# $\frac{\text{CSCI4150U: Data Mining}}{\text{Lab } 03}$

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October 9, 2024

# Part I:

#### 1.

Average and individual trial results across 5 randomized trials using accuracy, precision and f1 scores as performance metrics based on a (90%-train and 10%-test) **holdout** validation method, decision tree classifiers and Gini impurity.

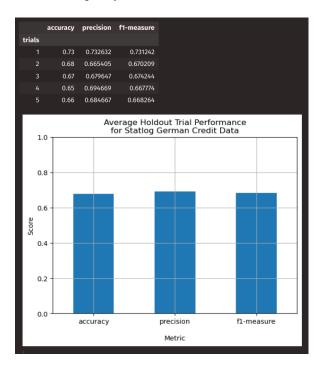


Figure 1: Decision tree performance based on holdout method and Gini impurity using Statlog German Credit Dataset

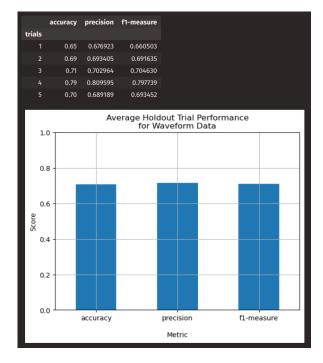


Figure 2: Decision tree performance basd on holdout method and Gini impurity using Waveform Dataset

# 2.

Average and individual trial results using accuracy, precision and f1 scores based on **10-fold cross-validation**, decision tree classifiers and Gini impurity.

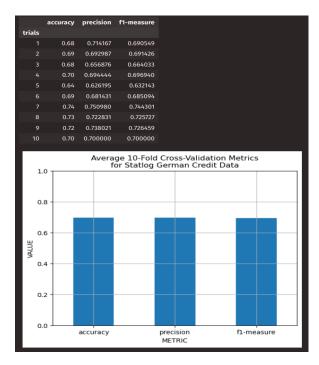


Figure 3: Decision tree performance based on 10-fold cross-validation and Gini impurity using Statlog German Credit Dataset

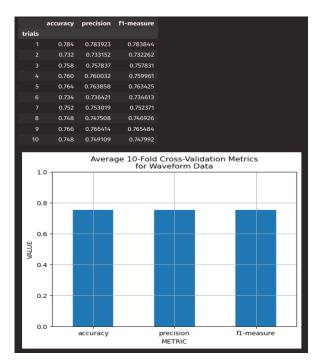


Figure 4: Decision tree performance based on 10-fold cross-validation and Gini impurity using Waveform Dataset

# Part II:

#### 1.

Repetition of Part I, this time using 'Entropy' instead of 'Gini; as the decision-tree impurity measure.

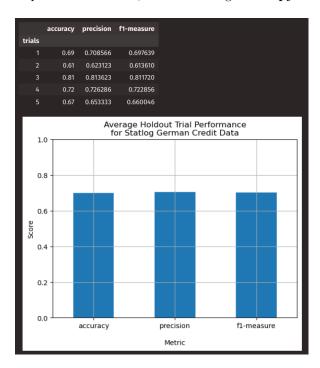


Figure 5: Decision tree performance based on holdout method and Entropy impurity using Statlog German Credit Dataset

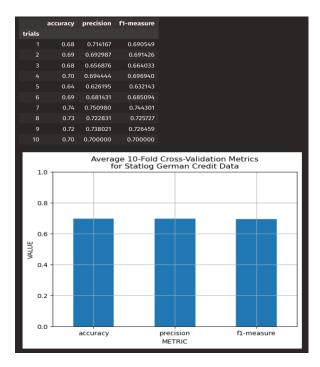


Figure 7: Decision tree performance based on 10-fold cross-validation and Entropy impurity using Statlog German Credit Dataset

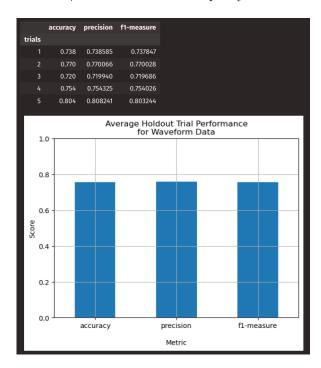


Figure 6: Decision tree performance based on holdout method and Entropy impurity using Waveform Dataset

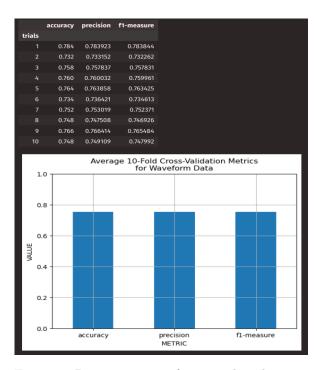


Figure 8: Decision tree performance based on 10-fold cross-validation and Entropy impurity using Waveform Dataset

Comparing the average 10-fold cross-validation based accuracy of decision-tree classifiers using 'Gini' vs 'Entropy' as impurity measures for both Statlog German Credit and Waveform Datasets.



Figure 9: Accuracy comparison of decision tree classifiers using Entropy vs Gini impurity measures

# Part III:

#### 1.

Plotting decision tree accuracies based on the (90%-train and 10%-test) **holdout** validation method and varying max tree depths.

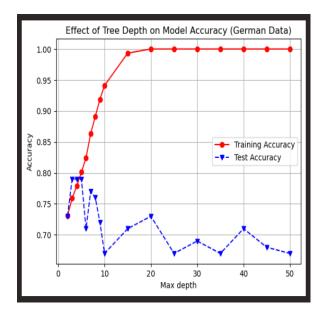




Figure 10: Decision tree accuracies for Statlog German Credit Dataset

Figure 11: Decision tree accuracies for Waveform Dataset

#### **2**.

We can see clearly that with increasing tree depth there is an overfitting phenomenon observable across both datasets. The model achieves an increasingly better fit to its training data until it can perfectly classify all records. However, we see consistently that after a short period of increasing test accuracy, the model experiences a net decrease in test accuracy with increasing tree depth. This indicates that after a certain tree depth, the model starts to become highly specialized and overfits to its training data. This results in a model that poorly generalizes to unseen test data.