Abstract. Decision forests, including random forests and gradient boosting trees, remain the leading machine learning methods for many real-world data problems, especially on tabular data. However, most of the current implementations only operate in batch mode, and therefore cannot incrementally update when more data arrive. Several previous works developed streaming trees and ensembles to overcome this limitation. Nonetheless, we found that those state-of-the-art algorithms suffer from a number of drawbacks, including low accuracy on some problems and high memory usage on others. We therefore developed the simplest possible extension of decision trees: given new data, simply update existing trees by continuing to grow them, and replace some old trees with new ones to control the total number of trees. In a benchmark suite containing 72 classification problems (the OpenML-CC18 data suite), we illustrate that our approach, Stream Decision Forest (SDF), does not suffer from either of the aforementioned limitations. On those datasets, we also demonstrate that our approach often performs as well, and sometimes even better, than conventional batch decision forest algorithm. Thus, SDFs establish a simple standard for streaming trees and forests that could readily be applied to many real-world problems.

1 Introduction

In recent decades, machine learning methods facilitate the utilization of modern data and have made significant scientific progress in health care, technology, commerce, and more [1]. Among these methods, random forests, hereafter referred to as decision forests (DFs), and gradient boosting trees are the leading strategies for tasks like classifications, outperforming all others on real-world datasets and machine learning competitions [2–6]. However, training forests with continuous inputs poses new challenges for these estimators. Larger sample sizes often require overwhelmingly more computational time and space, and different scenarios of streaming inputs need flexible strategies for model updates [7, 8]. This condition requires that, for batch tree estimators like DFs, all available sample data must be stored and refitted after each update [2, 9]. Even with enough computational resources to do so, out-of-distribution (OOD) problems could still undermine the validity of older data [10].

By incrementally updating the estimators with continuous batches of new training samples, streaming trees can continuously optimize the tree structures without storing old data [11–14]. Furthermore, in forest ensembles, older trees could be pruned to keep up with the current data distribution. Attempts have been made to adapt decision trees (DTs) to streaming tasks, including Hoeffding trees (HTs) which use statistical bounds to update node splits, and Mondrian forests (MFs) which create random partitions [11, 13]. These two state-of-the-art algorithms have been tested in many synthetic and real-world scenarios [15–18]. Nonetheless, we find them performing poorly in certain tasks and using excessive memories on large datasets, which significantly restrict their applications.

In this paper, we explore the simplest incremental update method to extend a fitted decision tree and introduce our streaming tree implementations: Stream Decision Tree (SDT) and Stream Decision Forest (SDF). After the initial fitting, an SDT takes in every new batch of training samples and splits its leaf nodes when satisfying the given criteria, such as a sample minimum. An SDF ensembles SDTs with bootstrapping and replaces old trees with new ones to control the total number of estimators. On three standard datasets with varying complexities, the performance of streaming and batch estimators are compared, and we illustrate the consistently high performance of SDFs without the aforementioned limitations of HTs and MFs. Then in the OpenML-CC18 benchmark suite, which contains 72 diverse classification tasks, we demonstrate that SDFs often achieve accuracy similar to, or even better than, those of batch mode DFs [19, 20]. Overall, we believe our simplest approach to streaming trees could be readily applied to many real-world problems, including OOD problems and continual learning [10, 21].

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Figure 1: Stream Decision Tree structures after the first batch (left) and the second batch of samples (right). After satisfying the splitting criteria, the leaf nodes (left) are splitted with respect to the second data batch. The orange circles represent the added nodes. The internal splits are never modified, preserving earlier partitions of the feature space.

Algorithm 1 Incrementally update a decision tree with a batch of training samples.

Input:
1. \( T \) \( \triangleright \) current tree
2. \( D_n = (x, y) \in \mathbb{R}^{n \times p} \times \{1, \ldots, K\}^n \) \( \triangleright \) batch of training samples
3. split criteria \( \triangleright \) e.g., minimum node size

Output: \( T \)

1: function SDT.UPDATE_TREE(\( T, x, y \))
2: for each \( i \in [n] \) do
3: find the leaf node \( x_i \) would fall into
4: label that leaf node as a “false root”
5: update index set for this leaf node to include \( i \)
6: end for
7: for each “false root” do
8: split the node if satisfying split criteria
9: for both child nodes do
10: mark as “false roots”
11: end for
12: mark the node as internal or leaf
13: end for
14: return \( T \)
15: end function

2 Methods

2.1 Streaming Trees SDTs are based on a fork of the scikit-learn python package (BSD-3-Clause), which we customized by adding a new \texttt{partial_fit} function to the \texttt{DecisionTreeClassifier} for extending fitted trees [22]. Thus, an SDT is initialized almost in the same way as a DT, where the tree is fitted to the first batch of training samples. The only difference is the input of predefined class labels, as the first batch might not include all possible classes. For each incremental update afterwards (Algorithm 1), the SDT takes in one batch of training samples: \( D_n = (x, y) \in \mathbb{R}^{n \times p} \times \{1, \ldots, K\}^n \). Then for every training sample \( x_i \) in the batch, the algorithm locates the leaf node it would fall into and associates the node with the sample. All the leaf nodes found in such a manner are marked as “false roots.” These “false roots” are then split and extended if satisfying the prespecified splitting criteria (e.g. a minimum node sample size of two). If the splitting occurs, both child nodes would be recursively marked as “false roots” and associated with their separate training samples, just like how batch splitting works in DTs. If not fulfilling the splitting criteria, the “false roots” would become the new leaf nodes. Figure 1 shows an
example of how SDT structures evolve.

**Algorithm 2** Incrementally update a decision forest with a batch of training samples.

**Input:**
1. \( T \) \( \triangleright \) current forest
2. \( D_n = (x, y) \in \mathbb{R}^{n \times p} \times \{1, \ldots, K\}^n \) \( \triangleright \) batch of training samples
3. split criteria \( \triangleright \) e.g., minimum node size
4. \( r \) \( \triangleright \) number of trees to replace

**Output:** \( T \) \( \triangleright \) updated forest

```markdown
1: function SDF.UPDATE_FOREST(T, x, y, r)
2:     for each tree in the forest do
3:         resample \((x, y)\) with bootstrapping
4:         limit the number of features used for splitting
5:         update the tree with resampled data
6:     end for
7:     record \( b \), the number of batches seen
8:     if \( b \) is greater than 1 then with \( 1/b \) probability:
9:         find the accuracy of trees with respect to the current batch
10:        sort the indices of worst performing trees
11:        for each \( i \in [r] \) do
12:            resample \((x, y)\) with bootstrapping
13:            create a new tree with resampled data
14:            replace the \( i \)-th worst tree with the new tree
15:        end for
16:    end if
17:    return T
18: end function
```

An SDF, defined as StreamDecisionForest on our website\(^1\) and GitHub repository,\(^2\) is initialized as a collection of SDTs (100 by default) and modeled after scikit-learn’s DF implementation: RandomForestClassifier \[22\]. As in Algorithm 2, it incrementally updates the trees by bootstrapping the training batches and limiting the number of features selected per split (“max_features”). The default “max_features” is defined as \( p = \sqrt{d} \), where \( d \) is the total number of features. After each incremental update, with \( 1/b \) probability, where \( b \) is the number of batches seen, the forest replaces its worst performing trees (one tree by default) with new trees fitted only to the current batch. This step would remove SDTs that are negatively affected by earlier partitions and reduce the computational space taken. All predictions are generated via majority voting, which helps improving the ensemble’s consistency \[2, 23, 24\]. Furthermore, the algorithm uses the joblib python package (BSD-3-Clause) and takes advantage of parallel computing \[25\].

In all benchmarks, we incrementally updated SDTs and SDFs with fixed-sized data batches (100 random samples per batch) and measured their performance on separated test sets.

**2.2 Reference Algorithms** For comparison with state-of-the-art streaming tree algorithms, we experimented with two existing estimators: Hoeffding trees and Mondrian forests \[11, 13, 15–18\].

HTs are designed to grow tree learners incrementally using Hoeffding bounds \[11, 26\]. After observing \( n \) samples within range \( R \), the bound states that, with \( 1 - \delta \) probability, the variable’s true mean

\(^1\)[https://sdtf.neurodata.io]
\(^2\)[https://github.com/neurodata/SDTF]
is no smaller than the sample mean minus $\epsilon$, where

\begin{equation}
\epsilon = \sqrt{\frac{R^2 \ln(\delta^{-1})}{2n}}
\end{equation}

Thus, the algorithm’s robustness is determined by specifying the $\delta$ value. This statistical bound is independent of heuristic measures (e.g. Gini index and information gain), and the tree splits the current leaf node after observing enough samples.

When training with large datasets, HTs could take up excessive memories to account for all growing leaves [11, 27]. Thus, resource constraints would temporarily deactivate low performing leaves and reactivate them as needed. The algorithm constantly monitors the error rates of all leaf nodes and the probabilities of samples falling into them. For experiments, we used HoeffdingTreeClassifier from the river python package (BSD-3-Clause) [28]. The max size of HTs was set as 1,000 MB, and the minimum sample size for splitting (“grace_period”) was changed to two.

On the other hand, MFs utilize Mondrian processes to incrementally grow Mondrian trees, which are named after Piet Mondrian’s paintings[13, 29]. The Mondrian processes recursively construct random and hierarchical partitions in the feature space. They assign probabilities in a consistent way, and new splits cannot intercept the existing splits [13]. Specifically in the one-dimensional case, the partitions are shown to be a Poisson point process [29]. The forests utilize up to three types of operations when introducing a new sample: splitting existing leaves, updating existing partitions, and creating new splits from internal nodes [13]. We used MondrianForestClassifier from the scikit-garden python package (BSD-3-Clause) [30]. The total number of estimators (“n_estimators” = 10) was limited in some tasks to ensure enough computational space, which is further explored in Section 3.1.

For comparison with batch tree estimators, we included batch decision trees and decision forests [2]. An DF contains a collection of DTs (100 by default) and uses bootstrapping to resample the training data. Each tree in the forest limits the number of features selected at each node split (“max_features”) and tries to find the best partitions available [2]. With majority voting as predictions, a DF is non-parametric and universally consistent, so it will approach Bayes optimal performance with sufficiently large sample sizes, tree depths, and number of trees [23, 24]. Implementations for both algorithms were from the scikit-learn package: DecisionTreeClassifier and RandomForestClassifier [22]. All hyperparameters were kept as default except the number of trees.

In all tasks, we incrementally updated HTs and MFs with fixed-sized data batches (100 random samples per batch). At each sample size, DTs and DFs were trained with all available data, including current and previous batches.

2.3 Data

We used the OpenML-CC18 data suite\(^3\) for experiments. It represents a collection of 72 real-world datasets organized by OpenML, functioning as a comprehensive benchmark suite [19, 20]. These datasets vary in sample size, feature space, and unique target classes. About half of the tasks are binary classifications, and the other half are multiclass classifications with up to 50 classes. The range of total sample sizes is between 500 and 100,000, while the range of features is from a few to a few thousand [20].

Among the data suite, we selected three standard datasets (Table 1) for more in-depth analyses: Splice-junction Gene Sequences (Splice), Pen-Based Recognition of Handwritten Digits (Pendigits), and CIFAR-10 [27, 31–33].

For the Splice dataset, we randomly reserved 25% of all genetic sequences for testing [34, 35]. Each sequence contains 60 nucleotide codes, which are converted into numerical features by the OpenML curation [36]. This task tests MFs’ performance on DNA data without feature engineering, which was not satisfactory in the original paper [13]. The Pendigits dataset contains handwritten images represented by 16 pixel features, which are generated through spatial resampling [37].

\(^3\)https://www.openml.org/s/99
The CIFAR-10 dataset contains RGB-colored images, each high-dimensional image represented by \(32 \times 32 \times 3 = 3,072\) pixel features [33]. We used the provided training and test sets for Pendigits and CIFAR-10, and ran each of the three tasks 10 times by randomizing the training sets.

| Dataset | Splice | Pendigits | CIFAR-10 |
|---------|--------|-----------|----------|
| # Features | 60 | 16 | 3,072 |
| # Classes | 3 | 10 | 10 |
| # Train | 2,392 | 7,494 | 50,000 |
| # Test | 798 | 3,498 | 10,000 |

Table 1: Dataset attributes for three selected tasks.

Datasets were imported using the OpenML-Python package (BSD-3-Clause) [36]. In the OpenML-CC18 tasks, we used all available samples and ran 5-fold cross validations with forests.

2.4 Evaluation Metrics  Classifier performance is evaluated by classification accuracy, classifier size, maximum training space, and training wall times. On the three selected datasets, we use the psutil python package (BSD-3-Clause) to measure memory usage for all the repetitions [38]. The training wall times calculate the fitting times for the given model without hyperparameter tuning (Appendix B). All estimators’ times are calculated by accumulating the training times of data batches, which account for batch estimators’ refitting. We do not report any error bars as they are minimal. To accommodate the space and time constraints of MFs and HTs, the three selected tasks were run without parallelization on a Microsoft Azure 6-core (Intel Xeon E5-2690 v3) Standard_NC6 instance with 56 GB memory and 340 GB SSD storage. The OpenML-CC18 experiments were run with parallelization on a Microsoft Azure 4-core (Intel Xeon E5-2673 v4) Standard_D4_v3 instance with 16 GB memory and 100 GB SSD storage.

![Figure 2: Classifier accuracy on three selected datasets.](image)

Figure 2: Classifier accuracy on three selected datasets. The panel titles include the maximum sample size, the number of features, and the number of classes. The classifiers include: Stream Decision Forest with 100 trees (SDF-100T) and 10 trees (SDF-10T), Stream Decision Tree (SDT), Hoeffding Tree (HT), and Mondrian Forest with 10 trees (MF-10T). Each line represents averaged results from 10 randomized repetitions. The shaded regions highlight the 25th through 75th percentiles. SDFs perform better than all other estimators on the Splice and CIFAR-10 datasets. After certain sample sizes, the accuracy of HTs experiences significant fluctuations and becomes invalid. Those results are not shown, and the sample sizes are marked with the cross symbol. MFs perform slightly better than SDFs in the Pendigits task, but their accuracy significantly drops in the Splice task, only surpassing that of HTs.

3 Results
3.1 Accuracy Comparisons with Streaming Algorithms  SDFs consistently achieve high accuracy across all sample sizes and classification tasks, as compared to MFs and HTs. Specifically in the Splice and CIFAR-10 tasks (Figure 2, left and right), the algorithm always performs the best among streaming classifiers. Its accuracy is also very close to the highest on the Pendigits dataset (Figure 2, center). Single SDTs also outperform HTs in the Splice and CIFAR-10 tasks (Figure 2, left and right). These results clearly show that our streaming trees and ensembles incrementally optimize the tree structures with new information, benefitting from streaming data batches.

Figure 3: Accuracy differences between Stream Decision Forest with 100 trees (SDF-100T) and Mondrian Forest with 100 trees (MF-100T). The results include 67 datasets from the OpenML-CC18 data suite, up to 30,000 training samples. Larger sample sizes and more datasets could not be included due to MFs’ space constraints. Positive and negative differences are averaged separately at each sample size, reducing biases.

HTs always have the lowest accuracy when training on the Splice dataset, which remains almost constant as sample size increases (Figure 2, left). In this case, the classifier fails to learn any new information from streaming data batches. Its performance also shows significant fluctuations when training on the other two datasets. The accuracy starts shifting sharply around 4,000 samples in the Pendigits task and around 32,000 samples in the CIFAR-10 task. We speculate that the fluctuations are due to how HT regulates low performing leaves under resource constraints [11]. However, increasing the maximum size of HTs, even to excessive amounts over the memory limits, would not alleviate the problem. Thus, we attribute these fluctuations to possible implementation errors and mark the problematic sample sizes with the cross symbol (Figure 2, center and right) instead of showing unreliable plots. Such disadvantages could prevent HTs from producing meaningful results on certain datasets or maintaining consistent performance at larger sample sizes. Based on these results, we exclude forest ensembles of HTs from our benchmarks.

In the Pendigits task, MFs perform well at larger sample sizes (Figure 2, center). However, their accuracy is worse than single SDTs’ on the Splice dataset, only surpassing the almost constant plots of HTs (Figure 2, left). We find MFs’ worse performance in the Splice task as expected due to previous results on DNA data [13]. The accuracy could be improved if feature engineering is implemented, demonstrating the drawbacks of label-independent random splits on certain data domains [29, 39]. Moreover, MFs perform worse than SDFs on the CIFAR-10 dataset (Figure 2, right). The results show
Figure 4: Streaming algorithm space complexities on the CIFAR-10 dataset. The classifiers include: Stream Decision Forest with 10 trees (SDF-10T), Stream Decision Tree (SDT), Hoeffding Tree (HT), and Mondrian Forest with 10 trees (MF-10T). Each line represents averaged results from 10 randomized repetitions. Classifier size measures the pickled python objects, and training space checks the maximum virtual memories during fitting. SDFs are the most efficient forest, and SDTs also show very low usage. HTs’ nodes fail to increase linearly with sample size, showing little improvement from new samples. MFs are the most space inefficient and take up excessive memories as sample size increases.

that SDFs are better at handling more feature dimensions.

Further comparisons on the OpenML-CC18 data suite (Figure 3) show that SDFs and MFs have similar performance across different sample sizes. According to their signs, we average and plot the differences separately, minimizing the biases of particular datasets. Accuracy results use 5-fold cross validations on all available samples, and separate accuracy plots for each task are included in Appendix A.

3.2 Complexity Comparisons with Streaming Algorithms

In terms of computational space, SDFs are the most efficient forests on the CIFAR-10 dataset (Figure 4). SDTs also show space efficiency by taking up small training space and low storage sizes. However, the other two streaming classifiers: HTs and MFs both show abnormal space usage. HTs’ number of nodes remains constant until very large samples sizes (Figure 4, center). Despite fitting new batches of training data, the classifier fails to generate new splits, and the results correspond to its suboptimal accuracy (Figure 2, right). Moreover, MFs take up excessive training space as sample size increases, substantially surpassing all other algorithms after 1,000 samples (left and right). At the maximum size, they use six times more resources than SDFs. Such space constraints significantly limit the algorithm’s applications. The total number of trees in MFs must be restricted to ensure task completion, limiting their potential performance. Thus, SDFs would be considered the optimal choice for streaming tasks with limited resources. We do not report the other two tasks’ virtual memories as the changes are minimal.

See Appendix B for training wall times on the three selected datasets.

3.3 Accuracy Comparisons with Batch Algorithms

In the OpenML-CC18 tasks, SDFs achieve high classification accuracy and consistent improvements as more data batches come in. They often achieve performance as well as, sometimes even better than, that of DFs (Appendix A). These results illustrate that the ensemble can maintain its performance on datasets across a variety of data domains, including tabular, image, audio, and more [20]. Such consistency makes SDFs applicable to diverse real-world scenarios, avoiding the disadvantages of HTs and MFs.

We then evaluate SDFs’ and DFs’ performance similarities by calculating the effect sizes. We average the classification accuracy across five folds and measure the difference ratios as:

\[
\frac{SDF - DF}{DF}
\]
Positive percentages represent the better performance of SDFs, while negative values represent that of DFs. As sample size increases, 37 of the 72 tasks show very small shifts on effect sizes (Figure 5), each having a minimum $\geq -5\%$ and a maximum $\leq 5\%$. On these datasets, SDFs usually perform better than DFs at sample sizes smaller than 2,000, and they maintain similar accuracy at larger sizes. In the latter situation, having more data available allows batch DFs to establish finer tree structures and achieve better performance. Nevertheless, this scenario is unreasonable in real-world applications, and refitting batch DFs at large sample sizes demands much more computational resources than incrementally updating SDFs.

In conclusion, we demonstrate that our algorithms, the simplest approach to streaming trees and ensembles, achieve consistently high performance on a variety of real-world datasets. We also illustrate that SDFs avoid the current problems of HTs and MFs, which perform catastrophically on certain datasets and take up excessive memories at large sample sizes.

4 Theoretical Efficiency and Comparisons

We explore and compare the theoretical complexities of SDFs and DFs. SDFs are shown to be more efficient than DFs in learning new data. Theses comparisons show the effects of streaming batches on estimator complexities.

4.1 Learning Time

Lemma 1. In terms of learning time complexity, stream decision forests are more efficient than batch decision forests.

Proof. An algorithm’s learning time complexity represents the theoretical learning time for a new dataset. It depends on both input properties and model hyperparameters. Let $T$ be the number of trees, $n$ the total number of training samples, $b$ the number of batches, $d$ the total number of features, and $p$ the number of features sampled at each split. For building DFs, the average time complexity is $O(Tpn \log^2 n)$. The $pn \log n$ term corresponds to sorting $p$ features at each node, and $\log n$ accounts...
for the average number of nodes [40].

The average learning time of SDF only differs from DF’s in terms of sample size. When training a new tree with one data batch, the average number of nodes is reduced to \( \log(n/b) \), and sorting features in all nodes takes \( O(p(n/b) \log^2(n/b)) \). Each time to update the tree with one new batch, SDF potentially visits all the existing nodes, taking a loose-bounded complexity of \( O(p(n/b) \log(n/b) \log(n)) \). In early updates, the actual number of nodes visited would be much fewer than \( \log(n) \). When considering all the batches, the updating complexity becomes:

\[
O(bp(n/b) \log(n/b) \log(n)) = O(pm \log(n/b) \log(n))
\]

At the forest level, fully building the estimator includes additions and updates for every single tree:

\[
O(T(p(n/b) \log^2(n/b) + pn \log(n/b) \log(n)))
\]

As the updating process is slower, the complexity can be simplified as \( O(Tpn \log(n/b) \log(n)) \), which is faster than building DFs when \( b \geq 2 \).

### 4.2 Learning Space

**Lemma 2.** In terms of learning space complexity, stream decision forests are more efficient than batch decision forests.

**Proof.** An algorithm’s learning space complexity describes the theoretical maximum computational space during training, which scales with sample size and hyperparameters. Let \( c \) be the number of classes and \( T, d, n, \) and \( b \) be defined as in 4.1.

Building DFs requires keeping all the samples in memory, so the data matrix requires a complexity of \( O(dn) \). When splitting nodes, two \( c \)-length arrays record the class counts on either end of the split point. They are also used to evaluate the splitting criteria, such as Gini impurity and entropy. Fully grown trees have totally \( 2n - 1 \) nodes, which contain exactly one sample in every leaf. This term is dominated by the \( dn \) term, making DF’s space complexity \( O(dn + c) \).

SDF updates the tree structure with streaming data batches, discarding the old data after each fitting (Algorithm 2). Data storage only accounts for the current batch and has an average complexity of \( O(dn/b) \). The class counts remain the same, and fully grown trees also have the same maximum. Thus, SDF’s learning space complexity becomes \( O(dn/b + c) \), which is more efficient than DF’s.

### 5 Discussion

Our streaming tree algorithms: SDT and SDF utilize the simplest strategy of extending fitted decision trees (Algorithm 1 and 2). It maintains all the existing partitions and further splits the feature space with new data batches (Figure 1). This approach is easier to implement than Hoeffding bounds and Mondrian processes, as both methods modify the tree splitting mechanisms [11, 13, 26, 29]. Furthermore, SDFs achieve consistently high accuracy in diverse classification tasks and often perform as well as, occasionally even better than, state-of-the-art forests (Figure 2, 3 and 6). It is also more time and space efficient for SDFs to learn new information (Section 4). These results show that our methods avoid the problems of HTs and MFs, including low accuracy in some tasks and excessive memories in others (Figure 2 and 4). Thus, SDTs and SDFs establish a simple standard for streaming trees that could be readily applied to many real-world problems.

On some datasets with high complexities, batch trees and ensembles could achieve more accurate results if all samples are given at once (Figure 6 and 5). Nonetheless, this assumption is unreasonable in many real-world scenarios [7, 8]. In our experiments and actual practices, batch decision trees and forests need to store all available data and refit them every time a new batch of samples comes in. Even by restricting the number of refitting with certain criteria (e.g. a minimum amount of new samples), it would still cost significantly more computational resources than incremental updates (Section 4). Thus, our streaming trees provide an alternative solution to such tasks. As an SDF continuously improves
its partitions with new information, any differences in performance would eventually be eliminated by enough data batches. It is therefore more economical to keep updating an established streaming model than constructing a new batch forest from time to time.

Although our experiments focus on single in-distribution tasks, SDFs’ applications could be extended to solve OOD problems like distribution shift and continual learning [10, 21]. Technically, each extension of decision trees does not have to rely on samples from the same distribution or use the same splitting criteria. Old trees can also be replaced anytime if previous partitions fail to perform well on current data streams. Moreover, as supplemental data arrive, continual learning models could leverage SDFs to incrementally update existing tasks.

Overall, our method of incremental updates excels at simplicity, consistency, learning time and space efficiency, and extensibility. This approach could offer great development potentials and set a clear standard for streaming tree algorithms, focusing on real-world applications.

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Appendix A. Accuracy for OpenML-CC18 Tasks.

| Number of Train Samples | Accuracy | SDF-100T | DF-100T | MF-100T | Chance |
|-------------------------|----------|----------|----------|----------|---------|
| 2600,36,2              | 1        |          |          |          |         |
| 1600,16,26             |          |          |          |          |         |
| 500,4,3                |          |          |          |          |         |
| 1600,216,10            |          |          |          |          |         |
| 1600,76,10             |          |          |          |          |         |
| 600,9,2                |          |          |          |          |         |
| 1600,10                |          |          |          |          |         |
| 1600,6,10              |          |          |          |          |         |
| 1600,47,10             |          |          |          |          |         |
| 1200,9,3               |          |          |          |          |         |
| 4500,64,10             |          |          |          |          |         |
| 600,15,2               |          |          |          |          |         |
| 800,20,2               |          |          |          |          |         |
| 8800,16,10             |          |          |          |          |         |
| 600,8,2                |          |          |          |          |         |
| 3700,57,2              |          |          |          |          |         |
| 2600,60,3              |          |          |          |          |         |
| 800,9,2                |          |          |          |          |         |
| 700,18,4               |          |          |          |          |         |
| 36200,8,2              |          |          |          |          |         |
| 5100,36,6              |          |          |          |          |         |
| 600,19,5               |          |          |          |          |         |
| 3000,29,2              |          |          |          |          |         |
| 800,12,11              |          |          |          |          |         |
| 6200,617,26            |          |          |          |          |         |
| 700,70,4               |          |          |          |          |         |
| 600,4,6                |          |          |          |          |         |
| 60000,784,10           |          |          |          |          |         |
| 1200,37,2              |          |          |          |          |         |
| 1300,37,2              |          |          |          |          |         |
| 8700,21,2              |          |          |          |          |         |
| 400,21,2               |          |          |          |          |         |
| 1700,21,2              |          |          |          |          |         |
| 900,21,2               |          |          |          |          |         |
| 39100,14,2             |          |          |          |          |         |
| 3000,177,2             |          |          |          |          |         |
| 500,30,2               |          |          |          |          |         |
| 4300,5,2               |          |          |          |          |         |
| 800,41,2               |          |          |          |          |         |
| 4400,24,4              |          |          |          |          |         |
| 1300,256,10            |          |          |          |          |         |
| 500,10,2               |          |          |          |          |         |
| 2100,500,2             |          |          |          |          |         |
| 27600,118,2            |          |          |          |          |         |
| 2000,72,2              |          |          |          |          |         |
| 900,856,9              |          |          |          |          |         |
| 4900,51,6              |          |          |          |          |         |
| 1100,4,2               |          |          |          |          |         |
| 600,4,2                |          |          |          |          |         |
| 8800,30,2              |          |          |          |          |         |
| 400,39,2               |          |          |          |          |         |
| 36200,16,2             |          |          |          |          |         |
| 7900,32,5              |          |          |          |          |         |
| 8200,561,6             |          |          |          |          |         |
| 400,12,2               |          |          |          |          |         |
| 4400,40,11             |          |          |          |          |         |
| 54000,42,3             |          |          |          |          |         |
| 900,81,8               |          |          |          |          |         |
| 1600,27,7              |          |          |          |          |         |
| 400,20,2               |          |          |          |          |         |
| 3900,5,2               |          |          |          |          |         |
| 1400,6,4               |          |          |          |          |         |
| 1800,19,7              |          |          |          |          |         |
| 1600,240,10            |          |          |          |          |         |
| 56000,784,10           |          |          |          |          |         |
| 35900,6,3              |          |          |          |          |         |
| 77100,21,2             |          |          |          |          |         |
| 73600,1024,46          |          |          |          |          |         |
| 84800,3072,10          |          |          |          |          |         |
| 2600,1558,2            |          |          |          |          |         |
| 2500,180,3             |          |          |          |          |         |
| 400,20,2               |          |          |          |          |         |

Figure 6: Classifications on the OpenML-CC18 datasets with max sample size, number of features, and number of classes. The classifiers include: Stream Decision Forest (SDF) and Decision Forest (DF). All plots show averaged accuracy over five folds and are listed in the order of dataset IDs. Sample sizes correspond to respective datasets. In many tasks, SDFs perform as good, sometimes even better, than DFs. Moreover, SDF accuracy consistently increases with new samples across different data domains, which makes SDFs applicable to diverse real-world problems.
Appendix B. Wall Times for Three Selected Tasks.

Figure 7: Training wall times on the Splice (left), Pendigits (center), and CIFAR-10 (right) datasets. The panel titles include the maximum sample size, the number of features, and the number of classes. The classifiers include: Stream Decision Forest with 10 trees (SDF-10T), Decision Forest with 10 trees (DF-10T), Stream Decision Tree (SDT), Decision Tree (DT), Hoeffding Tree (HT), and Mondrian Forest with 10 trees (MF-10T). Each line represents averaged results from 10 randomized repetitions. Cumulative fitting times are shown for all estimators, and two batch estimators’ times include refitting at each sample size. SDTs are the most efficient in the CIFAR-10 task. SDFs take longer times in the Splice and Pendigits tasks, but are overtaken by HTs, batch DTs, and DFs in the CIFAR-10 task. MFs maintain similar time efficiency as SDFs. DFs are faster than DTs in the CIFAR-10 task, which could be attributed to the feature reductions.

In terms of training wall times, SDTs are the most efficient on the CIFAR-10 dataset (Figure 7, right). SDFs take longer times in the Splice and Pendigits tasks (Figure 7, left and center). However, on the CIFAR-10 dataset, HTs are the most inefficient streaming trees, even slower than the two streaming ensembles. Also, as sample size increases, time usage of batch estimators grows more quickly due to refitting, and they surpass SDFs around 2,000 samples. MFs take similar training times as SDFs. All training wall times grow linearly as sample size increases. Results are subject to implementation details of packages used (Section 2).