COL774: Machine Learning. Assignment 3

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1 Decision Trees (and Random Forests)

1.1 Multi-Way Decision Tree

First the data was preprocessed and each numerical attribute was converted into a Boolean attribute.

Next tree was grown using the training data, and train, validation and test set accuracies were plotted against the number of nodes in the tree. (Fig. 1)

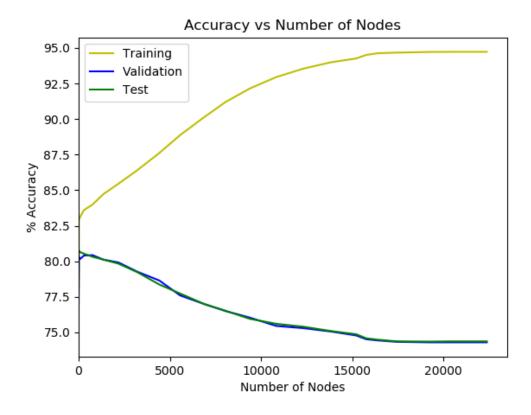


Figure 1: Decision Tree

The tree is grown using DFS. For the plots, trees were grown multiple times with different possible max. depths, in an iterative deepening (ID) pattern.

Final Accuracies for the full tree:

• Training Accuracy: 94.73 %

• Validation Accuracy: 74.30 %

• Test Accuracy: 74.37 %

1.2 Pruning

In this part the tree was grown fully and then pruned bottom-up using the validation set. The accuracies with the number of nodes is shown in Fig. 2

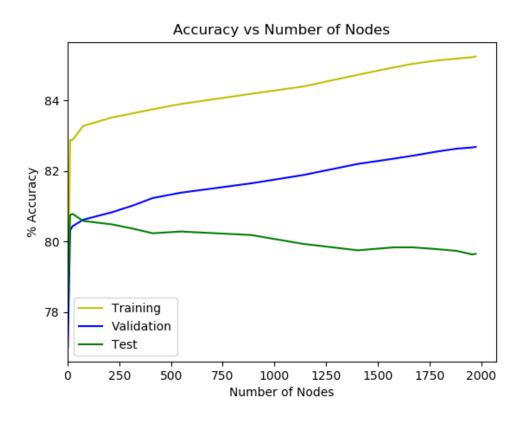


Figure 2: Decision Tree with Pruning

Final Accuracies for the full tree:

 \bullet Training Accuracy: 85.25 %

• Validation Accuracy: 82.68 %

• Test Accuracy: 79.65 %

Observations

- 1. The model performs better than the model in part (a)
- 2. In part (a) the model overfits only on the train set, but in this the model starts to overfit on the validation set as well.

1.3 Continous Attributes

Numerical attributes weren't preprocessed using the median and the median was calculated at each node online for the respective features. Further the respective feature was not dropped and was reused in some further depth.

The trees were grown for different depths. The plots of accuracies vs. number of nodes is shown in Fig. 3

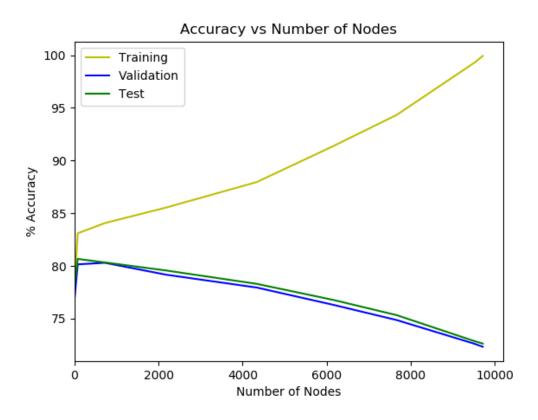


Figure 3: Decision Tree with Continuous Attributes

For depth 20:

• Training Accuracy: 99.93 %

• Validation Accuracy: 72.33 %

• Test Accuracy: 72.63 %

Observations

- 1. The model highly overfitted as depth increased.
- 2. For the same number of nodes, the accuracies of this model is better than part (a) initially. However with more depth this model severely overfit and thus the accuracy drops.
- 3. With more depth the model approaches 100 % training accuracy due to leafs becoming purer.

1.4 Decision Trees with scikit-learn

Scikit-learn was used to learn the decision tree over the Training Data.

Various values of the following parameters were experimented with and these are the best values which we get:

• max_depth: 7

• min_samples_split: 2

• min_samples_leaf: 55

Accuracies on the above best parameters:

 \bullet Training Accuracy: 83.34 %

 \bullet Validation Accuracy: 80.767 %

• Test Accuracy: 81.033 %

Observations

- 1. The accuracies are much higher than in part (c), because the model in part (c) had essentially overfitted
- 2. The testing accuracy is higher than in part (b), but the validation accuracy is less than part (b), since while doing pruning the model had partly overfit the validation data.

1.5 One Hot Encoding

Numerical features were one-hot encoded and then passed to Scikit-learn model for training. Various values of the following parameters were experimented with and these are the best values which we get:

 \bullet max_depth: 6

 \bullet min_samples_split: 2

• min_samples_leaf: 60

Accuracies on the above best parameters:

• Training Accuracy: 80.461 %

• Validation Accuracy: 79.583 %

• Test Accuracy: 78.333 %

Observations

1. The accuracies are lower than those of non-one-hot encoded data.

2. One possible reason is that making the features as one-hot data introduced sparsity in the data, and with so many features we need considerably more amount of data.

1.6 Random Forests

Scikit-learn random forests were used for learning the model over the training data.

Various values of the following parameters were experimented with and these are the best values which we get:

• n_estimators: 7

• max_features: 0.7

• bootstrap: False

• max_depth: 4

Accuracies on the above best parameters:

• Training Accuracy: 83.183 %

• Validation Accuracy: 80.833 %

• Test Accuracy: 80.867 %

Observations

1. The test accuracy is the best till now.

2. The validation accuracy is the best excluding part(b) where it was more than 82 %.

2 Neural Networks

2.1 Preprocessing

Each categorial feature was one-hot-encoded and saved in the processed file.

2.2 Neural Network Architecture

A fully connected neural network was implemented using SGD, MSE loss and sigmoid activations.

Results of training are shown in Fig. 4 and Fig. 5

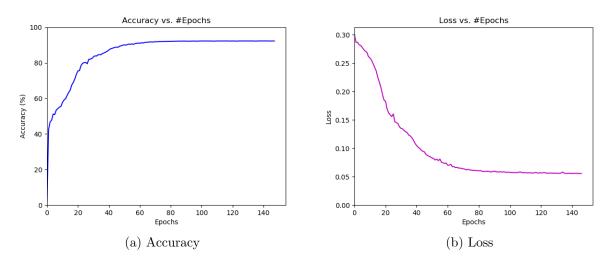


Figure 4: Training Accuracy and Loss

The following parameters were used in the training:

• Input Layer Size: 85

• Output Layer Size: 10

• Number of Hidden Layers: 1

• Hidden Layer Sizes: 20

• Learning Rate: 0.1

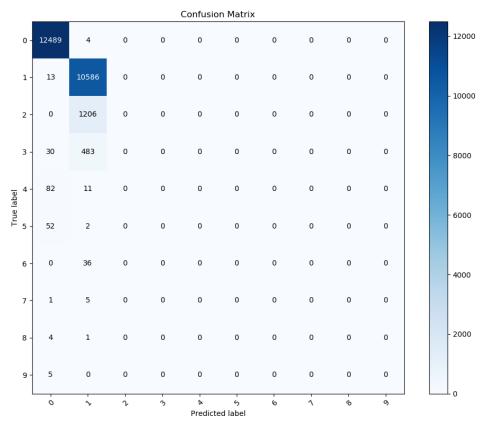
• Batch Size: 1

Result of training and testing

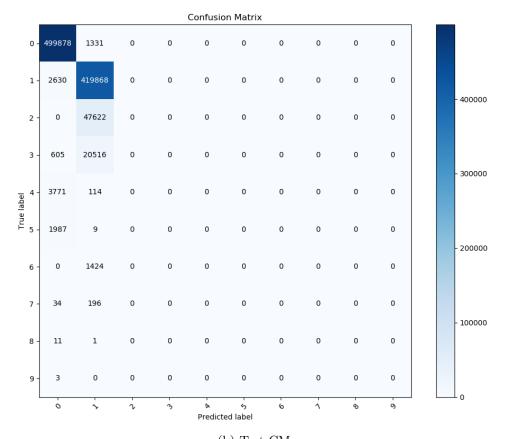
• Training Accuracy: 92.26 %

 \bullet Testing Accuracy: 91.97 %

• Time Taken: 515 secs



(a) Train CM



(b) Test CM

Figure 5: Train and Test Confusion Matrices

2.3 Single Hidden Layers

The network was trained with a single hidden layer with the size from the set {5, 10, 15, 20, 25}.

Here are the metrics:

\mathbf{Size}	Train Acc.	Test Acc.	Time Taken
5	69.01	67.31	555.44
10	78.77	77.38	472.89
15	82.58	80.35	180.06
20	90.73	89.93	189.71
25	92.30	92.19	629.61

Plot of the metrics is shown in Fig. 6.

Confusion Matrices of the above are shown in Fig. 7 and are available in the Q2/plots/PartC folder.

Observations

- 1. Accuracy increase with larger size of the hidden layer
- 2. With size = 5, most examples are classified in class 0 only, but with larger class size the model learns to predict class 1 too.
- 3. The data for other classes is too low and the dataset too skewed for it to be able to learn the representation for the other classes.

2.4 Two Hidden Layers

The network was trained with two hidden layers with the size from the set {5, 10, 15, 20, 25}. Both layers had the same size.

Here are the metrics:

\mathbf{Size}	Train Acc.	Test Acc.	Time Taken
5	58.37	56.12	115.85
10	85.09	84.07	1013.93
15	81.87	79.61	354.33
20	91.40	90.79	228.04
25	92.29	92.06	381.41

Plot of the metrics is shown in Fig. 8.

Confusion Matrices of the above are shown in Fig. 9 and are available in the Q2/plots/PartD folder.

Observations

1. The accuracy increases marginally over single hidden layer.

2.5 Adaptive Learning Rate

The network was trained with a single hidden layer with the size from the set $\{5, 10, 15, 20, 25\}$. The training is expensive and so for comparision purposes network was trained using single layer only.

Here are the metrics:

\mathbf{Size}	Train Acc.	Test Acc.	Time Taken
5	68.36	66.88	262.30
10	76.80	75.59	299.55
15	88.06	86.82	406.45
20	92.25	92.08	253.65
25	92.28	92.13	300.02

Plot of the metrics is shown in Fig. 10.

Confusion Matrices of the above are shown in Fig. 11 and are available in the Q2/plots/PartE folder.

Observations

- 1. The accuracies increases marginally.
- 2. This happens as the model tries to get closer and closer to the local minima it is on, by decreasing the learning rate.

2.6 RELU Activation

The network was trained with a single hidden layer with the size from the set $\{5, 10, 15, 20, 25\}$. The training is expensive and so for comparision purposes network was trained using single layer only. RELU was used as the activation function in all the layers except the last layer where sigmoid was used.

Here are the metrics:

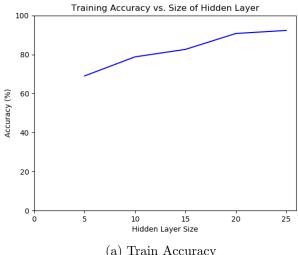
\mathbf{Size}	Train Acc.	Test Acc.	Time Taken
5	57.72	56.61	105.58
10	60.37	56.52	200.19
15	82.99	80.54	453.32
20	87.49	85.50	285.86
25	90.73	89.63	466.99

Plot of the metrics is shown in Fig. 12.

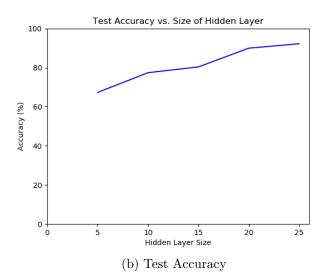
Confusion Matrices of the above are shown in Fig. 13 and are available in the Q2/plots/PartF folder.

Observations

- 1. The model converges in less number of epochs and trains much faster as compared to the sigmoid activation.
- 2. It gives similar results on train and test accuracies. (Marginal lower accuracy)



(a) Train Accuracy



Training time vs. Size of Hidden Layer 600 500 Time (secs) 300 200 10 15 Hidden Layer Size 25 20 (c) Train Time

Figure 6: Metrics – Part C

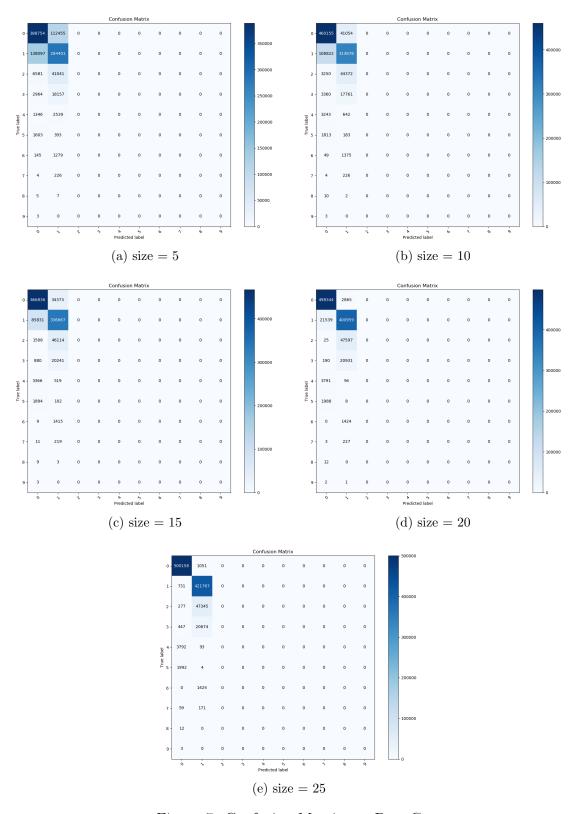
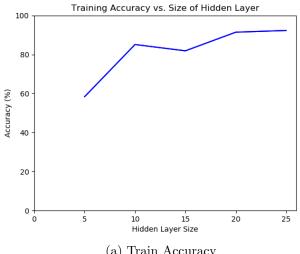
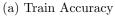
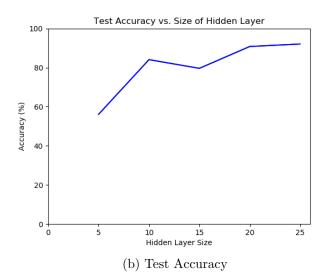


Figure 7: Confusion Matrices – Part C







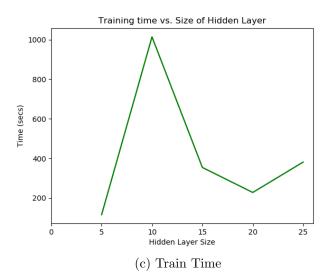


Figure 8: Metrics – Part D

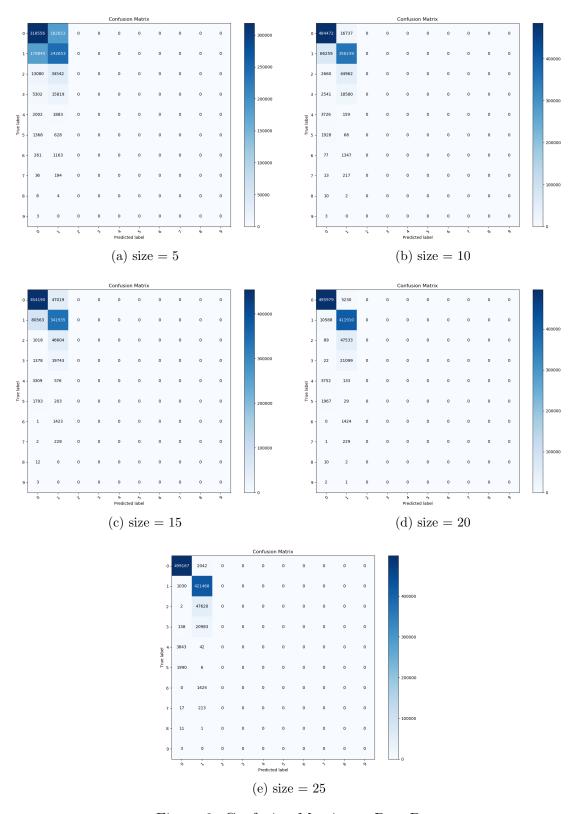
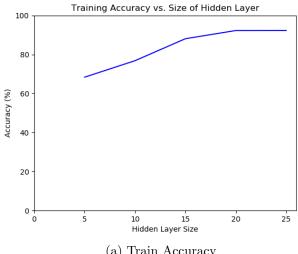
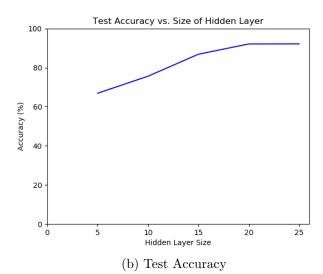


Figure 9: Confusion Matrices – Part D



(a) Train Accuracy



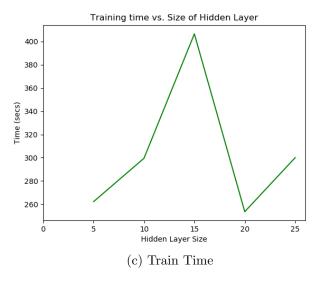


Figure 10: Metrics – Part E

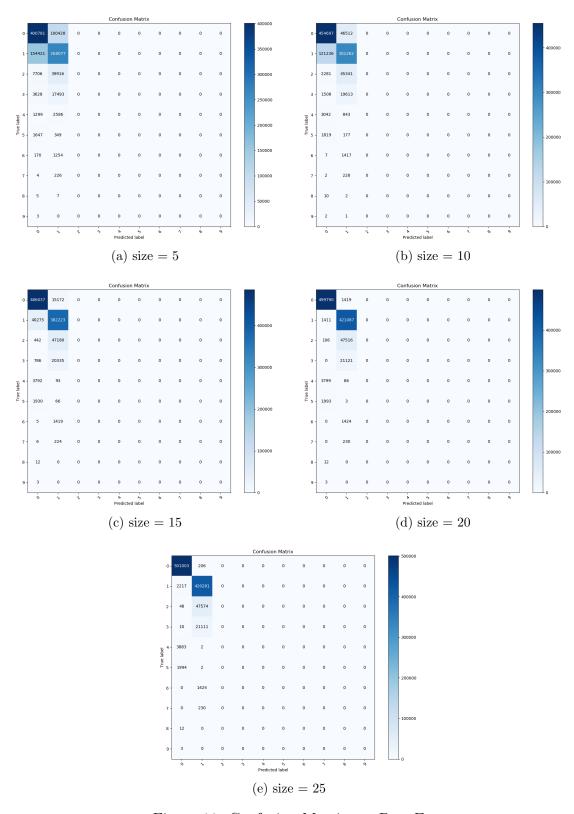
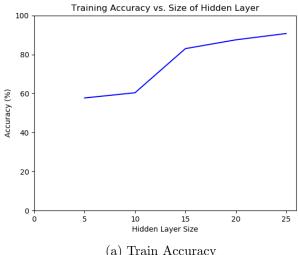
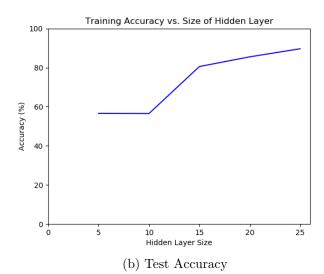


Figure 11: Confusion Matrices – Part E



(a) Train Accuracy



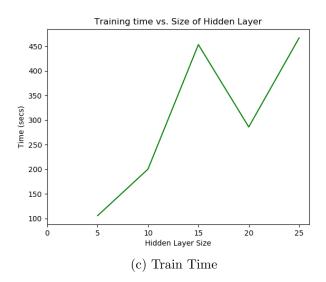


Figure 12: Metrics – Part R

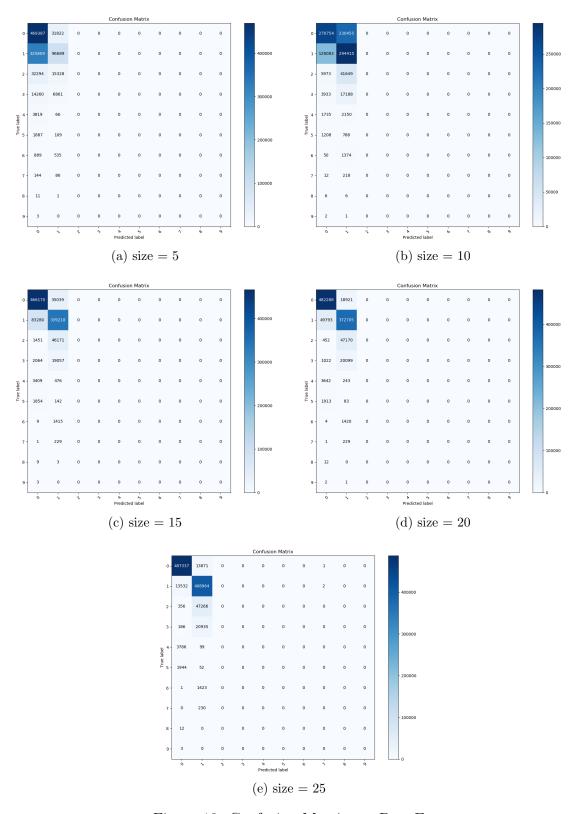


Figure 13: Confusion Matrices – Part F