

# Systems Optimizations for Learning Certifiably Optimal Rule Lists

Nicholas Larus-Stone  
Computer Lab, University of  
Cambridge  
nl363@cl.cam.ac.uk

Elaine Angelino  
EECS, UC Berkeley  
elaine@eecs.berkeley.edu

Daniel Alabi, Margo Seltzer  
SEAS, Harvard University  
{alabid@g, margo@eecs}.harvard.edu

Aditya Saligrama  
Weston High School  
20saligramaa@my.weston.org

Cynthia Rudin  
Duke University  
cynthia@cs.duke.edu

## 1 INTRODUCTION

Decision trees are an extremely influential prediction technique in AI. They are interpretable, simple to store, and easy to use [3]. However, not enough work has been done on speeding up the creation of decision trees for large datasets. As big data becomes even more common in machine learning applications, decision trees risk falling in disuse due to computationally prohibitive construction costs. This work focuses on a set of optimizations that aids with the construction of a specific subset of decision trees: one-sided decision trees, also known as decision lists or rule lists [9]. Our goal is to find the rule list that is provably optimal with respect to our objective function, the regularized empirical risk, for a given set of pre-mined rules. Our algorithm, Certifiably Optimal Rule Lists (CORELS), uses a combination of tight bounds and systems optimizations to achieve reasonable runtimes for moderately sized real datasets [1, 2]. Our implementation is at <https://github.com/nlarusstone/corels>.

Finding the optimal rule list from a set of rules is a computationally hard combinatorial problem with no polynomial-time approximation. Most decision tree construction strategies solve this by quickly finding an approximate solution through greedy methods [3, 8]. Other fields solve similar computationally hard combinatorial problems through the use of branch-and-bound algorithms [4]. Traditionally, branch-and-bound has only been applied to small problems, because the search space is otherwise enormous, even when tight bounds allow for the pruning of the space. Our previous work presents a branch-and-bound search strategy, full description of CORELS, and proofs of the bounds we use [1, 5]. Unlike prior greedy approaches, branch-and-bound allows us to both find and certify the optimal rule list.

A rule list is composed of an ordered list of rules, an example of which can be seen in Fig 1. Rules are features or conjunctions of features that uniformly classify a subset of the observations. We generate rule lists by adding a rule to the end of a pre-existing rule list. For a given rule list, any longer rule list that starts with the same rules will make the same mistakes as the shorter one. To

```
if (age = 18 – 20) and (sex = male) then predict yes
else if (age = 21 – 22) and (priors = 2 – 3) then predict yes
else if (priors > 3) then predict yes
else predict no
```

**Figure 1: Example optimal rule list that predicts two-year recidivism for the ProPublica COMPAS dataset (122 rules), found by CORELS, across 10 cross-validation folds.**

encapsulate this relationship, we call the original rule list a parent and the longer rule list a child. We calculate both how many observations the list incorrectly classifies as well as a lower bound on the number of mistakes made by any child rule lists. Calculating each of these metrics from scratch each time would be inefficient; instead, metrics are calculated incrementally using metadata recorded for the parent rule list. The incremental computation takes advantage of a specialized, space-efficient prefix tree by reusing previous computation from parent rule lists. We systematically search the entire space of rule lists, evaluating them in an order specified by our search policy; for example, a breadth-first search policy examines shorter rule lists before longer ones.

Our objective function combines the number of incorrectly classified observations, normalized to measure misclassification error, with a regularization term that penalizes longer rule lists. The maximum number of mistakes provides a bound for how well the children of a rule list could ever perform. Using those two metrics, we are able to compare the potential performance of all of a rule list’s children to the current best rule list we have seen so far. If the best potential performance is worse than the performance of a rule list we have already seen, then we know it cannot be the optimal rule list, and thus we can prune it. We also proved a suite of additional algorithmic bounds that interact to aggressively prune the search space. In our implementation, we exploit these bounds via several data structures. Together with additional systems optimizations, our approach efficiently searches the space of rule lists to find a provably optimal solution.

In previous work, we performed experiments using the ProPublica COMPAS dataset [6], focusing on the prediction problem of whether or not an individual would recidivate within two years. This dataset contains 122 rules; therefore, a brute force search of all possible rule lists up to length 10 would require evaluating  $5.0 \times 10^{20}$  rule lists. Due to our algorithmic bounds, CORELS examines only 28 million rule lists, a reduction of  $1.8 \times 10^{13}$ . Between the bookkeeping required to search and prune the state space and the numerous bit vector operations required to evaluate each rule list, a non-optimized implementation of our algorithm would not complete. However, with CORELS, each evaluation takes only  $1.3 \mu\text{s}$ , allowing us to complete that moderately sized problem in 36s. Systems optimizations, even on just a single processor, allow us to solve a computationally hard problem of reasonable size in under a minute.

## 2 IMPLEMENTATION

Our algorithm is feasible due to the use of three core data structures. First, we use a prefix tree to represent the search space. The incremental nature of our algorithm requires that we store rule lists that we examined but did not discard. The prefix tree structure allows us to efficiently access values in a parent rule list to calculate bounds for a new rule list. Second, we implement our scheduling policy with a priority queue. Third, we use a symmetry-aware map to implement one of our critical bounds. It allows us to compare and prune permutations of rule lists.

To support incremental execution, we use a prefix tree to cache rule lists that we have already evaluated and have not pruned. Each node in the tree represents a rule, so any rule list can be reconstructed by following a path from the root to a leaf in the tree. The node stores metadata to aid in the computation of our bounds including: the lower bound, objective value, and a list of unpruned children. Nodes also have parent pointers, so each node is created incrementally by using the parent’s bounds to calculate the new bounds. This structure also means that a rule list can be represented and passed around as a pointer to a single node in the tree or as an ordered list of rules. In most cases the pointer is more efficient, though the list representation is useful as a hashable index.

We represent our worklist with a priority queue. This allows us to try different exploration orders simply by changing the priority metric. We implement breadth-first search (BFS), depth-first search (DFS), and a best-first search that can take a custom metric. Our implementation supports ordering by the lower bound and the objective, though any function that maps a prefix to a real value in a stable manner would work. In general, we find that ordering by lower bound (best-first) yields the best results on most datasets.

To take advantage of the symmetry inherent to our problem, we designed a data structure we call a symmetry-aware map. We use this map to keep track of the best possible permutation of a given set of rules. When a new permutation of that set of rules is encountered, we add the new permutation to our prefix tree only if it is strictly better than the permutation we already have stored. We experimented with multiple key types that could represent permutations of rule lists and found that a simple optimization of the key type led to a 3x reduction in memory usage for the map [7].

An important part of our implementation is that we calculate accuracy and other metrics using bit vector operations. Each rule is represented as a bit vector, whose length is equal to the number of items in the training set. Bit  $i$  is set to 1 if the rule evaluates true for data item  $i$  and 0 otherwise. We use the high performance bit vector rule library [10] that uses the GMP multiple-precision library to represent and manipulate the vectors. This is more efficient than built-in C++ constructs such as a vector of bools or a bitset. CORELS profiling shows that these bit vector operations account for the majority of algorithm’s execution time. Thus, improving the performance of these computations will improve algorithm performance and is a promising direction for future work.

Each one of these structures and optimizations is critical for the success of our algorithm. For example, we briefly experimented with a stochastic search policy that did not use a queue at all but instead followed random paths from the queue to a leaf. However,

this search strategy performed worse than any strategy involving our queue, so we proceeded only by using the queue.

Table 1 empirically validates the importance of data structure design (symmetry-aware map) on several datasets. We conducted trials on small personal laptops<sup>1</sup>. The method for both symmetry-aware and non-symmetry aware tests used lower-bound ordering (best-first search) in the queue as described above. The symmetry-aware map led to an average reduction of over 81% in runtime and memory usage. On more computationally complex datasets, such as the NYPD stop-and-frisk dataset, the symmetry-aware map allows an otherwise unsolvable problem to be solved to optimality on a machine with only 8GB of memory.

**Table 1: Tabulation of average runtime and memory usage (in square brackets) over 3 runs on different datasets with and without symmetry-aware map, tested on a 2.6 GHz i7-6700HQ and 16 GB RAM, capped at 12 GB. Standard deviations are within 1% of reported values in all cases.**

Dataset	Avg runtime (s) symmetry-aware	Avg runtime (s) not symmetry-aware	Speedup gain (%)	Memory savings (%)	#Samples
Breast Cancer	3206.03 [3078 MB]	14038.50 [8598 MB]	77.16	64.20	684
Haberman	8.45 [60.68 MB]	33.37 [104.00 MB]	74.67	41.65	307
MONKS-1	0.29 [<0.1 MB]	0.36 [<0.1 MB]	19.4	<1	432
MONKS-3	0.10 [<0.1 MB]	0.14 [<0.1 MB]	28.6	<1	432
Votes	8.26 [43.73 MB]	24.06 [78.56 MB]	65.65	44.34	436
NYPD Stop-and-frisk	1,728.27 [641 MB]	- [>12288 MB]	>72.0	>95.0	566,839
Average	644.63 [955.85 MB]	3373.91 [>5267 MB]	>81.0	>81.0	

## 3 CONCLUSION

We demonstrated that it is possible to learn certifiably optimal rule lists, but only through a combination of algorithmic bounds, systems optimizations, and efficient data structures. While much of the theory in this area was developed in the 1980s and 1990s, to the best of our knowledge there have been few dedicated systems approaches that take advantage of modern hardware to work on real problems. Future work on CORELS involves parallelizing the algorithm both for a single machine with many cores and for distributed systems. Additionally, further scaling could be realized by porting the algorithm to an FPGA. We are optimistic that other classic AI algorithms may benefit from investigations of systems level optimizations.

## REFERENCES

- [1] E. Angelino, N. Larus-Stone, D. Alabi, M. Seltzer, and C. Rudin. Learning certifiably optimal rule lists for categorical data. *Preprint at arXiv:1704.01701*, November 2017.
- [2] E. Angelino, N. Larus-Stone, D. Alabi, M. Seltzer, and C. Rudin. Learning certifiably optimal rule lists for categorical data. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD’17)*, 2017.
- [3] L. Breiman, J. Friedman, R. Olshen, and C. Stone. *Classification and regression trees*. 1984.
- [4] Jens Clausen. *Branch and bound algorithms - principles and examples*. 1999.
- [5] S. Ertekin and C. Rudin. Learning customized and optimized lists of rules with mathematical programming. Unpublished, 2017.
- [6] J. Larson, S. Mattu, L. Kirchner, and J. Angwin. How we analyzed the COMPAS recidivism algorithm. *ProPublica*, 2016.
- [7] N. L. Larus-Stone. *Learning Certifiably Optimal Rule Lists: A Case For Discrete Optimization in the 21st Century*. 2017. Undergraduate thesis, Harvard College.
- [8] J. R. Quinlan. *C4.5: Programs for Machine Learning*. Morgan Kaufmann, 1993.
- [9] R. L. Rivest. Learning decision lists. *Machine Learning*, 2(3):229–246, November 1987.

<sup>1</sup>2.6 GHz i7-6700HQ and 16 GB of RAM, and 2.6 GHz i5-2540M and 8GB of RAM

- [10] H. Yang, C. Rudin, and M. Seltzer. Scalable Bayesian rule lists. In *Proceedings of the 34th International Conference on Machine Learning, ICML '17*, 2017.