Exploring the Impact of Decision Tree Depth

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ABSTRACT

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CCS CONCEPTS

• **Computing methodologies → Machine learning**; *Supervised learning by classification*; *Classification and regression trees*; Cross-validation.

KEYWORDS

decision trees, model selection

1 BACKGROUND AND MOTIVATION

Machine learning algorithms fall into one of two categories: classification and regression. In regression, input data is consumed and transformed by a function which can produce values along a numeric range; in classification, data is categorized into a finite number of possible values, and machine learning algorithms seek only to label data sets. These classification problems can use both numeric and categorical data attributes. For purely categorical data, decision trees are a way to build machine learning algorithms that are understandable by both humans and machines. Rather than a sort of "black box" in which numbers are passed in and answers are returned, there is a logical tree hierarchy that is familiar to anyone who has played the game Twenty Questions.

Decision trees require both a way to construct them, and a way to use them to categorize data. This categorization is a trivial tree traversal, and so many of the innovations regarding decision trees has to do with their construction. Most decision tree construction algorithms use a two-phase approach: first a *growing* phase, followed by a *pruning* phase. In the growing phase, the decision tree is built out, trying to fit the provided training data as closely as possible. To combat over-fitting, the pruning phase determines which branches of the tree are too "noisy" using χ^2 tests and removes them.

Additionally, decision tree models can be constrained by size to combat overfitting. Russell and Norvig [6] showcase an implementation of restricting a decision tree to be beneath a maximum size by generating the tree in breadth-first fashion, and stopping when the maximum number of nodes has been reached. As stated in Garofalakis, Hyun, Rastogi, and Shim [3], there is no point in creating a branch when it is guaranteed to be pruned later.

The amount of pruning which occurs is heavily dependent on the data set chosen. As such, the exact values which optimize our trained decision trees are relatively unimportant. However, our goal was to examine how impactful depth-based pruning was, and how much it assisted with reducing overfitting.

2 METHODS

Our first step was selecting datasets to use as the foundation for our programs. We used four UCI data sets [2]:

1. `MUSHROOMS`, a dataset to classify mushrooms as edible or inedible
2. `BALANCE`, a dataset to classify whether or not a scale with objects of varying weights and distances was balanced
3. `CARS`, a dataset of car evaluations
4. `TICTACTOE`, a dataset of Tic-Tac-Toe board states.

The foundation of our decision tree algorithm was the one provided by Russell and Norvig [6] which, in turn, is based on the ID3 algorithm [5].

A two-program approach was used: first, a decision tree generator was developed, called `dtl`. This program would take in a flag to determine which of our data sets was represented by the input. As the ordering of attributes and classes was inconsistent between datasets, this allowed us to significantly simplify the process of importing data.

A second program, `classify`, was used to classify data using a decision tree generated from `dtl`. To communicate a decision tree between these two programs, a JSON representation of the decision tree was used. This data format allowed us to produce human-readable representations of the decision trees, which we could use as a sanity check during development.

Function DecisionTreeLearning(*examples*, *attributes*, *parent_examples*, *depth*)

if *examples is empty* **then**
  return `Plurality-Value`(*parent_examples*)
else if *depth* = 0 **then**
  return `Plurality-Value`(*examples*)
else if *all examples have the same classification c* **then**
  return *a leaf node c*
else if *attributes is empty* **then**
  return `Plurality-Value`(*examples*)
end
$A \leftarrow argmax_{a \in attributes}$`Importance`(*a, examples*);
tree ⟵ a new decision tree with root test *A*;
foreach *value* v_k *of A* **do**
  exs ⟵ $\{e : e \in examples$ and $e.A = v_k\}$;
  subtree ⟵
   `DecisionTreeLearning`(*exs, attributes - A, examples, depth - 1*);
  add a branch to *tree* with label ($A = v_k$) and subtree
   subtree;
end
return *tree*;

Finally, we used Python to generate data for k-fold cross-validation for both our decision tree program as well as the decision tree algorithm provided by scikit-learn [4]. This provided a simple baseline for our experimentation.

We then ran each of our datasets through the DecisionTreeLearning algorithm with maximum depths ranging from 1 to 10 and performed k-fold cross-validation to determine error rates, with $k = 4$. As we noticed that subsequent experiments could obtain dramatically varying error rates, we repeated each of these experiments for 100 trials, to determine both average error rates and the variance of these error rates.

3 RESULTS

The results of our experimentation varied quite a bit between datasets. For `MUSHROOMS` in particular, our algorithm was able to achieve significantly greater accuracy than scikit-learn for smaller maximum depth constraints. However, for other datasets, such as `TICTACTOE`, our algorithm produced consistently more error-prone results at all depth values, as seen in Figure 1.

4 DISCUSSION

We were surprised at the discrepancies between our algorithm and the one provided by scikit-learn, as we expected both decision tree algorithms to produce similar results. While an effort was made to produce similar constraints on both algorithms (scikit-learn was used with the "entropy" heuristic, as well as the same tree depth constraint), there were a few differences that we were unable to resolve. First, scikit-learn uses "an optimised version of the CART [1] algorithm." Additionally, scikit-learn cannot be used with categorical data. To get around this restriction, we used one-hot encoding for the scikit-learn algorithm.

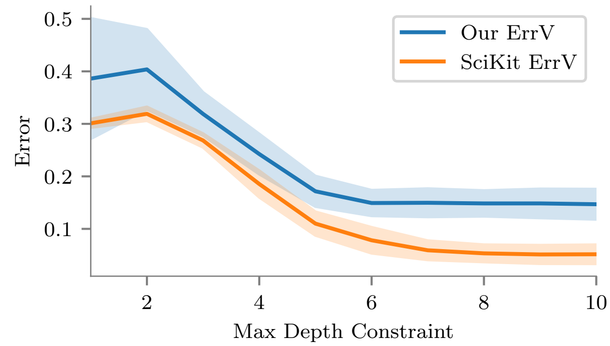

Figure 1: Error for our algorithm versus scikit-learn on the Tic-Tac-Toe dataset

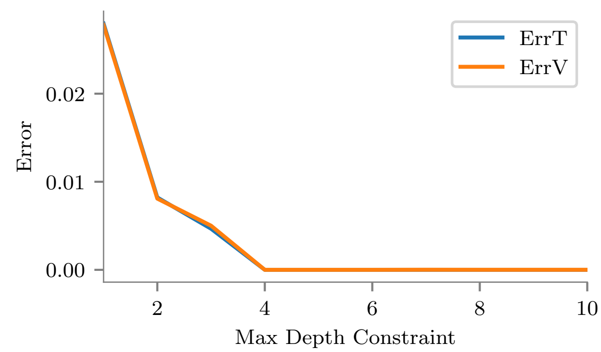

Figure 2: The error on training and validation data for the `MUSHROOMS` data set

ACKNOWLEDGMENTS

This work was supported in part by the University of Iowa.

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[6] Stuart J. Russell and Peter Norvig. 2010. *Artificial intelligence: a modern approach* (3rd ed.). Prentice Hall.

A ERRATA

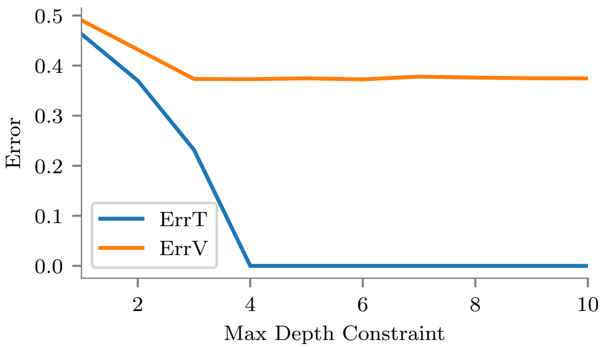

Figure 3: The error on training and validation data for the `BALANCE` data set

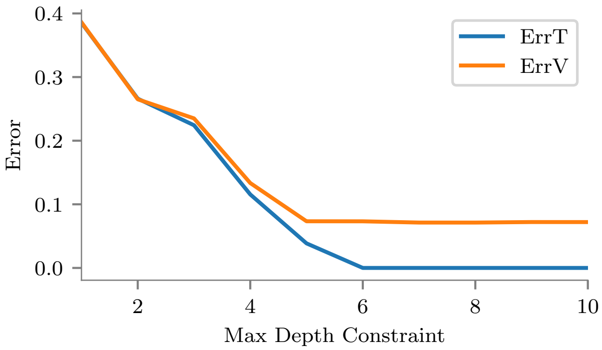

Figure 4: The error on training and validation data for the `CARS` data set

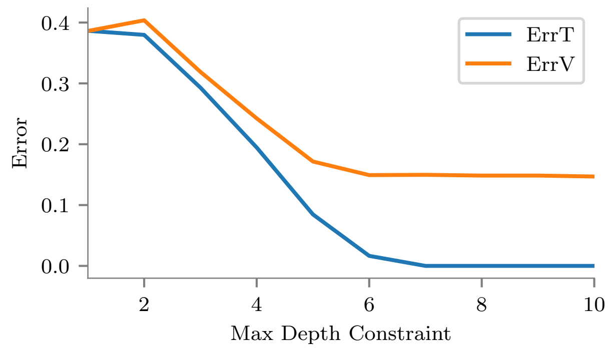

Figure 5: The error on training and validation data for the `TICTACTOE` data set