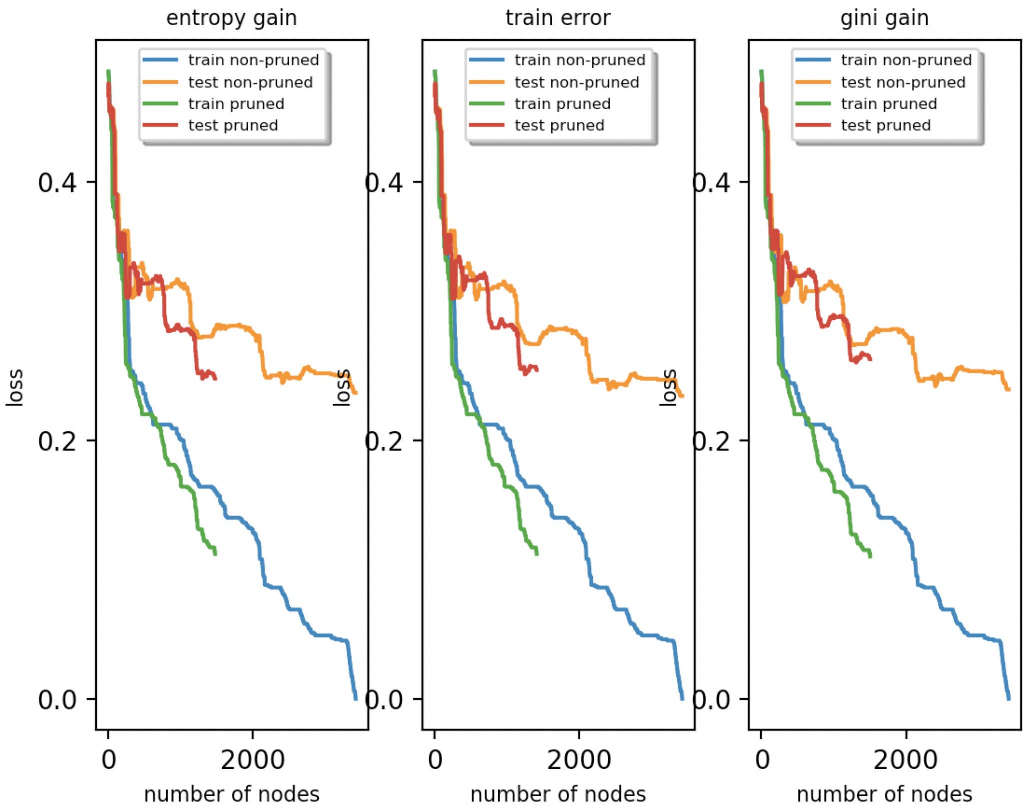
Problem 1

Looking at the train and test error differences between pruned vs. non-pruned trees, it is clear that pruned trees, on average, across all gain functions, had overall lower test errors, compared to the non-pruned trees (this is particularly clear in the Spam Dataset). Although the difference may be slight (as seen in the two tables below), the test loss is still lower for the pruned trees. Of the three measures of gain, the most effective at reducing training error was the gini gain function, as seen in both datasets. Overall, although the difference made by pruning was not major, pruning still was more effective (for the test loss, that is), compared to not pruning.

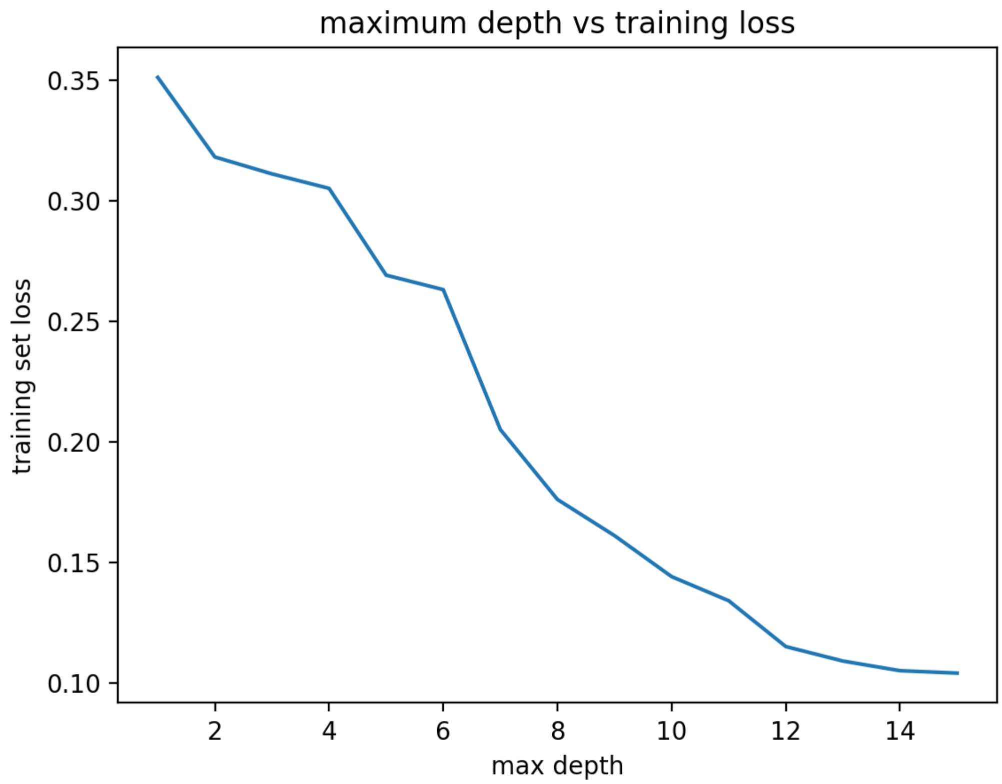
Chess Dataset for *won* Class			
	Training Error	**Entropy**	**Gini**
Training Loss	0.0	0.0	0.0
Training Loss Pruned	0.112	0.112	0.11
Test Loss	0.234	0.247	0.239
Test Loss Pruned	0.254	0.232	0.263

Spam Dataset for *1* Class			
	Training Error	**Entropy**	**Gini**
Training Loss	0.014	0.014	0.014
Training Loss Pruned	0.104	0.104	0.102
Test Loss	0.203	0.2	0.208
Test Loss Pruned	0.19	0.188	0.19



Problem 2

As seen in the figure below, as the depth increases, the training set loss decreases. This means that, with an increase in maximum depth, we get a better training set accuracy value. This is because, the deeper the tree is allowed to be, the more complex the model becomes–which allows for there to be an increased performance on the training set. Thus, as the maximum depth variable is increased, the training loss decreases. The image below plots this relationship.



Problem 3

Upon reading the excerpt, I found myself agreeing with the author. Once a metric becomes a target, it no longer is a 'good' measure. Given that machine learning models can impact (both negatively and positively) various social groups, it is of the utmost importance that they are learned in the most fair, unbiased manner possible. Honestly, I was surprised that this had never occurred to me before. What Thomas and Uminsky wrote is completely true– a model learning to predict outcomes we find appealing is not exactly fair, so to speak. Otherwise, it is possible that a model can learn to predict outcomes which favor certain social groups over others, rather than producing unbiased, accurate results. Thus, it is important that Goodhart's Law is followed when statisticians learn their models on data sets.