Machine Learning

Assignment 3, Group Assignment

Group 1

Q1: Import Pre-Processed Data and Splitting

The loans data has been preprocessed using Python. We first read the `.csv` file which contains the pre-processed data with 8 columns in total, including the outcome of the loans, which can be either *"Charged off"* or *"Fully Paid"*.

Next, we split the data into:

- Training Set (20,000 records)
- Validation Set (8,000 records)
- Test Set (Remaining 10,697 records)

Q2: Classification Tree Using C50

The total number of loans in the data that fall each category is

Table 1: Number of instances in each class

Charged Off	Fully Paid
5435	33262

The proportion of repaid loans in the dataset is 0.8595. We will now try to achieve an accuracy greater than this using classification trees. We first train a decision tree based on the training set.

The confusion matrix of the training set for the classifier we trained is

Table 2: Confusion Matrix for Training Set

actual / predicted	Charged Off	Fully Paid
Charged Off	0	2797
Fully Paid	0	17203

As observed, the classification tree classifies all training samples as *"Fully Paid"* and its accuracy is simply the proportion of *"Fully Paid"* loans in the training set.

We will now use the classifier to predict the outcome of each lean in the validation set.

The resulting confusion matrix of the validation set for the classifier is

Table 3: Confusion Matrix for Validation Set

actual / predicted	Charged Off	Fully Paid
Charged Off	0	1132
Fully Paid	0	6868

Again, all the validation records are predicted to be *"Fully Paid"*. Hence, its accuracy is the proportion of *"Fully Paid"* loans in the validation set, which in this case is 0.8585, close to the target accuracy of the total proportion of repaid loans.

The number of *"Fully Paid"* loans greatly outnumbers the number of *"Charged Off"* loans. Consequently, during the training phase, the algorithm discovers that doing a majority prediction using a single leaf node produces the best training accuracy. Splitting the tree using any of the seven features of the data will result in two child nodes with instances belonging primarily in the *"Fully Paid"* class. Consequently, the algorithm does not perform any split. Thus, the trained classification tree simply predicts all loans as *"Fully Paid"*.

The algorithm might end up with leaf nodes that might contain a majority of *"Charged Off"* loans after a significantly large number of splits. However, they myopic approach of classification trees prevents us from reaching that possible point.

Q3: C50 Classification Tree with Costs Adjustments

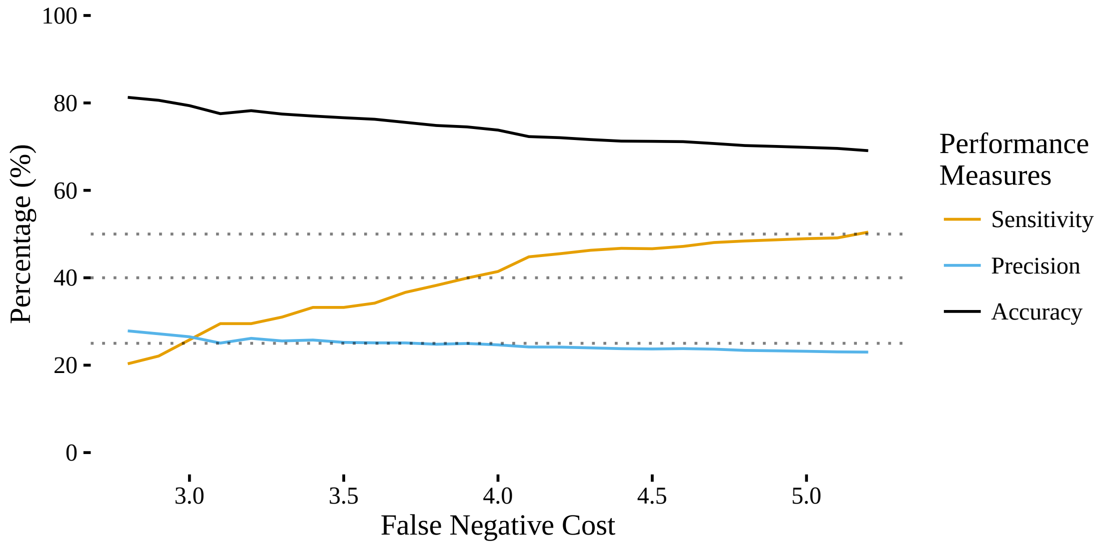
We will need to train the classification tree with a cost matrix to correct the default behaviour of `C50` in maximising the accuracy.

Granting a loan to a customer who is likely to default is much more costlier (i.e. False Negative) than denying loan to a customer who is likely able to pay back (i.e. False Positive). In the cost matrices, we set the cost of False Positive to 1 to test out different values of the cost of False Negative (ranging from 2.8 to 5.2, in increment of 0.1).

Table 4: Validation Performance Using Different Cost Matrices

False Negative Cost	Sensitivity	Precision	Accuracy
2.8	0.2032	0.2785	0.8128
2.9	0.2208	0.2717	0.8060
3.0	0.2580	0.2650	0.7938
3.1	0.2951	0.2506	0.7754
3.2	0.2951	0.2613	0.7822
3.3	0.3101	0.2555	0.7745
3.4	0.3322	0.2575	0.7700
3.5	0.3322	0.2522	0.7661
3.6	0.3419	0.2511	0.7626
3.7	0.3666	0.2509	0.7555
3.8	0.3825	0.2479	0.7484
3.9	0.3993	0.2496	0.7451
4.0	0.4143	0.2465	0.7379
4.1	0.4479	0.2417	0.7230
4.2	0.4549	0.2413	0.7205
4.3	0.4629	0.2396	0.7161
4.4	0.4673	0.2378	0.7126
4.5	0.4664	0.2371	0.7121
4.6	0.4717	0.2379	0.7114
4.7	0.4806	0.2366	0.7071
4.8	0.4841	0.2338	0.7025
4.9	0.4867	0.2329	0.7005
5.0	0.4894	0.2318	0.6982
5.1	0.4912	0.2304	0.6959
5.2	0.5044	0.2299	0.6908

From the previous table we observe that as the cost of False Negative increases, the overall accuracy and the precision of the classifier decreases while its sensitivity increases.



The sensitivity levels we are interested in are 25%, 40% and 50%.

25% Sensitivity

The costs matrix which achieves sensitivity as close as possible to 25% is

Table 5: Cost Matrix for 25% Sensitivity

actual / predicted	Charged Off	Fully Paid
Charged Off	0	3
Fully Paid	1	0

From the previous table, we can see that the specific cost matrix achieves sensitivity of 0.258 and precision of 0.265.

40% Sensitivity

The costs matrix which achieves sensitivity as close as possible to 40% is

Table 6: Cost Matrix for 40% Sensitivity

actual / predicted	Charged Off	Fully Paid
Charged Off	0	3.9
Fully Paid	1	0

From the previous table, we can see that the specific cost matrix achieves sensitivity of 0.3993 and precision of 0.2496.

50% Sensitivity

The costs matrix which achieves sensitivity as close as possible to 50% is

Table 7: Cost Matrix for 50% Sensitivity

actual / predicted	Charged Off	Fully Paid
Charged Off	0	5.2
Fully Paid	1	0

From the previous table, we can see that the specific cost matrix achieves sensitivity of 0.5044 and precision of 0.2299.

Q4: Cost Parameter Matrix for Identifying Dubious Loan Applications

To lower the credit risk, we will need to identify as many dubious loan applicants as possible. However, we can see in the earlier section, the precision is very low. This means that out of all those applications that are highlighted as risky, only around 23% are indeed *"Charged Off"* in the validation set. The drawback in reaching a sensitivity level of close to 50% is that the loan officers will need to manually cross-check large number of applications before 50% of the risky loans are identified.

Nevertheless, the cost of granting a loan to risky applicants still far outweighs this labour cost. Hence we pick the cost matrix which achieves sensitivity close to 50%.

Q5: Test Set Performance

Using the cost matrix for 50% sensitivity, we retrain the classification tree using both training and validation data. The trained model is then tested against the test set. Below tabulates the test set performance and confusion matrix.

The final performance of the test set, using the cost matrix that previously resulted in 50% sensitivity, is

Table 8: Test Set Performance

Sensitivity	Precision	Accuracy
0.5166	0.2111	0.6602

The resulting confusion matrix for the test set is

Table 9: Confusion Matrix for Test Set

actual / predicted	Charged Off	Fully Paid	*Total*
Charged Off	778	728	*1506*
Fully Paid	2907	6284	*9191*
Total	*3685*	*7012*	*10697*