Incremental Random Forest Classifiers in Spark

by

Kathryn I. Siegel

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Author . . . .
Department of Electrical Engineering and Computer Science
May 20, 2016

Certified by . . . .
Samuel Madden
Professor, EECS
Thesis Supervisor

Accepted by . . . .
Christopher Terman
Chairman, Department Committee on Graduate Theses

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Abstract

This thesis presents a series of implementations of incremental random forests in Spark. My work draws from existing methods in online learning literature, but include several novel techniques. Through analysis of the performance of these implementations on varying workloads, I determine that tree regeneration is the best singular strategy for augmenting an existing random forest given an additional batch of training data. I also evaluate many hybrid strategies and show that regrowing a small proportion of trees is the best combined strategy with regards to time and performance. My results indicate that incremental growth strategies for online random forests are not useful for batched workflows. Overall, the system demonstrates significant performance gains when compared to the standard method of regrowing the random forest.

Thesis Supervisor: Samuel Madden
Title: Professor, EECS

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Chapter 1

Introduction

Random forests have become one of the most popular machine learning classifiers due to their robustness to noisy data, accuracy, and ability to handle "big data" workloads. However, the downside to using random forests is that, given additional training data, the random forest must be regrown from scratch. This work proposes several techniques to update a random forest incrementally without fully regrowing the classifier, as well as insight into the performance and robustness of these techniques on different workloads. Specifically, I explore incremental methods that are responsive to shifts in overall data distribution. I develop a custom incremental random forest classifier and provide a Scala API through which users can call incremental random forest methods.

Chapter two describes the existing literature in online and incremental random forests.

Chapter three describes the strategies I implemented for incrementally training random forests.

Chapter four contains performance and robustness metrics for each of the random forest implementations.

Chapter five describes a methodology for choosing a strategy for incremental random forests, as well as the overlying system that intelligently chooses between strategies at runtime.

Chapter six describes how my implementation fits into a larger system, Sherlock, a data science tool for accelerating the process of model building. I also address additional areas for research.

1.1 Batched Workflows

A common pattern in data science workflows involves training the same model on increasing amounts of data. Such workloads are common in analytics, where observations are continuously collected in log entries, as well as in Internet of Things (IoT) networks, where extensive data collection takes place offline and data is transmitted periodically. Existing machine learning tools retrain a model on the entire dataset when new data is added. This entails reiterating over every single data point in the dataset, even when the added batch has a minimal effect on the resulting classifier. As such, implementing incremental training in Spark random forests should drastically improve the performance of these classifiers on batched workloads. This research seeks to implement and expose a Scala API that will allow data scientists to add data to the random forest using one of several incremental strategies.

1.2 Random Forest Classifiers

This section introduces the mechanics of random forest classifiers. At a high level, random forests are collections of decision trees used for classification. Once grown, each decision tree classifies an unlabeled point by casting a vote, and the random forest reports the label with the most votes. [10]

My research involves the Spark Machine Learning (ML) implementation of random forest classifiers. Apache Spark is a scalable system developed at Berkeley that provides an engine for processing big data workloads. At its core is a structure called the resilient distributed dataset (RDD), which can be distributed over a cluster of machines and is fault-tolerant. A series of powerful libraries run on Spark and take advantage of its powerful cluster-computing capabilities. One such library is Spark MLlib, which contains a wide array of machine learning tools. In this research, I model my incremental random forest classifier on the Spark random forest classifier, for the purposes of maintaining optimizations within the codebase that take advantage of Spark's strengths. Since each batch in a batched workload may contain a large dataset, implementing an incremental classifier in Spark allows us to take advantage of Spark's distributed computing capabilities for every batch.

The Spark ML random forest classifier favors batched and aggregated computation over single-datapoint processing. Each dataset is first preprocessed into RDDs with aggregated information about each point and its features. The Spark random forest classifier then randomly samples the data (with replacement) according to a Poisson distribution, and assigns a random sample to each decision tree in the forest. Each decision tree is grown from the root using its sampled dataset; the splitting criterion for each node in a decision tree is determined with an element of randomness. Specifically, at each node, the set of features is subsampled randomly. For each of the resulting set of features, the classifier examines all possible values for that feature on which the data can be split. Among all of these candidate splits, the classifier chooses the split that maximizes the decrease in Gini impurity–the probability that a point randomly selected from the node would be misclassified. The algorithm terminates when the maximum tree height is reached or no training points are misclassified within each individual decision tree.

The existing Spark ML random forest classifier performs well given a large dataset. However, like all implementations of random forests, a change in the training dataset would mean retraining the random forest from scratch. Retraining from scratch would lead to a lot of repetitive computation; the aggregate composition of the dataset might not change significantly with the new batch, especially if each batch has far fewer data points than the overall dataset. This thesis presents work that allows random forest classifiers to be updated with each new batch of training data more efficiently, therefore saving time for data scientists and other users of Spark MLlib.

Chapter 2

Previous Work

Since Leo Breiman introduced random forests to the data science community in 2001 [10], researchers have tested various refinements of the algorithm. One area of focus has been augmenting the algorithm for online learning. This chapter describes the existing literature on incremental and online random forests.

2.1 Ensemble models

A random forest is a type of ensemble model, which average the predictions of many different "reasonably good" models to produce a prediction that better estimates the true hypothesis. Ensemble models are highly successful as machine learning tools, because they avoid the chance-dependent pitfalls of many singular models. For example, gradient descent methods can get stuck in local minima, but combining many models increases the chance that one will find the global minimum. Alternatively, even if none of the models in the ensemble produce the true hypothesis, averaging every prediction can lead to a a prediction that more closely matches the underlying truth. [3]

There are several established methods for aggregating model predictions in ensembles. The Bayesian voting algorithm iterates through all hypotheses produced by models in the ensemble, and then combines the results based on how likely the hypothesis is given the sample. Another method is to manipulate the training data via bagging, known as bootstrap aggregation, and boosting, known as weighted training. Bagging involves randomly sampling points with replacement from a common dataset; the default Spark implementation of random forests uses bagging over boosting. Other ensemble methods exist but are not utilized in Spark ML.

2.2 Online random forests

Standard random forests are offline classifiers; trees are built on static datasets. Offline classifiers are poorly suited for datasets for which additional data points become available incrementally. A prevalent example is logging; logs are published as actions take place within a system, and a classifier for these logs must take into account the new information to avoid becoming inaccurate. Similar problems requiring an online classifier are found throughout industry. For example, Yahoo uses an online classifier to characterize relevant articles to show each user on its homepage. In many of these use cases, retraining the classifier from scratch would take an excessive amount of time, given the enormous amount of existing training data. Since new batches of data are often far smaller than the size of the aggregate training data, the new data only shifts a classifier's behavior slightly. Retraining an entire classifier from scratch to capture slight shifts seems wasteful; online classifiers provide a far more efficient approach.

In this thesis, I study incremental random forest classifiers–forests that update themselves with new batches of data. Incremental forests are a subset online random forests; they are updated with new batches of data, rather than with one new point at a time. Batched updates can take advantage of Spark's strength, which is distributed, batched computation. Simply implementing an online random forest classifier in Spark would be computationally wasteful, as it would require a new Spark job for every additional point. Focusing on batched updates plays to Spark's strengths and addresses a sparser area of the machine learning literature. Existing online methods are easily extended into batched methods, and batched computation provides an opportunity for optimizations.

2.2.1 Saffari online random forests

The most well-known implementation of an online random forest is the Saffari implementation. [9] In offline mode, a Saffari random forest behaves like a typical random forest: each tree is created by sampling the original training set, the split at each node is chosen as the best among a random set of feature candidates, and predictions are made by summing conditional probabilities among all of the trees.

In online mode, trees receive a serial string of points and are grown in an extremely randomized fashion; at every node, tests and thresholds are chosen randomly. Specifically, when a node is created, it establishes a set of N random tests and maintains statistics on the left and right partitions created by each test. When a new point is added to the tree, the point's features place it in a leaf node. The algorithm then recalculates the gain $\mathrm{G_n}$ with respect to each test in that node n according to the following equation:

$$\mathrm{G_n} = \ell_n - \frac{|samples_l|}{|samples_n|} * \ell_l - \frac{|samples_r|}{|samples_n|} * \ell_r, \tag{2.1}$$

where ℓ indicates loss, l represents the left partition of a split, and r represents the right partition of a split. The Saffari algorithm splits a leaf based on two hyperparameters: α, the minimum number of samples a node must see, and β, the minimum gain a split must achieve. When both conditions are satisfied, the node splits.

The Saffari algorithm also specifies that trees can be discarded randomly, where the probability that a tree is discarded increases with its out-of-bag error. This trait allows the random forest to adapt to changes in the data distribution.

Saffari claims this algorithm is better than alternatives such as the Hoeffding tree algorithm (addressed later in this chapter), because it fits better to the inherent nature of decision trees. Empirically, Saffari random forests perform better than boosted forests. In my research, I test the efficacy of using the extremely randomized trees of the Saffari algorithm. I also experiment with the aforementioned split hyperparameters, tweaking my algorithm to select more optimal gain and points thresholds. Since the Spark random forest implementation closely matches the Saffari offline random forest implementation, many of my initial modifications to the Spark code to provide online learning capability are in line with the Saffari online-mode algorithm.

2.2.2 Denil online random forests

In "Consistency of Online Random Forests," Misha Denil et al. proposes and evaluates improvements to the Saffari online random forest algorithm. Denil online forests partition the sequence of data points into "structure" points and "estimation" points. [2] Structure points influence the structure of the tree but do not affect the predictions made in tree leaves. Estimation points do not influence the structure of the tree, but are used to re-estimate probabilities. The Denil algorithm uses the same split selection procedure as the Saffari algorithm. The paper shows that this refined implementation achieves a higher accuracy on complex datasets compared to a comparable implementation of the Saffari algorithm.

Much of the existing literature around online random forests acknowledges one primary setback: due to decision trees recursive structure, lower data cannot be used to correct earlier decisions. Both the Saffari and the Denil implementations have this flaw. The new few subsections address algorithms that involve regrowing part or all of select decision trees within a random forest. My research draws on both classes of techniques–incremental growth and regeneration.

2.2.3 Mondrian forests

Another type of online random forest is a Mondrian forest [7], which are comprised of augmented extremely randomized decision trees. The algorithm for building each Mondrian decision tree is as follows. We start at the root and allocate a budget, λ, for this node. Then, we recursively process each node by randomly choosing split locations on the ranges of feature values. For each point j, dimension d, and dimension-wise maximum and minimum u_{jd} and l_{jd}, let $E = \sum_d (u_{jd} - l_{jd})$. Then, these cuts each cost $\lambda' = \lambda - E$. If we can "afford" the cut, we split the node and assign budget λ' to each subinterval. The tree stops growing when no more cuts can be afforded at any leaf node. Throughout the growing process, we denote a split hierarchy using a time variable. A node's time variable τ is set when a split is made within that node; the value of this variable is equivalent to $E + \tau_{parent}$.

To adapt Mondrian trees for online learning, we use the time parameter to determine where a new cut should be inserted. Starting at the root, we recurse down the tree until the cost coefficient E_{new} for this new node is less than the cost coefficient E_{old} for some node. We then insert the new node as the parent of this old node and adjust all children nodes accordingly.

Mondrian forests achieve an accuracy very close to offline Breiman random forests and extremely randomized forests trained on the same fraction of the data. The Mondrian algorithm significantly outperforms the Saffari algorithm when trained in online mode on the same fraction of data. Furthermore, Mondrian forests were shown to adapt to new data an order of magnitude faster than simply regrowing a forest from scratch.

The drawbacks of Mondrian forests include its relative intolerance of irrelevant data. Because splits are random, irrelevant and relevant features are equally likely to be chosen; noisy features can then harm the overall accuracy of each tree. Additionally, a Mondrian forest in online mode might choose to insert a node close to a root, thus initiating recalculation of a large section of the tree.

While Mondrian forests outperform Saffari online random forests, regrowing a tree section requires passing through all of the data points yet seen. As datasets grow larger, the overhead incurred by additional passes through the data will outweight the efficiency gains of the algorithm. Mondrian forests have only been shown as more efficient than Saffari online random forests on datasets of a few thousand data points. As such, the optimal strategy should regrow parts of a random forest but should not require multiple passes over the data.

2.3 Concept drift

Concept drift describes changes in data distribution in an online learning setting that cause the mathematical relationships between the input variables and output predictions to change. These shifts cause ML classifiers trained on earlier data points to become inaccurate. The online random forest algorithms discussed earlier in this chapter adapt poorly to concept drift, as they accommodate new data by splitting leaves or regrowing small sections of trees in the forest. Concept drift can cause splits in nodes higher in the trees to become inaccurate, and a poor decision higher in the tree more significantly impacts performance than a mistake closer to the bottom. Online random forests adapt more poorly than other online classifiers to concept drift, as splits made in nodes are essentially permanent. In contrast, classifiers that use, for example, linear or logistic regression could just shift internal weights until the concept drift is accounted for.

Therefore, accounting for concept drift in online random forests requires regrowing trees–the decisions from these trees must counteract bad decisions from other trees resulting from wrong splits. Purely incremental strategies, or those that just split leaves, should not be the only methods by which online random forests adapt to change.

2.4 Combined strategies

Several papers in the literature use Hoeffding trees to grow online random forests. Hoeffding trees for online learning were first proposed in a paper by Domingos and Hulten; when growing, these trees maintain several candidate splits in each leaf, with the quality of each split estimated in an online manner. [4] In contrast with the minimum gain parameter controlling splits in Denil and Saffari random forests, Hoeffding trees use a measure of the Hoeffding bound to ensure that a split is optimal. Hoeffding trees split leaves when the Hoeffding bound indicates that the current best split is the optimal split, within reasonable certainty.

A paper by Bifet et al. describes an implementation of the Hoeffding tree algorithm that adapts to concept drift. [1] The algorithm grows Hoeffding trees of different sizes; the authors reason that smaller trees can adapt more quickly to concept drift, whereas larger trees are less sensitive to noisy deviations. The trees are occasionally either partly or fully regrown, depending on a metric called ADWIN that estimates drift. The Bifet paper's results show that the method is effective on small generated datasets with concept drift.

Abdusalam et al. developed an algorithm that grows random forests incrementally by using Hoeffding trees and selecting entire trees for replacement. Unlike the algorithm from the paper by Bifet et al., the system chunks a data stream, then processes data chunks serially. The algorithm detects concept drift using a two-window technique; if a tree's classification error between the two windows differs by an amount less than a threshold, it is not grown further. Otherwise, grow the tree incrementally. With every given batch, 25% of the trees are automatically regrown, with additional trees regrown if the system detects concept drift.

I take into account these algorithms when developing my system in Spark. Namely, my implementation heavily involves a balance between incremental growth and tree replacement, much like the algorithms in the Bifet and Abdusalam papers. I refer back to these previously-developed algorithms in my discussion of the Spark incremental random forests system developed in this thesis.

Chapter 3

Methods

This chapter describes the two main strategies I implemented for incrementally training random forests. I go into depth about the details of each implementation, hybrid strategies, and the API I exposed for use in Spark ML pipelines. My experiments seek to shed insight into which algorithms work best on different workloads.

3.1 Tree regeneration strategy

The first implemented strategy involves regrowing trees within the random forest. For every new incremental batch, the exposed Spark API allows an existing model to be updated with the new data. A set proportion of trees are randomly selected for replacement. The system then grows a random forest with the number of trees selected, and creates a new hybrid model with the maintained trees from the old model and the newly grown trees from the new model. To allow for the creation of hybrid models, I introduce an incremental random forest classification model. This model tracks metadata from previously-seen data and information about each tree in the forest.

3.2 Incremental growth strategy

The second implemented strategy involves incrementally growing existing trees in the forest, and is based off of the Saffari and Denil algorithms. A user can update an existing incremental random forest classification model with a new batch of data via the exposed Spark API. Because this model tracks metadata from previous batches of data, the system can determine the candidate splits that were considered during previous growth phases of the tree. The new data is divided into bins specified by the previously-calculated splits and used to split leaves of the tree.

I augmented the RandomForest class in Spark ML to store metadata about past runs in leaves. Specifically, the random forest metadata maintains a list of data splits by feature; these splits determine the "bins" to which each new point belongs. After the new batch of data is processed into bins, I merge this information with the information stored in each leaf. To provide leaves with ability to store metadata and merge in new batches of data, I implemented a custom incremental leaf node class that replaces the customary Spark-provided leaf node class. This class maintains the capabilities of the original Spark leaf node, but allows for changes to be made to each tree in the random forest.

Once the new metadata is aggregated at each leaf, the system splits leaves that newly pass both requisite thresholds: the minimum number of points a leaf must account for and the minimum information gain from the split. After each tree is incrementally grown, the system returns a new incremental random forest model with updated metadata to the user.

3.3 Optimizations

3.3.1 Bounding incremental growth

Since datasets can have many features, unbounded tree growth can result in extremely deep trees after just a few batches. The largest tree height supported by Spark ML is 30, after which trees can no longer be grown incrementally. Additionally, splitting leaves in tall trees imposes a large performance overhead, as the algorithm must examine a large number of candidate leaves. As a result, the system restricts the maximum initial tree height to a set value h, relaxing this restriction by one for each incrementally grown tree that receives a new batch of data. In all hybrid strategies, a tree is replaced when it reaches a certain threshold depth. When a tree is regrown, its maximum height is reset to the original value h. This technique prevents the incremental random forest from overfitting to earlier batches and allows the forest to better adapt to concept drift, as it ensures that later batches can significantly impact tree predictions.

3.3.2 Batched processing

The incremental random forest implementations in the Saffari and Denil papers describe accumulating points in leaves until the leaf is split. In the purely online setting, accumulating points one at a time is the only option. Since batched workloads allow for many points to be processed at one time, we can preprocess the batch into metadata structures that are passed to the relevant leaves and merged with the existing leaf metadata. This optimization prevents the system from having to run back over all previous batches to decide on a split.

3.3.3 Tree reweighting

In the batched incremental learning setting, the classifier receives an unlabeled batch of points, predicts the label for each point, and then views the labels to assess its accuracy. Each tree in the random forest has a different accuracy on a particular new batch of data. To increase the overall accuracy of the forest, after the system assesses the accuracy on each new batch, it weights the trees with lower accuracy to have less voting power on the next batch. Because this increases the chances of overfitting, the system restricts the extent to which tree weights can shift.

To account for concept drift, I weight trees by age. With every new batch, trees that are not regrown are weighted to have less voting power. As a result, the classifier captures information from previous batches, but uses information from the most recent batch more heavily in the classification of the next batch.

3.3.4 Leaf subsampling

As tree height increases, the amount of computation required to grow the tree one level increases significantly. However, adapting an existing tree to a new batch of data does not necessarily require splitting every leaf in the the tree on the new data. Instead, the system can select a random sample of the leaves in the tree, and only consider these leaves for incremental growth. While this optimization decreases the performance of shallow random forests, for deep forests, it helps improve the training time without significantly impacting the performance.

3.4 Hybrid approach

The tree regeneration and incremental growth strategies are compatible; both can be used simultaneously within an incremental random forest. This thesis explores various hybrid approaches and provides insight into which approaches work best on datasets with and without concept drift. For each hybrid approach, I vary the proportion of trees that are grown with each strategy. The system selects trees without replacement to be replaced or grown incrementally; the remaining trees are unchanged. I also implement several optimizations for this approach that are applied to all trees after every batch.

3.5 Experiments

In my research, I experiment with several different parameters that affect the error rate of my incremental random forest classifier. I hypothesize that certain parameters used to build each incremental random forest will affect the optimal incremental strategy for that forest on my test datasets. I vary the following parameters in my experiments and report the effect on the optimal hybrid incremental algorithm.

1. **Tree depth.** I vary the initial maximum height of each tree in the random forest. In my experiments, I use two initial heights: shallow and deep, which represent heights of 5 and 10, respectively. I chose 10 to be the sample height for deep trees, as it is the most commonly used height in the literature to obtain a high accuracy without overfitting. A shallow tree height of 5 still provides some accuracy, but allows the tree to adapt more significantly to concept drift in incremental batches.

2. **Tree count.** I vary the number of trees in the forest. In my experiments, I test two tree quantities: narrow and wide, which represent tree counts of 10 and 100, respectively. These two tree quantities are most common in the literature; 10 trees are used when training time is a large concern, whereas forests with 100 trees are typically more accurate.

3. **Concept drift.** I test the performance of the incremental random forest classifier on two datasets: one with concept drift and one without concept drift. The dataset with concept drift is sampled from the United States Department of Transportation Airline On-Time Statistics and Delay Causes dataset; the classifier predicts whether a flight is delayed, and flight delays naturally shift over the course of a year. [8] The dataset without concept drift is from the Homesite Quote Conversion Kaggle competition; the classifier predicts whether a quote will convert into a purchase. [5]

3.6 API

My custom incremental random forest classifier class, IncrementalRandomForestClassifier, exposes a Scala API for data scientists to use. I introduce a new model class, the IncrementalRandomForestClassificationModel class, which is an augmented adaptation of the Spark ML RandomForestClassificationModel class that allows for incremental optimizations. The table in figure 3.1 details the methods available for use in Spark ML pipelines.

Method	**Description**
def train(df: DataFrame): IncrementalRFClassificationModel	Trains a model for future online learning by maintaining tree and leaf metadata.
def update(old: IncrementalRFClassificationModel, df: DataFrame): IncrementalRFClassificationModel	Updates an existing model with a new batch of data by regrowing some trees and incrementally growing others.
def addTrees(oldModel: IncrementalRFClassificationModel, df: DataFrame, addedTrees: Int): IncrementalRFClassificationModel	Trains a model using a warm start by adding more trees to the existing forest.
def setRegrowProportion(prop: Int)	Set the proportion of trees in the forest that should be regrown with every new batch.
def setIncrementalProportion(prop: Int)	Set the proportion of trees in the forest that should be regrown with every new batch.
def setInitialMaxDepth(depth: Int)	Set the initial depth of newly-grown trees.

Table 3.1: Scala API for the incremental random forest (RF) classifier developed in this thesis.

Chapter 4

Results

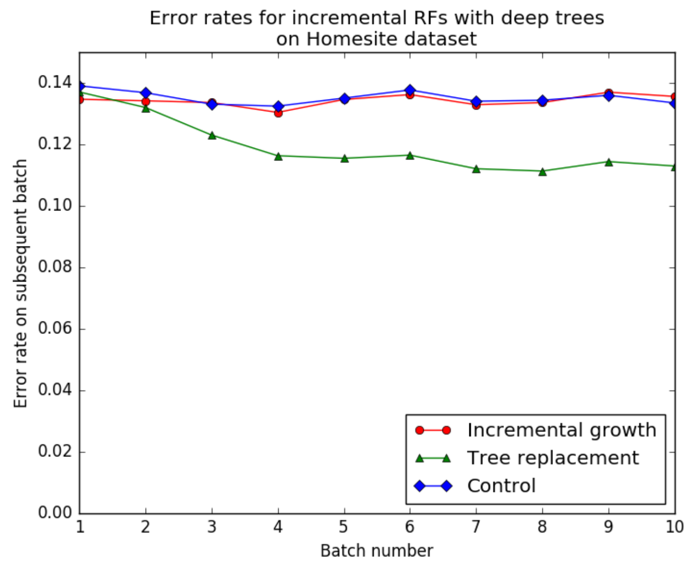
In this chapter, I analyze the benchmark results and discuss their implications for data scientists using incremental random forest classifiers. In each trial, each incremental random forest classifier received batches sequentially, retraining itself after every new batch. For each tested workload, I first contrast the performances of the incremental growth and tree replacement strategies, and then I analyze a range of hybrid strategies and explore the ideal hybrid strategy based on concept drift.

4.1 Workload A: Large batches, no concept drift

The Homesite Quote Conversion dataset is a Kaggle dataset that provides over fifty numerical and categorical metrics on each of 200,000 customers. The classification goal is to determine whether a potential customer will purchase home insurance given the provided metrics about their quoted price, previous activity, coverage information, and more. [5]

To study how incremental random forests would perform on workloads with large batch sizes and no concept drift, I randomly divided the Homesite dataset into ten batches of 20,000 data points each, and ran tests using both deep and shallow random forests. By contrasting the error rates over time, I provide insight into how these forests adapt over time.

As seen in Figures 4-1 and 4-2, in forests with deep trees, the incremental growth



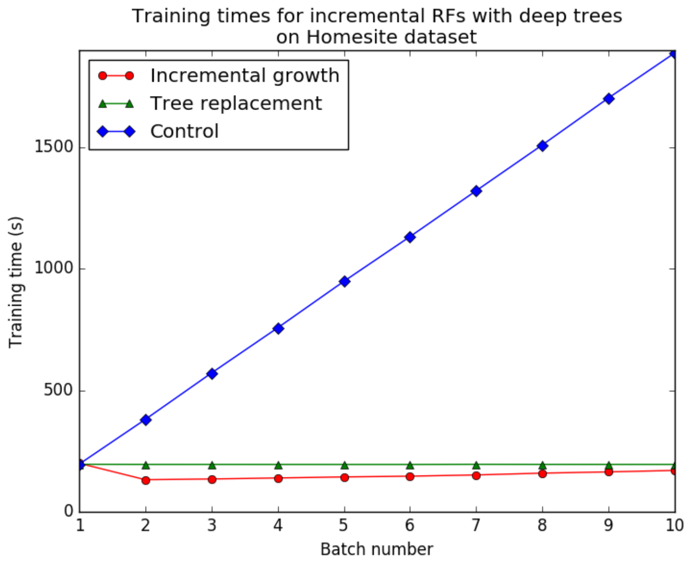
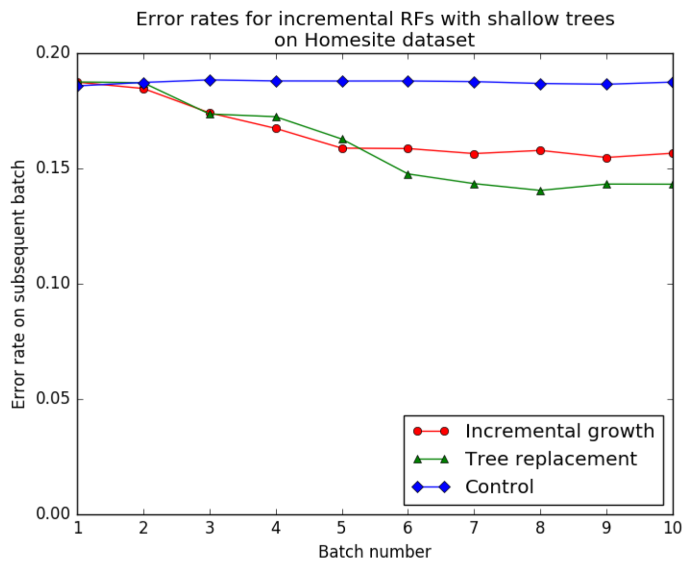


Figure 4-1: These graphs show the error rates and training times for the incremental growth strategy, the tree replacement strategy, and the control setting on the batched Homesite Quote Conversion dataset. In this benchmark, the random forest classifiers grow deep trees.



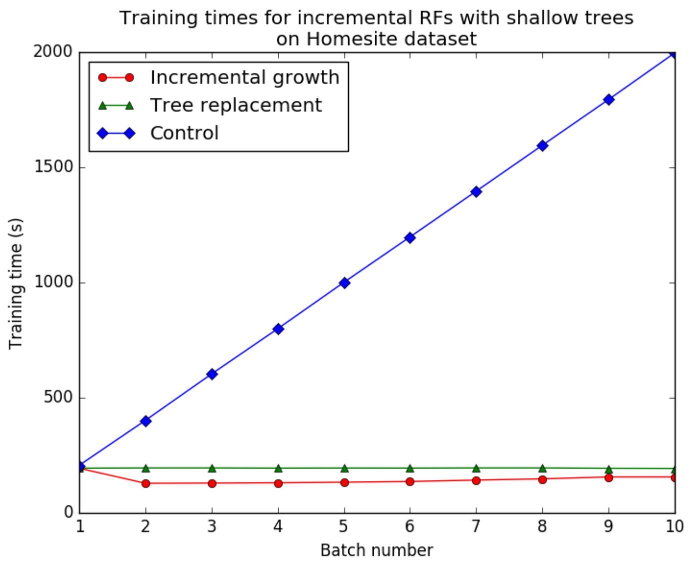


Figure 4-2: As with the graphs on the previous page, these graphs show the error rates and training times for the two experimental strategies, as well as the control. This benchmark, in contrast, measures random forest classifiers grown with shallow trees.

strategy performed just as well as the control, while the tree replacement strategy achieved an error rate over 2% lower. Because each batch contained 20,000 data points, the random forest classifier was able to fit the data distribution accurately by just training on the first batch of data. Since the dataset exhibited no concept drift, once the data distribution was learned to a sufficient degree of accuracy, incrementally growing each tree on new batches did not change the classification behavior of the forest. As a result, the incremental growth strategy did not improve the performance of the random forest. Similarly, incorporating each additional batch into the tree by regrowing from scratch did not improve the accuracy of the random forest. However, the tree replacement strategy was able to better fit to the data over time by replacing the trees with a lower overall classification accuracy; since the batch size was large, if a tree had poor classification performance on one batch, it likely would have poor performance on future batches.

In contrast, in forests with shallow trees, the incremental growth strategy performed far superior to the control, and almost as well as the tree replacement strategy. Shallow trees more easily adapt to new data; in traversing a decision tree from the root to a leaf, the information gain in each leaf necessarily decreases with every level. Initially growing shallow trees allows for future batches to more significantly impact the decisions made by the forest.

As expected, retraining the entire tree from scratch on all data caused the training time for the control setting to be much higher on later batches than the training time for the experimental settings. The training times for the incremental growth strategy were slightly smaller than the times for the tree replacement strategy, regardless of tree depth.

Overall, for workloads such as the Homesite Quote Conversion batched dataset, a large batch size and stationary distribution of data points indicates that a pure replacement strategy is optimal to minimize error rate.

TODO hybrid strategies

TODO

Figure 4-3: These two plots show the average error rates of various hybrid tree replacement and incremental growth strategies on the Homesite batched dataset. The axes indicate the percentage of trees that are modified according to each strategy.

4.2 Workload B: Small batches, no concept drift

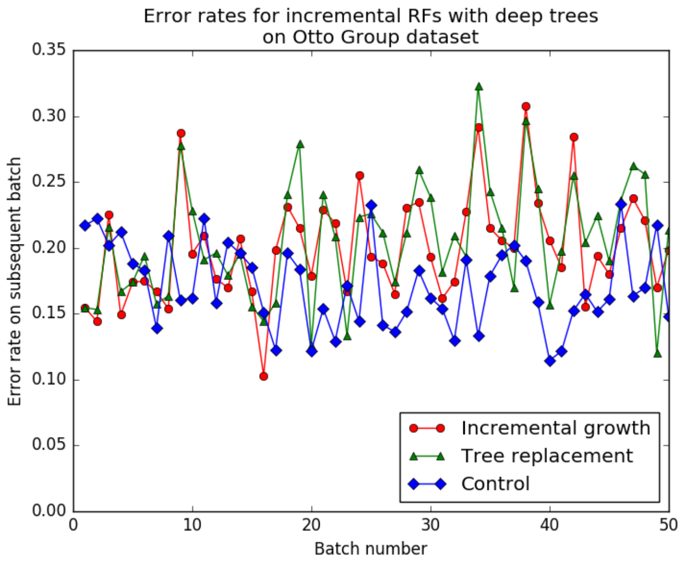
The Otto Group Product Classification dataset contains 200,000 data points representing products sold by the Otto Group. Each data point is characterized by nearly 100 numerical features representing qualities of each product; the classification task is to distinguish one particular product category, "Class 2," from the others. By randomly downsampling the dataset, I segmented the data into batched workloads of approximately 100 points per batch, much smaller than the 20,000-point batches of the Homesite dataset. [6]

My initial analysis, as with the Homesite dataset, involved contrasting the performance of the two incremental random forest strategies on the data. I trained random forest classifiers using each of the two strategies on fifty 100-point batches of the Otto dataset to demonstrate any trends over time.

As seen in Figures 4-4 and 4-5, unlike with the Homesite workload, there is no pure strategy that demonstrates the lowest error rate across all batches. This observation is consistent both in random forest classifiers with deep trees and in those with shallow trees. As expected, the control again demonstrates the largest training time after each batch, as it must be retrained from scratch on the aggregate data.

Because the results do not indicate a clear dominant strategy, I instead examine various hybrid approaches—strategies that combine both incrementally growing and replacing trees. As seen from the data in Figure 4-6, for smaller batch sizes such as 100, strategies that involve only incremental growth generally perform better than strategies that incorporate some proportion of regrown trees. This trend is present in both random forest classifiers comprised of deep trees and those with shallow trees, though the trend is stronger among forests with shallow trees.

Trees grown on one batch naturally overfit to that batch. With a small batch



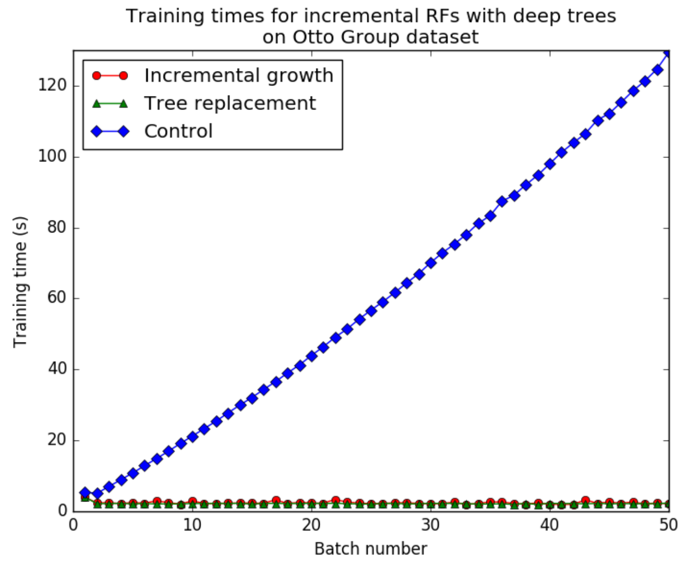
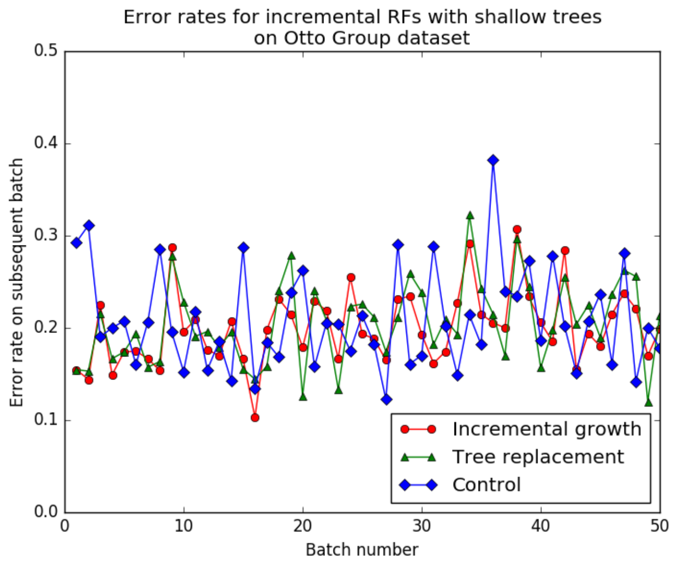


Figure 4-4: These graphs show the error rates and training times for the incremental growth strategy, the tree replacement strategy, and the control setting on the batched Otto Group Product Classification dataset. These metrics were taken on online random forest classifiers growing deep trees.



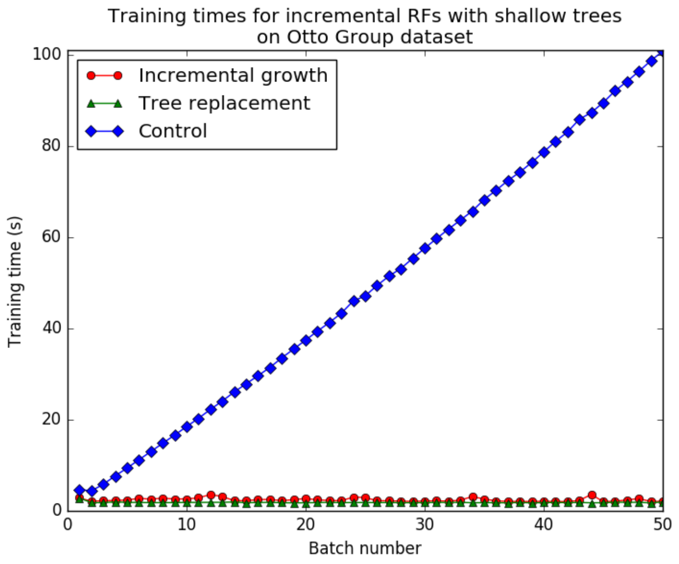
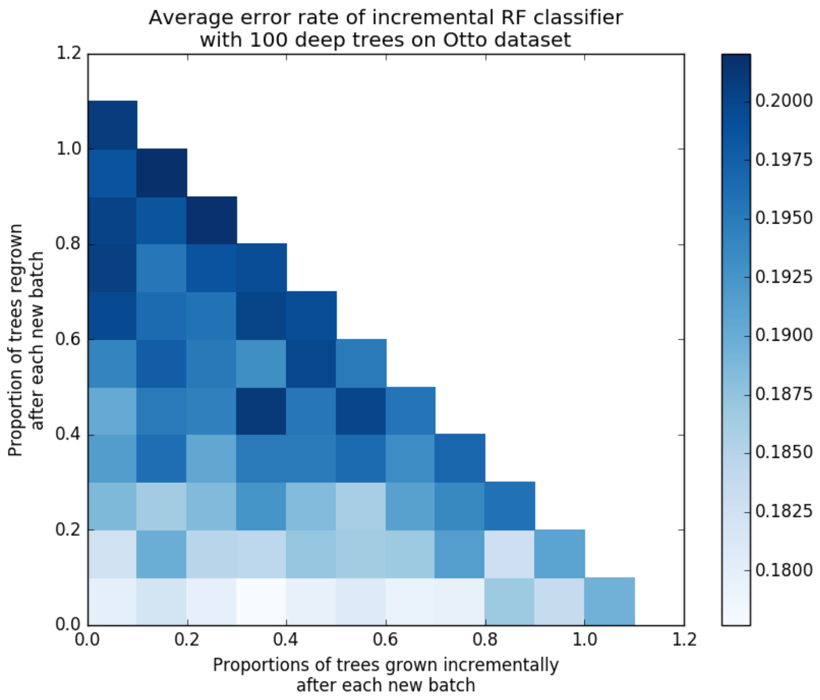


Figure 4-5: As in the previous figure, these graphs show the error rates and training times for the two experimental strategies and the control on the Otto Group dataset. These benchmarks were measured on online random forest classifiers growing shallow trees.



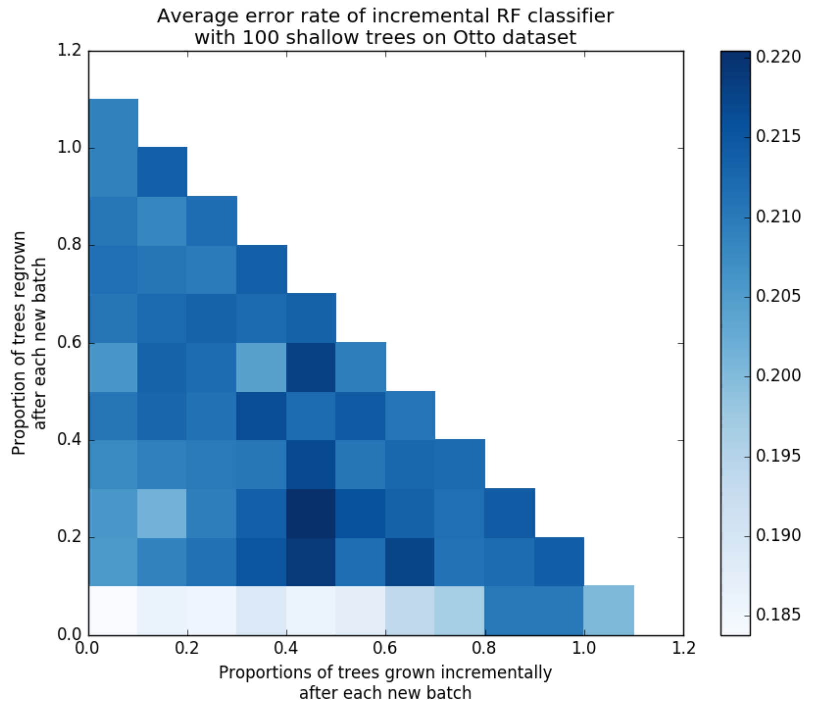


Figure 4-6: These two plots show the average error rates of various hybrid tree replacement and incremental growth strategies on the Otto Group batched dataset. The axes indicate the percentage of trees that are modified according to each strategy.

size, there is a higher likelihood that data distribution differs from the overall data distribution of the full dataset. As such, tree replacement strategies could grow trees that fit well to one batch, but that fit poorly to the rest of the data, increasing the error rate. Incremental growth incorporates the data from multiple batches into each tree, mitigating the effect of overfitting to the wrong data distribution.

Overall, these results demonstrate that data scientists using incremental random forests on workloads with small data batches should utilize a strategy that only involves incremental growth. Figure 4-6 indicates that the specific proportion of trees that are incrementally grown can vary with little impact on accuracy, so data scientists should choose a smaller ratio to minimize training time.

4.3 Workload C: Large batches, concept drift

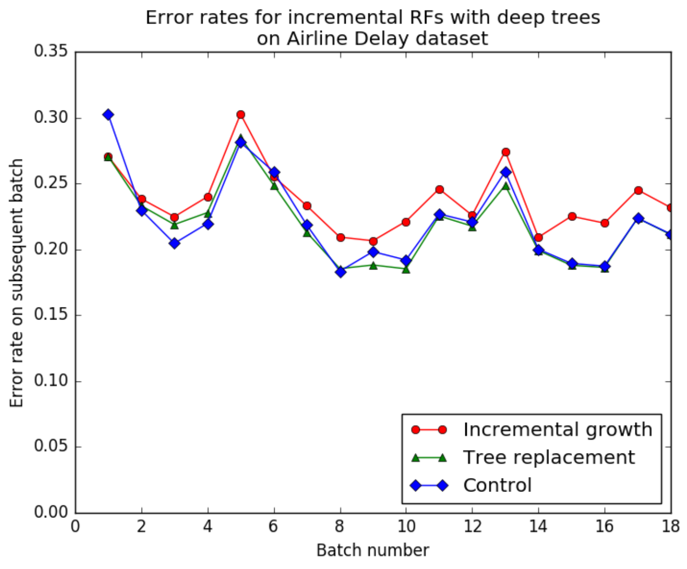
The US Department of Transportation Airline On-Time Statistics and Delay Causes dataset contains information about every flight that took place in the last decade. I used 18-months of this dataset, beginning in January 2014, for my analysis. Because the distribution of airline delay data varies seasonally, this dataset exhibits concept drift. Each month of data translated to a 10,000-point batch in an 18-batch data workload. [8]

TODO plane data analysis

TODO force extreme concept drift with otto dataset

4.4 Workload D: Small batches, concept drift

TODO plane data analysis



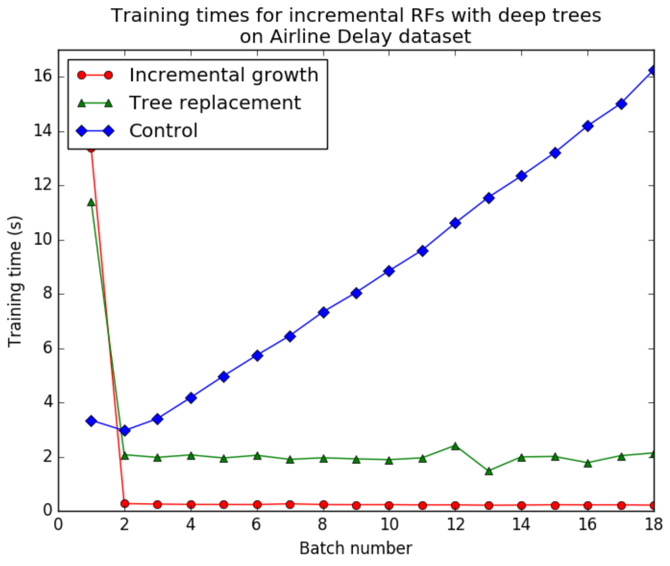
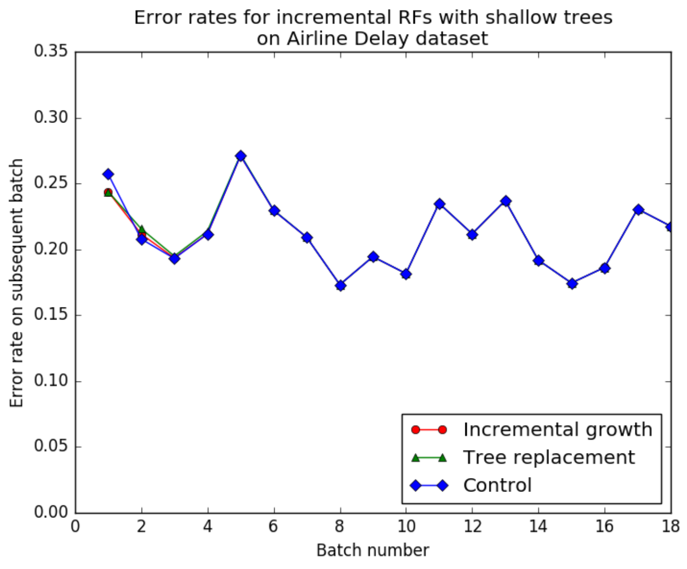


Figure 4-7: airline data

Figure 4-8: These graphs show the error rates and training times for the incremental growth strategy, the tree replacement strategy, and the control setting on the batched Airline Delay dataset. These metrics were taken on online random forest classifiers growing deep trees.



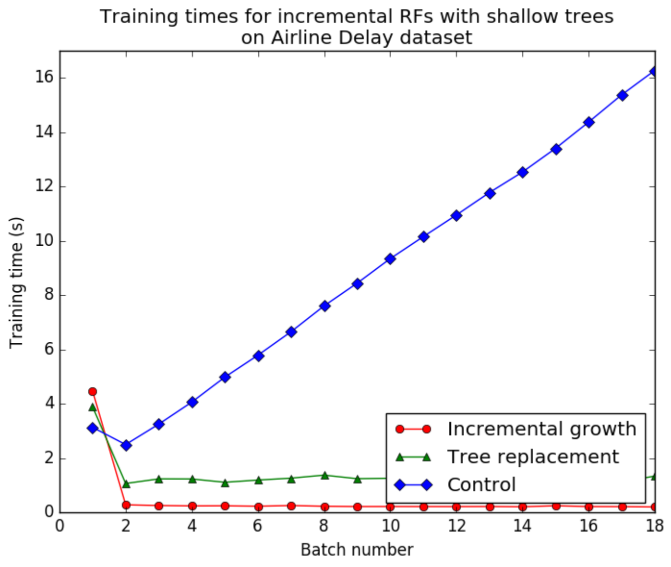
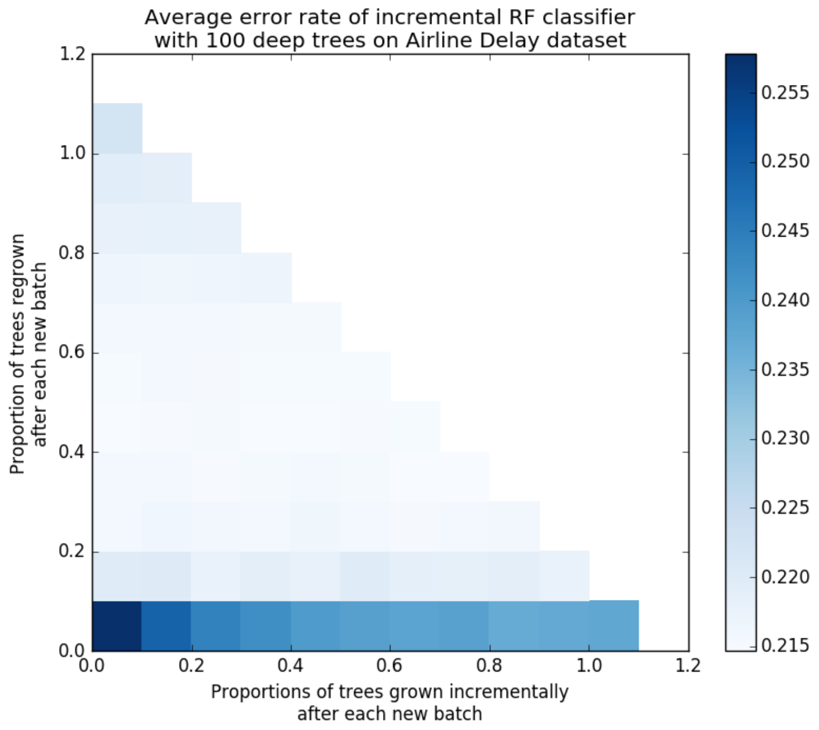


Figure 4-9: airline data

Figure 4-10: As in the previous figure, these graphs show the error rates and training times for the two experimental strategies and the control on the batched Airline Delay dataset. These benchmarks were measured on online random forest classifiers growing shallow trees.



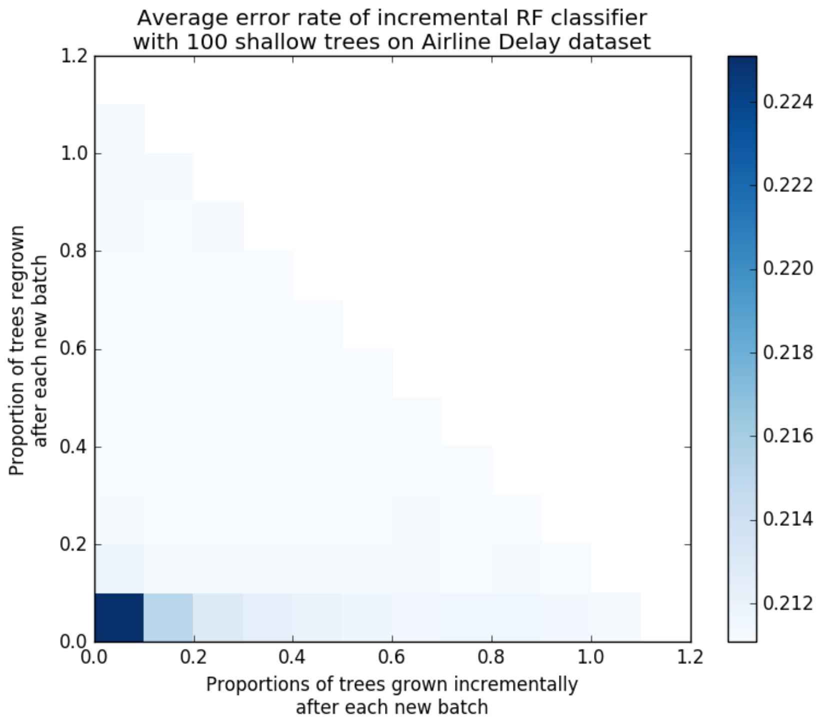
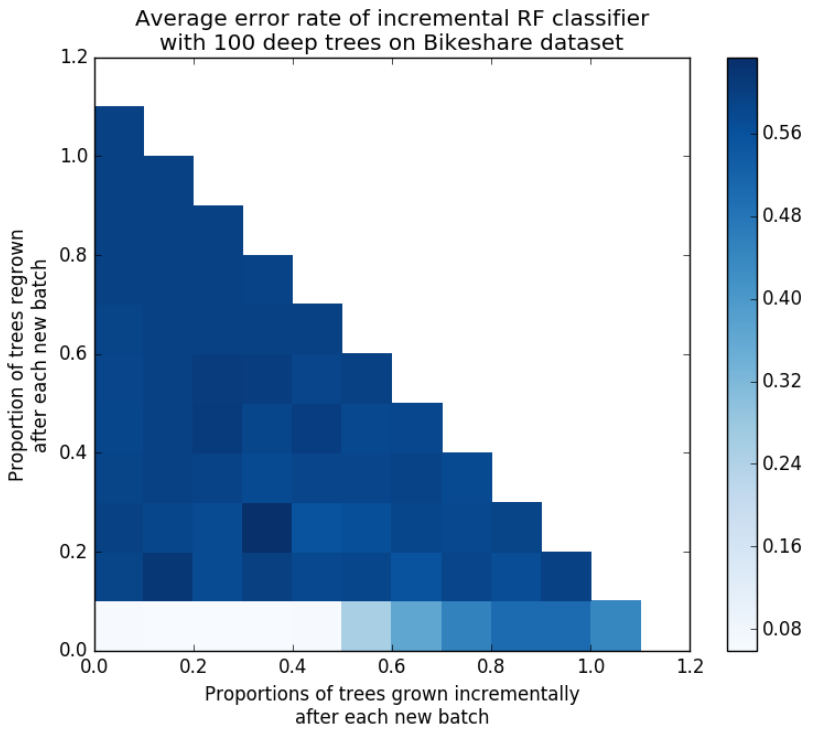


Figure 4-11: These two plots show the average error rates of various hybrid tree replacement and incremental growth strategies on the Airline Delay batched dataset. The axes indicate the percentage of trees that are modified according to each strategy.



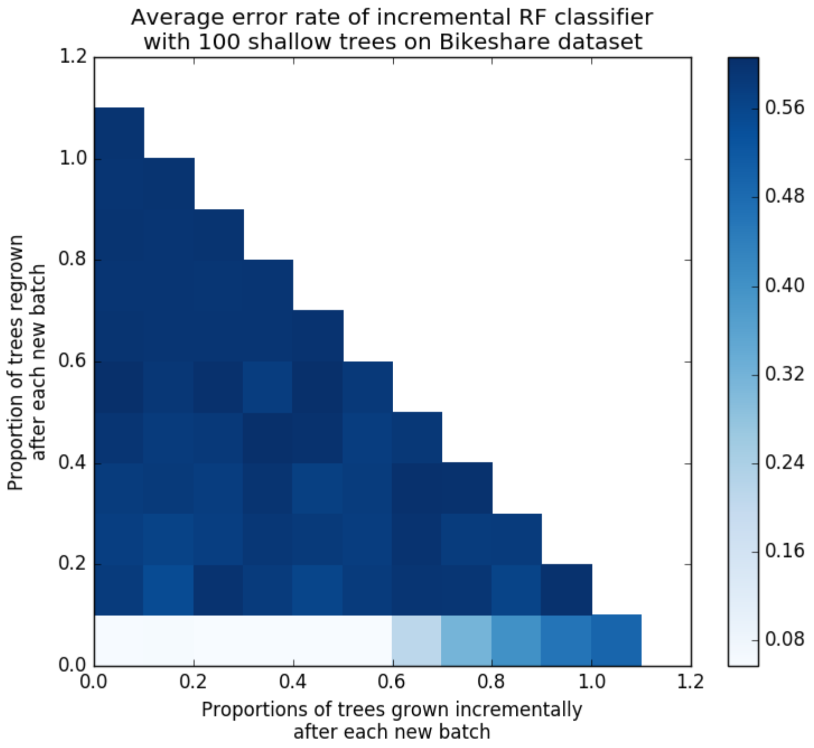


Figure 4-12: These two plots show the average error rates of various hybrid tree replacement and incremental growth strategies on the Bike Sharing batched dataset. The axes indicate the percentage of trees that are modified according to each strategy.

Chapter 5

Conclusion

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