

COURSEWORK 1

IMPERIAL COLLEGE LONDON

DEPARTMENT OF COMPUTING

CO395: Machine Learning

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Please see the Appendix for information on running and testing our code.

1 Implementation Details

The decision tree has been implemented using Python 3 and the third party libraries numpy, scipy & etc. Instructions on running the Emotion Recognition project can be found in the Appendix.

The Decision Tree is implemented by following the algorithm provided in the Coursework Manual and does not include pruning of the tree. The IE3 algorithm is used in order to choose the attribute at each node in the tree and in the case that two or more attributes are joint best contenders to be the chosen attribute then the lowest-indexed attribute is chosen.

Following testing of both modal and mean average functions of binary targets as majority value functions for leaf nodes values, the latter has been chosen. This function differs from the spec by instead of returning the mode it returns a mean of the binary targets, which is more useful when combining the trees. The Evaluation section contains the quantitative evidence used to make this judgment.

10-fold cross validation was used in order to evaluate the performance of the classifiers on clean and noisy data. Each fold contains 10% of the data hence the classifier was trained on 90% of the data and evaluated against the unseen 10%.

The results of this evaluation were combined by summing the confusion matrices of each fold together into one total confusion matrix, such that:

$$TotalMatrix\{i\}\{j\} = \sum_{i=1}^{10} fold_i ConfusionMatrix\{i\}\{j\}$$

Statistics for each emotion, True/False Positive/Negative numbers, were then produced from this total matrix that were then used to produce the average Recall, Precision and F1 Measure for the cross validation run

2 Evaluation of implementation

2.1 Clean data set

2.1.1 Modal function as majority function

Average Classification Rate: 0.558

Emotion Number	Recall %	Precision %	F1 Measure
1	67.2	30.8	42.2
2	87.4	60.9	71.2
3	8.5	38.5	13.9
4	56.7	74.8	64.6
5	33.3	72.1	45.6
6	58.7	67.2	62.7

Table 1: Recall, Precision and F1 for each emotion for clean data trained using modal value function

		Predicted					
		1	2	3	4	5	6
Actual	1	88	24	2	7	6	4
	2	17	173	1	2	4	1
	3	39	17	10	6	5	41
	4	47	33	4	122	1	8
	5	54	21	2	6	44	5
	6	41	16	7	20	1	121

Table 2: Confusion matrix for clean data trained using modal value function

2.1.2 Mean function as majority function

Average Classification Rate: 0.631

Emotion Number	Recall %	Precision %	F1 Measure
1	51.1	52.8	51.9
2	80.8	63.7	71.3
3	29.6	50	37.2
4	72.6	72.6	72.6
5	49.2	59.1	53.7
6	71.8	65.2	68.4

Table 3: Recall, Precision and F1 for each emotion for clean data trained using mean value function

		Predicted					
		1	2	3	4	5	6
Actual	1	67	25	8	10	16	5
	2	11	160	4	13	7	3
	3	10	12	35	6	7	48
	4	6	21	10	156	8	14
	5	25	21	4	8	65	9
	6	8	12	9	22	7	148

Table 4: Confusion matrix for clean data trained using mean value function

2.1.3 Clean Data Results Evaluation

Modal function as majority function When modal function is used as majority, as shown in subsection 2.1.1, the emotion 2 is recognized with high recall rate of 87.4%. Followed by emotion 1, 4 and 6 with recall rate of 67.2%, 56.7% and 58.7%. The emotion 3 and 5 have relatively low recall rate, each 8.5% and 33.3%. Meaning that emotion 3 has the fraction of relevant instances that have been retrieved over the total amount of relevant instances is the lowest among other emotions. In terms of precision, the emotion 4 has the highest precision of 74.8% followed by 5, 6 and 2. The emotion 1 and 3 have relatively low precision, each 30.8% and 38.5%. Meaning that the fraction of relevant instances among the retrieved instances is low. F measure generally follows the pattern of recall rate.

Mean function as majority function When mean function is used as majority, as shown in subsection 2.1.2, The emotion 2, 4 and 6 are recognized with high accuracy(recall rate) of 80.8%, 72.6% and 71.8%. And the emotion 1, 5 have the recall rates of 51.1%, and 49.2% which is roughly about half. Especially, the emotion 3 has very low accuracy of 29.6% so as F1 Measure. Meaning that the performance of decision tree is poor for emotion 3. In terms of precision rate, the emotion 4 has highest precision of 72.6%. Whereas all emotions have good precision rates in general. To conclude, the decision tree works well for emotion 2, poor for 3. However, it works moderate for other emotions.

2.2 Noisy data set

2.2.1 Modal function as majority function

Average Classification Rate: 0.576

Emotion Number	Recall %	Precision %	F1 Measure
1	38.6	25.6	30.8
2	88.8	54.4	67.5
3	71.1	55.6	67.5
4	61.5	74.4	67.4
5	3.63	40.0	6.66
6	50.5	78.7	61.5

Table 5: Recall, Precision and F1 for each emotion for noisy data trained using modal value function

		Predicted					
		1	2	3	4	5	6
Actual	1	34	12	20	12	3	7
	2	8	166	9	2	1	1
	3	8	35	133	3	1	7
	4	17	36	25	128	0	2
	5	43	19	20	11	4	13
	6	23	37	32	16	1	111

Table 6: Confusion matrix for noisy data trained using modal value function

2.2.2 Mean function as majority function

Average Classification Rate: 0.562

Emotion Number	Recall %	Precision %	F1 Measure
1	28.4	34.2	31.0
2	66.8	57.6	61.9
3	52.4	53.6	53.0
4	76.9	55.9	64.8
5	29.1	50.8	37.0
6	55.5	68.5	61.3

Table 7: Recall, Precision and F1 for each emotion for noisy data trained using mean value function

		Predicted					
		1	2	3	4	5	6
Actual	1	25	8	17	12	15	11
	2	6	125	15	31	2	8
	3	5	22	98	44	5	13
	4	10	19	8	160	3	8
	5	17	12	19	14	32	16
	6	10	31	26	25	6	122

Table 8: Confusion matrix for noisy data trained using mean value function

2.2.3 Noisy Data Results Evaluation

Modal function as majority function When modal function is used as majority, emotion 2 has the best recall rate as 88.8%. Followed by emotion 3, 4 and 6, 71.1%, 61.5% and 50.5% respectively. In terms of precision, emotion 6 was the highest as 78.7%, followed by emotion 4 with 74.4%. Emotion 2 and 3 have similar values, which implies that they have the similar fraction of relevant instances among the retrieved instances. In terms of precision rate, the emotion 1 has the lowest precision rate of 25.6%. Emotion 2, 3 and 5 have similar precision rate roughly 50%, implies that the emotion tree F1 measure has the same pattern as recall rate, the emotion with higher recall rate has the higher F1 measure value. To conclude, generally all emotions are classified well except emotion 1 and 6. Which means that the decision trees perform well in those well classified well emotions (i.e. f1 measure indicates the performance of the tress).

Mean function as majority function When mean function is used as majority, in terms of sensitivity, the emotion 4 has the highest accuracy of 76.9%. Followed by emotion 2 with recall rate of 66.8%. Emotion 3 and 6 of each 52.4% and 55.5%, meaning that the emotions are classified correctly roughly about 50% times (i.e. the emotion tree makes correct decision on emotion 3 and 6 with the probability of 50%). Emotion 1 and 5 have the lowest recall rate of 28.4% and 29.1%, implies that their true positive rate is low. In terms of precision, all emotions generally have good classification rate above the standard but emotion 1. Emotion 1 has the lowest precision rate of 34.2% which is below 50%, which means the emotion has the low fraction of relevant instances among the retrieved instances. To conclude, the emotion 2 and 4 are classified well above the standard.

3 Dataset questions

3.1 Noisy-Clean Datasets Question

Performance (using an average of 2 different methods) is better for clean data set as could be expected. Training on clean data should give better results. In clean data set, emotion 3 has a particularly bad F1 measure (13.9 and 37.2 for different methods of combining the trees). This is caused by a very small number of input data that actually maps to emotion 3. This shows it is important to have a balanced data set. The very same situation is true for a noisy data set and emotion 5. Small number of input examples results in bad F1 measures (6.66 and 37.0).

3.2 Ambiguity Question

The first method we tried was to just iterate over all trees for given input and return a label that returns to the first positive answer from the tree. That would mean that our results would be skewed towards first couple of emotions. This is true for both data sets as precision for emotion 1 is considerably lower than for all other emotions. The second approach that we have tried is to use an average of majority function rather than a simply mode. The values at leaf nodes represent that probability that given input matches this emotion. We then get a probability for each emotion and return a label that corresponds to the one with the highest probability. We expected this approach to be better than just picking a first positive emotion. Our prediction turned out to be true for a clean data set (0.631 and 0.558 classification rate), but for noisy set, mode majority function gives just a bit better results (0.014 difference in classification rate), while when comparing by F1 measures on average the mean function is better for noisy data.

3.3 Pruning Question

The `pruning_example` function prunes its tree branches to reduce the number of nodes that are required to be evaluated. Therefore, the performance of tree is increased by avoiding unneeded computation.

These curves represent the cost(i.e. difference between actual and prediction) when running the test. Blue and red line represents cost 1 and 2 respectively. According to their shape, in common, their costs decrease as the number of terminal nodes increases. It implies that as the leaf length is increased, the precision also increases and the symptom seems natural.

In terms of difference between figure 1 and 2, as shown, the notable difference is a fluctuation in figure 2 when noisy data is used for input. This occurs because the decision tree in the latter case has trained its data with wrong input so the difference between actual and prediction is higher in some unseen data.

The optimal tree size is presented when there is an intersection between blue (cost1) and red (cost2) line in each figure. Therefore, when the number of terminal nodes is about 20.

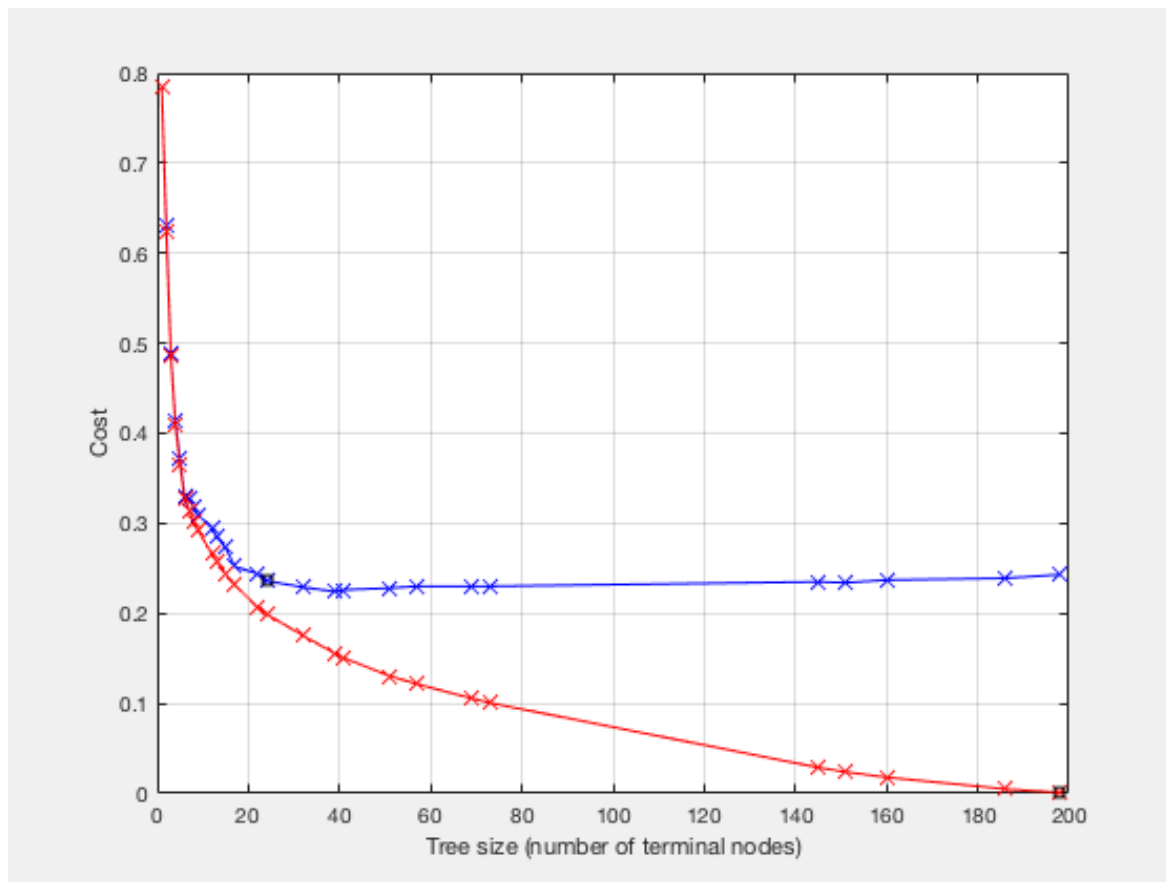


Figure 1: The result of pruning example with clean dataset.

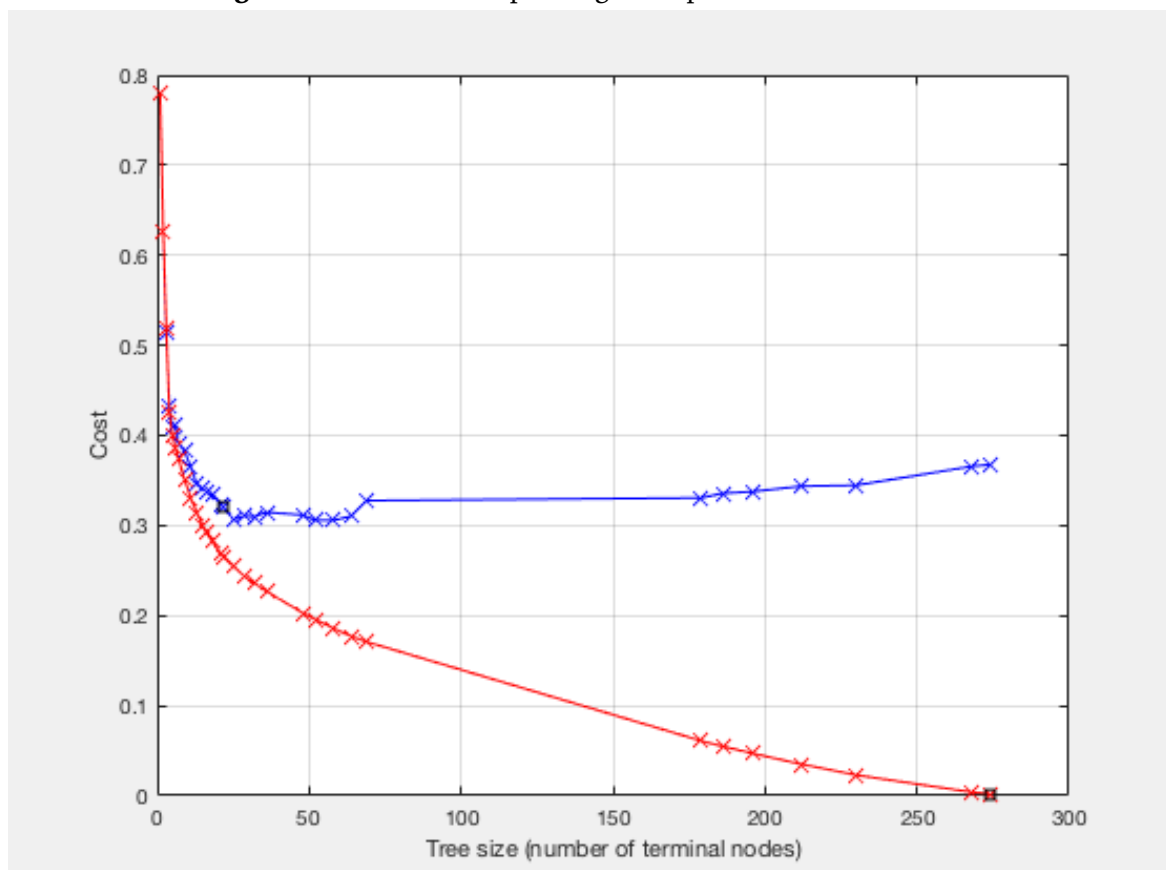


Figure 2: The result of pruning example with noisy dataset.

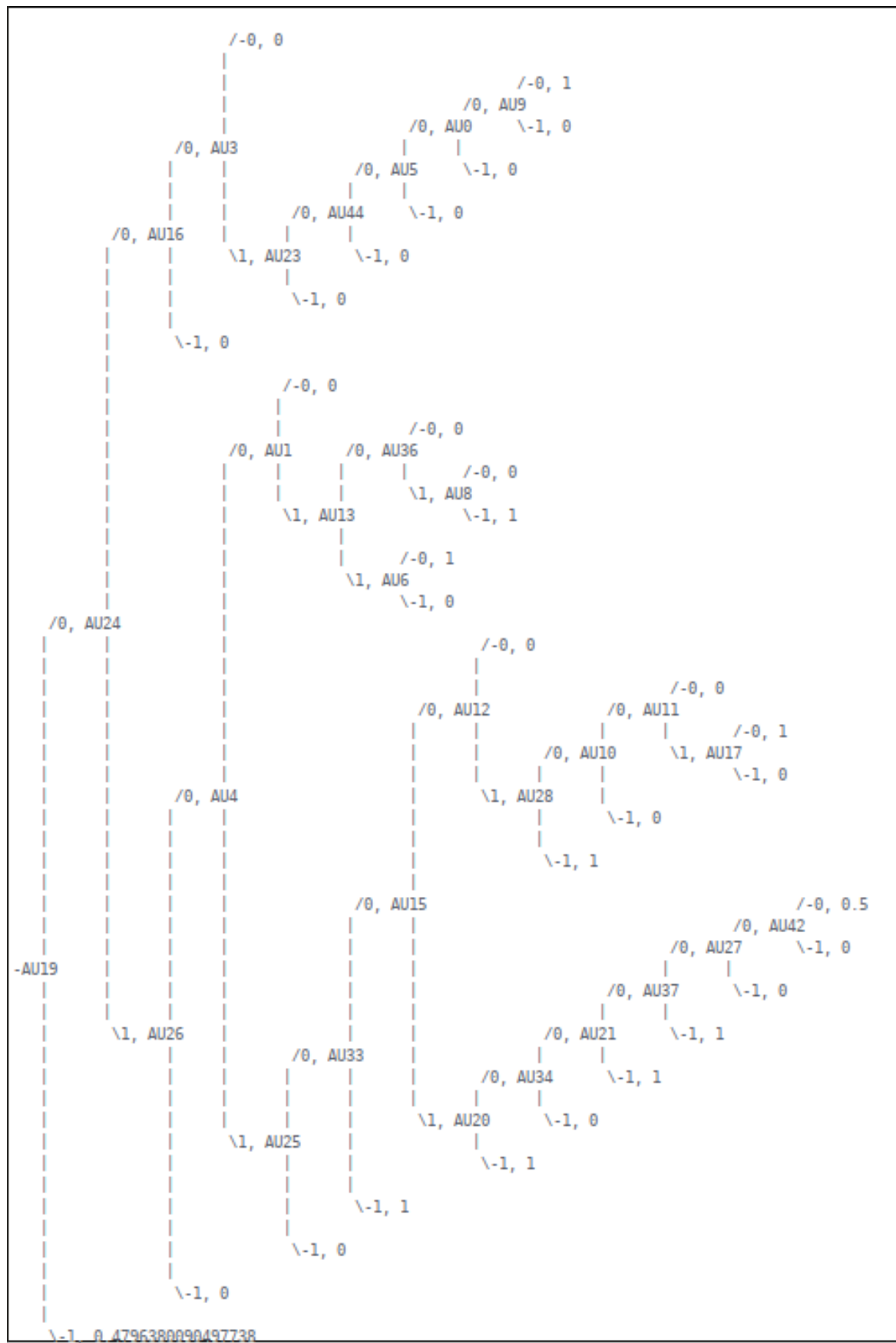


Figure 5: Tree for emotion three

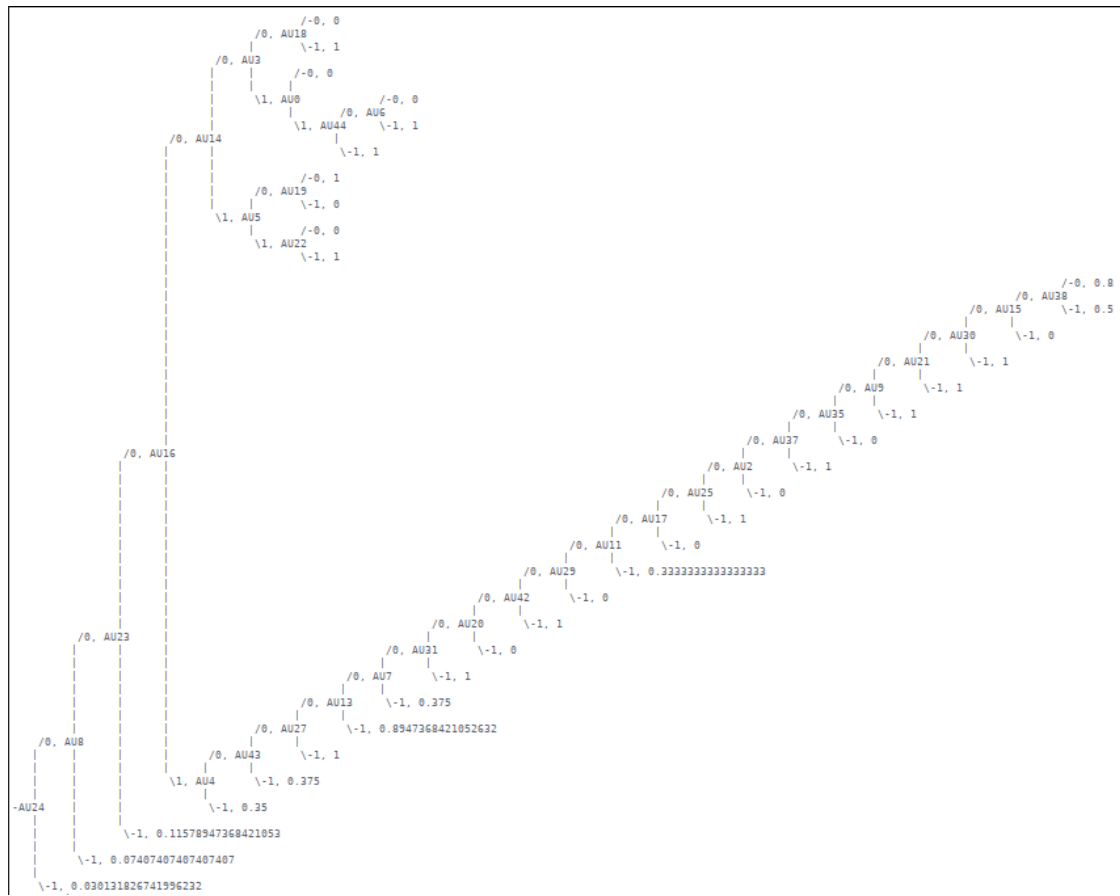


Figure 7: Tree for emotion five

Appendix

Running emotion-recognition on custom data

The simplest way to run the project on a custom data source is to use the Dockerfile within the repository. A directory containing the data file can be mounted into the container and its name passed to the Docker run command. An example from within the project directory is:

```
$ docker build -t emotion-recognition .
$ docker run --rm -v 'pwd'/Data:/usr/src/app/Data emotion-
  recognition Data/cleandata_students.mat
```

Alternatively the project can be ran from a standard Python 3 interpreter once the requirements have been installed using pip.

```
$ pip install -r requirements.txt
$ python3 EmotionRecognition.py Data/cleandata_students.mat
```

Advice for testers

The above section on running the project will execute all code related to testing the trees including calling the `testTrees` function and the cross-validation routine, producing several statistics about the implementation. The last line of output shows the number of examples from input which are correctly classified by the Decision Tree when run on the data it was trained on.

`EmotionRecognition.py` is the file we used to construct the data for this report and it is recommended that the file `AssessorTesting.py` should be used for testing our trees as this will take a data set as an input, load our saved trees that were trained on the clean dataset, and run `testTrees` on our trees and the loaded data to produce predictions, whose accuracy is reported. This file should be easy to modify as the assessor wishes.

Running AssessorTesting on custom data

The simplest way to run `AssessorTesting.py` on a custom data source is to use the commands:

```
$ pip install -r requirements.txt
$ python3 AssessorTesting.py Data/nosydata_students.mat
```