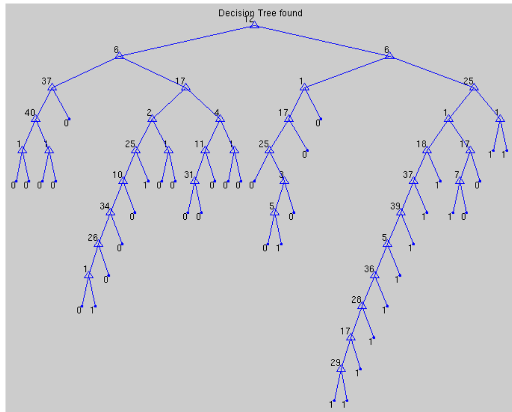
Tree for anger



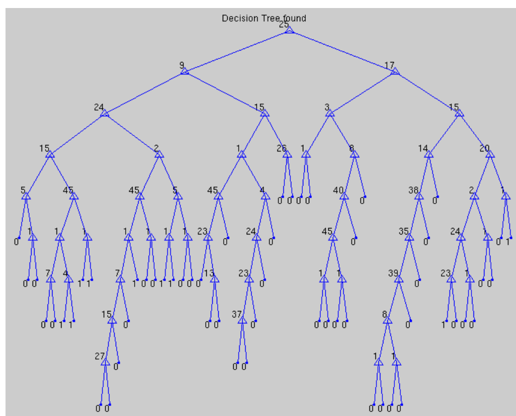
Tree for disgust



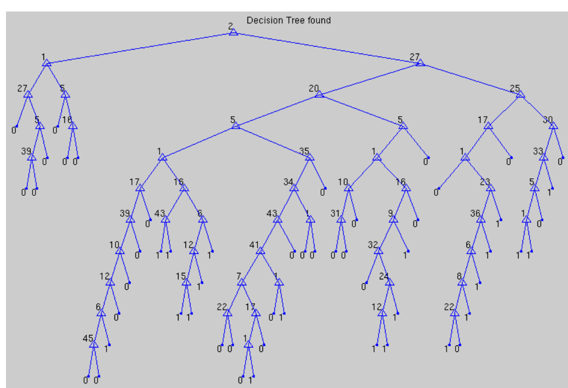
Tree for fear



Tree for happiness



Tree for sadness



Tree for surprise

		Predicted class					
		Anger	Disgust	Fear	Happiness	Sadness	Surprise
	Anger	7.4	1.4	0.4	2.0	0.9	1.1
	Disgust	1.2	15.0	0	2.1	0.6	0.9
Actual class	Fear	0.5	2.3	3.9	1.8	0.8	2.6
	Happiness	0.2	2.0	0	18.8	0.1	0.5
	Sadness	0.7	2.8	0.4	2.6	4.5	2.2
	Surprise	0	4.3	1.1	6.2	0.4	8.7

Table 1: Confusion matrix

Emotion	Recall rate (%)	Precision rate (%)
Anger	56.0606	74.0000
Disgust	75.7576	53.9568
Fear	32.7731	67.2414
Happiness	87.0370	56.1194
Sadness	34.0909	61.6438
Surprise	42.0290	54.3750

Table 2: Recall and precision rates

Evaluation results

Confusion matrix: The happiness tree was very good, perhaps overfit. Disgust and Happiness were quite often misclassified as well as correctly. They probably produced better trees because there was more data for them. Classification rate: The average classification rate is semi-successful as it succeeds most of the time. But it is far from perfect. Precision/Recall rate: F-measure: The F measures suggest as suspected that the Disgust and Happiness have well trained trees. Perhaps Sadness and Surprise did not have enough data. Anger is likely an easy emotion to classify given the trees high performance given a relatively small amount of data

Average classification rate = 0.5808

Ambiguity

Emotion	F_1 measure
Anger	63.7931
Disgust	63.0252
Fear	44.0678
Happiness	68.2396
Sadness	43.9024
Surprise	47.4114

Table 3: F1 measures

There are 2 cases when a decision must be made about classification, which cannot be made by the trees themselves. The first case occurs when none of the trees have returned a positive value, and the second when multiple trees positively classify the same example. Initially, we chose to randomise the classification, and this became our benchmark. The obvious drawbacks of choosing randomly are that it is a complete guess, and should intuitively not be used if there is more information available. Generation of pseudo random numbers is also a rather expensive task if time is a factor.

We then decided to select the value which had been chosen the most so far, without contention. This was slightly worse than random on average, it is highly dependent on the order of the data. This method was then superseded by choosing the most common label in the test set. Statistically, choosing the most common label should be better on average, but it fared worse when used for examples that had no classification. Of course the drawback of this method is that the statistically most common labels need to be known in advance. This method proved to be slightly better on average than the random choices.

Finally, we made a score system for trees when competing against each other. If there were multiple trees with positive classifications, then the tree that was chosen would receive a point if it correctly classified the result, but lose one if it provided a false positive. For the next classification, the tree with the highest score would be chosen if there was contention. This improved the F_1 measure, but could not be used when no classes were found. Another drawback is that a different measure must be used the first time there is contention, since there are no scores, and this can have a large impact on the path of evaluation. Also, it may not always be possible to get immediate feedback on the classification whilst learning, which would impose limits on its usefulness. This method is also bound by the complexity of sorting the label priorities (n log n), so it may not be the best choice if there are a very large number of labels, and time is a factor.

If we had more time, I would like to have trained a decision tree to choose which label to trust in the event of multiple positives, or even in other cases (for instance, if it was always the case that when the two positive-valued trees were Anger and Surprise, then the actual label was Happy). It is worth noting that this would require a much larger sample of data.

Pruning

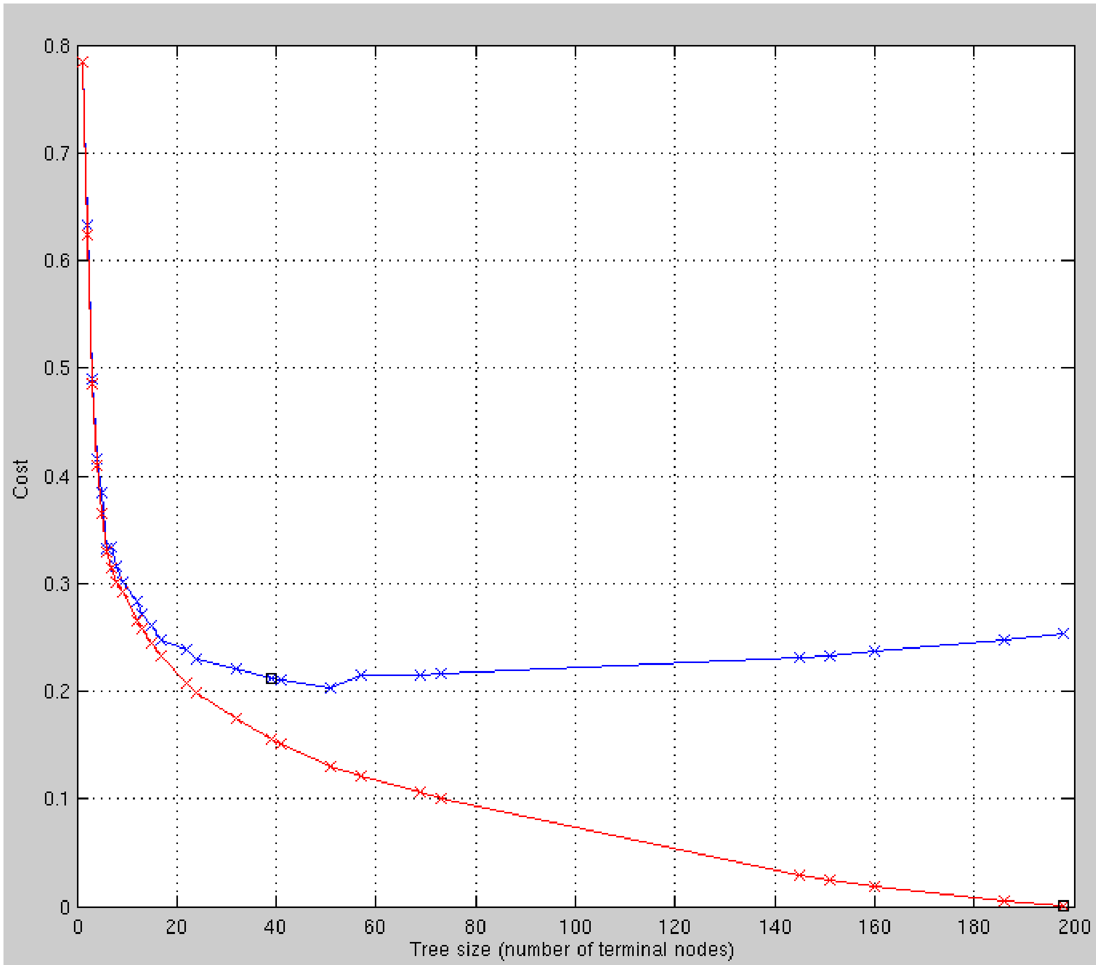
The pruning_examples function shows a graph where tree pruning is used on a decision tree built using the default matlab libraries. We imagine that tree pruning will first remove extraneous branches, where any choice would lead to the same answer.

The pruning algorithm used is resubstitution pruning, which substitutes leaf nodes with the most common attribute until the error value is intolerably high.

The cost variable on the y-axis is the average number of comparisons for each classification. This is calculated by multiplying the probability that a leaf node is reached by the cost it took to reach, and summing the results.

We think that this cost is calculated based on trees of different sizes, showing the value of cost for each size of tree. The blue line is most likely the cost without using pruning, and the red line the cost after pruning.

The optimal tree size when using the pruning algorithm is one where the cost is as small as possible, yet still having an error rate of the tree using cross validation.


0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Cost
0
20
40
60
80
100
120
140
160
180
200
Tree size (number of terminal nodes)

Code Flowchart