ABSTRACT
Decision forest algorithms model data by learning a binary tree structure recursively where every node splits the feature space into two regions, sending examples into the left or right branches. This “decision” is the result of the evaluation of a condition. For example, a node may split input data by applying a threshold to a numerical feature value. Such decisions are learned using (often greedy) algorithms that attempt to optimize a local loss function. Crucially, whether an algorithm exists to find and evaluate splits for a feature type (e.g., text) determines whether a decision forest algorithm can model that feature type at all. In this work, we set out to devise such an algorithm for textual features, thereby equipping decision forests with the ability to directly model text without the need for feature transformation. Our algorithm is efficient during training and the resulting splits are fast to evaluate with our extension of the QuickScorer inference algorithm. Experiments on benchmark text classification datasets demonstrate the utility and effectiveness of our proposal.

CCS CONCEPTS
• Computing methodologies → Classification and regression trees;

KEYWORDS
Decision Forests, Decision Tree Algorithm, Text Classification

1 INTRODUCTION
Machine Learning (ML) algorithms often consume observations in the form of feature vectors in order to train models. The semantics of each feature defines how it should be consumed by the algorithm and ultimately used in the resulting model. A typical decision tree algorithm, for example, learns to model data with a binary tree where each node recursively bifurcates the training examples according to a “split” of the feature space; how an optimal split is found for a feature depends entirely on semantics.

ML algorithms either have the ability to consume a feature type as is or otherwise require that it be transformed to a supported type. Virtually all algorithms, decision trees included [6, 16, 19], are able to ingest numerical features, sometimes exclusively so. The record is mixed for other feature types such as graphs, time series, text, or categorical features. Neural networks, for example, require that categorical features be transformed to one-hot vectors or another numerical form. On the other hand, decision forests that do not generalize as well as CART-powered decision trees— that is the driving reason for the use of CART in decision forest libraries such as LightGBM [20]. Such empirical observations have motivated researchers to study ways of extending decision trees to consume other feature types such as time series [11, 31] and timestamped symbol sequences [17] among others.

In this work, we set out to enable decision trees to consume another common feature type that remains unsupported to date: categorical sets. A categorical-set feature value is defined as a set of categorical terms. For example, consider a data point that is represented by the following 4 features: \( f_1 = 5, f_2 = \text{“cat”}, f_3 = \{\text{“blue”}, \text{“red”}, \text{“green”}\}, f_4 = \emptyset \). In this example, \( f_1 \) is a numerical feature, \( f_2 \) is a categorical feature, and \( f_3 \) and \( f_4 \) are two categorical-set features. Note that, an empty categorical-set feature value is semantically different from a missing value.

A decision tree learning algorithm equipped with a split-finding algorithm that is specialized for categorical-set features may naturally consume text, as text can be trivially (though incompletely) expressed in that form. Such an extension of decision trees, in turn, allows the application to text corpora of an array of decision forest algorithms such as Random Forest (RF) [5], Multiple Additive Regression Trees (MART) [15], Dropout Multiple Additive Regression Trees (DART) [30], and Extremely Randomized Trees [16].

Our work formalizes categorical-set splits and offers a greedy algorithm to find them efficiently. Our formulation of a categorical-set split tests the presence of any one of a set of terms (called “mask”) in the feature value set: When the intersection of the mask and feature value is nonempty, the split decision is in the affirmative. This mask itself is built incrementally using a stochastic, greedy process guided by the decision tree loss function: From a subsample of vocabulary terms, the term that minimizes the loss the most is added to the mask. This process is repeated until the loss cannot be further reduced, at which point the resulting mask is our split.

Our contributions can be summarized as follows:
• We define and formulate splits (conditions) on categorical-set features in the context of decision trees;
• We propose an efficient algorithm to learn such splits;
• We report an empirical comparison of our proposed algorithm with methods that require feature transformation;
• We present an analysis of the stability of the algorithm’s hyperparameters; and,
• We extend the QuickScorer [26] algorithm for efficient inference of models with categorical-set splits.

The remainder of this paper is organized as follows. We begin with a brief review of the literature in Section 2. We present our
proposed algorithm in Section 3 and evaluate it in Section 4. That is followed by a detailed analysis in Section 5. Section 6 provides details on efficient model inference. Finally, we conclude this work in Section 7.

2 BACKGROUND AND RELATED WORK

A decision forest is a collection of decision trees. A decision tree itself is typically a binary tree that routes an example recursively until a leaf is reached. The decision at every intermediate node to take the left or right branch is, in most cases, made based on a condition on a single feature. We refer to this condition as a split. For example, a split for a numerical feature typically compares the value of that feature with a threshold—that threshold and the comparison operator are what define the split. When a decision tree is learned, the training algorithm finds the best split (e.g., threshold for a numerical feature) for each node greedily, selecting the split that optimizes a given scoring function (e.g., information gain, Gini index). For brevity, we refer to such split finding algorithms as “splitters.”

The Machine Learning literature offers many splitters that are suitable for numerical features [6, 16, 19], categorical features [5, 6, 29], time series [11, 31], and timestamped symbol sequences [17]. However, to the best of our knowledge, no published work has addressed the challenge of finding splits on categorical-set features—defined in Section 1. However, multiple methods exist that may be utilized to transform categorical-set features into numerical or categorical values.

BagOfWords replaces a categorical-set feature with a histogram: the count of occurrences of each term in the vocabulary set \( D \). More precisely, a feature value \( X \subset D \) is replaced with a set of numerical features \( \{ f_i \}_{i=1}^{\|D\|} \) with \( f_i = |X \cap \{d_i\}| \) where \( d_i \in D \) is a term in the vocabulary.

A fixed pre-trained representation, also known as fixed pre-trained embedding, projects every term individually [27, 28], or the set of terms as a whole [12], into a multi-dimensional dense vector space where terms that are “close” in the original representation—for some implicit or explicit definition of closeness—are also close in the target space. Such functions can be learned with a neural network using back-propagation [12] or other algorithms [28] capable of learning intermediate representations.

A number of recent publications have explored joint training of decision forests and neural networks [2, 8, 14, 21, 22, 24] as a way to harvest the power of deep learning [23] to consume text [12], images [18], graphs [32] and sets [34]. While not demonstrated, DeepSet [34] is another neural network-based transformation that may be used to incorporate categorical-set features in a decision forest. Note, however, that in this work we are interested in enabling decision trees to consume categorical-set features without transformation of any kind, including representation learning using neural networks.

3 FINDING CATEGORICAL-SET SPLITS

Decision forest learning algorithms such as RF, MART, or DART all rely on a splitter subroutine to find an optimal split for every node in the tree. During training, splitters are called frequently to search a large space of feature values given a large number of training examples in order to arrive at a sensible split that optimizes a split scoring function. The resulting split must also be efficient to compute as, during evaluation or inference, every intermediate node in the tree must quickly determine which branch an example should be routed towards under tight latency constraints. As such, splits and splitters play an outsize role in the efficiency of the training and inference procedures. It is therefore imperative that any proposed split and splitter be computationally cheap.

Splitters also affect the generalizability of decision forest models: an overzealous splitter that produces a split that overfits the training data leads to poor generalization. This behavior can be controlled with regularization (e.g. loss term, examples or feature sub-sampling). Alternatively or additionally, one could afford a certain degree of stochasticity to a splitter to prevent overfitting. For example, presenting a splitter with only a subsample of training examples or of feature values is one way to introduce uncertainty. We incorporate a similar idea in our proposed algorithm.

Algorithm 1 presents our proposed splitter for categorical-set features. To understand the algorithm, let us define its output first: a categorical-set split. Like splits on numerical features, a categorical-set split consists of an operator and a “threshold.” We choose intersection as the operator and a fixed subset of the vocabulary as the threshold, or more appropriately, mask. A split on a categorical-set feature is a test of whether its intersection with the mask is nonempty. The following definition formalizes this concept.

**Definition 1.** Given a vocabulary of possible terms \( D \) and a categorical-set feature \( X \subset D \), a Categorical-Set Split is the result of \( X \cap M \neq \emptyset \), where \( M \subset D \), a mask, is a fixed set of terms associated with the split.

The objective is then to construct a mask \( M \subset D \) such that the split formulated above optimizes a split scoring function on a given set of training examples—a list of \( n \) categorical-set feature values \( X = \{X_i\}_{i=1}^{n} \) with \( X_i \subset D \), and their corresponding labels \( Y = \{y_i\}_{i=1}^{n} \). We note that any scoring function may be used but typical examples are information gain for classification with Random Forests, and mean squared error for Gradient Boosted Decision Trees.

Let us now describe how the algorithm constructs \( M \). It first samples a random subset \( \hat{D} \subset D \) with each term sampled independently with probability \( p \), a hyperparameter that controls the stochasticity of the split. \( M \) is then initialized to an empty set and, in an iterative

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**Algorithm 1** Greedy algorithm for finding categorical-set splits

**Input:** Collection of categorical-set features \( X \) and labels \( Y \).

- Sampling rate \( p \in (0, 1) \).
- Vocabulary \( D = \{d_j\}_{j=1}^{m} \).

**Output:** Split mask \( M \).

1. \( \hat{D} \leftarrow \{ d \mid d \in D \text{ with probability } p \} \).
2. \( M \leftarrow \emptyset \) \( \rightarrow \) Initial empty mask.
3. **while true do**
4. \( d \leftarrow \arg \max_{d \in \hat{D}} \text{score}(X, Y, M \cup \hat{d}) \).
5. **if** \( \text{score}(X, Y, M \cup \hat{d}) \leq 0 \) **then**
6. \( \text{break} \rightarrow \) No further improvement possible.
7. **end if**
8. \( D \leftarrow D \setminus \hat{d} \).
9. **end while**
We consider several learning algorithms including Neural Networks, Linear classifiers, Random Forests (RF) and Multiple Additive Regression Trees (MART)—the last two being decision forest algorithms. In order to evaluate our proposal we make two measurements. In one, we measure the effectiveness of our proposed split score is maximized. The algorithm stops when no additional vocabulary term improves the score.

4 EXPERIMENTAL EVALUATION

This section reports the empirical evaluation of our proposed splitter algorithm on RF and MART algorithms on 5 public text classification datasets. We begin with a description of these datasets, list the methods under evaluation, and finally present and discuss the results.

4.1 Datasets

We consider 5 binary classification datasets of the cleaned Sentiment Analysis dataset repository [10]. Table 1 shows the names and statistics of our datasets. We tokenize the text features by white space, thereby representing each piece of text as a set of unigrams. Once classifiers are trained, we measure the Area Under the Receiver Operating Characteristic Curves (AUC), averaged in a 5-fold cross-validation scheme.

| Dataset                          | #Examples | #terms/examples |
|---------------------------------|-----------|-----------------|
| Stf. sentiment treebank (SST)   | 68.8k     | 9.8             |
| Product review (CR)             | 8k        | 20.1            |
| Movie review (MR)               | 22k       | 21.6            |
| Subjectivity status (SUBJ)      | 20k       | 24.6            |
| Opinion-polarity (MPQA)         | 22k       | 3.1             |

4.2 Methods

We consider several learning algorithms including Neural Networks (NN), Linear classifier (Linear), Random Forests (RF) and Multiple Additive Regression Trees (MART)—the last two being decision forest algorithms. In order to evaluate our proposal we make two measurements. In one, we measure the effectiveness of our categorical-set splits for decision forests, applied directly to the datasets. The second trains a model using the learning algorithms above with text features transformed using one of the following functions:

- **TargetMean**, inspired by CatBoost [29], replaces a categorical feature by the conditional label distribution of its values, estimated on the training set. For example, in a binary classification setting, the categorical value “A” is replaced by the ratio of positive label among examples with value “A”;
- **MaxHash**, inspired by MinHash [7] and Bloom filters [4], replaces a categorical-set feature by the maximum of a hash function applied to each term separately. The resulting value can be treated categorically or numerically. The process is applied multiple times using different, randomly selected hash seeds. In other words, a categorical-set feature value is defined as:
  \[ f_i = \max_{x \in X} h(x, h_i), \]
  \[ h(\cdot) \] a hash function, and \( h_i \) a random seed;
- **BAGOfWORDS** as described in section 2;
- **OneHot**, reduces BAGOfWORDS to categorical features; and,

- **PreTrained** is a 128-dimension text-based text embedding [3] trained on the English Google News 200B corpus. 1

In the sections that follow, we adopt the following naming format: Method names begin with the learning algorithm (e.g., RF) followed by a sequence of pre-processing steps (if any) separated by the plus sign. For example, “RF MaxHash + TargetMean” indicates that a Random Forest model is trained where the raw text features were transformed using MaxHash first, followed by TargetMean. CatCart indicates that a categorical feature is consumed with the CART splitter [6]. Finally, the proposed method is denoted by GreedyMask.

Many of the hyperparameters we used in this work are set to reasonable default values guided by previous publications [9, 20, 29], while a subset (e.g., vocabulary size, sampling rate) are determined by a small-scale validation and fixed across experiments. The following provides a summary:

- Tokenization: We keep the 5000 most frequent terms that appear at least 5 times. This is computed independently on the training partition of each cross-validation iteration.
- RF: We train 500 trees with a maximum depth of 32; the number of features randomly chosen to find a split in a node is the square root of the total number of features.
- MART: shrinkage is set to .1; maximum depth is 6 and number of trees is set to 500 with early stopping using 10% of the training dataset as validation; feature subsampling is disabled; and we use exact splitting for numerical features.
- NN: 3 layers with 32 units each; batch size is 32; train for a maximum of 20 epochs; early stopping using 10% of the training dataset as validation; finally, we use the AdaGrad [13] optimizer.
- Linear: 32 examples per batch; train for 20 epochs with the AdaGrad optimizer.
- GreedyMask: sampling rate of .2. We provide an analysis of the effect of this hyperparameter in Section 5.2.

4.3 Results

Table 2 shows the AUCs of the methods under consideration (in rows) on all datasets (in columns), averaged over 5-fold cross-validation trials. We also report the mean and median rank of each method in the same table.

The results in Table 2 show that our proposed algorithm when applied to Random Forests leads to considerable gains: The method comes first in terms of median rank, and is the best performing method on 3 of the 5 datasets. However, the method ranks poorly (13/20) on the MPQA dataset, falling far behind Linear PreTrained. We believe this unusual gap is an artifact of the dataset itself. Sentences in MPQA are very short, rarely exceeding a handful of terms—the average number of terms per example, as shown in Table 1, is a measly 3.1. With so few terms, it is easy for CatCart and GreedyMask to overfit. PreTrained, in contrast, is at an advantage as its representations are learned using another, larger dataset, making it less prone to overfitting.

As anticipated, the impact of pre-trained embeddings depends on the dataset. Pre-trained embeddings perform well on the MPQA dataset—the top four approaches use embeddings—whereas on other datasets the advantage is somewhat limited. Interestingly,

1 Available at https://tfhub.dev/google/nnlm-en-dim128/1
Table 2: Five-fold cross-validation AUC of the various methods on the 5 binary classification datasets. The mean AUC is accompanied by the standard deviation and, in parentheses, the rank of the method for each dataset. Our methods are bold-faced.

| Method                  | Median Rank | Avg Rank | SST | MR | CR | MPQA | SUBJ |
|-------------------------|-------------|----------|-----|----|----|------|------|
| RFGreedyMask            | 1           | 3.8      | .9636Â±.0039 (1) | .842Â±.0145 (1) | .8723Â±.0148 (1) | .8432Â±.0181 (13) | .9675Â±.0104 (3) |
| MART BagOfWords         | 3           | 4.6      | .9561Â±.00556 (3) | .8351Â±.00491 (2) | .8559Â±.00439 (3) | .8384Â±.0157 (14) | .9691Â±.0094 (1) |
| MART GreedyMask         | 5           | 5.2      | .9568Â±.00359 (2) | .8327Â±.00522 (3) | .852Â±.00438 (4) | .8374Â±.0134 (15) | .9681Â±.0092 (2) |
| Linear PreTrained       | 6           | 6.4      | .9187Â±.0122 (15) | .8213Â±.0157 (8) | .8655Â±.0186 (2) | .9342Â±.0115 (1) | .9643Â±.0136 (6) |
| RF MaxHash+TargetMean   | 7           | 6.8      | .9407Â±.00766 (9) | .8302Â±.0014 (4) | .8439Â±.0047 (7) | .8887Â±.0104 (6) | .9635Â±.0138 (8) |
| MART MaxHash+TargetMean | 7           | 7.8      | .9375Â±.00764 (11) | .8293Â±.0188 (6) | .8305Â±.0293 (11) | .8897Â±.00715 (5) | .964Â±.0114 (7) |
| RF PreTrained           | 9           | 9.4      | .9482Â±.00763 (7) | .8023Â±.0298 (13) | .8423Â±.0324 (9) | .9278Â±.00954 (3) | .9458Â±.0020 (13) |
| NN PreTrained           | 9           | 9.4      | .9129Â±.0113 (16) | .7992Â±.0286 (14) | .8466Â±.0235 (6) | .9324Â±.0188 (2) | .963Â±.0149 (9) |
| Linear MaxHash+TargetMean| 9          | 9.8      | .8991Â±.0102 (17) | .8294Â±.0179 (5) | .7713Â±.1211 (14) | .8634Â±.0121 (9) | .9662Â±.0106 (4) |
| MART PreTrained         | 10          | 10.4     | .9388Â±.00842 (10) | .8056Â±.0313 (11) | .8299Â±.0532 (12) | .9259Â±.0164 (4) | .9658Â±.0148 (10) |
| Linear MaxHash+OneHot   | 10          | 11       | .9448Â±.00652 (8) | .8062Â±.0205 (10) | .7113Â±.4711 (15) | .8763Â±.0114 (7) | .7953Â±.6265 (15) |
| NN BagOfWords           | 11          | 10       | .9308Â±.00643 (14) | .8073Â±.0389 (8) | .8486Â±.0641 (5) | .8578Â±.0195 (11) | .9393Â±.0131 (11) |
| Linear BagOfWords       | 12          | 12       | .937Â±.00557 (12) | .7907Â±.0338 (18) | .8437Â±.0548 (5) | .8593Â±.0169 (10) | .9649Â±.0193 (12) |
| NN MaxHash+TargetMean   | 12          | 11       | .8921Â±.0112 (18) | .8279Â±.0175 (7) | .8146Â±.0604 (13) | .8488Â±.0194 (12) | .9651Â±.0119 (5) |
| NN MaxHash+OneHot       | 13          | 13       | .9365Â±.00815 (13) | .8042Â±.0284 (12) | .7064Â±.4633 (16) | .8724Â±.0153 (8) | .7965Â±.6516 (16) |
| RF CatCartMaxHash       | 17          | 14.6     | .9335Â±.00495 (4) | .7913Â±.0167 (17) | .6964Â±.4597 (18) | .8246Â±.0152 (16) | .7717Â±.6867 (19) |
| MART CatCartMaxHash     | 17.5        | 15.1     | .9512Â±.00447 (5.5) | .7922Â±.0271 (15.5) | .6707Â±.4333 (19.5) | .822Â±.0127 (17.5) | .7735Â±.694 (17.5) |
| MART MaxHash+OneHot     | 17.5        | 15.1     | .9512Â±.00447 (5.5) | .7922Â±.0271 (15.5) | .6707Â±.4333 (19.5) | .822Â±.0127 (17.5) | .7735Â±.694 (17.5) |
| RF BagOfWords           | 19          | 16.4     | .8063Â±.0072 (19) | .7416Â±.0405 (19) | .8309Â±.0268 (10) | .7365Â±.042 (20) | .9119Â±.0272 (14) |
| RF MaxHash+OneHot       | 20          | 19.4     | .7794Â±.0219 (20) | .7166Â±.0226 (20) | .6864Â±.394 (18) | .7453Â±.0408 (19) | .7525Â±.517 (20) |

5 ANALYSIS

In this section, we take a closer look at the methods considered in this work. We begin with a comparison of the structure of the learned models. We then examine the effect of hyperparameters on model performance.

5.1 Structure

Table 3 reports model statistics resulting from the utilization of different pre-processing transformations with the RF algorithm on two datasets. We note that similar conclusions can be drawn from the other 3 datasets, which we have omitted for brevity.

Figure 1: Relative accuracy headroom reduction (RAHR) of methods on 5 datasets relative to RF BagOfWords. The red circles traced across methods are mean RAHR of each method and the solid horizontal line around each circle represents one standard deviation in both directions.
Table 3: Structure statistics of the RF models for the MR and SST datasets. Balance ratio is the ratio of the log of the number of nodes per tree (log(#Nodes/Tree)) to the average depth—a balance ratio of 1 indicates a fully balanced tree.

| Method                   | Avg Depth | #Nodes/Tree | Balance  |
|--------------------------|-----------|-------------|----------|
|                          | MR  | SST  | MR  | SST  |             |
| RFGreedyMask             | 11.5 | 17.5 | 477 | 3499 | .771 .671   |
| RF BagOfWords            | 20.5 | 21.6 | 815 | 1642 | .472 .494   |
| RFCATCARTMaxHash         | 12.0 | 12.6 | 369 | 855  | .713 .775   |
| RF MaxHash+TargetMean    | 13.5 | 17.0 | 1493| 6109 | .782 .739   |
| RF MaxHash+OneHot        | 19.9 | 20.1 | 722 | 1099 | .477 .503   |

We observe that BagOfWords and MaxHash+OneHot lead to deeper trees, while other solutions learn much shallower trees. One possible interpretation is that node splits resulting from features transformed using BagOfWords and MaxHash+OneHot afford little separability powers, and as a consequence, more splits are required to obtain better decision boundaries. It is also worth noting that BagOfWords effectively tests one term at a time, leading to larger trees that generalize poorly.

It does not come as a surprise then that BagOfWords and MaxHash+OneHot have significantly smaller balance ratios relative to other methods, indicating that trees are on average less balanced. This phenomenon too can be explained by the fact that splits consider a single term (or a single random hash) at a time, thereby repeatedly forcing training examples down the negative branch, ultimately resulting in unbalanced trees.

5.2 Hyperparameter Stability

Our proposed method has a single hyperparameter, a sampling rate p, which introduces randomness in the splitter. By incorporating this hyperparameter, we hoped to allow a form of regularization and prevent overfitting. In this section, we study the effect of the sampling rate on the final model across different datasets.

Figure 2 shows the change in mean AUC for different values of sampling rate. As before, AUCs are estimated with 5-fold cross-validation. Other hyperparameters are left unchanged (see Section 4), with the exception of the vocabulary size which is adjusted from 5000 to 2000 terms to facilitate faster experiments.

Model performance is relatively stable and does not change dramatically with changes in the sampling rate: Excluding the sampling rate of .01, the average difference between the best and worst AUCs for p ∈ [0.05, 0.5] is only .0078. The optimal sampling rate naturally depends on the dataset, ranging from the smallest to the largest tested values. While not reported in Figure 2, for some datasets the optimal sampling rate appears to be 1.0, meaning no sampling at all. On average, however, p = .2 is a reasonable default value for RF with an average .0026 AUC drop from the best setting.

Confirming the results of Section 4, RF performs better than MART by an average 0.0063 in AUC. By construction, RF is less prone to overfitting than MART and, as such, can better correct our splitting algorithm’s tendency to overfit to the training data. More work, however, is required to understand and improve our proposed solution for use with MART.

Figure 2: Mean AUC with respect to sampling rate. The cross represents the highest AUC for each method-dataset pair.

6 EFFICIENT MODEL INFERENCE

The naive way to evaluate a decision tree on an input example is to start at the root and evaluate its condition in order to route the example to one of its (left or right) branches, and repeat that operation until we reach a leaf [1]. Though trivial to implement, that approach is suboptimal. Researchers have thus developed more optimized inference algorithms such as QuickScorer [26] (QS) and its extensions vQuickScorer [25] (v-QS) and RapidScorer [33]. The core idea is to evaluate a tree by evaluating all its nodes simultaneously, and then retrieving the active leaf. These methods, despite having an exponentially higher time complexity, run orders of magnitude faster than the top-down approach on modern CPUs because of their more predictable memory access pattern and branching.

In this section, we present an extension of QS to support conditions generated by Algorithm 1. To understand this extension, let us briefly describe the mechanism by which QS determines which leaf is active given an input example with numerical features: QS begins by constructing a “leaf mask,” a bit vector, initially all set, whose size is equal to the number of leaves in the tree. Each node too has a “node mask,” a bit vector of the same size that encodes the leaves that are unreachable if an example fails to satisfy that node’s split condition. QS proceeds by taking one numerical feature at a time and iterating over all nodes that split on that feature. If the node’s threshold is smaller than the feature value, that node’s mask is applied (with AND) to unset unattainable leaves. In the end, the index of the lowest set bit in the leaf mask is the active leaf. Note that, a separate leaf mask is maintained per tree.

Algorithm 2 presents our extension of QS. We adopt the same notation as in Algorithm 1 in the original work [26] and refer the reader to that work for a complete account. For our algorithm to work, we prepare the following data structure for each categorical-set feature separately: We compile what we refer to as “term masks,” bit vectors that are similar to node masks in QS but that encode, for each term in the vocabulary, the leaves that are unreachable if an example contains that term. Figure 3 shows an example decision forest with categorical-set splits along with its term masks.
The QS implementation for categorical-set split is nearly 13x faster than the VPred implementation, demonstrating that such splits are well-suited for the QS algorithm. GreedyMask (without SIMD instructions) runs nearly 20% faster than BagOfWords (with SIMD instructions).

7 CONCLUSION

In this work, we proposed a novel algorithm that enables decision forests to consume categorical-set features, effectively allowing them to model text without a need for feature transformation. Our solution equipped decision forests with the ability to efficiently find (greedy) splits in the space of sets of objects. We also extended QuickScorer, an inference algorithm to evaluate decision forests efficiently on modern CPUs, to include our proposed split.

Experiments on text classification showed that our method is competitive in terms of quality and inference speed compared to existing methods. Furthermore, an examination of the resulting models in terms of structure and sensitivity to our method’s hyperparameter shows that our proposed method yields balanced trees and its performance is stable across various datasets and settings.

This work gives rise to a number of future research directions. Having established the feasibility of consuming raw textual features with decision forests, we are interested in variants of the proposed algorithm (e.g., ngram-based splits) and in better understanding their effect on different decision forest algorithms (RF vs. MART). Preventing the splitter from overfitting to training data, particularly on small datasets, is a topic worth exploring. Another question left unanswered is the interpretability of our proposed split: How one systematically assesses the role a particular term or split plays in the model needs to be studied.

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