Explainable AI
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1. Display/visualised the resultant model created by the decision tree.
[20 marks]

To view the tree, you can either check the file Tree_text_form.txt to view the tree in a text format or check Source.gv.png to view the tree in an image format.

2. Explain how, and why, the algorithm made a specific decision. [10 marks]

If we look at the top node on the tree, the gini index that it gave is 0.444 = 1 – (419/1262)^2 – (843/1262)^2. Since the gini index has a max value of 0.5, 0.444 is quite high, which makes sense since we are at the top of the tree which means it is normal to have high impurity this early in the tree path. We can see that it made the decision to split Country at the threshold of 0.605. The reason it chose the specific threshold of 0.605 was by calculating the information gain at each split point and then choosing the best split, which in this case was the midpoint between 0.96082 and 0.24923. This results with when we pass in the element at the first row of our test set, since the element has a Country value of 0.96082, it will go to the right branch (the false branch) of our tree, and continues its path from there.

3. Explain why the algorithm didn’t do something else. [10 marks]

If we look at the left most node, we can see that the algorithm chose a threshold at Escore<= -1.37 to create a clean split. This explains why it didn't choose the threshold, for instance, at 0.32197 which would then result with the left leaf receiving 8 elements of class ‘1’ and 1 element of class ‘0’, which would not be a clean split.

4. Discuss when the algorithm succeeded and when it failed. [10 marks]

After we have trained our model on our training set, lets look at the first row of the test set:

ID	Age	Gender	Education	Country	Nscore	Escore	Oscore	Ascore	Cscore	Impulsive	SS
1086	-0.95197	0.48246	0.45468	0.96082	-0.05188	-0.15487	0.44585	0.28783	0.41594	-1.37983	-0.21575

The label for this sample is ‘1’ which means Consumer. When passing this row in the model for prediction, it successfully returns ‘1’. When looking at our decision tree, This makes sense. Using the gini Index for bestSplit, it went down the resulting tree at Country > 0.605, then SS <= -0.068, then Age<=0.796, then Oscore >0.37, then Escore>-1.698, then Education>-0.919, then ID>333.5, then ID<= 1500.5 which then returns 1.

Lets now look at the 8th row of the test set where we can spot a mistake.

ID	Age	Gender	Education	Country	Nscore	Escore	Oscore	Ascore	Cscore	Impulsive	SS
767	-0.95197	-0.48246	-0.61113	-0.57009	1.02119	-0.80615	0.29338	2.23427	-0.65253	0.52975	0.07987

Here, the algorithm returned 1 when the label was actually 0. The reason it didn’t pick 1 was since it went down the tree starting with Country <= 0.605, then ID > 421.0, then Oscore > -1618, then Age <= 0.21, then SS > -0.371, then Cscore > -2.498, then Escore <= 1.37, then ID <= 1813.5 which then returns 1.

5. Explain how you would decide if the resultant model can be trusted.
[10 marks]

If we are not interested in true negatives, which would mean in our case we are mostly interested on how well it can correctly classify a drug user and not preoccupied with wether or not it can accurately predict a non-user, we could look at recall, precision and f1. If we want to take both true positives and negatives into account, implying that our distribution for training is representative in the real world, we could use accuracy.

6. Explain how the algorithm could potentially improve its predictions.
[10 marks]

Decision Trees a prone to overfitting, hence one potential idea to deal with that could be pruning. Decision Trees can also be prone to high variance, meaning they can change greatly their results with small changes to the training set, which can be reduced with an ensemble that uses bagging like Random Forest.